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Science-based emission targets and risk-adjusted portfolio return: An analysis using global SBTi-validated stocks*

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Abstract

While a growing body of research analyzes how the considerable increase in the intensity and frequency of extreme weather and the failure to mitigate climate change causes major risks and damages to the economy, we study whether investors value that companies have set climate targets in line with science based goals. Investors are likely to be concerned about how tomorrow's market barriers, policy instruments and other conditions linked to climate actions will affect returns. Applying a portfolio approach, our paper investigates the financial importance of voluntarily disclosing climate commitments and independent expert validated action plans. Building portfolios of 1,518 firms from 13 industries in 60 countries observed during 1,482 trading days between 2017-2022, we perform coarsened exact matching to create portfolios of stocks otherwise similar to firms that have set science-based (SBTi) emission targets in line with the goals of the Paris Agreement. Applying a five-factor Fama-French model, the results show a positive and statistically significant larger risk-adjusted excess returns for the target portfolio.

JEL: G11, G23, G30, D62

Keywords: Risk-adjusted return, carbon emission, emission disclosure, Fama-French, SBTi

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1 Introduction

In response to a considerable increase in the intensity and frequency of extreme weather, assessments of how global warming may influence value chains, insurers, and financial markets, financial signaling models have been extended to climate and environmental disclosure. Christensen, Hail and Leuz (2021); Clarkson, Fang, Li and Richardson (2013); Plumlee, Brown, Hayes and Marshall (2015). Studies using voluntary signals of climate-related risk, mainly ESG scores and carbon disclosure give inconclusive evidence on whether such risks are reflected in stock returns. ¹

Drawing on the discrepant Corporate Responsible Investments (CRI) literature, this paper considers firms w ith p ublicly a vailable ESG a ssessments and c arbon emissions and examines the financial effect of v oluntarily a dopting the STBi s tandard for setting s cience-based carbon emission targets and investments to achieve those targets.² 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.³

The validation for the target firms we observe occurs in January 2020 and is considered an "event" that may imply a financial i mpact. To investigate whether climate-related risks are reflected in p ortfolio p erformance, we p erform coarsened exact matching to construct a control group consisting of comparable firms which did not join the SBTi, r etrieved from the Eikon database conditional on having information on ESG scores and carbon emission. Assuming that investors prefer a portfolio of stocks that has lower carbon emission-related risks, we test whether, once information on SBTi-validation is disclosed, investors are incentivized to invest in these target stocks, and thus, whether a portfolio of target-validated stocks may offer higher risk-adjusted returns and/or lower volatility. Building portfolios of 1,518 firms from 13 industries in 60 countries observed during 1,482 trading days during the period 2017-2022 and considering the announcement of externally validated emission targets as an event, our five-factor Fama-French model shows a robust and positive post-event material impact of climate-related commitments by firms. Estimating six sub-portfolios, the results suggest that high CO2 intensity and regional heterogeneity contribute to the results.

¹See Avramov, Cheng, Lioui and Tarelli (2022); DasGupta (2022); Ciciretti, Dalò and Dam (2023); Landi and Sciarelli (2018); Lööf, Sahamkhadam and Stephan (2022) for the impact of ESG indicators, Bolton and Kacperczyk (2021); Antoniuk (2022) regarding compensation for voluntary exposure of carbon-emission risk, Basse Mama and Mandaroux (2022); Downar, Ernstberger, Reichelstein, Schwenen and Zaklan (2021) for market reactions on EU emission trading system (ETS) and other mandatory programs for disclosing carbon emission.

²Scientific B ased T arget i nitiative (SBTi) i s a c ollaboration b etween t he C DP (Carbon D isclosure P roject), the United Nations Global Compact, World Resources Institute (WRI), and the World Wide Fund for Nature (WWF). See https://sciencebasedtargets.org/companies-taking-action/

³SBTi 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).

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 data and provides descriptive statistics. Section 4 describes the methods used for the analysis. Section 5 present the results. Section 6 concludes.

2 Background and hypotheses

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 Car-

bon 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 a round the world, the paper reports that firms are more likely to set sciencebased 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)⁴ and the Climate Action 100+ (CA100+).⁵ 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 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.

⁴https://www.fsb-tcfd.org

⁵https://www.unpri.org/collaborative-engagements/climate-action-100/6285.article

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))⁶, 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 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. 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 ex-

⁶https://www.cdp.net/en

⁷For a review, see Velte, Stawinoga and Lueg (2020)

ceptions 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.

2.3 Hypotheses

Against the background of the lack of previous research on how publicly announced, validated, standardized, and independent evaluations of set climate goals affect the aversion to portfolio investments, the support from the previous research is limited for the formulation of our hypotheses. However, the existing research shows that credibility, exposure, and location can be important for how the financial market assesses the importance of carbon disclosure.

Although there are factors that speak both for and against credibility and the financial significance of making public a firm's strategy to reduce and ultimately cease carbon emissions, on balance our a priori assumption is that validation of a firm's announcement of implementing a decarbonization strategy will have a market impact. The literature shows that there are doubts about all current carbon-disclosure initiatives and existing research does not provide clear evidence of financial market reactions. What sets SBTi apart from other initiatives is the standardized external and independent evaluation to approve/validate the strategy to achieve a science-based goal. This can mean reduced uncertainty for the financial market and, thus, that the portfolio with validated SBTi stocks will outperform a portfolio of non-SBTi stocks. However, there may be other mechanisms at work, which simultaneously impact the control group in a similar way as the SBTi-validated firms, and thus, influence investors' choices.

Firms facing regulatory risks, in form of policies and legislation to limit emissions, may prepare for the future, regardless of joining the SBT initiative or not (Delmas and Toffel, 2008; Freiberg et al., 2021). An example of such a mechanism may be the EU Corporate Sustainability Reporting Directive (CSRD) recently extended to apply to more European and non-European firms listed and operating in the EU-regulated markets aiming to reach the goal of zero net emissions of greenhouse gases by 2050. A second mechanism is that disclosing gradually improved information on firms' carbon footprints may mitigate but still not eliminate market efficiencies related to climate risks. On balance between different options, we state the following hypothesis for publicly listed firms with ESG scores and CO2 emissions already disclosed:

Hypothesis 1 (Credibility) A target portfolio consisting of stocks of SBTi-validated firms has a higher

risk-adjusted return compared to a control portfolio with matched stocks of firms not participating in the SBT initiative.

Next, we consider carbon exposure. One possibility is that investors recognize that the SBTi portfolio carries lower climate-related risk. Furthermore, SBTi validation transmits stronger signals to investors in CO2-intensive industries⁸ and in firms with above average CO2-emissions within industries, since both categories are high CO2 polluters from the beginning. Based on this assumption, we formulate the following two hypotheses:

Hypothesis 2 (Industrial Exposure) A target portfolio consisting of SBTi-validated stocks of firms from high CO2 industries has a higher risk-adjusted return than a control portfolio of stocks of firms from high CO2 industries.

Hypothesis 3 (Firm Exposure) A target portfolio consisting of SBTi-validated stocks of firms with CO2 emissions above the industry average has a higher risk-adjusted return than a control portfolio of stocks of firms with CO2 emissions above the industry average.

Finally, we test whether regional institutional differences between Europe, North America, and the Rest of The World affect performance differences between SBTi-validated stock portfolios and control portfolios. Our a priori assumption is that a process of global convergence increases market efficiencies around the world. Hence, we state the following final hypothesis:

Hypothesis 4 (Location) There are no regional differences in risk-adjusted returns between target portfolios of stocks of SBTi-validated firms and portfolios of stocks of matched control firms.

3 Data and descriptive statistics

3.1 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 form a portfolio with 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

⁸following the Eikon TRBC classification, we define Basic Materials, Energy, Industrials, and Utilities as high-emission industries.

analysis. Therefore, the final SBTi p ortfolio consists of 759 fi rms. 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 759 peers obtained from the control group are included in a benchmark portfolio.

The sample period is from January 2017 until December 2022. We calculate returns for the portfolios on a daily frequency by using total shareholder return from the Eikon database. To calculate value-weighted portfolio return, we give each stock a weight based on market capitalization.

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.

3.2 Descriptive statistics

Table 1 presents descriptive statistics on annualized return, annualized standard deviation, Sharpe Ratio, Kurtosis, and Value-at-Risk for each portfolio. Statistics for the time period before 2020 are presented in Panel A, whereas Panel B shows the same statistics for the period after 2020. Before 2020, the annualized return is 13.4% for SBTi and 11.9% for the benchmark. We are particularly interested in the change for the SBTi portfolio relative to the benchmark. The annualized return for SBTi decreases slightly, from 13.4% to 13.3%, whereas annualized return for the benchmark portfolio decreases more, from 11.9% to 9.4%. Standard deviation increases for both portfolios after 2020 compared to before. This is not surprising since the validation coincides with the volatile

period related to the Covid-19 pandemic in early 2020. A similar development is observed for Value-at-Risk, which is significantly more negative after 2020, but the difference between the two portfolios is small. Kurtosis is a measure of tail risk in the distribution of returns. It is expected to increase in response to the Covid-19 crisis, and this is what we observe for both portfolios. To conclude, the two portfolios display similar risk exposure in both periods, but returns decrease less for the SBTi portfolio.

Methodology

We regress the excess return R_{it}^P of the well-diversified SBTi portfolio and the matched benchmark portfolio on five Fama-French factors for each portfolio i on day t::

$$R_{it}^{P} = \alpha_i + \beta_1 M k t_{it} + \beta_2 S M B_{it} + \beta_3 H M L_{it} + \beta_4 R M W_{it} + \beta_5 C M A_{it} + \varepsilon_{it}$$
(1)

where α represents Jensen's alpha capturing risk-adjusted excess return, MKT is market excess return, SMB is the performance of small versus big companies, and HML is the performance of high book/market versus low book/market stocks. RMW measures robust versus weak return and CMA captures conservative minus aggressive investment portfolios. The estimated residuals provide information regarding the remaining portfolio risk not captured by the Fama-French factors. 10

We also test whether the announcement of the SBTi decision has any impact on the riskadjusted excess return by using the specification: 11

$$R_{it}^{P} = \alpha_{i} + \alpha_{\text{PostDecision}} \text{PostDecisionPeriod}_{it} + \beta_{\text{Pandemic}} \text{PandemicPeriod}_{it} + \beta_{1} M k t_{it} + \beta_{2} S M B_{it} + \beta_{3} H M L_{it} + \beta_{4} R M W_{it} + \beta_{5} C M A_{it} + \varepsilon_{it}$$
 (2)

The coefficient $\alpha_{\text{Post decision}}$ provides an estimate of Jensen's alpha after SBTi approval. Robust standard errors are estimated using the Newey-West procedure with automatic bandwidth selection. To investigate the impact of SBTi approval on conditional volatility, we estimate also GARCH models for portfolio returns where we allow for multiplicative heteroscedasticity. Variables PostDecisionPeriod and PandemicPeriod are assumed to affect the conditional volatility of portfolio returns. The specification of the volatility equation is

$$\sigma_{it}^2 = \exp\{\gamma_0 + \gamma_1 \text{PostDecisionPeriod} + \gamma_2 \text{PandemicPeriod}\} + \alpha_0 + \alpha_1 \epsilon_{i,t-1}^2 + \alpha_2 \sigma_{i,t-1}^2. \quad \text{(3)}$$

⁹Modified Cornish-Fisher VaR as proposed in Favre and Galeano (2002)

 $^{^{10}}$ We apply Fama-French factors for developed markets, retrieved from Ken French webpage

https://mba.tuck.dartmouth.edu//pages/faculty/ken.french/data_library.html

11 The specification follows Pavlova and de Boyrie (2022) but we use a constant term and add the specific subperiods as dummy variables.

Finally, in addition to estimating the models for the portfolio returns of SBTi and matched benchmark portfolio, we also estimate the models for the difference portfolio, SBTi minus matched benchmark portfolio. The result of this estimation reveals whether investors being long in the SBTi portfolio and short in the benchmark portfolio earn a positive risk-adjusted return after the validation.¹²

5 Results

In this section, we test our four hypotheses and analyze the results from the empirical specifications presented above. Using the overall sample of global stocks, we first examine whether stocks of SBTi-validated firms have a higher risk-adjusted return compared to the control portfolio of stocks of matched firms not participating in the SBT initiative, **H1**. We then conduct three additional robustness tests to investigate whether the main results hold for portfolios with stocks in high CO2-emission industries, **H2**, portfolios with stocks with CO2-emission above the industry average, **H3**, and portfolios with stocks in different regions **H4**.

5.1 Overall sample portfolios

Table 2 reports OLS results for the regression model specified in Eq. (2). The first column shows results where the dependent variable is the excess return for an equally weighted portfolio of SBTi stocks. The first row shows the coefficients for Jensen's alpha in the period prior to 2020. The coefficient is 0.02 and significant at the 5% level. The second row shows the coefficient for *PostDecisionPeriod* which measures Jensen's alpha after the validation by SBTi. The coefficient is 0.0154 but statistically insignificant. This means that Jensen's alpha is higher after 2020, but not statistically different from before 2020. The third row presents results for *PandemicPeriod* dummy. In the fourth row the coefficient for MKTRF can be seen, which is the measure of systematic market risk. The coefficient is 0.85, which means that SBTi has a lower systematic risk relative to the market portfolio of all global stocks. Rows 5 to 8 show the coefficient for SMB, HML, RMW, and CMA, respectively. All coefficients are statistically significant.

The second column displays results where the dependent variable is the excess return for an equally weighted portfolio of benchmark stocks. Jensen's alpha in the period prior to 2020 (first row) is 0.0149 and close to being significant at the 5% level. Jensen's alpha in the period after 2020 (second row) is statistically not different from zero.

The third column shows results for the difference between the SBTi and benchmark portfolio. Jensen's alpha in the period prior to 2020 (first row) is small and statistically insignificant. Jensen's alpha in the period after 2020 (second row) is 0.0138 and statistically significant at the 5% level.

¹²Investors maintain long security positions in the expectation that the stock will rise in value in the future, and short when the expectation is that the future price is likely to decrease.

This means that investors being long in the SBTi portfolio and short in the benchmark portfolio earn a positive risk-adjusted return after the validation.

Table 3 displays the results for the GARCH model. The third column presents results for the difference between the SBTi and the benchmark portfolio. The coefficient for Jensen's alpha in the period after 2020 (second row) is 0.0162 and statistically significant at the 5% level. This confirms the results from Table 2: investors being long in the SBTi portfolio and short in the benchmark portfolio earn a positive risk-adjusted return after the validation.

5.2 Tests for sub-group portfolios

Table 4 presents results for the specification of Eq. (2) for sub-portfolios. The purpose is to test whether the coefficients for Jensen's alpha differ between SBTi and the benchmark portfolio after validation of the SBTi firms. The first sub-portfolio includes firms with CO2 emissions above the 80th percentile and is shown in column one. Columns 2 to 6 display results for firms in high CO2 emission industries, firms having CO2 emissions above the industry average, firms in North America, firms in Europe, and firms in our category Rest of The World. We find that the coefficient for Jensen's alpha in the period after 2020 is positive and significant for firms in high CO2 industries and for firms with CO2 emissions above the average in their respective industries. We also find that the coefficient for Jensen's alpha in the period after 2020 is positive and significant for Europe. This points towards the existence of regional differences. Consistent with Table 3, Table 5 displays the estimates for the sub-samples using the GARCH model. The main difference compared to the estimate reported in Table 4 is that the coefficient for portfolios with CO2 emissions above average now is highly significant.

6 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, ¹⁴ 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 returns of their investments. Applying a portfolio approach, we test how investors value external validation of the companies' strategies to achieve targets that ultimately lead to zero net emissions. The aggregate effect on the economy depends on to what extent investors incorporate climate related risks in their investments. Moreover, the effect is likely contemporaneous since more companies' adopt to the new conditions and investors becomes more

¹³It should be noted that we have not taken into account that several companies in our study are global and have different operations around the world.

¹⁴See for instance Hänsel, Drupp, Johansson, Nesje, Azar, Freeman, Groom and Sterner (2020); Nordhaus (2019); Pindyck (2021)

informed when more and better information on reduction strategies becomes available.

Using a Fama-French approach, we investigate whether the risk-adjusted return of a portfolio consisting of stocks of firms that have set science-based targets to reduce their CO2 emission and got their strategy validated, outperforms a portfolio of stocks of control firms. Since SBTi validated a subset of firms in January 2020, this enables us to analyze how investors reacted to this information disclosure. We formulate our main hypothesis 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. Furthermore, we conjecture that firms with high CO2 emissions transmit stronger signals to investors once they get validated by SBTi and, therefore, experience stronger stock market reactions. We also test possible regional differences in perceived market signals from STBi validation.

We form two global portfolios by matching stocks of SBTi firms with stocks of peer firms and track the two portfolios from 2017 until 2022. These two portfolios represent a significant part of the global market capitalization, including many of the world's largest firms. We test whether the SBTi portfolio performs better relative to the benchmark portfolio. Moreover, we construct different sub-portfolios for firms with high CO2 emissions and conduct similar tests.

The empirical analysis applies a Fama-French five-factor model and tests whether Jensen's alpha as a measure of risk-adjusted return is different for the SBTi-portfolio relative to the benchmark after the validation in 2020. We find evidence of a positive alpha with respect to our main portfolios, as well as for the sub-portfolios.

These findings highlight that investors recognize that a portfolio of SBTi stocks carries lower climate-related risk. This finding is more pronounced for stocks from high CO2 emission industries as well as for stocks of firms with CO2 emissions above the industry average. We hypothesize that SBTi validation for these firms transmits a stronger signal to investors as those firms are high CO2 polluters and have a high decarbonization risk exposure. Regarding regional heterogeneity, the findings of the positive and statistically significant Jensen's alpha estimate for target European portfolios versus the control portfolio may be explained by idiosyncratic factors such as climate-action groups and similar stakeholders. Validation reduces the risk of the companies being subject to future boycotts or lawsuits for environmental crimes, and this signal may have more relevance for European stocks compared to stocks in other regions with less public climate engagement. However, this issue is left for further research. Another research question along the same trajectory is the relationship between SBTi validation and clean-tech investments to reduce carbon emissions.

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Appendices

A Figure

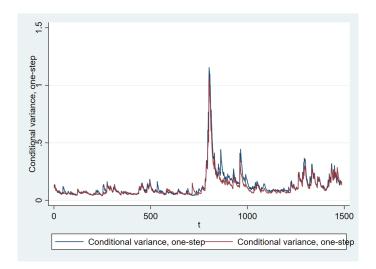


Figure 1: Conditional volatility plot of SBTi portfolio and matched benchmark portfolio based on GARCH results reported in Table 3

B Tables

Table 1: Performance measures for SBTi and matched benchmark portfolio

	SBTi	Benchmark				
Panel A: Before SBTi decision in 2020						
Return (%)	13.4	11.9				
Std deviation	8.6	8.7				
Sharpe ratio	1.56	1.37				
Kurtosis	4.66	4.57				
VaR 5%	-14.3	-14.8				
Panel B: After SBTi decision in 2020						
Return (%)	13.3	9.4				
Std deviation	18.8	18.7				
Sharpe ratio	0.71	0.50				
Kurtosis	16.8	16.6				
VaR 5%	-30.7	-30.7				

Notes: All measures annualized.

Table 2: SBTi decision and risk-adjusted excess returns

	(1)	(2)	(3)
	R_1	$ m R_2^{'}$	R_1 - R_2
Jensen's α	0.0200*	0.0149	0.00512
	(2.47)	(1.96)	(1.21)
Jensen's $\alpha_{\text{Post decision}}$	0.0154	0.00164	0.0138*
Jensen 3 a Post decision	(1.11)	(0.13)	(2.12)
	(1111)	(0.10)	(=:1=)
Pandemic period dummy	-0.00810	0.000405	-0.00850
	(-0.22)	(0.01)	(-0.51)
MktRF	0.851***	0.859***	-0.00812
WIKUKI	(30.49)	(32.19)	(-1.59)
	(50.17)	(02.17)	(1.07)
SMB	0.407^{***}	0.436***	-0.0297**
	(9.00)	(10.52)	(-2.92)
HML	0.324***	0.326***	-0.00142
1114112	(4.42)	(5.70)	(-0.07)
	(1.12)	(0.70)	(0.07)
RMW	0.183**	0.180***	0.00322
	(3.12)	(3.64)	(0.18)
CMA	-0.241*	-0.189*	-0.0522
CIVIA	(-2.28)	(-2.25)	(-1.81)
37			
$N \over R^2$	1488 0.852	1488 0.866	1488
n .	0.632	0.000	0.028

Notes: Dependent variables, R_1 = returns of equally weighted SBTi portfolio, R_2 = returns of equally weighted matched benchmark portfolio. Newey and West (1994) robust t statistics in parentheses, kernel Bartlett with automatic bw selection=21. Robust to heteroskedasticity and autocorrelation. * p < 0.05, *** p < 0.01, **** p < 0.001

Table 3: SBTi decision and risk-adjusted excess returns, GARCH model results

Jensen's α 0.0179^* (1.97) 0.0155 (0.00110 (0.26) Jensen's $\alpha_{Post \ decision}$ 0.0211 (0.00371 (0.24) 0.0162^* (0.24) Pandemic period -0.0147 (0.00525 (0.18) -0.0181 (-1.43) MktRF 0.818^{***} (0.828^{***} (0.18) (-1.43) SMB 0.285^{***} (0.325^{***} (-0.0294^{**} (-2.59) SMB 0.285^{***} (0.325^{***} (-0.0294^{**} (-0.055) HML 0.192^{***} (0.233^{***} (-0.0116 (-0.95) RMW 0.133^{***} (-0.141^{***} (-0.095) RMW 0.133^{***} (-0.141^{***} (-0.0000402 ($-0.00000000000000000000000000000000000$		(1) R ₁	(2) R ₂	(3) R ₁ -R ₂
Jensen's $α_{Post decision}$ 0.0211 (1.29) 0.00371 (0.24) 0.0162* (2.28) Pandemic period -0.0147 (0.45) 0.00525 (0.18) -0.0181 (-1.43) MktRF 0.818*** (47.14) 0.828*** (51.57) -0.0134** (-2.59) SMB 0.285*** (47.14) 0.325*** (-2.59) SMB 0.285*** (9.75) (11.65) (-3.05) HML 0.192*** (5.82) (7.61) (-0.95) RMW 0.133*** (4.25) 0.0000402 (3.81) (4.25) (0.00) CMA -0.100 (-1.96) -0.102* (-0.0410* (-2.11) -0.0410* (-2.17) (-2.11) Multiplicative heteroskedasticity Post decision 0.564** (0.397 (0.214* (2.75) (1.72) (2.09) Pandemic period 0.595 (1.72) 0.404 (0.578*** (2.09) Pandemic period 0.595 (-8.09) (-5.75) ARCH _{t-1} 0.0718*** (-9.35) (-8.09) (-5.75) ARCH _{t-1} 0.880*** (0.897*** (0.074) GARCH _{t-1} 0.880*** (0.897*** (0.564 (19.10) (19.34) (1.46) In df(t) 1.6629*** (1.696*** (1.696***)	Jensen's α	0.0179*	0.0155	0.00110
Pandemic period (1.29) (0.24) (2.28) Pandemic period (-0.0147) (0.00525) (-0.0181) (-0.45) (0.18) (-1.43) MktRF (47.14) (51.57) (-2.59) SMB (9.75) (11.65) (-3.05) HML (51.57) (-3.05) RMW (0.133^{***}) (0.141^{***}) (0.0000402) (3.81) (4.25) (0.00) CMA (-0.100) (-0.102^*) (-0.0410^*) (-1.96) (-2.17) (-2.11) Multiplicative heteroskedasticity Post decision (0.564^{**}) (0.397) (0.214^*) (2.75) (1.72) (2.09) Pandemic period (2.75) (1.72) (2.09) Pandemic period (0.595) (0.404) (0.578^{***}) (0.76) (3.79) Cons (-5.583^{***}) (-5.825^{***}) (-5.035^{***}) (-9.35) (-8.09) (-5.75) ARCH $_{t-1}$ (0.0718^{***}) (0.0657^{**}) (0.0187) (3.49) (3.05) (0.74) GARCH $_{t-1}$ (0.880^{***}) (0.897^{***}) (0.564) (1.46) (1.46) (1.46)	•	(1.97)	(1.72)	(0.26)
Pandemic period (1.29) (0.24) (2.28) Pandemic period (-0.0147) (0.00525) (-0.0181) (-0.45) (0.18) (-1.43) MktRF (47.14) (51.57) (-2.59) SMB (9.75) (11.65) (-3.05) HML (51.57) (-3.05) RMW (0.133^{***}) (0.141^{***}) (0.0000402) (3.81) (4.25) (0.00) CMA (-0.100) (-0.102^*) (-0.0410^*) (-1.96) (-2.17) (-2.11) Multiplicative heteroskedasticity Post decision (0.564^{**}) (0.397) (0.214^*) (2.75) (1.72) (2.09) Pandemic period (2.75) (1.72) (2.09) Pandemic period (0.595) (0.404) (0.578^{***}) (0.76) (3.79) Cons (-5.583^{***}) (-5.825^{***}) (-5.035^{***}) (-9.35) (-8.09) (-5.75) ARCH $_{t-1}$ (0.0718^{***}) (0.0657^{**}) (0.0187) (3.49) (3.05) (0.74) GARCH $_{t-1}$ (0.880^{***}) (0.897^{***}) (0.564) (1.46) (1.46) (1.46)	Jensen's α _{Post decision}	0.0211	0.00371	0.0162*
MktRF (-0.45) (0.18) (-1.43) MktRF 0.818^{***} (47.14) 0.828^{***} (51.57) -0.0134^{**} (-2.59) SMB 0.285^{***} (9.75) 0.325^{***} (11.65) -0.0294^{**} (-3.05) HML 0.192^{***} (5.82) (7.61) 0.233^{***} 	, Tost decision			
MktRF (-0.45) (0.18) (-1.43) MktRF 0.818^{***} (47.14) 0.828^{***} (51.57) -0.0134^{**} (-2.59) SMB 0.285^{***} (9.75) 0.325^{***} (11.65) -0.0294^{**} (-3.05) HML 0.192^{***} (5.82) (7.61) 0.233^{***} (-0.95) -0.0116 (-0.95) RMW 0.133^{***} (3.81) (4.25) 0.0000402 (-0.00) CMA -0.100 (-1.96) -0.102^* (-2.17) -0.0410^* (-2.11) Multiplicative heteroskedasticity Post decision 0.564^{**} (2.75) (1.72) 0.214^* (2.09) Pandemic period 0.595 (1.68) (0.76) 0.404 (3.79) 0.578^{***} (-5.75) Cons -5.583^{***} (-9.35) (-8.09) (-5.75) -5.035^{***} (-5.75) ARCH $_{t-1}$ 0.0718^{***} (3.49) (3.05) 0.0187 (3.05) (0.74) GARCH $_{t-1}$ 0.880^{***} (19.10) (19.34) (19.34) (1.46) 0.564^{***} (1.46) In df(t) 1.629^{***} 1.696^{***} 1.060^{***}	Pandemic period	-0.0147	0.00525	-0.0181
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	F			
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	MktRF	0.818***	0.828***	-0.0134**
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$				
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	SMB	0.285***	0 325***	-0 0294**
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	SIVID			
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	TIMI	0.103***	0.222***	0.0117
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	HML			
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$, ,	, ,	, ,
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	RMW			
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		(3.81)	(4.25)	(0.00)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	CMA	-0.100	-0.102*	-0.0410*
$\begin{array}{cccccccccccccccccccccccccccccccccccc$		(-1.96)	(-2.17)	(-2.11)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Multiplicative heterosl	kedasticity		
$\begin{array}{cccccccccccccccccccccccccccccccccccc$			0.397	0.214*
Cons -5.583^{***} -5.825^{***} -5.035^{***} (-9.35) (-8.09) (-5.75) ARCH $_{t-1}$ 0.0718^{***} 0.0657^{**} 0.0187 (3.49) (3.05) (0.74) GARCH $_{t-1}$ 0.880^{***} 0.897^{***} 0.564 (19.10) (19.34) (1.46) In df(t) 1.629^{***} 1.696^{***} 1.060^{***}		(2.75)	(1.72)	(2.09)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Pandemic period	0.595	0.404	0.578***
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	1	(1.68)	(0.76)	(3.79)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Cons	-5.583***	-5.825***	-5.035***
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	$ARCH_{t-1}$	0.0718***	0.0657**	0.0187
(19.10) (19.34) (1.46) In df(t) 1.629*** 1.696*** 1.060***		(3.49)	(3.05)	(0.74)
(19.10) (19.34) (1.46) In df(t) 1.629*** 1.696*** 1.060***	$GARCH_{t-1}$	0.880***	0.897***	0.564
	, <u>1</u>			
$(7.28) \qquad (6.83) \qquad (4.25)$	ln df(t)	1.629***	1.696***	1.060***
		(7.28)	(6.83)	(4.25)

Notes: The number of observations in all models is 1488. Dependent variables, $R_1=$ returns of equally weighted SBTi portfolio, $R_2=$ returns of equally weighted matched benchmark portfolio. Semirobust t statistics in parentheses. ARCH family regression – multiplicative heteroskedasticity, t-distributed residuals. * p<0.05, ** p<0.01, *** p<0.001. A likelihood ratio test does not reject H0 that the estimates for the Post decision dummy are different for models (1) and (2), which implies that the SBTi decision does not significantly reduce volatility.

Table 4: SBTi decision and risk-adjusted excess returns, subportfolio results

	(1)	(2)	(3)	(4)	(5)	(6)
	HighCO2	HighCO2Industry	AboveAverage	NorthAM	EU	RoW
Jensen's α	-0.0131	-0.00937	-0.00605	0.00180	0.00555	0.00716
	(-1.56)	(-1.51)	(-0.49)	(0.26)	(0.89)	(0.94)
Jensen's $\alpha_{\mathrm{Post\ decision}}$	0.0240	0.0238*	0.0451*	0.00718	0.0199*	0.00640
	(1.48)	(2.28)	(2.27)	(0.62)	(2.02)	(0.48)
Pandemic period	-0.0111	-0.0353	-0.0692*	-0.0108	0.00467	-0.0317
	(-0.42)	(-1.31)	(-2.25)	(-0.69)	(0.21)	(-1.31)
MktRF	0.112***	-0.0154	0.0656***	0.00217	-0.0119	-0.0109
	(10.07)	(-1.74)	(5.25)	(0.14)	(-1.35)	(-1.00)
SMB	-0.0300	-0.0453*	-0.0620	-0.0315	-0.00944	-0.0657***
	(-1.12)	(-2.08)	(-1.59)	(-1.72)	(-0.49)	(-3.75)
HML	0.272***	0.0378	0.181**	-0.00448	-0.00876	0.00743
	(7.88)	(1.43)	(3.17)	(-0.15)	(-0.36)	(0.23)
RMW	-0.0371	0.0198	0.0643	-0.00282	0.00559	0.00260
	(-0.88)	(0.65)	(1.28)	(-0.14)	(0.20)	(0.09)
CMA	-0.265***	-0.107*	-0.109	-0.205***	0.0104	-0.0308
	(-4.73)	(-2.38)	(-1.25)	(-3.51)	(0.31)	(-0.69)
$\frac{N}{R^2}$	1488	1488	1488	1488	1488	1488
	0.268	0.025	0.101	0.151	0.005	0.015

Notes: Dependent variables are difference between returns of equally weighted SBTi sub-portfolio and returns of equally weighted matched benchmark sub-portfolio. The sub-portfolios are (1) firms with CO2 emission above the 80th percentile, (2) firms in high CO2 emission industries, (3) firms having CO2 emission above the industry average, (4) firms in North America, (5) firms in Europe, (6) firms in the rest of the world. Newey and West (1994) robust t statistics in parentheses, kernel Bartlett with automatic bw selection=21. Robust to heteroskedasticity and autocorrelation. * p < 0.05, ** p < 0.01, *** p < 0.001

Table 5: SBTi decision and risk-adjusted excess returns, subportfolio, GARCH model results

Table 0. OBTI decisi	(1)	(2)	(3)	(4)	(5)	(6)
	HighCO2	HighIndustry	AboveAverage	NorthAM	EU	RoW
Jensen's $\alpha_{\text{Post decision}}$	0.0340*	0.0217*	0.0525**	0.00810	0.0199*	0.0102
	(2.23)	(2.03)	(2.97)	(0.73)	(2.01)	(0.75)
Pandemic period	-0.0141	-0.0167	-0.0767*	-0.0109	-0.00558	-0.0265
	(-0.52)	(-0.83)	(-2.29)	(-0.55)	(-0.32)	(-1.18)
MktRF	0.121***	-0.0258**	0.0406**	0.0133	-0.0285***	-0.0194
	(10.21)	(-3.07)	(3.03)	(1.45)	(-4.45)	(-1.94)
SMB	-0.0401	-0.0615***	-0.115***	-0.0250	-0.0169	-0.0619**
	(-1.75)	(-3.95)	(-3.89)	(-1.39)	(-1.27)	(-3.14)
HML	0.231***	0.0164	0.121***	-0.0312	-0.00771	-0.00653
	(7.74)	(0.86)	(3.41)	(-1.52)	(-0.50)	(-0.28)
RMW	-0.0370	0.0100	0.0165	0.00300	0.0148	-0.00531
	(-1.30)	(0.47)	(0.45)	(0.15)	(0.83)	(-0.20)
CMA	-0.187***	-0.0841**	-0.0313	-0.158***	0.00253	-0.0180
	(-4.15)	(-2.87)	(-0.56)	(-4.68)	(0.10)	(-0.50)
Jensen's α	-0.0172	-0.00821	-0.0115	0.00336	-0.00199	0.00394
	(-1.94)	(-1.32)	(-1.11)	(0.49)	(-0.36)	(0.48)
Multiplicative heterosi	kedasticity					
Post decision	0.252	0.292*	0.389**	0.187	0.389***	0.196
	(1.42)	(2.23)	(3.17)	(1.31)	(3.80)	(1.80)
Pandemic period	0.540*	0.623**	0.713*	0.454*	0.479**	0.371*
	(2.23)	(3.26)	(2.49)	(2.12)	(3.07)	(2.32)
Cons	-5.488***	-5.361***	-5.013***	-5.656***	-4.345***	-4.916***
	(-11.88)	(-11.25)	(-18.08)	(-13.75)	(-13.08)	(-11.50)
$ARCH_{t-1}$	0.0534**	0.0822***	0.0536***	0.0554***	0.0114	0.0368*
	(3.21)	(3.29)	(4.32)	(3.45)	(1.19)	(2.32)
$GARCH_{t-1}$	0.885***	0.767***	0.866***	0.852***	0.565***	0.819***
	(22.71)	(8.49)	(35.76)	(18.65)	(4.16)	(12.64)
ln df(t)	2.024***	2.423***	34.81***	2.062***	0.573*	2.933***
	(7.49)	(6.86)	(1.40e+18)	(7.31)	(2.20)	(5.78)

Notes: t statistics in parentheses. * p < 0.05, ** p < 0.01, *** p < 0.001. The number of observations in all models is 1488.

På vilket sätt statens insatser bidrar till svensk tillväxt och näringslivsutveckling står i fokus för våra rapporter.

Läs mer om vilka vi är och vad nyttan med det vi gör är på www.tillvaxtanalys.se. Du kan även följa oss på LinkedIn och YouTube.

Anmäl dig gärna till vårt <u>nyhetsbrev</u> för att hålla dig uppdaterad om pågående och planerade analys- och utvärderingsprojekt.

Varmt välkommen att kontakta oss!



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