Asset pricing of carbon emission disclosure*

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Abstract

The Science Based Targets initiative (SBTi) aims to reduce carbon emissions among participating firms. We suggest a multi-factor specification that augments the traditional factor models with the SBTi risk factor. We then apply the EIV-bias-corrected cross-sectional regression approach to investigate whether (i) there exists a SBTi transition premium, and (ii) this premium is priced as a systematic risk or firm-level characteristic. Based on a sample of 757 SBTi committed international firms and a control group consisting of 748 peers as non-committed firms over the period 2018-2022, we find a positive SBTi transition premium. The statistically significant alphas indicate inabilities in pricing this SBTi transition premium via the classical Fama-French multi-factor models. We find that the SBTi characteristic explains the transition premium.

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1 Introduction

Investors often take the environmental, social, and governance (ESG) aspects of companies into account when making investment choices, as evidenced by studies such as Avramov, Cheng, Lioui and Tarelli (2022). However, there is less research regarding the extent investors incorporate carbon emission uncertainty in their decisions. This is particularly intriguing considering the direct connection between global warming concerns and human-generated carbon dioxide emissions. The Science Based Targets initiative (SBTi) aims to reduce carbon emissions among participating firms, and we investigate whether investors recognize the reduction efforts from these firms.

While the existence of an ESG risk premium is well documented (e.g., Pástor, Stambaugh and Taylor, 2021; Avramov et al., 2022), the literature on carbon emission disclosure is less conclusive. Bolton and Kacperczyk (2021) discover that stocks associated with higher total carbon dioxide emissions generate greater returns. This suggests that investors require compensation for investing in firms that carry higher risk. In a separate study, Antoniuk (2022) examines Norwegian firms involved in the Carbon Disclosure Project and observes that stocks with lower carbon risk consistently outperform stocks with higher risk, thus suggesting a premium for low-risk stocks.

We propose that the validation of carbon emission reduction targets by SBTi (Science-Based Targets initiative) serves to decrease uncertainty and amplify investor demand. This notion bears similarity to investors' preference for stocks with lower ESG rating uncertainty, as demonstrated in Avramov et al. (2022). To investigate carbon emission disclosure, we employ the methodology developed by Chordia, Goyal and Shanken (2017), which has been utilized in studying the ESG premium by Ciciretti, Dalò and Dam (2023). This approach enables us to discern whether investors favor SBTi validated firms due to factors unrelated to risk and return or if the premium is connected to an underlying common carbon risk factor.

This paper considers firms with publicly available ESG assessments and carbon emissions and examines the risk premia of voluntarily adopting the STBi standard for setting science-based carbon emission targets and investments to achieve those targets.[1] Our study uses SBTi information to identify a selected group of firms that set an emission target and received an expert validation of these targets. Targets adopted by companies to reduce carbon emissions are considered "science-based" if they are in line with what the latest climate science says is necessary to meet the goals of the Paris Agreement to limit global warming to well below 2°C above pre-industrial levels and pursue efforts to limit warming to 1.5°C.[2]

The validation for the target firms we observe occurs in January 2020 and is considered an

[1]Scientific Based Target initiative (SBTi) is a collaboration between the CDP (Carbon Disclosure Project), the United Nations Global Compact, World Resources Institute (WRI), and the World Wide Fund for Nature (WWF). See https://sciencebasedtargets.org/companies-taking-action/

[2]SBTi covers firms' climate emissions from their own operations (scope 1), purchased energy (scope 2), value chains both upstream, in the form of emissions from input goods, and downstream, such as user routes and waste management (scope 3).

"event" that may imply a financial impact. Only a minor fraction of listed firms in the Eikon database have been SBTi-validated in early 2020. While we provide evidence of positive risk-adjusted returns those might not be persistent as more firms will adopt stricter emission regulations, and investors will become better informed about the emission reduction strategies of firms. Consequently, information asymmetries will be reduced as more firms disseminate trustworthy information on reduction strategies.

We contribute to the literature on carbon emission disclosure in several ways. First, we provide evidence on a negative risk premium for SBTi validated stocks. We argue that validation by SBTi is an event well suited for testing whether a reduction in uncertainty regarding carbon emission disclosure is priced by investors. Second, our methodology is not only robust for testing the existence of a risk premium, it also offers the possibility to discern whether the premium is connected to an underlying common risk factor or whether investors value SBTi validation as a firm characteristic.

The remainder of this paper is organized as follows. Section 2 provides a background, reviews related literature, and develops our hypotheses. Section 3 describes the methods used for the analysis including the SBTi risk factors and cross-sectional regressions. Section 4 describes the data, and presents the results, as well as, robustness checks. Section 5 concludes.

2 Background

2.1 Climate-related disclosures

By linking the quantitative backward-looking performance of a firm with forward-looking strategic, qualitative information, legally binding documents, such as annual reports, provide fundamental mandatory information to the financial market on risk and opportunities (see e.g., Edmans, Heinle and Huang, 2016). The key explanatory variable for this paper, however, is voluntary disclosure of firm information with a focus on the link between climate action and market response. Although firms experience increasing pressure from shareholders and stakeholders to disclose information on plans and strategies to lower their greenhouse gas emissions (Plantinga and Scholtens, 2021; Qian and Schaltegger, 2017), many companies still choose to refrain from openly reporting how they manage their impact on the climate.

Why do some companies decide to openly report their strategy for reducing their climate footprint and also allow independent experts to review both goals and methods, while others do not? Different branches of the literature discuss firms' consideration of the option to share non-mandatory information that can have both positive and negative financial effects. While the adverse selection theory, for instance, assumes that firms voluntarily disclose information only if they benefit from revealing what they know (Milgrom, 1981; Grossman and Hart, 1980), Diamond

(1985) suggest that a policy of disclosure of information improves risk sharing and may make all shareholders better off than a policy of no disclosure. The self-categorization theory (Hogg, 2000) relates disclosure to agents' attempts to reduce uncertainty in external evaluations of their quality by projecting a clear definition of what it stands for by attaching itself to a specific social identity of high status.

Voluntary climate-related disclosure is an attempt by firms to identify, signal, and communicate to the market about their awareness and, thereby, show that they belong to a category of firms that are taking actions towards climate protection (Smaldino, 2022). A main aim of signaling and credibility-motivated disclosures of specific climate commitments may be to reduce information costs for investors, thereby reducing a general or sector-specific climate risk uncertainty premium Bolton and Kacperczyk (2021). These arguments are in compliance with Matsumura, Prakash and Vera-Munoz (2014), while Hösli (2021) gives evidence of the opposite. Exploring carbon emissions data from 2006 to 2008, which were voluntarily disclosed according to the Carbon Disclosure Project by S&P 500 firms, Matsumura et al. (2014) find that the markets penalize all firms for their carbon footprints, but a further penalty is imposed on firms that do not disclose emissions information. Using the District Court of The Hague's decision in the matter of the oil fossil-fuel company Shell as an example, Hösli (2021) suggests that firms, in general, have the incentive to rely on vague wording in their climate disclosures to mitigate the risk of being sued for potentially misleading information.

Since jurisdictions generally do not ask for mandatory climate target setting, it is up to the market itself–together with different stakeholders–to set up frameworks for reporting climate actions and performances. Many of these initiatives set standards based on a science-based premise. Freiberg, Grewal and Serafeim (2021) examine determinants and consequences of adopting such external science-based standards for setting carbon-emission reduction targets. Studying nearly 1,800 firms from around the world, the paper reports that firms are more likely to set science-based emission targets if they perceive climate-change-related risks and have carbon-intensive operations, while the study does not provide any general conclusions about the effect of setting targets on carbon emissions. In related research, Bingler, Kraus, Leippold and Webersinke (2022) study three major climate initiatives aimed at creating frameworks to help public firms and other organizations disclose climate-related risks and opportunities. The authors apply textual analysis on climate disclosures in close to 15,000 annual reports for the years 2010-2020 to study the major climate initiatives SBTi, the Task Force on Climate-Related Financial Disclosures (TCFD)[3] and the Climate Action 100+ (CA100+).[4] The analysis reveals that the CA100+ engagement initiatives by institutional investors considerably increase the quality and decision relevance of investees' disclosures of climate-related commitments and actions. However, voluntary or mandatory TCFD

[3] https://www.fsb-tcfd.org
[4] https://www.unpri.org/collaborative-engagements/climate-action-100/6285.article

disclosures need additional standardization and guidance to ensure that the disclosed information is valid. They also find that the SBTi third-party climate target setting and action validation lack information on the timeline, the actual implementation of precise measures, the progress tracking of the targets, and what happens for the periods between the commitment to set the target, the target submission, and the target verification.

Summarizing the growing body of literature on climate-related disclosures, including Bolton and Kacperczyk (2021); Bingler et al. (2022); Grewal, Riedl and Serafeim (2019); Freiberg et al. (2021); Hong, Li and Xu (2019); Kölbel, Heeb, Paetzold and Busch (2020); Krueger, Sautner and Starks (2020) and others, a general conclusion is that disclosures are important for financial management of risk and opportunities at the same time as the various contemporary initiatives are characterized by shortcomings regarding methods and standards, such as being imprecise, inaccurate, and greenwashing prone.

2.2 Empirical evidence

The financial impact of firms' actions to reduce their own climate risks as well as to contribute to science-based emission goals is still an open research question. The empirical results from a huge and growing number of studies using more or less open data sources vary substantially depending on indicators (ESG retrieved from various providers, TCFD, CA100+, the Carbon Disclosure Project (CDP))[5], or to a small degree SBTi), type of asset (stock or portfolio of stocks), and performance measure (ROE, Tobin's Q, return, excess return, Value of Risk, Value of Return, and so on).

Using portfolio analysis to investigate whether sustainable strategies outperform benchmark portfolios, as we do in this paper, the existing studies provide mixed results, regardless of whether the sustainability measure is ESG scores, CDP information, or other corporate social responsibility (CRS) data. Below are a few examples across regions from a number of studies. Exploring portfolios with Chinese data, He, Ren and Zeng (2022) report that environmentally validated stocks do not outperform control portfolios. Most studies on European stocks suggest no difference between CSR portfolios and benchmarks (see Antoniuk, 2022; Auer and Schuhmacher, 2016; Fiskerstrand, Fjeldavli, Leirvik, Antoniuk and Nenadić, 2020; Leite, Cortez, Silva and Adcock, 2018; Steen, Moussawi and Gjolberg, 2020). A conflicting result for Europe is reported by Alsaifi, Elnahass and Salama (2020) who find that investors respond significantly negatively to carbon disclosure announcements via CDP. Using portfolios of Brazilian stocks, Cunha, de Oliveira, Orsato, Klotzle, Cyrino Oliveira and Caiado (2020) find evidence that carbon-efficient companies outperform the market as well as the sustainability index. Soler-Domínguez, Matallín-Sáez, de Mingo-López and Tortosa-Ausina (2021) find that American and Canadian stock portfolios

[5] https://www.cdp.net/en

that disclose information on sustainability outperform the European ones in terms of annualized returns.

So far, the still limited numbers of empirical studies based on emission data have produced mixed results when examining the relationship between carbon performance and disclosure and firms' financial performance.[6] Our approach is distinctly different in that we examine whether disclosure of information regarding SBTi validation is recognized by investors. We use market information beyond the announcement and the analysis is conditioned on current carbon emissions as well as information from ESG scores. Our empirical strategy is to form a portfolio and examine whether returns for a portfolio comprising firms with STBi-validated targets outperform the returns of a portfolio of otherwise similar stocks of firms not participating in the SBT initiative. The focus is to investigate how disclosure affects risk-adjusted returns (those returns are deviations from expected returns related to systematic portfolio risk).

Research on the financial significance of joining SBTi is extremely limited. One of the few exceptions is Bendig, Wagner and Lau (2023) examining the relationship between carbon emission and Return on Assets as well as Tobins Q for SBT firms for the period 2015-2020. The paper finds evidence of a positive association between decarbonization efforts and Tobins Q. Our paper uses similar data as Bendig et al. (2023) but focuses on investors' stock market reactions in response to information disclosure. We assume that investors can form well-diversified portfolios of stocks with the aim to outperform a benchmark concerning risk-adjusted returns. However, the specific effect of announcing that a goal has been validated and approved has been, to date, not investigated.

3 Methodology

We investigate whether there is SBTi risk premium, i.e., the SBTi risk factor is priced in the cross-section of stock returns, and compare the relative contribution of SBTi firm characteristics and factor betas with the relative contribution of ESG and CO2 emission characteristics to returns variation. In doing so, we apply the cross-sectional regressions approach suggested in Chordia et al. (2017) and Ciciretti et al. (2023). This approach is an extension of the method suggested by Fama and MacBeth (1973), where in a first-pass, time-varying factor betas are estimated using time-series regressions for individual stock. In the second-pass, cross-sectional regressions are performed using factor betas and firm-level characteristics. This approach allows pricing errors to include both the factor risk premiums and firm-level characteristics. By extending the correction presented in Shanken (1992) to incorporate conditional heteroscedasticity of error terms, this approach accounts for the error-in-variable (EIV) problem caused by including explanatory variables, i.e., factor betas, in the second-pass regressions that are estimated with errors (see Kim,

[6] For a review, see Velte, Stawinoga and Lueg (2020)

1995, for more details). We first present several SBTi risk factors combined with the Fama-French traditional risk factors in Fama and French (2012) and Fama and French (2015). Then, we describe the cross-sectional regression approach. Finally, we provide detailed steps involved in constructing risk portfolios and estimation of the risk premium coefficients.

3.1 SBTi risk factors

To construct portfolios representing SBTi-related risk factors, let $\boldsymbol{r}_t = \{r_{1t}, r_{2t}, ..., r_{dt}\}$ and $\boldsymbol{\nu}_t = \{\nu_{1t}, \nu_{2t}, ..., \nu_{dt}\}$ be vectors of assets returns and market capitalization at time t. Let $\mathcal{C}$ and $\mathcal{NC}$ be sets of SBTi- committed and non-committed firms, with their total numbers, denoted as $d_t^{\mathcal{C}}$ and $d_t^{\mathcal{NC}}$. We define value-weighted committed and non-committed portfolios as:

$$w_{jt}^{\mathcal{C}} = \nu_{jt}[\sum_{i\in\mathcal{C}} \nu_{it}]^{-1}, \forall j \in \mathcal{C}, \quad R_t^{\mathcal{C}} = [\boldsymbol{w}_t^{\mathcal{C}}]^\intercal \boldsymbol{r}_t^{\mathcal{C}}, \tag{1}$$

and

$$w_{jt}^{\mathcal{NC}} = \nu_{jt}[\sum_{i\in\mathcal{NC}} \nu_{it}]^{-1}, \forall j \in \mathcal{NC}, \quad R_t^{\mathcal{NC}} = [\boldsymbol{w}_t^{\mathcal{NC}}]^\intercal \boldsymbol{r}_t^{\mathcal{NC}}, \tag{2}$$

where, $\boldsymbol{r}_t^{\mathcal{C}}$ and $\boldsymbol{r}_t^{\mathcal{NC}}$ are vectors of asset returns for committed and non-committed firms, with the corresponding portfolio weights $\boldsymbol{w}_t^{\mathcal{C}}$ and $\boldsymbol{w}_t^{\mathcal{NC}}$. An alternative is to construct the risk factors as equally-weighted portfolios, where $w_{jt}^{\mathcal{C}} = \frac{1}{d_t^{\mathcal{C}}}$ and $w_{jt}^{\mathcal{NC}} = \frac{1}{d_t^{\mathcal{NC}}}$.

We suggest the SBTi risk factors consisting of a long position in the committed firms, and a short position in the non-committed ones and define the $\mathcal{CMN}$ dimension; $R_t^{\mathcal{CMN}} = R_t^{\mathcal{C}} - R_t^{\mathcal{NC}}$. This dimension suggests that investors expect to achieve higher risk-adjusted returns from the SBTi-committed firms.

To extend the SBTi risk factors to incorporate classical Fama-French factors, we follow Fama and French (2015) and construct 2×2 and 2×3 sorts, combining the $\mathcal{CMN}$ dimension with the *Size*; small-minus-big ($\mathcal{SMB}$), *BM*; high-minus-low ($\mathcal{HML}$), *OP*; robust-minus-weak ($\mathcal{RMW}$); and *Inv*; conservative-minus-aggressive ($\mathcal{CMA}$).

Let $\mathcal{S}$ and $\mathcal{B}$ be sets of small and big firms based on independent sorts using the median of the market values. We obtain the $\mathcal{CMN}_{\mathcal{SIZE}}$ risk factor as:

$$
\begin{aligned}
w_{jt}^{\mathcal{C}_{\mathcal{S}}} &= \nu_{jt}[\sum_{i \in \mathcal{C} \cap \mathcal{S}} \nu_{it}]^{-1}, \forall j \in \mathcal{C} \cap \mathcal{S}, \\
w_{jt}^{\mathcal{NC}_{\mathcal{S}}} &= \nu_{jt}[\sum_{i \in \mathcal{NC} \cap \mathcal{S}} \nu_{it}]^{-1}, \forall j \in \mathcal{NC} \cap \mathcal{S}, \\
w_{jt}^{\mathcal{C}_{\mathcal{B}}} &= \nu_{jt}[\sum_{i \in \mathcal{C} \cap \mathcal{B}} \nu_{it}]^{-1}, \forall j \in \mathcal{C} \cap \mathcal{B}, \\
w_{jt}^{\mathcal{NC}_{\mathcal{B}}} &= \nu_{jt}[\sum_{i \in \mathcal{NC} \cap \mathcal{B}} \nu_{it}]^{-1}, \forall j \in \mathcal{NC} \cap \mathcal{B}, \\
R_t^{\mathcal{CMN}_{\mathcal{SIZE}}} &= 0.5\left[[\boldsymbol{w}_t^{\mathcal{C}_{\mathcal{S}}}]^\intercal \boldsymbol{r}_t^{\mathcal{C}_{\mathcal{S}}} + [\boldsymbol{w}_t^{\mathcal{C}_{\mathcal{B}}}]^\intercal \boldsymbol{r}_t^{\mathcal{C}_{\mathcal{B}}}\right] - 0.5\left[[\boldsymbol{w}_t^{\mathcal{NC}_{\mathcal{S}}}]^\intercal \boldsymbol{r}_t^{\mathcal{NC}_{\mathcal{S}}} + [\boldsymbol{w}_t^{\mathcal{NC}_{\mathcal{B}}}]^\intercal \boldsymbol{r}_t^{\mathcal{NC}_{\mathcal{B}}}\right]. \quad (3)
\end{aligned}
$$

To combine $\mathcal{CMN}$ with the growth dimension, let $\mathcal{H}$, $\mathcal{L}$, and $\mathcal{N}$ denote sets of value (high book-to-market ratio) , growth (low book-to-market ratio) and neutral stocks based on independent sorts using 30^{th} and 70^{th} percentiles of *BM* as breakpoints. We define the $\mathcal{CMN}_{\mathcal{BM}}$ risk factor as:

$$
\begin{aligned}
w_{jt}^{\mathcal{C}_{\mathcal{H}}} &= \nu_{jt}[\sum_{i \in \mathcal{C} \cap \mathcal{H}} \nu_{it}]^{-1}, \forall j \in \mathcal{C} \cap \mathcal{H}, \\
w_{jt}^{\mathcal{NC}_{\mathcal{H}}} &= \nu_{jt}[\sum_{i \in \mathcal{NC} \cap \mathcal{H}} \nu_{it}]^{-1}, \forall j \in \mathcal{NC} \cap \mathcal{H}, \\
w_{jt}^{\mathcal{C}_{\mathcal{N}}} &= \nu_{jt}[\sum_{i \in \mathcal{C} \cap \mathcal{N}} \nu_{it}]^{-1}, \forall j \in \mathcal{C} \cap \mathcal{N}, \\
w_{jt}^{\mathcal{NC}_{\mathcal{N}}} &= \nu_{jt}[\sum_{i \in \mathcal{NC} \cap \mathcal{N}} \nu_{it}]^{-1}, \forall j \in \mathcal{NC} \cap \mathcal{N}, \\
w_{jt}^{\mathcal{NC}_{\mathcal{L}}} &= \nu_{jt}[\sum_{i \in \mathcal{NC} \cap \mathcal{L}} \nu_{it}]^{-1}, \forall j \in \mathcal{NC} \cap \mathcal{L}, \\
w_{jt}^{\mathcal{NC}_{\mathcal{L}}} &= \nu_{jt}[\sum_{i \in \mathcal{NC} \cap \mathcal{L}} \nu_{it}]^{-1}, \forall j \in \mathcal{NC} \cap \mathcal{L}, \\
R_t^{\mathcal{CMN}_{\mathcal{BM}}} &= \frac{1}{3}\left[[\boldsymbol{w}_t^{\mathcal{C}_{\mathcal{H}}}]^\intercal \boldsymbol{r}_t^{\mathcal{C}_{\mathcal{H}}} + [\boldsymbol{w}_t^{\mathcal{C}_{\mathcal{N}}}]^\intercal \boldsymbol{r}_t^{\mathcal{C}_{\mathcal{N}}} + [\boldsymbol{w}_t^{\mathcal{C}_{\mathcal{L}}}]^\intercal \boldsymbol{r}_t^{\mathcal{C}_{\mathcal{L}}}\right] \\
&\quad - \frac{1}{3}\left[[\boldsymbol{w}_t^{\mathcal{NC}_{\mathcal{H}}}]^\intercal \boldsymbol{r}_t^{\mathcal{NC}_{\mathcal{H}}} + [\boldsymbol{w}_t^{\mathcal{NC}_{\mathcal{N}}}]^\intercal \boldsymbol{r}_t^{\mathcal{NC}_{\mathcal{N}}} + [\boldsymbol{w}_t^{\mathcal{NC}_{\mathcal{L}}}]^\intercal \boldsymbol{r}_t^{\mathcal{NC}_{\mathcal{L}}}\right]. \quad (4)
\end{aligned}
$$

Similarly, for the profitability dimension, we define $\mathcal{R}$, $\mathcal{W}$, and $\mathcal{N}$ denote sets of robust, weak and neutral stocks with *OP* breakpoints of 30^{th} and 70^{th} percentiles. Therefore, the $\mathcal{CMN}_{\mathcal{OP}}$ risk factor is obtained as:

$$w_{jt}^{\mathcal{C}_{\mathcal{R}}} = \nu_{jt}[\sum_{i\in\mathcal{C}\cap\mathcal{R}} \nu_{it}]^{-1}, \forall j \in \mathcal{C}\cap\mathcal{R},$$

$$w_{jt}^{\mathcal{NC}_{\mathcal{R}}} = \nu_{jt}[\sum_{i\in\mathcal{NC}\cap\mathcal{R}} \nu_{it}]^{-1}, \forall j \in \mathcal{NC}\cap\mathcal{R},$$

$$w_{jt}^{\mathcal{C}_{\mathcal{N}}} = \nu_{jt}[\sum_{i\in\mathcal{C}\cap\mathcal{N}} \nu_{it}]^{-1}, \forall j \in \mathcal{C}\cap\mathcal{N},$$

$$w_{jt}^{\mathcal{NC}_{\mathcal{N}}} = \nu_{jt}[\sum_{i\in\mathcal{NC}\cap\mathcal{N}} \nu_{it}]^{-1}, \forall j \in \mathcal{NC}\cap\mathcal{N},$$

$$w_{jt}^{\mathcal{NC}_{\mathcal{W}}} = \nu_{jt}[\sum_{i\in\mathcal{NC}\cap\mathcal{W}} \nu_{it}]^{-1}, \forall j \in \mathcal{NC}\cap\mathcal{W},$$

$$w_{jt}^{\mathcal{NC}_{\mathcal{W}}} = \nu_{jt}[\sum_{i\in\mathcal{NC}\cap\mathcal{W}} \nu_{it}]^{-1}, \forall j \in \mathcal{NC}\cap\mathcal{W},$$

$$R_t^{\mathcal{CMN}_{\mathcal{OP}}} = \frac{1}{3}\left[[\boldsymbol{w}_t^{\mathcal{C}_{\mathcal{R}}}]^\intercal \boldsymbol{r}_t^{\mathcal{C}_{\mathcal{R}}} + [\boldsymbol{w}_t^{\mathcal{C}_{\mathcal{N}}}]^\intercal \boldsymbol{r}_t^{\mathcal{C}_{\mathcal{N}}} + [\boldsymbol{w}_t^{\mathcal{C}_{\mathcal{W}}}]^\intercal \boldsymbol{r}_t^{\mathcal{C}_{\mathcal{W}}}\right] - \frac{1}{3}\left[[\boldsymbol{w}_t^{\mathcal{NC}_{\mathcal{R}}}]^\intercal \boldsymbol{r}_t^{\mathcal{NC}_{\mathcal{R}}} + [\boldsymbol{w}_t^{\mathcal{NC}_{\mathcal{N}}}]^\intercal \boldsymbol{r}_t^{\mathcal{NC}_{\mathcal{N}}} + [\boldsymbol{w}_t^{\mathcal{NC}_{\mathcal{W}}}]^\intercal \boldsymbol{r}_t^{\mathcal{NC}_{\mathcal{W}}}\right]. \quad (5)$$

Finally, for investment dimension, let $\mathcal{CO}$, $\mathcal{A}$, and $\mathcal{N}$ be sets of conservative, aggressive, and neutral firms grouped based on 30th and 70th percentiles of *Inv*. We compute $\mathcal{CMN}_{\mathcal{INV}}$ risk factor as:

$$w_{jt}^{\mathcal{C}_{\mathcal{A}}} = \nu_{jt}[\sum_{i\in\mathcal{C}\cap\mathcal{A}} \nu_{it}]^{-1}, \forall j \in \mathcal{C}\cap\mathcal{A},$$

$$w_{jt}^{\mathcal{NC}_{\mathcal{A}}} = \nu_{jt}[\sum_{i\in\mathcal{NC}\cap\mathcal{A}} \nu_{it}]^{-1}, \forall j \in \mathcal{NC}\cap\mathcal{A},$$

$$w_{jt}^{\mathcal{C}_{\mathcal{N}}} = \nu_{jt}[\sum_{i\in\mathcal{C}\cap\mathcal{N}} \nu_{it}]^{-1}, \forall j \in \mathcal{C}\cap\mathcal{N},$$

$$w_{jt}^{\mathcal{NC}_{\mathcal{N}}} = \nu_{jt}[\sum_{i\in\mathcal{NC}\cap\mathcal{N}} \nu_{it}]^{-1}, \forall j \in \mathcal{NC}\cap\mathcal{N},$$

$$w_{jt}^{\mathcal{NC}_{\mathcal{CO}}} = \nu_{jt}[\sum_{i\in\mathcal{NC}\cap\mathcal{CO}} \nu_{it}]^{-1}, \forall j \in \mathcal{NC}\cap\mathcal{CO},$$

$$w_{jt}^{\mathcal{NC}_{\mathcal{CO}}} = \nu_{jt}[\sum_{i\in\mathcal{NC}\cap\mathcal{CO}} \nu_{it}]^{-1}, \forall j \in \mathcal{NC}\cap\mathcal{CO},$$

$$R_t^{\mathcal{CMN}_{\mathcal{INV}}} = \frac{1}{3}\left[[\boldsymbol{w}_t^{\mathcal{C}_{\mathcal{CO}}}]^\intercal \boldsymbol{r}_t^{\mathcal{C}_{\mathcal{CO}}} + [\boldsymbol{w}_t^{\mathcal{C}_{\mathcal{N}}}]^\intercal \boldsymbol{r}_t^{\mathcal{C}_{\mathcal{N}}} + [\boldsymbol{w}_t^{\mathcal{C}_{\mathcal{A}}}]^\intercal \boldsymbol{r}_t^{\mathcal{C}_{\mathcal{A}}}\right] - \frac{1}{3}\left[[\boldsymbol{w}_t^{\mathcal{NC}_{\mathcal{CO}}}]^\intercal \boldsymbol{r}_t^{\mathcal{NC}_{\mathcal{CO}}} + [\boldsymbol{w}_t^{\mathcal{NC}_{\mathcal{N}}}]^\intercal \boldsymbol{r}_t^{\mathcal{NC}_{\mathcal{N}}} + [\boldsymbol{w}_t^{\mathcal{NC}_{\mathcal{A}}}]^\intercal \boldsymbol{r}_t^{\mathcal{NC}_{\mathcal{A}}}\right]. \quad (6)$$

3.2 Cross-sectional regressions

As mentioned before, the cross-sectional approach in Fama and MacBeth (1973) starts with the estimation of factor betas using time series regressions. Let R_{jt}^e denote the excess return for stock

j at time t, $\boldsymbol{\zeta}_t$ be a $\iota_1 \times 1$ vector of factors, $\boldsymbol{\beta}_j$ be a $\iota_1 \times 1$ vector of factor betas that can be estimated as:

$$R^e_{jt} = \beta_{0j} + \boldsymbol{\beta}_j^\intercal \boldsymbol{\zeta}_t + \epsilon_{jt}, \tag{7}$$

where β_{0j} is the contact term, and ϵ_{jt} is the error term. To estimate time-varying factor betas, one could apply a rolling window approach (see section 3.3).

Let $d_t = d_t^{\mathcal{C}} + d_t^{\mathcal{NC}}$ denote the number of active stocks at time t, $\hat{\boldsymbol{\beta}}_{t-1}$ be a $\iota_1 \times d_t$ matrix of estimated factor betas, $\hat{\boldsymbol{\Lambda}}_{t-1}$ be a $\iota_2 \times d_t$ matrix of firm-level characteristics. Following Chordia et al. (2017) and Ciciretti et al. (2023), we define the expected stock returns as:

$$\mathbb{E}_{t-1}[R^e_{jt}] = \gamma_0 + \boldsymbol{\gamma}_1^\intercal \boldsymbol{\beta}_{j,t-1} + \boldsymbol{\gamma}_2^\intercal \boldsymbol{\Lambda}_{j,t-1} =: \hat{\boldsymbol{X}}_t \boldsymbol{\Gamma}, \tag{8}$$

where $\boldsymbol{\Gamma} := [\gamma_0, \gamma_1^\intercal, \gamma_2^\intercal]^\intercal$ is a $1 + \iota_1 + \iota_2 \times 1$ vector consisting of the excess zero-beta rate (γ_0), factor risk premiums ($\gamma_1^\intercal$), and firm characteristic premiums ($\gamma_2^\intercal$); and $\hat{\boldsymbol{X}}_t := [\mathbf{1}_{d_t}, \hat{\boldsymbol{\beta}}_{t-1}, \boldsymbol{\Lambda}_{t-1}]$ is a $1 + \iota_1 + \iota_2 \times d_t$ matrix consisting of a constant ($\mathbf{1}_{d_t}$), estimated factor betas and ($\hat{\boldsymbol{\beta}}_{t-1}$), and firm characteristics ($\boldsymbol{\Lambda}_{t-1}$).

To obtain time-varying premiums, at each time t, a cross-sectional regression is run using d_t stock returns,i.e. $\boldsymbol{R}^e_t$, as the dependent variable and $\hat{\boldsymbol{X}}_t$ as the independent variables. To apply the EIV correction suggested in Chordia et al. (2017), let $\boldsymbol{\Omega} = [\mathbf{0}_{\iota_1 \times 1}, \boldsymbol{I}_{\iota_1 \times \iota_1}, \mathbf{0}_{\iota_1 \times \iota_2}]$ be an adjustment matrix, $\hat{\boldsymbol{\Sigma}}_{\boldsymbol{\beta}_{j,t-1}}$ be the $\iota_1 \times \iota_1$ White (1980) heteroskedasticity-consistent (HC) covariance matrix obtained from the time series regressions in Eq. (7). We obtain the EIV-corrected estimator $\hat{\boldsymbol{\Gamma}}_t$ as:

$$\hat{\boldsymbol{\Gamma}}_t = \left[\hat{\boldsymbol{X}}_t^\intercal \hat{\boldsymbol{X}}_t - \sum_{j=1}^{d_t} \boldsymbol{\Omega}^\intercal \hat{\boldsymbol{\Sigma}}_{\boldsymbol{\beta}_{j,t-1}} \boldsymbol{\Omega} \right]^{-1} \hat{\boldsymbol{X}}_t^\intercal \boldsymbol{R}^e_t, \tag{9}$$

and by taking time series averages of $\hat{\boldsymbol{\Gamma}}_t := [\hat{\gamma}_{0t}, \hat{\gamma}_{1t}, \hat{\gamma}_{2t}]$, we have the final estimates $\tilde{\boldsymbol{\Gamma}} := [\tilde{\gamma}_0, \tilde{\gamma}_1^\intercal, \tilde{\gamma}_2^\intercal]^\intercal$.

To estimate the relative contribution of factor-beta premiums and firm characteristic premiums, we use the final estimates for premiums, i.e., $\tilde{\boldsymbol{\Gamma}}$, and calculate these contributions at each time t, such that:

$$C_t^{\hat{\boldsymbol{\beta}}} = \frac{(d_t - 1)^{-1} \sum_{j=1}^{d_t} [\tilde{\boldsymbol{\gamma}}_1^\intercal \hat{\boldsymbol{\beta}}_{j,t-1} - d_t^{-1} \sum_{j=1}^{d_t} \tilde{\boldsymbol{\gamma}}_1^\intercal \hat{\boldsymbol{\beta}}_{j,t-1}]^2}{(d_t - 1)^{-1} \sum_{j=1}^{d_t} [(\tilde{\gamma}_0 + \tilde{\boldsymbol{\gamma}}_1^\intercal \hat{\boldsymbol{\beta}}_{j,t-1} + \tilde{\boldsymbol{\gamma}}_2^\intercal \boldsymbol{\Lambda}_{j,t-1}) - d_t^{-1} \sum_{j=1}^{d_t} (\tilde{\gamma}_0 + \tilde{\boldsymbol{\gamma}}_1^\intercal \hat{\boldsymbol{\beta}}_{j,t-1} + \tilde{\boldsymbol{\gamma}}_2^\intercal \boldsymbol{\Lambda}_{j,t-1})]^2}, \tag{10}$$

where $C_t^{\hat{\boldsymbol{\beta}}}$ is a ratio that presents the contribution of factor betas in the cross-sectional expected returns' variation at time t. The numerator is the cross-sectional variance of risk premiums, and the denominator in this ratio is the cross-sectional variance of expected returns. Similarly, we obtain the relative contribution for firm characteristics as :

$$C_t^{\mathbf{\Lambda}} = \frac{(d_t-1)^{-1}\sum_{j=1}^{d_t}[\tilde{\gamma}_2^{\intercal}\mathbf{\Lambda}_{j,t-1} - d_t^{-1}\sum_{j=1}^{d_t}\tilde{\gamma}_2^{\intercal}\mathbf{\Lambda}_{j,t-1}]^2}{(d_t-1)^{-1}\sum_{j=1}^{d_t}[(\tilde{\gamma}_0+\tilde{\gamma}_1^{\intercal}\hat{\boldsymbol{\beta}}_{j,t-1}+\tilde{\gamma}_2^{\intercal}\mathbf{\Lambda}_{j,t-1}) - d_t^{-1}\sum_{j=1}^{d_t}(\tilde{\gamma}_0+\tilde{\gamma}_1^{\intercal}\hat{\boldsymbol{\beta}}_{j,t-1}+\tilde{\gamma}_2^{\intercal}\mathbf{\Lambda}_{j,t-1})]^2}, \tag{11}$$

where the numerator represents the cross-sectional variance of firm characteristic premiums. Since the firm-level characteristics might be correlated with the factor betas, the sum of time-series averages for $C_t^{\hat{\boldsymbol{\beta}}}$ and $C_t^{\mathbf{\Lambda}}$ is not necessarily 1 (see Chordia et al., 2017, for more details).

3.3 Steps

As mentioned before, we apply a rolling window estimation to obtain the time-varying factor betas and firm characteristic premiums. Notice in Eqs. (8)-(9), we estimate these premiums using stock returns at time t, $\boldsymbol{R}_t^e$, and factor betas and firm characteristics at time $t-1$, $\hat{\boldsymbol{X}}_t$. Thus, we are performing cross-sectional regressions using out-of-sample returns, which is more realistic as one uses the information set available until time $t-1$ and applies this information to estimate premiums for t. In doing so, we set the following parameters: L =the estimation window length,e.g. 102 weeks (24 months), and $\forall k \in [L+1, T]$: t_k =out-of-sample iteration. The steps include:

1. Initialize by setting $k = L+1$. For all trading day t in weekly intervals $[t_{k-L}, t_k[$: compute daily excess (adjusted) returns $R_{jt}^e, \forall j \in [1, 2, ..., d_{t_k}]$, and obtain daily factor portfolio returns $R_t^{\mathcal{CMN}}$, $R_t^{\mathcal{MKT}}$, $R_t^{\mathcal{SMB}}$, $R_t^{\mathcal{HML}}$, $R_t^{\mathcal{RMW}}$, $R_t^{\mathcal{CMA}}$, $R_t^{\mathcal{WML}}$ in Eqs. (1)-(6). [7]

2. $\forall j \in [1, 2, ..., d_{t_k}]$: set $\boldsymbol{\zeta}_t = [R_t^{\mathcal{MKT}}, R_t^{\mathcal{SMB}}, R_t^{\mathcal{HML}}, R_t^{\mathcal{RMW}}, R_t^{\mathcal{CMA}}, R_t^{\mathcal{WML}}, R_t^{\mathcal{CMN}}]$, and using R_{jt}^e as the dependent variable, estimate $\hat{\boldsymbol{\beta}}_{j,t_k} = (\hat{\beta}_j^{\mathcal{MKT}}, \hat{\beta}_j^{\mathcal{SMB}}, \hat{\beta}_j^{\mathcal{HML}}, \hat{\beta}_j^{\mathcal{RMW}}, \hat{\beta}_j^{\mathcal{CMA}}, \hat{\beta}_j^{\mathcal{WML}}, \hat{\beta}_j^{\mathcal{CMN}})$, and obtain the HC covariance matrix $\hat{\mathbf{\Sigma}}_{\boldsymbol{\beta}_{j,t_k}}$ for these factor beta estimates.

3. Using the factor betas from Step (2), $\hat{\boldsymbol{\beta}}_{t_k} = [\hat{\boldsymbol{\beta}}_{t_k}^{\mathcal{MKT}}, \hat{\boldsymbol{\beta}}_{t_k}^{\mathcal{SMB}}, \hat{\boldsymbol{\beta}}_{t_k}^{\mathcal{HML}}, \hat{\boldsymbol{\beta}}_{t_k}^{\mathcal{RMW}}, \hat{\boldsymbol{\beta}}_{t_k}^{\mathcal{CMA}}, \hat{\boldsymbol{\beta}}_{t_k}^{\mathcal{WML}}, \hat{\boldsymbol{\beta}}_{t_k}^{\mathcal{CMN}}]$ and observed firm characteristics $\mathbf{\Lambda}_{t_k}$ and asset returns $\boldsymbol{R}_{t_k}^e$, estimate EIV-corrected coefficients $\hat{\mathbf{\Gamma}}_{t_k} = [\hat{\gamma}_{0t_k}, \hat{\gamma}_{1t_k}^{\intercal}, \hat{\gamma}_{2t_k}^{\intercal}]^{\intercal}$ as described in Eq. (9).

4. Repeat Steps (1)-(3) for all out-of-sample iterations in $[L+2, T]$ and obtain the equity premium matrix $(1 + \iota_1 + \iota_2 \times T - L)$, $\hat{\mathbf{\Gamma}} = [\hat{\gamma}_0, \hat{\gamma}_1, \hat{\gamma}_2]$.

5. Take the time-series averages using the estimated time-varying premiums from Step (4) and compute ultimate second-pass estimates $\tilde{\mathbf{\Gamma}} := [\tilde{\gamma}_0, \tilde{\gamma}_1^{\intercal}, \tilde{\gamma}_2^{\intercal}]^{\intercal}$.

6. $\forall k \in [L+1, T]$: use equity premiums $\tilde{\mathbf{\Gamma}}$ from Step (5), first-pass estimates $\hat{\boldsymbol{\beta}}_{t_k}$ from Step (3), and observed firm characteristics $\mathbf{\Lambda}_{t_k}$ and compute relative contributions for factor betas $C_{t_k}^{\hat{\boldsymbol{\beta}}}$ and firm characteristics $C_{t_k}^{\mathbf{\Lambda}}$ in Eqs. (10)-(11). Finally, take time-series averages for these relative contributions.

[7] For this step, one could also use the Fama-French six factors available in http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html.

To estimate the risk premiums for combined risk factors, replace $R_t^{\mathcal{CMN}}$ with $R_t^{\mathcal{CMN}_{\mathcal{SIZE}}}$, $R_t^{\mathcal{CMN}_{\mathcal{BM}}}$, $R_t^{\mathcal{CMN}_{\mathcal{OP}}}$, or $R_t^{\mathcal{CMN}_{\mathcal{INV}}}$, and repeat Steps (1)-(6) separately for each dimension.

4 Empirical Results

4.1 Sample Structure

We collect data on firms' emission strategy from the SBTi's target dashboard containing information on each firm's progression in the initiative. Firms being publicly traded having an ISIN code can be used in the analysis. Next, we include stocks that have joined SBTi and were approved in early 2020. Stocks in the STB initiative that were not approved by early 2020 but appear in the list from SBTi are used as (control). There are 803 firms that got their target validated in January 2020.

Data on stock returns and supplemental information including market capitalization, ESG rating, and CO2 emission is collected from Thomson Reuters Eikon. SBTi validated firms must have data on stock returns and market capitalization for 2017 and onwards to be eligible in the analysis. Therefore, the final SBTi portfolio consists of 757 firms. The firms are located in 60 different countries and include many large and well-known firms.

To create our control group, we screen the Eikon database for publicly traded firms having data on CO2 emissions and ESG-ratings. Based on this screening, we get 3,610 potential firms to be included in the control group. We match firms in the STBi portfolio to their most suitable peers' in the control group. We use coarsened exact matching (Iacus, King and Porro, 2012) on region, industry, and market capitalization. The final 748 peers obtained from the control group are included in a benchmark portfolio.

The sample period is from January 2018 until December 2022. We obtain daily, weekly, and monthly total returns for both committed and non-committed firms from Thomson Reuters Refinitiv Eikon. Furthermore, we retrieve annual firm-level data including market value of equity; total assets; common equity; net sales or revenues; selling, general, and administrative expenses; interest expense on debt; cost of goods sold; ESG scores; and estimated CO2 equivalents emission from Refinitiv Eikon Datastream. Following Fama and French (2015), we use the firm-level data and construct the firm-specific characteristics as follows: size (ME); book-to-market ratio (BM); operating profitability (OP) measured as revenues minus cost of goods sold minus selling, general and administrative expense all divided by the book value of equity; investment (Inv) measures as an annual percentage change in total assets. We utilize these firm-specific characteristics to construct the SBTi risk factors discussed in Section 3.1. We also use the Fama-French developed markets' database in Fama and French (2012) and Fama and French (2017), and collect daily excess returns of the market $R^{\mathcal{MKT}}$, the size factor ($R^{\mathcal{SMB}}$), the value factor ($R^{\mathcal{HML}}$), the profitability risk factor ($R^{\mathcal{RMW}}$), the investment risk factor ($R^{\mathcal{CMA}}$), and the momentum risk factor ($R^{\mathcal{WML}}$). For the risk-free rate, we use the one-month T-bill rate from the Fama-French database.[8]

Moreover, we hypothesize that firms with high CO2 emissions are affected differently compared to low CO2 emission firms. First, we calculate scaled CO2 emission defined as CO2 emission divided by market capitalization. The SBTi stocks with scaled CO2 emission being higher than the 80th percentile are used to form the SBTi portfolio and their associated peers are included in the benchmark portfolio. The purpose of this is to analyze high CO2 polluters after they join the SBT initiative. Additional sub-portfolios are constructed as follows. Based on previous literature, we are particularly interested in high CO2 emission industries. Our industry classification follows the Eikon TRBC Sectors and we consider Basic Materials, Energy, Industrials, and Utilities to be high-emission industries. These industries have the highest CO2 emissions in our data. Lastly, we construct portfolios including firms with CO2 emissions that exceed the industry average. Again, we form two portfolios for the above-industry-average firms; one for SBTi firms and a benchmark for the associated peers. To analyze regional differences, we construct portfolios for SBTi and control group conditional on three geographic regions, Europe, North America, and the Rest of The World.

4.2 Cross-sectional distributions

Using the constructed risk factors described in Section 3.1, we estimate the weekly coefficients for the Fama-French seven-factor model, including the $\mathcal{CMN}$ factor, for all firms. Table 1 presents the time-series averages for the cross-sectional distributions (Panel A) and correlations (Panel B) for these factor betas and firm-level characteristics. According to Panel A, the firms in our sample have on average a market value of 15.6497 in logarithmic form. Considering lBM, most of the firms show a book-to-equity ratio below one. Furthermore, the cross-sectional distributions for Pro and Inv indicate that our sample includes firms with different operating profitability and total asset changes. Looking at the median for ESG, almost half of the firms have medium to high ESG scores. Considering the cross-sectional correlations between the firm characteristics, the results in Panel B suggest that big firms have lower book-to-market ratios, and higher revenues are more aggressive, which is in line with the results in Chordia et al. (2017). For the cross-sectional correlations between firm characteristics and factor betas, there is a negative correlation between the size characteristics lME and the size factor loadings $\hat{\beta}^{\mathcal{SMB}}$. This is due to the fact that the size risk factor is constructed as a portfolio consisting of short positions in small firms and long positions in big firms. Similarly, there are negative correlations reported between investment characteristics Inv and its corresponding risk factor betas $\hat{\beta}^{\mathcal{CMA}}$, as well as,

[8]The symbols for collected data from Datastream are $WC08001$ (market value of equity), $WC02999$ (total assets), $WC03501$ (common equity), $WC01001$ (net sales or revenues), $WC01101$ (selling, general, and administrative expenses), $WC01251$ (interest expense on debt), $WC01051$ (cost of goods sold), $ENERDP123$ (estimated CO2 equivalents emission), $TRESGS$ (ESG score).

positive correlations between value lBM, profitability Pro, momentum $lRet6$, and $SBTi$ characteristics and their risk factors, i.e. $\hat{\beta}^{\mathcal{HML}}$, $\hat{\beta}^{\mathcal{RMW}}$, $\hat{\beta}^{\mathcal{WML}}$, and $\hat{\beta}^{\mathcal{CMN}}$, respectively. In addition, we found a positive (negative) correlation between ESG (CO2 emission) characteristics and the market and the SBTi risk factors, which indicates that higher (lower) ESG scores (CO2 emission) lead to more (lower) market and SBTi transition risk exposure. Overall, the correlations between the SBTi risk factor $\hat{\beta}^{\mathcal{CMN}}$ and firm characteristics indicate that firms with larger size, lower book-to-market (growth), lower revenues (weak), and higher investment (aggressive) are less exposed to SBTi transition risk. The cross-sectional correlations between the SBTi dummy variable and other firm characteristics and factor betas indicate that the SBTi-committed firms are larger with lower book-to-market, more revenues and investments, higher ESG scores, and lower CO2 emissions, compared to non-committed firms. Also, these firms are more exposed to market risk. In general, consistent with Ciciretti et al. (2023), we find low correlations between the firm's characteristics and factor betas, which is suitable when estimating separate contributions of characteristic and risk premiums to the cross-sectional variation of expected returns. [9]

4.3 Risk-adjusted performance for SBTi risk portfolios

Table 2 reports the descriptive statistics (Panel A) and pricing errors (Panel B), utilizing several factor models described in (Fama and French, 2015) and (Carhart, 1997), for value-weighted SBTi portfolios described in Section 3.1. We use daily adjusted returns from January 2018 to February 2023 and construct SBTi committed $R^{\mathcal{C}}$ and non-committed $R^{\mathcal{NC}}$ portfolios. In Panel (A), the positive average return (0.017) for the long-short portfolio ($R^{\mathcal{CMN}}$) reveals a positive SBTi transition premium, which is statistically significant ($t = 2.220$). We find similar results when controlling for $\mathcal{SIZE}$, $\mathcal{BM}$, $\mathcal{OP}$, and $\mathcal{INV}$ dimensions. The highest Sharpe ratio (0.095) is reported for the long-short portfolio based on both $\mathcal{CMN}$ and $\mathcal{SIZE}$ dimension.

Table 2, Panel (B), reports the performance of multi-factor models, including (1) one-factor, i.e. CAPM, (2) Fama-French three-factor model, (3) Fama-French five-factor, and (4) Fama-French six-factor model, including momentum, in correctly pricing the SBTi transition premium. The positive pricing errors are reported for all long-short SBTi portfolios. The test statistics in parentheses indicate statistically significant alphas, revealing a positive return-SBTi transition relation. Comparing the alphas from different time-series multi-factor models shows that using more risk factors reduces the pricing errors, though these models are incapable of correctly pricing the SBTi portfolios. Applying the GRS test (Gibbons, Ross and Shanken, 1989), we reject the null hypothe-

[9]Our results for the correlation between ESG characteristics and market beta is not in line with Albuquerque, Koskinen and Zhang (2019) and Ciciretti et al. (2023). We also find a positive correlation between ESG and CO2 emission characteristics (0.3368). To motivate these findings, one should consider that our sample includes firms with relatively high ESG scores. For instance, we find a higher value for cross-sectional mean and median of 63.55 and 65.43 for ESG scores, compared to those in Ciciretti et al. (2023). In addition, our sample only includes 757 SBTi committed firms and a matched control group with 748 peers, which constitutes a lower number of firms compared to that in Albuquerque et al. (2019) and Ciciretti et al. (2023). Finally, one should also consider that our sample period is only from January 2020 until December 2022.

sis that the pricing errors (alphas) are jointly equal to zero for all factor models at a 1% significance level.

In summary, the results reported in Table 2 indicate that (1) there exists a positive SBTi transition premium, and (2) there are statistically significant and positive alphas revealing inabilities in pricing this SBTi transition premium using the classical Fama-French multi-factor models.

4.4 SBTi transition risk & characteristic premium

Having concluded the existence of SBTi transition premium, we apply the EIV-corrected cross-sectional time-series approach described in Section 4.2 and investigate whether this premium is a systematic risk premium or a firm-level characteristic premium. Table 3 provides the cross-sectional regression results for the multifactor models with several specifications including (1) the CAPM, (2) the Fama and French's (2012) three-factor model, (3) the Fama and French's (2017) five-factor model, and (4) the Carhart's (1997) six-factor model including the momentum factor, all augmented with the $\mathcal{CMN}$ risk factor defined as a long-short value-weighted portfolio defined as SBTi committed minus non-committed, as well as, firm-level characteristics.

In Table 3, we find negative, while insignificant, coefficients for the weekly SBTi risk factor $\hat{\beta}^{\mathcal{CMN}}$ indicating that the SBTi transition is not priced as a risk premium. However, the dummy variable $SBTi$ has statistically significant and positive coefficients across all the specifications, ranging from 0.0506 to 0.0627. In economic terms, joining the SBTi commitment leads to a 3.26% (0.0627×52) increase for the annual expected returns. Furthermore, we find a greater contribution to returns' cross-sectional variation explained by the SBTi characteristic $\bar{C}_{SBTi}$, compared to that by the SBTi risk factor $\bar{C}_{\hat{\beta}^{\mathcal{CMN}}}$.

The estimated weekly expected return on a zero-beta portfolio (constant term) is mostly negative and insignificant (see Frazzini and Pedersen, 2014, for more details on high-beta assets' alphas). In line with Chordia et al. (2017) and Albuquerque et al. (2019), we find that the market beta is positive, however, not priced when firm-level characteristics are included in the second-stage cross-sectional regressions. The premium for size risk factor $\hat{\beta}^{\mathcal{SMB}}$ is positive across all factor models, which is in line with Ciciretti et al. (2023). Similar to Ciciretti et al. (2023), but in contrast to Chordia et al. (2017), we find a statistically significant and positive premium for the growth risk factor $\hat{\beta}^{\mathcal{HML}}$, ranging from 0.178 to 0.395, and non-significant risk premium for the profitability factor $\hat{\beta}^{\mathcal{RMW}}$. In accordance with the results in Chordia et al. (2017), the risk premium for the investment factor is positive and statistically significant at 5% level. In contrast to both Chordia et al. (2017) and Ciciretti et al. (2023), our estimate for the momentum risk factor $\hat{\beta}^{\mathcal{WML}}$ is not statistically significant. We notice that both the beta premiums for investment and momentum factors have different signs compared to their average values in Table 1, which seems in conflict with the common restriction that the beta premiums are equal to the average values for their factors. This, together with some non-significant coefficients for beta premiums, is due to controlling for the firm-level characteristics, causing the beta premiums to capture a partial effect on expected returns. As regards characteristic premiums, we find negative and statistically significant premiums for book-to-market and investment ratios (in line with Ciciretti et al., 2023). However, our results for the size, profitability, and momentum characteristics are in contrast to those in Chordia et al. (2017) and Ciciretti et al. (2023).

To summarize, the results in Table 3 indicate that (i) the SBTi transition premium is derived by the SBTi as a firm characteristic, not as a systematic risk, and (ii) a greater proportion of cross-sectional variation in expected returns is explained by the SBTi characteristic, compared to the SBTi risk factor.

4.5 Robustness checks

To investigate whether the insignificance of the SBTi transition premium as a systematic risk is due to factor construction and possible missing information not captured by pure $\mathcal{CMN}$ dimension, and the data frequency, we perform several robustness checks.

First, we combine the $\mathcal{CMN}$ dimension with the size, growth, operational profitability, and investment dimensions as described in Section 3.1. Tables 2-7 report the results. We find similar results for most combined risk factors, i.e., the SBTi transition premium is priced as a characteristic premium rather than a systematic risk premium. In all model specifications using the combined risk factors, there are statistically significant and positive coefficients for the SBTi characteristic, while the SBTi risk premium is not significant. Similar to the results in Table 3, these combined risk factors contribute less to returns' cross-sectional variation for most specifications. These results are in favor of our main findings in Section 4.4.

Second, we extend our analysis to monthly frequency and investigate whether we find consistent results for monthly SBTi premiums. Table 8 provides the results. We find monthly positive and significant SBTi characteristic premiums. For instance, in column (4), the SBTi characteristic has a coefficient of 0.2489, indicating an annual return of 2.98% (0.2489×12). Only in one specification, column (4), do we find a significant coefficient for the SBTi risk factor beta, $\hat{\beta}^{\mathcal{CMN}}$, at a 10% confidence level. However, the low t statistics (-1.8102) indicate that we can not strongly conclude the existence of a monthly SBTi transition risk premium.

Third, we construct the SBTi risk factor, $R^{\mathcal{CMN}}$, using equal weights, rather than value-weighting the committed and non-committed firms. The reason for this robustness analysis is to not allow bigger firms to contribute more to the SBTi risk factor. Even when alternating the construction of the risk factor in Table 9, we find consistent results that the SBTi transition premium is firm-related.

Finally, we control for possible characteristic premiums explained by firms' ESG and CO2 emission information. Considering the results in Table 10, we still find positive and significant SBTi characteristic premium. In contrast to the results in Ciciretti et al. (2023), the ESG characteristic is not statistically significant, which might be due to the inclusion of several firm-level information in all specifications. On the other hand, the CO2 characteristic is positive and significant, ranging from 0.016% to 0.0283%, with a higher contribution to cross-sectional variation than those of firms' SBTi transition and ESG information.

5 Conclusions

While a growing body of research analyzes how the failure to mitigate climate change in accordance with international agreements causes major risks to the economy,[10] this paper studies how investors value companies that have gotten their climate reduction targets validated. Investors are likely to evaluate how tomorrow's market barriers, policy instruments, and other conditions linked to climate action affect the returns of their investments. We formulate our research question based on the idea that investors strive to lower their climate-related risk exposure and therefore seek stocks with lower climate risk once this information becomes validated. Applying the classical cross-sectional approach for stock returns, we investigate whether (i) there exists a SBTi transition premium, and (ii) this premium is priced as a systematic risk or firm-level characteristic.

Utilizing a sample of 757 SBTi committed international firms and a control group consisting of 748 peers as non-committed firms, we construct the SBTi risk factor as a long-short (committed minus non-committed) portfolio. We also construct several SBTi portfolios Combining the SBTi dimension with the classical size, growth, profitability, and investment dimensions using 2 and 2×3 sorts. We study the risk-adjusted performance of the SBTi risk portfolios and investigate whether there is an SBTi premium by testing the pricing errors (alphas). Using the time-series regressions, in the first step, we estimate the risk factor betas. Then, we augment the traditional multi-factor models with the SBTi risk factor and apply the EIV-bias-corrected cross-sectional regression approach suggested in Chordia et al. (2017) and Ciciretti et al. (2023) and further examine the SBTi transition premium.

The results of the risk-adjusted performance and testing the alphas signal a positive SBTi transition premium, and inabilities in pricing this SBTi transition premium via the classical Fama-French multi-factor models. As regards the cross-sectional regressions, we find that the SBTi characteristic derives the transition premium. We could not find a systematic risk related to this SBTi transition. Furthermore, we conclude that the SBTi as a firm-level characteristic can contribute more to the cross-sectional variation in the expected returns, compared to its risk factor

[10] See for instance Hänsel, Drupp, Johansson, Nesje, Azar, Freeman, Groom and Sterner (2020); Nordhaus (2019); Pindyck (2021)

beta. In addition, we perform several robustness checks in terms of the construction of risk factors, data frequency, and controlling for ESG and CO2 information. The results of the robustness checks provide more support for our findings.

Overall, our findings highlight that investors may earn excess returns by investing in a portfolio of SBTi stocks which also carry lower climate-related risk. There are good reasons to believe that the estimated divergent risk-adjusted returns are transitory. As more and more firms adopt an increasingly rigorous regulation of carbon dioxide emissions, investors will become better informed about firms' emission reduction strategies through trustworthy disclosure of information from voluntary or mandatory sources. Future research may look into the difference between voluntary and regulatory emission disclosure, and analyze the relationship between SBTi adoption and its impact on the pace of carbon emission reduction.

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Appendices

A Tables

Table 1: Descriptive statistics and correlation matrix

	lME	lBM	Pro	Inv	$lRet6$	ESG	$lCO2$	$\hat{\beta}^{\mathcal{MKT}}$	$\hat{\beta}^{\mathcal{SMB}}$	$\hat{\beta}^{\mathcal{HML}}$	$\hat{\beta}^{\mathcal{RMW}}$	$\hat{\beta}^{\mathcal{CMA}}$	$\hat{\beta}^{\mathcal{WML}}$	$\hat{\beta}^{\mathcal{CMN}}$
Panel (A): Cross-sectional distributions														
Mean	15.6497	-0.8618	0.3597	0.1041	-0.0047	63.55	11.8456	0.7447	0.3927	0.0369	0.1229	-0.1118	-0.1559	-0.0391
St. Deviation	1.6235	0.9366	0.3948	0.2246	0.2238	16.89	2.4643	0.293	0.5629	0.5985	0.546	0.7624	0.2874	0.4176
10%	13.5732	-2.114	0.0769	-0.0806	-0.2746	39.28	8.7789	0.3732	-0.3409	-0.6999	-0.5028	-1.0438	-0.552	-0.5835
25%	14.5696	-1.428	0.1712	-0.0161	-0.1373	52.91	10.2022	0.5242	0.0257	-0.3335	-0.1899	-0.5432	-0.3277	-0.2782
50%	15.6688	-0.7696	0.2711	0.0598	-0.0023	65.43	11.8922	0.7296	0.3806	0.0359	0.1123	-0.0747	-0.1158	0.0013
75%	16.7906	-0.2101	0.419	0.1506	0.1324	76.72	13.5267	0.9302	0.7169	0.388	0.4468	0.3757	0.043	0.2417
90%	17.7283	0.2901	0.7027	0.2955	0.2668	83.89	14.9719	1.1361	1.1355	0.7575	0.7973	0.7952	0.1731	0.4478
Panel (B): Cross-sectional correlations														
lME	1													
lBM	-0.4426	1												
Pro	0.1059	-0.4109	1											
Inv	0.1125	-0.1602	0.0208	1										
$lRet6$	0.1265	-0.1644	0.025	-0.0076	1									
ESG	0.4613	-0.081	0.1075	-0.0262	0.0197	1								
$lCO2$	0.4017	0.1857	0.0036	-0.0756	0.0334	0.3368	1							
$\hat{\beta}^{\mathcal{MKT}}$	0.0748	-0.075	-0.0539	0.0774	0.0257	0.0332	-0.0183	1.000						
$\hat{\beta}^{\mathcal{SMB}}$	-0.3884	0.3318	-0.1953	-0.0102	-0.0501	-0.1393	-0.1318	0.0209	1.000					
$\hat{\beta}^{\mathcal{HML}}$	-0.2051	0.2872	-0.0935	-0.0928	-0.0112	-0.0804	0.1071	0.2431	0.254	1.000				
$\hat{\beta}^{\mathcal{RMW}}$	-0.1097	0.1077	0.0576	-0.0363	-0.0024	-0.0815	0.0027	-0.1396	0.4825	0.3686	1.000			
$\hat{\beta}^{\mathcal{CMA}}$	0.0776	0.0042	0.116	-0.0995	0.0319	0.1222	0.1081	-0.3934	-0.1769	-0.6524	-0.1436	1.000		
$\hat{\beta}^{\mathcal{WML}}$	0.0452	-0.0768	0.0433	0.0875	0.0408	-0.0918	0.025	-0.4656	0.0823	-0.0543	0.1761	0.1864	1.000	
$\hat{\beta}^{\mathcal{CMN}}$	-0.1487	0.0284	0.017	-0.0183	-0.0063	0.0082	-0.1745	-0.26	0.125	0.0821	0.0685	0.007	0.0018	1.000
$SBTi$	0.083	-0.0366	0.0334	0.0035	0.0242	0.2257	-0.007	0.0182	-0.0216	0.031	0.0129	-0.0642	-0.0644	0.1789

Notes: This table provides time-series average and standard deviation and correlation matrix for cross-sectional firm-specific characteristics and factor betas. The sample includes 1,435 firms from developed markets over a period starting from January 2020 until December 2022, resulting in 158 weeks. The firm-specific characteristics ($\Lambda_{j,t-1}$) include logarithm of weekly market capitalization (lME), logarithm of weekly book-to-market ratio (lBM), yearly operating profitability (Pro), yearly asset growth (Inv), logarithm of one plus six-month return lagged one week ($lRet6$), yearly ESG scores (ESG), logarithm of yearly CO2 emission ($lCO2$), and a dummy variable with value one if the firm is SBTi-committed or zero otherwise ($SBTi$). The cross-sectional factor betas are estimated using the suggested factor model in Eq. ((7)) and consist of the market risk factor ($\hat{\beta}^{\mathcal{MKT}}$), the size (small-minus-big) risk factor ($\hat{\beta}^{\mathcal{SMB}}$), the value (high-minus-low) risk factor ($\hat{\beta}^{\mathcal{HML}}$), the profitability (robust-minus-weak) risk factor ($\hat{\beta}^{\mathcal{RMW}}$), the investment (conservative-minus-aggressive) risk factor ($\hat{\beta}^{\mathcal{CMA}}$), the momentum (winners-minus-losers) risk factor ($\hat{\beta}^{\mathcal{WML}}$), and the SBTi (committed-minus-non-committed) risk factor ($\hat{\beta}^{\mathcal{CMN}}$).

Table 2: Properties of SBTi portfolios

Panel (A): Descriptive statistics				
Risk Portfolios	Ave. Return		Std. Deviation	SR
$R^{\mathcal{C}}$	0.032	(1.043)	1.126	0.029
$R^{\mathcal{NC}}$	0.021	(0.680)	1.106	0.019
$R^{\mathcal{CMN}}$	0.017**	(2.220)	0.287	0.061
$R^{\mathcal{CMN}_{\mathcal{SIZE}}}$	0.018***	(3.455)	0.195	0.095
$R^{\mathcal{CMN}_{\mathcal{BM}}}$	0.013**	(2.208)	0.222	0.061
$R^{\mathcal{CMN}_{\mathcal{OP}}}$	0.015*	(1.886)	0.294	0.052
$R^{\mathcal{CMN}_{\mathcal{INV}}}$	0.019**	(2.403)	0.291	0.066

Panel (B): Regression alphas				
	(1)	(2)	(3)	(4)
$R^{\mathcal{C}}$	0.011	0.007	0.007	0.008
	(1.411)	(1.134)	(1.091)	(1.194)
$R^{\mathcal{NC}}$	0.000	-0.002	-0.002	-0.002
	(-0.057)	(-0.278)	(-0.280)	(-0.215)
$R^{\mathcal{CMN}}$	0.017**	0.015**	0.015**	0.015**
	(2.172)	(2.093)	(2.076)	(2.073)
$R^{\mathcal{CMN}_{\mathcal{SIZE}}}$	0.018***	0.017***	0.017***	0.017***
	(3.380)	(3.420)	(3.471)	(3.455)
$R^{\mathcal{CMN}_{\mathcal{BM}}}$	0.015**	0.014**	0.012**	0.012**
	(2.489)	(2.400)	(2.215)	(2.202)
$R^{\mathcal{CMN}_{\mathcal{OP}}}$	0.015*	0.014*	0.015*	0.015*
	(1.829)	(1.801)	(1.953)	(1.946)
$R^{\mathcal{CMN}_{\mathcal{INV}}}$	0.019**	0.017**	0.016**	0.015**
	(2.390)	(2.348)	(2.283)	(2.255)
GRS	[2.917]	[2.921]	[2.896]	[2.871]

Notes: Panel (A) provides descriptive statistics for SBTi portfolio returns including mean, standard deviation and the Sharpe ratio (SR). Panel (B) reports estimated alphas from (1) CAPM, (2) Fama-French three factor model, (3) Fama-French five factor, and (4) Fama-French six factor model, including momentum, for value-weighted portfolios based on SBTi commited ($\mathcal{C}$), non-committed ($\mathcal{NC}$), committed minus non-committed ($\mathcal{CMN}$), and $\mathcal{CMN}$ dimension combined with $\mathcal{SIZE}$, $\mathcal{BM}$ (book-to-market), $\mathcal{OP}$ (operational profitability), INV (investment) described in Section 3.1. The sample includes daily portfolio returns from January 31^{st}, 2018 until February 28^{th}, 2023, resulting in 1,325 trading days. The F-statistics for the GRS on the regression alphas for $R^{\mathcal{CMN}}$, $R^{\mathcal{CMN}_{\mathcal{SIZE}}}$, $R^{\mathcal{CMN}_{\mathcal{BM}}}$, $R^{\mathcal{CMN}_{\mathcal{OP}}}$, $R^{\mathcal{CMN}_{\mathcal{INV}}}$ are reported in brackets. t-statistics are in parentheses. ***, **, * denote significance at 1%, 5%, and 510% level.

Table 3: Cross-sectional regression with value-weighted and weekly $\mathcal{CMN}$ risk factor

	(1)	(2)	(3)	(4)
Constant	-0.445	-0.6506	-0.6909*	-0.6547
	(-1.1922)	(-1.5993)	(-1.6724)	(-1.6239)
$\hat{\beta}^{\mathcal{MKT}}$	0.2176	0.1225	0.1034	0.1129
	(0.8839)	(0.4943)	(0.4303)	(0.537)
$\hat{\beta}^{\mathcal{SMB}}$		0.0666	0.1344	0.1389*
		(0.8432)	(1.6083)	(1.6673)
$\hat{\beta}^{\mathcal{HML}}$		0.178**	0.3433***	0.3596**
		(2.3754)	(3.0747)	(2.6059)
$\hat{\beta}^{\mathcal{RMW}}$			-0.0821	-0.0906
			(-1.1529)	(-1.2942)
$\hat{\beta}^{\mathcal{CMA}}$			0.1543**	0.1669**
			(2.0749)	(2.039)
$\hat{\beta}^{\mathcal{WML}}$				0.1207
				(0.5337)
$\hat{\beta}^{\mathcal{CMN}}$	-0.04	-0.0929	-0.1091	-0.1138
	(-0.5911)	(-1.313)	(-1.5138)	(-1.639)
lME	0.0151	0.0294	0.0302	0.0274
	(0.7731)	(1.3538)	(1.3898)	(1.3056)
lBM	-0.1727***	-0.2056***	-0.2396***	-0.2385***
	(-3.7084)	(-4.9487)	(-6.3891)	(-6.8285)
Pro	-0.1373**	-0.1357**	-0.1635***	-0.1674***
	(-2.4121)	(-2.4669)	(-3.1178)	(-3.2349)
Inv	-0.1934**	-0.1897**	-0.1399*	-0.1512**
	(-2.2172)	(-2.1931)	(-1.8184)	(-1.9852)
$lRet6$	-0.2563	-0.2528	-0.3186	-0.315
	(-0.9449)	(-0.9642)	(-1.2649)	(-1.3654)
$SBTi$	0.0524**	0.0506**	0.0575***	0.0627***
	(2.3223)	(2.3242)	(2.6297)	(2.8923)
$\bar{C}_{\hat{\boldsymbol{\beta}}}$	12.397	28.453	50.400	54.443
$\bar{C}_{\Lambda}$	81.496	111.465	139.948	138.861
$\bar{C}_{\hat{\beta}^{\mathcal{CMN}}}$	0.146	0.664	0.911	0.975
$\bar{C}_{SBTi}$	2.132	1.734	2.151	2.611

Notes: This table provides time-series averages (multiplied by 100) and t-statistics, in parentheses, for γ coefficients based on the EIV-bias-corrected cross-sectional regression:

$$R^e_{j,t} = \gamma_{0,t} + \boldsymbol{\gamma}^{\intercal}_{1,t}\hat{\boldsymbol{\beta}}_{j,t-1} + \boldsymbol{\gamma}^{\intercal}_{2,t}\boldsymbol{\Lambda}_{j,t-1} + \epsilon_{j,t}.$$

The weekly factor betas $\hat{\boldsymbol{\beta}}_{j,t}$ are estimated based on the suggested factor model in Eq. (7), using a rolling window approach with two years of daily returns with a minimum of 400 observations (see Section 3.3). The sample includes 1,435 firms from developed markets over a period starting from January 2020 until December 2022, resulting in 158 weeks. The firm-specific characteristics ($\Lambda_{j,t-1}$) include logarithm of weekly market capitalization (lME), logarithm of weekly book-to-market ratio (lBM), yearly operating profitability (Pro), yearly asset growth (Inv), logarithm of one plus six-month return lagged one week ($lRet6$), and a dummy variable with value one if the firm is SBTi-committed or zero otherwise ($SBTi$). The cross-sectional factor betas consist of the market risk factor ($\hat{\beta}^{\mathcal{MKT}}$), the size (small-minus-big) risk factor ($\hat{\beta}^{\mathcal{SMB}}$), the value (high-minus-low) risk factor ($\hat{\beta}^{\mathcal{HML}}$), the profitability (robust-minus-weak) risk factor ($\hat{\beta}^{\mathcal{RMW}}$), the investment (conservative-minus-aggressive) risk factor ($\hat{\beta}^{\mathcal{CMA}}$), the momentum (winners-minus-losers) risk factor ($\hat{\beta}^{\mathcal{WML}}$), and the SBTi (committed-minus-non-committed) risk factor ($\hat{\beta}^{\mathcal{CMN}}$). $\bar{C}_{\hat{\boldsymbol{\beta}}}$, $\bar{C}_{\Lambda}$, $\bar{C}_{\hat{\beta}^{\mathcal{CMN}}}$, and $\bar{C}_{SBTi}$ are the the contribution of factor betas, firm-level characteristics, SBTi risk factor, and SBTi characteristics to variation in expected returns, respectively. ***, **, * denote significance at 1%, 5%, and 10% level.

Table 4: Cross-sectional regression with value-weighted and weekly $\mathcal{CMN}_{\mathcal{SIZE}}$ risk factor

	(1)	(2)	(3)	(4)
Constant	-0.4298	-0.615	-0.6583*	-0.6324
	(-1.2088)	(-1.5836)	(-1.6692)	(-1.6343)
$\hat{\beta}^{\mathcal{MKT}}$	0.2332	0.1444	0.1225	0.1248
	(0.9672)	(0.6019)	(0.527)	(0.6007)
$\hat{\beta}^{\mathcal{SMB}}$		0.0563	0.1253	0.1328
		(0.7366)	(1.571)	(1.652)
$\hat{\beta}^{\mathcal{HML}}$		0.1851**	0.3467***	0.3692***
		(2.425)	(3.0878)	(2.6689)
$\hat{\beta}^{\mathcal{RMW}}$			-0.084	-0.092
			(-1.1892)	(-1.3305)
$\hat{\beta}^{\mathcal{CMA}}$			0.1484**	0.1634**
			(2.0438)	(2.0236)
$\hat{\beta}^{\mathcal{WML}}$				0.1041
				(0.4711)
$\hat{\beta}^{\mathcal{CMN}_{\mathcal{SIZE}}}$	-0.0209	-0.0554	-0.0623	-0.0606
	(-0.3741)	(-0.9815)	(-1.1095)	(-1.1545)
lME	0.0136	0.0261	0.0274	0.0253
	(0.7337)	(1.2748)	(1.3341)	(1.2689)
lBM	-0.1727***	-0.2061***	-0.2388***	-0.2398***
	(-3.7301)	(-5.0418)	(-6.4277)	(-6.9642)
Pro	-0.1339**	-0.1336**	-0.1597***	-0.1658***
	(-2.3653)	(-2.4308)	(-3.0553)	(-3.1995)
Inv	-0.1995**	-0.1935**	-0.1456*	-0.1545**
	(-2.2661)	(-2.2202)	(-1.8715)	(-2.0146)
$lRet6$	-0.2512	-0.2442	-0.3128	-0.3046
	(-0.9345)	(-0.9372)	(-1.2433)	(-1.3148)
$SBTi$	0.0557**	0.0579**	0.0625***	0.0656***
	(2.4216)	(2.5575)	(2.7649)	(2.9277)
$\bar{C}_{\hat{\boldsymbol{\beta}}}$	12.437	29.703	51.626	57.425
$\bar{C}_{\Lambda}$	82.504	110.368	139.181	138.080
$\bar{C}_{\hat{\beta}^{\mathcal{CMN}_{\mathcal{SIZE}}}}$	0.167	1.017	1.265	1.191
$\bar{C}_{SBTi}$	2.468	2.306	2.595	2.864

Notes: This table provides time-series averages (multiplied by 100) and t-statistics, in parentheses, for γ coefficients based on the EIV-bias-corrected cross-sectional regression:

$$R^e_{j,t} = \gamma_{0,t} + \boldsymbol{\gamma}^{\intercal}_{1,t}\hat{\boldsymbol{\beta}}_{j,t-1} + \boldsymbol{\gamma}^{\intercal}_{2,t}\boldsymbol{\Lambda}_{j,t-1} + \epsilon_{j,t}.$$

The weekly factor betas $\hat{\boldsymbol{\beta}}_{j,t}$ are estimated based on the suggested factor model in Eq. (7), using a rolling window approach with two years of daily returns with a minimum of 400 observations (see Section 3.3). The sample includes 1,435 firms from developed markets over a period starting from January 2020 until December 2022, resulting in 158 weeks. The firm-specific characteristics ($\Lambda_{j,t-1}$) include logarithm of weekly market capitalization (lME), logarithm of weekly book-to-market ratio (lBM), yearly operating profitability (Pro), yearly asset growth (Inv), logarithm of one plus six-month return lagged one week ($lRet6$), and a dummy variable with value one if the firm is SBTi-committed or zero otherwise ($SBTi$). The cross-sectional factor betas consist of the market risk factor ($\hat{\beta}^{\mathcal{MKT}}$), the size (small-minus-big) risk factor ($\hat{\beta}^{\mathcal{SMB}}$), the value (high-minus-low) risk factor ($\hat{\beta}^{\mathcal{HML}}$), the profitability (robust-minus-weak) risk factor ($\hat{\beta}^{\mathcal{RMW}}$), the investment (conservative-minus-aggressive) risk factor ($\hat{\beta}^{\mathcal{CMA}}$), the momentum (winners-minus-losers) risk factor ($\hat{\beta}^{\mathcal{WML}}$), and the SBTi (committed-minus-non-committed) size risk factor ($\hat{\beta}^{\mathcal{CMN}_{\mathcal{SIZE}}}$). $\bar{C}_{\hat{\boldsymbol{\beta}}}$, $\bar{C}_{\Lambda}$, $\bar{C}_{\hat{\beta}^{\mathcal{CMN}_{\mathcal{SIZE}}}}$, and $\bar{C}_{SBTi}$ are the the contribution of factor betas, firm-level characteristics, SBTi risk factor, and SBTi characteristics to variation in expected returns, respectively. ***, **, * denote significance at 1%, 5%, and 10% level.

Table 5: Cross-sectional regression with value-weighted and weekly $\mathcal{CMN}_{\mathcal{BM}}$ risk factor

	(1)	(2)	(3)	(4)
Constant	-0.4148	-0.6432	-0.6702	-0.6314
	(-1.1256)	(-1.5946)	(-1.6402)	(-1.5889)
$\hat{\beta}^{\mathcal{MKT}}$	0.196	0.1238	0.0957	0.1056
	(0.7789)	(0.4883)	(0.3891)	(0.4938)
$\hat{\beta}^{\mathcal{SMB}}$		0.0626	0.1323	0.135
		(0.7917)	(1.5871)	(1.616)
$\hat{\beta}^{\mathcal{HML}}$		0.1753**	0.348***	0.3637***
		(2.2915)	(3.1231)	(2.6437)
$\hat{\beta}^{\mathcal{RMW}}$			-0.082	-0.0907
			(-1.1709)	(-1.3171)
$\hat{\beta}^{\mathcal{CMA}}$			0.167**	0.1789**
			(2.1335)	(2.1299)
$\hat{\beta}^{\mathcal{WML}}$				0.1175
				(0.5361)
$\hat{\beta}^{\mathcal{CMN}_{\mathcal{BM}}}$	-0.0562	-0.0709	-0.0812	-0.0855*
	(-1.0767)	(-1.3482)	(-1.536)	(-1.6547)
lME	0.014	0.0292	0.0293	0.0263
	(0.7257)	(1.3496)	(1.3582)	(1.2635)
lBM	-0.1732***	-0.2028***	-0.2395***	-0.2383***
	(-3.7322)	(-4.8713)	(-6.4099)	(-6.9453)
Pro	-0.1338**	-0.1321**	-0.1632***	-0.1664***
	(-2.3544)	(-2.4095)	(-3.1023)	(-3.2101)
Inv	-0.1944**	-0.1903**	-0.1379*	-0.1492**
	(-2.2316)	(-2.203)	(-1.8023)	(-1.9859)
$lRet6$	-0.2596	-0.2521	-0.3252	-0.3205
	(-0.9651)	(-0.97)	(-1.3145)	(-1.4099)
$SBTi$	0.0586***	0.0506**	0.0612***	0.0668***
	(2.6216)	(2.3181)	(2.7555)	(2.9959)
$\bar{C}_{\hat{\boldsymbol{\beta}}}$	12.766	29.098	52.872	56.823
$\bar{C}_{\Lambda}$	82.361	109.3	137.327	135.459
$\bar{C}_{\hat{\beta}^{\mathcal{CMN}_{\mathcal{BM}}}}$	2.101	2.897	3.613	4.039
$\bar{C}_{SBTi}$	2.685	1.743	2.398	2.909

Notes: This table provides time-series averages (multiplied by 100) and t-statistics, in parentheses, for γ coefficients based on the EIV-bias-corrected cross-sectional regression:

$$R^e_{j,t} = \gamma_{0,t} + \boldsymbol{\gamma}^{\intercal}_{1,t}\hat{\boldsymbol{\beta}}_{j,t-1} + \boldsymbol{\gamma}^{\intercal}_{2,t}\boldsymbol{\Lambda}_{j,t-1} + \epsilon_{j,t}.$$

The weekly factor betas $\hat{\boldsymbol{\beta}}_{j,t}$ are estimated based on the suggested factor model in Eq. (7), using a rolling window approach with two years of daily returns with a minimum of 400 observations (see Section 3.3). The sample includes 1,435 firms from developed markets over a period starting from January 2020 until December 2022, resulting in 158 weeks. The firm-specific characteristics ($\Lambda_{j,t-1}$) include logarithm of weekly market capitalization (lME), logarithm of weekly book-to-market ratio (lBM), yearly operating profitability (Pro), yearly asset growth (Inv), logarithm of one plus six-month return lagged one week ($lRet6$), and a dummy variable with value one if the firm is SBTi-committed or zero otherwise ($SBTi$). The cross-sectional factor betas consist of the market risk factor ($\hat{\beta}^{\mathcal{MKT}}$), the size (small-minus-big) risk factor ($\hat{\beta}^{\mathcal{SMB}}$), the value (high-minus-low) risk factor ($\hat{\beta}^{\mathcal{HML}}$), the profitability (robust-minus-weak) risk factor ($\hat{\beta}^{\mathcal{RMW}}$), the investment (conservative-minus-aggressive) risk factor ($\hat{\beta}^{\mathcal{CMA}}$), the momentum (winners-minus-losers) risk factor ($\hat{\beta}^{\mathcal{WML}}$), and the SBTi (committed-minus-non-committed) value risk factor ($\hat{\beta}^{\mathcal{CMN}_{\mathcal{BM}}}$). $\bar{C}_{\hat{\boldsymbol{\beta}}}$, $\bar{C}_{\Lambda}$, $\bar{C}_{\hat{\beta}^{\mathcal{CMN}_{\mathcal{BM}}}}$, and $\bar{C}_{SBTi}$ are the the contribution of factor betas, firm-level characteristics, SBTi risk factor, and SBTi characteristics to variation in expected returns, respectively. ***, **, * denote significance at 1%, 5%, and 10% level.

Table 6: Cross-sectional regression with value-weighted and weekly $\mathcal{CMN}_{\mathcal{OP}}$ risk factor

	(1)	(2)	(3)	(4)
Constant	-0.4418	-0.658	-0.6965*	-0.6568
	(-1.184)	(-1.6151)	(-1.6847)	(-1.6276)
$\hat{\beta}^{\mathcal{MKT}}$	0.2186	0.126	0.1108	0.1204
	(0.8931)	(0.5105)	(0.4644)	(0.5736)
$\hat{\beta}^{\mathcal{SMB}}$		0.0675	0.1341	0.1386*
		(0.8576)	(1.621)	(1.6748)
$\hat{\beta}^{\mathcal{HML}}$		0.1793**	0.3437***	0.3593**
		(2.3834)	(3.0707)	(2.5897)
$\hat{\beta}^{\mathcal{RMW}}$			-0.0777	-0.0866
			(-1.0958)	(-1.2423)
$\hat{\beta}^{\mathcal{CMA}}$			0.1545**	0.167**
			(2.0755)	(2.0406)
$\hat{\beta}^{\mathcal{WML}}$				0.1246
				(0.5469)
$\hat{\beta}^{\mathcal{CMN}_{\mathcal{OP}}}$	-0.0444	-0.0733	-0.102	-0.1039
	(-0.6221)	(-1.0157)	(-1.39)	(-1.4573)
lME	0.0147	0.0296	0.0301	0.0271
	(0.7552)	(1.3664)	(1.3917)	(1.2974)
lBM	-0.1719***	-0.2049***	-0.2381***	-0.2368***
	(-3.6768)	(-4.8911)	(-6.3077)	(-6.6748)
Pro	-0.1367**	-0.1351**	-0.1627***	-0.1664***
	(-2.397)	(-2.4573)	(-3.0993)	(-3.1957)
Inv	-0.1909**	-0.1864**	-0.1376*	-0.1491*
	(-2.1896)	(-2.1596)	(-1.7908)	(-1.9562)
$lRet6$	-0.2603	-0.2577	-0.3226	-0.3202
	(-0.9585)	(-0.9826)	(-1.2816)	(-1.393)
$SBTi$	0.0536**	0.0492**	0.0567**	0.0623***
	(2.3616)	(2.2585)	(2.5828)	(2.8484)
$\bar{C}_{\hat{\boldsymbol{\beta}}}$	12.156	30.285	50.580	54.545
$\bar{C}_{\Lambda}$	81.306	108.551	138.816	137.418
$\bar{C}_{\hat{\beta}^{\mathcal{CMN}_{\mathcal{OP}}}}$	0.201	0.448	0.895	0.896
$\bar{C}_{SBTi}$	2.248	1.608	2.094	2.585

Notes: This table provides time-series averages (multiplied by 100) and t-statistics, in parentheses, for γ coefficients based on the EIV-bias-corrected cross-sectional regression:

$$R^e_{j,t} = \gamma_{0,t} + \boldsymbol{\gamma}^{\intercal}_{1,t}\hat{\boldsymbol{\beta}}_{j,t-1} + \boldsymbol{\gamma}^{\intercal}_{2,t}\boldsymbol{\Lambda}_{j,t-1} + \epsilon_{j,t}.$$

The weekly factor betas $\hat{\boldsymbol{\beta}}_{j,t}$ are estimated based on the suggested factor model in Eq. (7), using a rolling window approach with two years of daily returns with a minimum of 400 observations (see Section 3.3). The sample includes 1,435 firms from developed markets over a period starting from January 2020 until December 2022, resulting in 158 weeks. The firm-specific characteristics ($\Lambda_{j,t-1}$) include logarithm of weekly market capitalization (lME), logarithm of weekly book-to-market ratio (lBM), yearly operating profitability (Pro), yearly asset growth (Inv), logarithm of one plus six-month return lagged one week ($lRet6$), and a dummy variable with value one if the firm is SBTi-committed or zero otherwise ($SBTi$). The cross-sectional factor betas consist of the market risk factor ($\hat{\beta}^{\mathcal{MKT}}$), the size (small-minus-big) risk factor ($\hat{\beta}^{\mathcal{SMB}}$), the value (high-minus-low) risk factor ($\hat{\beta}^{\mathcal{HML}}$), the profitability (robust-minus-weak) risk factor ($\hat{\beta}^{\mathcal{RMW}}$), the investment (conservative-minus-aggressive) risk factor ($\hat{\beta}^{\mathcal{CMA}}$), the momentum (winners-minus-losers) risk factor ($\hat{\beta}^{\mathcal{WML}}$), and the SBTi (committed-minus-non-committed) profitability risk factor ($\hat{\beta}^{\mathcal{CMN}_{\mathcal{OP}}}$). $\bar{C}_{\hat{\boldsymbol{\beta}}}$, $\bar{C}_{\Lambda}$, $\bar{C}_{\hat{\beta}^{\mathcal{CMN}_{\mathcal{OP}}}}$, and $\bar{C}_{SBTi}$ are the the contribution of factor betas, firm-level characteristics, SBTi risk factor, and SBTi characteristics to variation in expected returns, respectively. ***, **, * denote significance at 1%, 5%, and 10% level.

Table 7: Cross-sectional regression with value-weighted and weekly $\mathcal{CMN}_{\mathcal{INV}}$ risk factor

	(1)	(2)	(3)	(4)
Constant	-0.4507	-0.6586	-0.6996*	-0.6639
	(-1.2001)	(-1.6119)	(-1.6867)	(-1.6342)
$\hat{\beta}^{\mathcal{MKT}}$	0.2223	0.1329	0.1149	0.1215
	(0.9141)	(0.5408)	(0.4822)	(0.577)
$\hat{\beta}^{\mathcal{SMB}}$		0.0648	0.1313	0.1364
		(0.8202)	(1.5806)	(1.6504)
$\hat{\beta}^{\mathcal{HML}}$		0.1771**	0.3402***	0.3583**
		(2.3766)	(3.0471)	(2.5916)
$\hat{\beta}^{\mathcal{RMW}}$			-0.0795	-0.0879
			(-1.1339)	(-1.2776)
$\hat{\beta}^{\mathcal{CMA}}$			0.1528**	0.1659**
			(2.0547)	(2.0195)
$\hat{\beta}^{\mathcal{WML}}$				0.1139
				(0.499)
$\hat{\beta}^{\mathcal{CMN}_{\mathcal{INV}}}$	-0.0425	-0.0827	-0.1016	-0.1089
	(-0.67)	(-1.1941)	(-1.439)	(-1.4925)
lME	0.0152	0.0298	0.0307	0.0279
	(0.775)	(1.3681)	(1.4084)	(1.3232)
lBM	-0.1715***	-0.2039***	-0.2371***	-0.2365***
	(-3.6861)	(-4.8829)	(-6.27)	(-6.582)
Pro	-0.1373**	-0.1363**	-0.1634***	-0.1677***
	(-2.4107)	(-2.4808)	(-3.1275)	(-3.2363)
Inv	-0.1922**	-0.1901**	-0.1418*	-0.1514**
	(-2.2189)	(-2.2054)	(-1.8507)	(-1.985)
$lRet6$	-0.2543	-0.2522	-0.3196	-0.3137
	(-0.9373)	(-0.9602)	(-1.2649)	(-1.3571)
$SBTi$	0.0525**	0.048**	0.0546**	0.0594***
	(2.1947)	(2.1023)	(2.3822)	(2.6691)
$\bar{C}_{\hat{\boldsymbol{\beta}}}$	12.650	28.408	49.592	53.971
$\bar{C}_{\Lambda}$	80.813	110.316	137.653	136.518
$\bar{C}_{\hat{\beta}^{\mathcal{CMN}_{\mathcal{INV}}}}$	0.170	0.563	0.841	0.954
$\bar{C}_{SBTi}$	2.149	1.568	1.929	2.325

Notes: This table provides time-series averages (multiplied by 100) and t-statistics, in parentheses, for γ coefficients based on the EIV-bias-corrected cross-sectional regression:

$$R^e_{j,t} = \gamma_{0,t} + \boldsymbol{\gamma}^{\intercal}_{1,t}\hat{\boldsymbol{\beta}}_{j,t-1} + \boldsymbol{\gamma}^{\intercal}_{2,t}\boldsymbol{\Lambda}_{j,t-1} + \epsilon_{j,t}.$$

The weekly factor betas $\hat{\boldsymbol{\beta}}_{j,t}$ are estimated based on the suggested factor model in Eq. (7), using a rolling window approach with two years of daily returns with a minimum of 400 observations (see Section 3.3). The sample includes 1,435 firms from developed markets over a period starting from January 2020 until December 2022, resulting in 158 weeks. The firm-specific characteristics ($\Lambda_{j,t-1}$) include logarithm of weekly market capitalization (lME), logarithm of weekly book-to-market ratio (lBM), yearly operating profitability (Pro), yearly asset growth (Inv), logarithm of one plus six-month return lagged one week ($lRet6$), and a dummy variable with value one if the firm is SBTi-committed or zero otherwise ($SBTi$). The cross-sectional factor betas consist of the market risk factor ($\hat{\beta}^{\mathcal{MKT}}$), the size (small-minus-big) risk factor ($\hat{\beta}^{\mathcal{SMB}}$), the value (high-minus-low) risk factor ($\hat{\beta}^{\mathcal{HML}}$), the profitability (robust-minus-weak) risk factor ($\hat{\beta}^{\mathcal{RMW}}$), the investment (conservative-minus-aggressive) risk factor ($\hat{\beta}^{\mathcal{CMA}}$), the momentum (winners-minus-losers) risk factor ($\hat{\beta}^{\mathcal{WML}}$), and the SBTi (committed-minus-non-committed) investment risk factor ($\hat{\beta}^{\mathcal{CMN}_{\mathcal{INV}}}$). $\bar{C}_{\hat{\boldsymbol{\beta}}}$, $\bar{C}_{\Lambda}$, $\bar{C}_{\hat{\beta}_{CMN\mathcal{INV}}}$, and $\bar{C}_{SBTi}$ are the the contribution of factor betas, firm-level characteristics, SBTi risk factor, and SBTi characteristics to variation in expected returns, respectively. ***, **, * denote significance at 1%, 5%, and 10% level.

Table 8: Cross-sectional regression with value-weighted and monthly $\mathcal{CMN}$ risk factor

	(1)	(2)	(3)	(4)
Constant	-0.4806	-1.3122	-1.4971	-1.3571
	(-0.2609)	(-0.6044)	(-0.6758)	(-0.6379)
$\hat{\beta}^{\mathcal{MKT}}$	1.3846	0.9471	0.7917	0.6052
	(1.1635)	(0.8095)	(0.7297)	(0.7044)
$\hat{\beta}^{\mathcal{SMB}}$		0.2709	0.5549*	0.6361**
		(0.8651)	(1.769)	(2.1352)
$\hat{\beta}^{\mathcal{HML}}$		0.8058***	1.4143***	1.5519***
		(3.0951)	(4.023)	(3.659)
$\hat{\beta}^{\mathcal{RMW}}$			-0.3489	-0.4145*
			(-1.6174)	(-1.945)
$\hat{\beta}^{\mathcal{CMA}}$			0.5394*	0.6294**
			(1.7935)	(2.1248)
$\hat{\beta}^{\mathcal{WML}}$				0.0032
				(0.0038)
$\hat{\beta}^{\mathcal{CMN}}$	-0.1754	-0.3523	-0.4043	-0.4636*
	(-0.6832)	(-1.3393)	(-1.5343)	(-1.8102)
lME	-0.0203	0.0385	0.0468	0.0407
	(-0.1937)	(0.3174)	(0.3882)	(0.3618)
lBM	-0.6721***	-0.8314***	-0.957***	-0.9866***
	(-3.1353)	(-3.9658)	(-4.6223)	(-5.4391)
Pro	-0.6675***	-0.676***	-0.7678***	-0.804***
	(-2.7713)	(-2.978)	(-3.6287)	(-4.0302)
Inv	-0.8628**	-0.8318**	-0.6471*	-0.6364*
	(-2.4605)	(-2.4122)	(-2.0233)	(-2.0081)
$lRet6$	-0.4792	-0.5755	-0.8658	-0.8514
	(-0.4918)	(-0.5741)	(-0.8855)	(-0.9413)
$SBTi$	0.2158*	0.2063*	0.2327**	0.2489**
	(1.9459)	(1.9508)	(2.2027)	(2.4248)
$\bar{C}_{\hat{\boldsymbol{\beta}}}$	30.644	46.446	63.683	70.676
$\bar{C}_{\Lambda}$	62.883	86.99	118.004	125.673
$\bar{C}_{\hat{\beta}^{\mathcal{CMN}}}$	0.181	0.579	0.818	1.081
$\bar{C}_{SBTi}$	2.324	1.729	2.257	2.622

Notes: This table provides time-series averages (multiplied by 100) and t-statistics, in parentheses, for γ coefficients based on the EIV-bias-corrected cross-sectional regression:

$$R^e_{j,t} = \gamma_{0,t} + \boldsymbol{\gamma}^{\intercal}_{1,t}\hat{\boldsymbol{\beta}}_{j,t-1} + \boldsymbol{\gamma}^{\intercal}_{2,t}\boldsymbol{\Lambda}_{j,t-1} + \epsilon_{j,t}.$$

The weekly factor betas $\hat{\boldsymbol{\beta}}_{j,t}$ are estimated based on the suggested factor model in Eq. (7), using a rolling window approach with two years of daily returns with a minimum of 400 observations (see Section 3.3). The sample includes 1,435 firms from developed markets over a period starting from January 2020 until December 2022, resulting in 38 months. The firm-specific characteristics ($\Lambda_{j,t-1}$) include logarithm of monthly market capitalization (lME), logarithm of monthly book-to-market ratio (lBM), yearly operating profitability (Pro), yearly asset growth (Inv), logarithm of one plus six-month return lagged one month ($lRet6$), and a dummy variable with value one if the firm is SBTi-committed or zero otherwise ($SBTi$). The cross-sectional factor betas consist of the market risk factor ($\hat{\beta}^{\mathcal{MKT}}$), the size (small-minus-big) risk factor ($\hat{\beta}^{\mathcal{SMB}}$), the value (high-minus-low) risk factor ($\hat{\beta}^{\mathcal{HML}}$), the profitability (robust-minus-weak) risk factor ($\hat{\beta}^{\mathcal{RMW}}$), the investment (conservative-minus-aggressive) risk factor ($\hat{\beta}^{\mathcal{CMA}}$), the momentum (winners-minus-losers) risk factor ($\hat{\beta}_{WML}$), and the SBTi (committed-minus-non-committed) risk factor ($\hat{\beta}^{\mathcal{CMN}}$). $\bar{C}_{\hat{\boldsymbol{\beta}}}$, $\bar{C}_{\Lambda}$, $\bar{C}_{\hat{\beta}^{\mathcal{CMN}}}$, and $\bar{C}_{SBTi}$ are the the contribution of factor betas, firm-level characteristics, SBTi risk factor, and SBTi characteristics to variation in expected returns, respectively. ***, **, * denote significance at 1%, 5%, and 10% level.

Table 9: Cross-sectional regression with equally-weighted and weekly $\mathcal{CMN}$ risk factor

	(1)	(2)	(3)	(4)
Constant	-0.4706	-0.6637	-0.7027*	-0.6656
	(-1.2798)	(-1.6386)	(-1.7039)	(-1.6502)
$\hat{\beta}^{\mathcal{MKT}}$	0.2299	0.1404	0.1195	0.1272
	(0.95)	(0.5808)	(0.5092)	(0.6121)
$\hat{\beta}^{\mathcal{SMB}}$		0.0581	0.1246	0.1283
		(0.7486)	(1.528)	(1.5586)
$\hat{\beta}^{\mathcal{HML}}$		0.1893**	0.3475***	0.3678***
		(2.5785)	(3.1225)	(2.6734)
$\hat{\beta}^{\mathcal{RMW}}$			-0.0794	-0.0869
			(-1.1386)	(-1.2563)
$\hat{\beta}^{\mathcal{CMA}}$			0.1446*	0.1584*
			(1.9629)	(1.9429)
$\hat{\beta}^{\mathcal{WMA}}$				0.1045
				(0.4897)
$\hat{\beta}^{\mathcal{CMN}}$	-0.023	-0.0338	-0.0495	-0.0538
	(-0.3571)	(-0.5407)	(-0.7854)	(-0.9501)
lME	0.0163	0.0294	0.0303	0.0274
	(0.8493)	(1.368)	(1.4034)	(1.308)
lBM	-0.1701***	-0.204***	-0.2354***	-0.2358***
	(-3.6338)	(-4.8808)	(-6.2464)	(-6.6125)
Pro	-0.135**	-0.1343**	-0.1596***	-0.1642***
	(-2.4217)	(-2.4637)	(-3.0874)	(-3.1697)
Inv	-0.1914**	-0.188**	-0.1419*	-0.151**
	(-2.1754)	(-2.1626)	(-1.8416)	(-1.9861)
$lRet6$	-0.2594	-0.2503	-0.3144	-0.3071
	(-0.9719)	(-0.9672)	(-1.2601)	(-1.3295)
$SBTi$	0.0518*	0.055*	0.0618**	0.0658**
	(1.8401)	(1.9649)	(2.2106)	(2.5018)
$\bar{C}_{\hat{\beta}}$	11.867	32.411	52.049	56.451
$\bar{C}_{\Lambda}$	81.964	105.474	132.977	132.701
$\bar{C}_{\hat{\beta}^{\mathcal{CMN}}}$	0.129	0.231	0.479	0.589
$\bar{C}_{SBTi}$	2.121	1.964	2.418	2.800

Notes: This table provides time-series averages (multiplied by 100) and t-statistics, in parentheses, for γ coefficients based on the EIV-bias-corrected cross-sectional regression:

$$R^e_{j,t} = \gamma_{0,t} + \boldsymbol{\gamma}^{\intercal}_{1,t}\hat{\boldsymbol{\beta}}_{j,t-1} + \boldsymbol{\gamma}^{\intercal}_{2,t}\boldsymbol{\Lambda}_{j,t-1} + \epsilon_{j,t}.$$

The weekly factor betas $\hat{\boldsymbol{\beta}}_{j,t}$ are estimated based on the suggested factor model in Eq. (7), using a rolling window approach with two years of daily returns with a minimum of 400 observations (see Section 3.3). The sample includes 1,435 firms from developed markets over a period starting from January 2020 until December 2022, resulting in 158 weeks. The firm-specific characteristics ($\Lambda_{j,t-1}$) include logarithm of weekly market capitalization (lME), logarithm of weekly book-to-market ratio (lBM), yearly operating profitability (Pro), yearly asset growth (Inv), logarithm of one plus six-month return lagged one week ($lRet6$), and a dummy variable with value one if the firm is SBTi-committed or zero otherwise ($SBTi$). The cross-sectional factor betas consist of the market risk factor ($\hat{\beta}^{\mathcal{MKT}}$), the size (small-minus-big) risk factor ($\hat{\beta}^{\mathcal{SMB}}$), the value (high-minus-low) risk factor ($\hat{\beta}^{\mathcal{HML}}$), the profitability (robust-minus-weak) risk factor ($\hat{\beta}^{\mathcal{RMW}}$), the investment (conservative-minus-aggressive) risk factor ($\hat{\beta}^{\mathcal{CMA}}$), the momentum (winners-minus-losers) risk factor ($\hat{\beta}^{\mathcal{WML}}$), and the SBTi (committed-minus-non-committed) risk factor ($\hat{\beta}^{\mathcal{CMN}}$). $\bar{C}_{\hat{\boldsymbol{\beta}}}$, $\bar{C}_{\Lambda}$, $\bar{C}_{\hat{\beta}^{\mathcal{CMN}}}$, and $\bar{C}_{SBTi}$ are the the contribution of factor betas, firm-level characteristics, SBTi risk factor, and SBTi characteristics to variation in expected returns, respectively. ***, **, * denote significance at 1%, 5%, and 10% level.

Table 10: Cross-sectional regression with equally-weighted and weekly $\mathcal{CMN}$ risk factor, controlling for firms' ESG information and CO2 emission

	(1)	(2)	(3)	(4)
Constant	-0.827**	-1.0246**	-1.1014**	-1.0512**
	(-2.0767)	(-2.3976)	(-2.5295)	(-2.4776)
$\hat{\beta}^{\mathcal{MKT}}$	0.3063	0.2195	0.1845	0.1836
	(1.2143)	(0.8777)	(0.7615)	(0.8611)
$\hat{\beta}^{\mathcal{SMB}}$		0.0748	0.1447*	0.1508*
		(0.9581)	(1.7591)	(1.8334)
$\hat{\beta}^{\mathcal{HML}}$		0.1518**	0.3176***	0.3384**
		(2.0509)	(2.9105)	(2.4798)
$\hat{\beta}^{\mathcal{RMW}}$			-0.094	-0.1011
			(-1.317)	(-1.4358)
$\hat{\beta}^{\mathcal{CMA}}$			0.1454*	0.1603*
			(1.9418)	(1.9343)
$\hat{\beta}^{\mathcal{WML}}$				0.1023
				(0.4525)
$\hat{\beta}^{\mathcal{CMN}}$	0.0013	-0.0501	-0.0747	-0.0835
	(0.0204)	(-0.7499)	(-1.0932)	(-1.2542)
lME	0.0165	0.0318	0.0424*	0.0401*
	(0.6623)	(1.265)	(1.685)	(1.6933)
lBM	-0.1808***	-0.2081***	-0.2324***	-0.2311***
	(-4.7057)	(-5.9272)	(-6.9388)	(-7.2799)
Pro	-0.1146**	-0.1131**	-0.1279***	-0.1315***
	(-2.353)	(-2.3955)	(-2.8333)	(-2.8697)
Inv	-0.1772**	-0.1706*	-0.1263	-0.1355*
	(-2.025)	(-1.9646)	(-1.5973)	(-1.7263)
$lRet6$	-0.2946	-0.282	-0.3507	-0.3389
	(-1.0498)	(-1.0359)	(-1.3434)	(-1.4138)
$SBTi$	0.0418*	0.0386	0.0466*	0.0514**
	(1.6807)	(1.6253)	(1.9698)	(2.1888)
ESG	-0.112	-0.0748	-0.1195	-0.1121
	(-0.7989)	(-0.518)	(-0.8243)	(-0.8565)
$CO2$	0.0283**	0.0241**	0.0177*	0.016
	(2.4101)	(2.2257)	(1.7286)	(1.6169)
$\bar{C}_{\hat{\boldsymbol{\beta}}}$	17.600	31.302	46.452	49.848
$\bar{C}_{\Lambda}$	77.600	98.757	129.422	131.305
$\bar{C}_{\hat{\beta}^{\mathcal{CMN}}}$	0.000	0.114	0.278	0.354
$\bar{C}_{SBTi}$	1.158	0.863	1.275	1.628
$\bar{C}_{ESG}$	0.962	0.374	0.978	0.899
$\bar{C}_{CO2}$	12.809	8.148	4.429	3.804

Notes: This table provides time-series averages (multiplied by 100) and t-statistics, in parentheses, for γ coefficients based on the EIV-bias-corrected cross-sectional regression:

$$R^e_{j,t} = \gamma_{0,t} + \boldsymbol{\gamma}^{\intercal}_{1,t}\hat{\boldsymbol{\beta}}_{j,t-1} + \boldsymbol{\gamma}^{\intercal}_{2,t}\boldsymbol{\Lambda}_{j,t-1} + \epsilon_{j,t}.$$

The weekly factor betas $\hat{\boldsymbol{\beta}}_{j,t}$ are estimated based on the suggested factor model in Eq. (7), using a rolling window approach with two years of daily returns with a minimum of 400 observations (see Section 3.3). The sample includes 1,435 firms from developed markets over a period starting from January 2020 until December 2022, resulting in 158 weeks. The firm-specific characteristics ($\Lambda_{j,t-1}$) include logarithm of weekly market capitalization (lME), logarithm of weekly book-to-market ratio (lBM), yearly operating profitability (Pro), yearly asset growth (Inv), logarithm of one plus six-month return lagged one week ($lRet6$), yearly ESG score (ESG), yearly CO2 emission ($CO2$),and a dummy variable with value one if the firm is SBTi-committed or zero otherwise ($SBTi$). The cross-sectional factor betas consist of the market risk factor ($\hat{\beta}^{\mathcal{MKT}}$), the size (small-minus-big) risk factor ($\hat{\beta}^{\mathcal{SMB}}$), the value (high-minus-low) risk factor ($\hat{\beta}^{\mathcal{HML}}$), the profitability (robust-minus-weak) risk factor ($\hat{\beta}^{\mathcal{RMW}}$), the investment (conservative-minus-aggressive) risk factor ($\hat{\beta}^{\mathcal{CMA}}$), the momentum (winners-minus-losers) risk factor ($\hat{\beta}^{\mathcal{WML}}$), and the SBTi (committed-minus-non-committed) risk factor ($\hat{\beta}^{\mathcal{CMN}}$). $\bar{C}_{\hat{\boldsymbol{\beta}}}$, $\bar{C}_{\Lambda}$, $\bar{C}_{\hat{\beta}^{\mathcal{CMN}}}$, $\bar{C}_{SBTi}$, $\bar{C}_{ESG}$, and $\bar{C}_{CO2}$ are the the contribution of factor betas, firm-level characteristics, SBTi risk factor, SBTi characteristic, ESG characteristic, and CO2 characteristic to variation in expected returns, respectively. ***, **, * denote significance at 1%, 5%, and 10% level.