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What drives companies' progress on their emission reduction targets?☆

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ABSTRACT

As the importance of non-state mitigation actions in the transition to a low-carbon economy becomes firmly established, a rapidly growing number of companies are setting corporate climate mitigation targets. Shareholders increasingly value these commitments, conveying the impression of good future carbon performance. However, a critical question emerges: why do some companies progress better than others toward their climate mitigation targets? There is currently a lack of empirical literature assessing companies' progress against their mitigation targets. Using a new indicator to evaluate the progress against individual corporate climate mitigation targets in a comparable manner, this study presents an explanatory analysis of 120 determinants applied to 4341 climate mitigation targets (scope 1 and 2 emissions) of 2975 companies reporting to the 2020 CDP questionnaire. The target progress assessment shows that 30% of targets have increased emissions since their base year, 15% have reduced their emissions but not at a sufficient pace, while 55% were on track to achieving or had already achieved their targets. In addition, 18% of targets were already achieved the year the target was set, which may be due to choosing a base year with unusually high emissions. The findings reveal 19 key determinants significantly associated with the progress against corporate targets and highlight future research orientation. Our results indicate better progression by companies having absolute targets with longer timeframes and disclosing additional, as well as remuneration links to climate-related issues. Companies with more ambitious targets progress less than others, except when the ambitious targets are approved by the Science-Based Targets initiative. The latter implies ambitious targets from some firms may only be symbolic, and that investors should consider both target ambition and progress. Clear guidance and regulations should be implemented by policymakers to prevent misleading target information. Future research should address limitations related to reliance on self-reported data and exclusion of scope 3 emissions targets, along with the research directions suggested by the findings.

1. Introduction

To mitigate climate change risks, a transition to a low-carbon economy is needed (Campiglio et al., 2018; Daumas, 2024; Lee et al., 2023; Semieniuk et al., 2020). The importance of non-state actor mitigation actions is increasingly recognized in order to achieve such a transition (Hampton and Whitmarsh, 2023; Hsu et al., 2023; Kuramochi et al., 2020). Indeed, investors and companies have a major role to play in climate change mitigation (Bolton et al., 2022; Busch et al., 2024; Millar et al., 2018).

To manage their climate risks, several institutional investors are transitioning their investment portfolio to align with a goal of global net-

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zero emissions by 2050 or sooner (Bolton et al., 2022; Gosling and Macneil, 2023; Hoepner and Rogelj, 2021; Popescu et al., 2021). In response to such external pressures, companies are setting climate mitigation targets (Abreu et al., 2021; Babcock et al., 2022; Bjørn et al., 2022b; Cadez et al., 2019; Sullivan and Gouldson, 2017) which are commonly expressed as a percentage reduction for a given emission scope[1] between a base year and target year (Bolay et al., 2022; Campbell, 2021). Investors react positively to corporate climate mitigation targets by adding a premium value when the reduction announced is aggressively ambitious (Cheng et al., 2023; He, 2022; Khandelwal et al., 2022). However, investors are currently rarely considering if these targets are likely to be met (Campbell, 2021). Without an assessment of target progress, there is increased risk that symbolic targets will mislead investors regarding the future carbon performance and reputation of companies (Campbell, 2021).

Existing studies have confirmed that companies are often not on track to achieving their climate mitigation targets (Bolay et al., 2022; Callery and Kim, 2021; Kuramochi et al., 2021; Ruiz Manuel and Blok, 2023; SBTi, 2023, 2022; Wang, 2017; Yeo et al., 2022). However, these studies have not explored why this is the case. Despite the growing number of companies setting climate mitigation targets (Bolton et al., 2022; Hale et al., 2022; SBTi, 2023), there is currently a gap in the literature in understanding why some companies progress better than others. Addressing this gap is crucial, as a better understanding of what makes a corporate climate mitigation target successful would guide various stakeholders, including investors, in recognizing best practices and increasing the credibility and accountability of such actions (Hale et al., 2021; Kuramochi et al., 2021). Moreover, identifying best practices would allow investors to engage with companies to ensure their implementation.

Most scientific literature on corporate climate mitigation targets have mainly focused on firms attributes and external context associated with the decision to set a target (Armour et al., 2023; Bryant et al., 2020; Cadez et al., 2019; Desai et al., 2023; Eleftheriadis and Anagnostopoulou, 2017; Reid and Toffel, 2009; Yin et al., 2017), target setting approach (Bjorn et al., 2021; Krabbe et al., 2015; Lux et al., 2023; Moshrefi et al., 2022; Poschmann et al., 2023; Randers, 2012; Schweitzer et al., 2023) and target ambition (Bolton and Kacperczyk, 2023; Dietz et al., 2018, 2021; Doda et al., 2016; Rekker et al., 2022, 2023), with an emerging literature on science-based and net-zero targets (Bjørn et al., 2023, 2022b; Fankhauser et al., 2022; Freiberg et al., 2021; Giesekam et al., 2021; Hale et al., 2024, 2022; Kuo and Chang, 2021; Robiou du Pont et al., 2024). However, only few studies have assessed the determinants of companies' progress against their targets, and these are often limited to specific aspects, including target type, specific company characteristics, or distinct emission reduction initiatives implemented by companies (Aldy et al., 2023; Dahlmann et al., 2019; Dragomir, 2023; Giesekam et al., 2021; Ioannou et al., 2016; Wang, 2017; Yeo et al., 2022). For instance, Giesekam et al. (2021) restricted their study to the influence of target type on the progression of 81 science-based targets, and concluded that firms progress less towards targets covering scope 3 emissions than other scopes. Wang (2017) constrained his study to a sectoral comparison of 989 European and US firms disclosing in 2013 and found that US target progression is significantly higher than European in 8 out of 24 sectors. Dahlmann et al. (2019) assessed the target type of 1335 firms disclosing between 2010 and 2013, and determined that firms with an absolute and ambitious target with a longer timeframe are associated with emission reductions (the study did not directly assess target progress). Ioannou et al. (2016) assessed 1127 companies and determined that firms with higher target ambitions and monetary incentives towards management have a higher target progression. Yeo et al. (2022) confirmed that firms with more ambitious targets are correlated to higher target progression, via an assessment of 1500 firms reporting in 2021. However, recent studies by Aldy et al. (2023) and Dragomir (2023) suggest the opposite: firms with less ambitious targets tend to progress better than others. These two studies assessed, respectively, the target progression of companies included in the Russell 3000 index (roughly 450 companies) and the STOXX All Europe 100 Index, focusing only on limited aspects of target type and company characteristics. In addition to target type, Ioannou et al. (2016) assessed other target progress determinants such as: monetary incentives to management (board members, executive team members, and managers), number of initiatives to reduce emissions, carbon savings per initiatives, and amount of investments per initiative. Meanwhile, Day et al. (2022) assessed target credibility with a wider extent of determinant categories (e.g., strategy, risks, opportunities, carbon pricing, engagement with the value chain actors, and third-party verification), without assessing target progression, and without exploring which determinants are key to their progress.

In summary, existing studies on determinants of target progress do not provide a complete overview as they focus on sub-groups of targets, specific company characteristics, or limited emission reduction initiatives. This leaves unanswered questions, such as: Do monetary management incentives produce better end-results towards target progression than having science-based targets, or other strategies such as engaging with value chain actors? Do companies progress better against science-based targets than against other ambitious targets? This literature gap highlights the need for an in-depth investigation with a more comprehensive analysis of the determinants of corporate climate target progress. Therefore, this study aims to assess the target progress of a wide range of companies (across several sectors and regions), target types, and determinants to address the following research question: What are the key determinants that explain companies' progress towards their climate mitigation targets?

To answer this research question, an explanatory analysis will be carried out to identify the key determinants (significant explanatory variables) explaining the variability of corporate climate mitigation target progress (dependent variable). Identifying the key determinants of target progression requires the ability to consistently harmonize the measurement of target progress across companies. Due to the limitations of existing indicators to measure target progress, including the specificity of the sample data used, a new corporate target progress indicator that includes time-left to achieve a target was first developed (see Section 2.2). By combining a broad extent of determinants and target types, answering this research question will provide guidance on best practices for shareholders. Furthermore, it will better inform future research orientation, i.e., characteristics of targets to be further assessed separately.

2. Methodology

The following provides an outline of methodological steps applied to address the previously posed research question. Section 2.1 describes the sample of companies and targets covered for this study. Section 2.2 presents the dependent variable (target progress), while a brief description of explanatory variables (key determinants) is given in Section 2.3. Section 2.4 outlines the model used to conduct the explanatory analysis. To confirm the significance of explanatory variables obtained, robustness analysis has been performed as explained in Section 2.5.

[1] Following the GHG Protocol corporate accounting and reporting standard, scope 1 describes the direct emissions of the company while scope 2 are indirect emissions linked to the purchased of electricity purchased and scope 3, any remaining indirect emissions within the value chain (Harangozo and Szigeti, 2017; Stridsland et al., 2024). Two methodological approaches can be used to report the scope 2 emissions; location-based (regional grid-average emission factor) and market-based (specific emission factors derived from a contractual agreement) (Bjørn et al., 2022a; Brander et al., 2018).

2.1. Sample: companies and targets covered

The Carbon Disclosure Project (CDP) database has been used for this study as it is the most comprehensive and inclusive data set containing companies across all sectors and various countries, as well as different target types and a wide range of explanatory variables. Indeed, the CDP database is the most extensive database of voluntary corporate carbon reporting (Busch et al., 2022; Ott et al., 2017) and is commonly used by academics (Stanny, 2018; Zhang and Liu, 2020). Furthermore, the CDP database is in a standardized format as it is compiled from questionnaires sent on behalf of investors and/or supply chain actors (Depoers and Jeanjean, 2016; Ott et al., 2017; Zhang and Liu, 2020). This standardized format further facilitates the comparison of information reported by companies. However, it is important to note that the data are entirely self-reported by companies, and the CDP does not systematically verify responses provided by companies, which means there could be inaccuracies (Busch et al., 2022; Callery and Perkins, 2021; CDP, 2023; Garcia-Vega et al., 2023).

All the input data required for this study were extracted from the 2020 CDP climate change questionnaire, and compiled into an aggregated dataset, except for base year emission information, which in some cases was extracted from previous questionnaires year due to its unavailability in the current year. Accordingly, the data sample assessed consist of all companies reporting to the 2020 CDP climate change questionnaire that disclosed one or more emission reduction target. No exclusions or limitations have been placed on the industry sector or operational region.

The targets assessed in this study include absolute and intensity targets covering scope 1 emissions, scope 2 location-based emissions, scope 2 market-based emissions, scope 1 and 2 location-based emissions combined, and scope 1 and 2 market-based emissions combined. Although scope 3 often dwarf scope 1 and 2 emissions (CDP, 2024a; Mejia and Kajikawa, 2024; Schmidt et al., 2022), our study excludes targets covering scope 3 emissions, due to previously documented pervasive accuracy and consistency issues in scope 3 emissions accounting and reporting (Blanco et al., 2016; Busch et al., 2022; Hansen et al., 2022; Klaaβen and Stoll, 2021) and due to the challenge of applying the data consistency filter developed for scope 1 and 2 emissions (described below) to scope 3 emissions.

To allow a direct comparison of different target types and scope coverage, all targets have been harmonized to absolute targets for combined scope 1 and 2 emissions, following the methodology of Bolay et al. (2022). For the harmonization of targets covering scope 1 only, scope 2 location-based emissions have been considered instead of scope 2 market-based for both the year assessed and base year emissions. Targets have been excluded from the sample if the input data required to calculate target progress were not disclosed or if the missing data on explanatory variables required estimation (see Section 2.3).

To filter inconsistent data to avoid biasing results, a basic set of criteria was applied. The first criterion involves checking for inconsistencies between the base year emissions reported for the scope covered by the target[2] and the corresponding base year emissions reported elsewhere in the 2020 CDP questionnaire. Targets have been excluded if there was a difference greater than ± 1% between these base year emissions values. Note that the structure of the CDP questionnaire prevents this filter from being applied to scope 3 emissions, which is one reason behind the exclusion of scope 3 targets from this study. Additionally, targets with obvious erroneous emissions values across the reporting scope have been excluded. For example, entries of zero annual scope 1 and 2 emission were assumed to be errors. Furthermore, a factor near 1000 or 1,000,000 between base year emissions and the reporting year, without appropriate justification, was assumed to be a 'unit error' and excluded from the analysis.

[2] Value proportionally adjusted to 100% from the percentage of scope covered by the target.

2.2. Target progress: dependent variable

To justify the development of a new target progress indicator, existing indicators are first presented and critically evaluated in the context of our study. Based on identified shortcomings, a new progress indicator is developed. Existing studies have used the three following progress indicators: a) percentage of the target achieved (Dragomir, 2023; Ioannou et al., 2016; SBTi, 2022; Yeo et al., 2022), b) categorical variables, such as 'on track' or 'not on track', under the assumption of a linear reduction trajectory between the base year and target year, (Aldy et al., 2023; Callery and Kim, 2021; Giesekam et al., 2021; Kuramochi et al., 2021; Wang, 2017; Yeo et al., 2022), and c) progress ratio, which is equivalent to the percentage of the target achieved divided by the percentage of the time elapsed with respect to a linear target reduction trajectory (Hsu et al., 2020). Below, we identify issues with these three existing progress indicators (details in the Supplementary Information; SI).

The two primary issues identified regard the lack of comparability between target progress results; 1) no integration of the remaining time left to achieve the target; indicator 'percentage of the target achieved' used alone (represented by Equation (2)), and 2) lack of differentiation between target progress results; indicator 'categorical variables' (as for example slightly or highly on track in a same category). To overcome these issues, the present study integrates the percentage of time elapsed since the base year (Equation (3)), and uses a continuous value for target progress results. The third issue identified is the high variability in the target progress results, which is most pronounced near the indicated base year of corporate climate mitigation targets (Yeo et al., 2022), i.e. with indicator 'progress ratio', a large numerator (high or low percentage target achieved) with a small denominator (low percentage time elapsed), results in extreme values, which poses challenges for statistical analysis. While outliers (extreme values) are often sacrificed to improve statistical analysis results, legitimate outliers (ones that are not data errors) may contain useful information (Hadi et al., 2009; Orr et al., 1991; Osborne and Overbay, 2004). To address variability and allow the inclusion of legitimate outliers in our study, our proposed target progress indicator does not use ratios and is bounded by construction.

Equation (1) presents our new target progress indicator $P_{k,t}$ for the target of the company k at year t. This indicator reflects that the more time a company has left to achieve its target, the higher the likelihood of achieving it, while accounting for the emission reductions occurring at the year assessed. In other words, this indicator penalizes more severely when closer to the target year, as there is less time left for the company to achieve its target.

$$P_{k,t} = E_{k,t} - T_{k,t} + 1 \tag{1}$$

$$\text{with } E_{k,t} = \frac{e_{k,t_k^{base}} - e_{k,t}}{e_{k,t_k^{base}} - e_{k,t_k^{target}}} \tag{2}$$

and

$$T_{k,t} = \frac{t_k^{base} - t}{t_k^{base} - t_k^{target}} \tag{3}$$

Where:

k: target of the company assessed.

t: year assessed.

$E_{k,t}$: percentage of the target achieved at t of the company k.

$T_{k,t}$: percentage of the time elapsed at t of the company k.

t_k^{base}, t_k^{target}: base year and the target year for the target of the company k.

$e_{k,t}$, $e_{k,t_k^{base}}$, $e_{k,t_k^{target}}$: scope 1 and 2 emissions for the company k at t, t_k^{base} *and* t_k^{target}.

The target progress indicator $P_{k,t}$ is bounded from 0 to 2 by artificially limiting $E_{k,t}$ and $T_{k,t}$ from 0% to 100%. Hence, when the year assessed has lower emissions than the target year (target achieved), $E_{k,t}$ is 100%, and when the year assessed has higher emissions than the base year (no emissions reduction), $E_{k,t}$ is 0%. When the year assessed passes the target year (target year reached), $T_{k,t}$ is 100%, while $T_{k,t}$ is 0% when the year assessed is the same as the base year (target not started). The latter leads to disregarding the target, as there is no progression to assess.

Fig. 1 depicts a hypothetical scenario to illustrate how a target progress with 60% of the target achieved and 70% of time left will obtain a higher progress value ($E_{k,t} = 60\%$ and $T_{k,t} = 30\%$, then $P_{k,t} = 1.3$) compared to another with the same percentage achieved but less time left ($E_{k,t} = 60\%$ and $T_{k,t} = 50\%$, then $P_{k,t} = 1.1$). Furthermore, Fig. 1 illustrates cases of different percentages target achieved and time elapsed can have the same progress value (for example, see $P_{k,t} = 1.5$). While having a same progress value, these targets deviate to the same extent from their linear reduction trajectory (perpendicular line to the $P_{k,t} = 1$). Assuming these companies continue to reduce emissions at the same rate initially targeted between the year assessed and the target year, they would reach the same progress value in their target year (same percentages target achieved and time elapsed).

Regarding the interpretation of the target progress results, a value between 1 and 2 indicates the company is on track to reaching the target faster than a linear reduction trajectory (yellow to green part in Fig. 1). A value of 1 implies the company is exactly following a linear reduction trajectory, or that the target is achieved in the target year ($E_{k,t} = 100\%$ and $T_{k,t} = 100\%$, then $P_{k,t} = 1$). The extreme case of $P_{k,t} = 2$ means that the target was already achieved in the base year ($E_{k,t} = 100\%$ and $T_{k,t} = 0\%$). A value between 0 and 1 indicates that the company reducing emissions at a slower pace than a linear reduction trajectory (orange to red part in Fig. 1). A value of 0 implies no emissions reduction between the base year and target year ($E_{k,t} = 0\%$ and $T_{k,t} = 100\%$).

2.3. Determinants of target progress: explanatory variables

The explanatory variables, i.e., determinants of the target progress, include data from each section of CDP questionnaire (CDP, 2020) and thereby includes determinants analyzed in previous studies (Aldy et al., 2023; CA100+, 2022; Dahlmann et al., 2019; Day et al., 2022; Dragomir, 2023; Giesekam et al., 2021; Ioannou et al., 2016; Yeo et al., 2022), to the extent they are covered in the CDP questionnaire.

A total of 120 explanatory variables are considered, grouped into 11 categories, of which 16 are continuous variables and 104 are categorical variables. Categorical variables facilitate qualitative answers and are here assigned a value of 1 or 0 for affirmative and negative statements

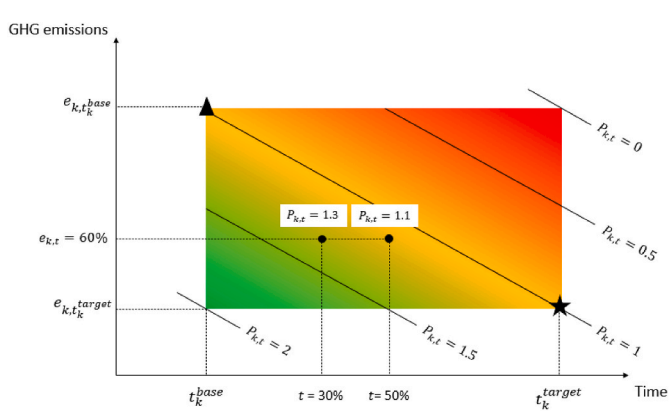

Fig. 1. Graphical representation of emissions for company k at the base year (triangle), year assessed (circle), and target year (star) with potential target progress indicator values, $\boldsymbol{P_{k,t}}$, displayed with color gradient and level lines.

respectively. Missing responses to CDP questions with qualitative answers were assigned a default value of 0 (negative). For example, if a company did not respond to the question 'Does the board oversight climate-related issues?', the response was assumed to be a no (negative). The model described in Section 2.4 permits the inclusion of both continuous and categorical variables.

Table 1 lists the 11 categories and the number of corresponding determinants evaluated, while providing examples of determinants and their respective units accordingly. The complete list of determinants including their corresponding CDP questions, preprocessing, and units are available in the SI. The following six categories are directly based on the CDP sections: 'Governance', 'Carbon price', 'Risks and Opportunities', 'Strategy', 'Engagement', and 'Verification' (CDP, 2020). The remaining five categories have been developed specifically for this

Table 1
Number of determinants assessed for each of the 11 categories. Examples of determinants per category are provided with their respective unit (complete list of determinants in the SI).

#	Category	Number of determinants	Examples of determinants	Unit
1	Target parameters	20	Annualized target ambition,	%
			Percentage of the target achieved at the year the target was set,	%
			Absolute target (not intensity target)	1 or 0
2	Emissions reporting and other targets	33	Energy target,	1 or 0
			Scope 3 target,	1 or 0
			Use renewable energy certificate in their scope 2 market-based accounting	1 or 0
3	Governance	6	Board oversight climate-related issues,	1 or 0
			Management remuneration link to climate-related issues,	1 or 0
			CEO remuneration link to climate-related issues	1 or 0
4	Carbon price	4	ETS or carbon taxes regulation,	1 or 0
			Internal carbon price	1 or 0
5	Risks and Opportunities	4	Physical risks considered relevant,	1 or 0
			Transition risks considered relevant	1 or 0
6	Strategy	13	Low-carbon transition plan,	1 or 0
			Revenue for low-carbon products,	%
			Climate-related scenario analysis (quantitative and qualitative)	1 or 0
7	Engagement	9	Engage with value chain actors,	1 or 0
			Direct influence on policymakers,	1 or 0
			Position consistent with trade associations where are members	1 or 0
8	Verification	1	Third-party verification	1 or 0
9	Additional reporting	4	Report for five years in CDP,	1 or 0
			Report in financial statement	1 or 0
10	Sector	13	CDP classification	1 or 0
11	Region	13	Based on the company headquarter location	1 or 0

study. The 'Target parameters' category includes determinants corresponding to the target analyzed. In the 'Targets and performance' and 'Emissions data' sections of the CDP, information for other targets or emissions reported than for the target analyzed are included in the 'Emissions reporting and other targets' category. The 'Additional reporting' category incorporates determinants relating to number of reporting years and additional reporting practices, and the 'Sector' and 'Region' categories describe company activities and headquarters information.

2.4. Statistical modelling

The main model used to identify key determinants of target progress is an Ordinary Least Squares (OLS) regression with a backward stepwise selection. The explanatory variables will be considered as key determinants of the target progress if they are significant, i.e., p-value of 0.05 as a threshold. To do so, all explanatory variables are entered into the model and the least significant variables are excluded one at a time until only statistically significant explanatory variables remain (Sanchez-pinto et al., 2018; Xu and Zhang, 2001). This method was chosen due to its wide use for variable selection in multiple fields (Sanchez-pinto et al., 2018).

To ensure the reliability and interpretability of results obtained, the correlation between explanatory variables have been tested to avoid multicollinearity as it can make significant explanatory variables statistically insignificant (Daoud, 2017; Shrestha, 2020). To identify multicollinearity, different methods have been applied depending on the variable types, i.e., categorical vs categorical variables; Phi Coefficient, categorical vs continuous variables; Point Biserial, continuous vs continuous variables; Pearson, Spearman, and Kendall correlation coefficients (Onwuegbuzie and Daniel, 1999; Shrestha, 2020). To ensure no significant multicollinearity remained in the model, the Variance Inflation Factor (VIF) has been used with a maximum threshold value of 5 (Akinwande et al., 2015; Daoud, 2017; Shrestha, 2020).

To make the explanatory variables comparable, a z score has been applied to scale their units into a standard deviation (Abdi, 2007; Turlach et al., 2005). The mean of each explanatory variable is normalized to a value of 0 and the standard deviation to 1 (Abdi, 2007; Turlach et al., 2005).

2.5. Robustness analysis

To ensure the robustness of results identifying key target progress determinants, two alternative models (i.e., Lasso and Random Forest Regressor), and a resampling technique (i.e., Bootstrapping) have been applied. The Least Absolute Shrinkage and Selection Operator (Lasso) model allows to test a different variable selection method than that used in the main model (i.e., p-value; Section 2.4). Indeed, Lasso is a regularization technique for regression models which applies a L1 penalty forcing some variable coefficients to 0 (Sanchez-pinto et al., 2018; Turlach et al., 2005; Zou and Hastie, 2005). Accordingly, explanatory variables with a coefficient higher than 0 are selected in this model.

Since the main model captures linear relationships between the dependent and explanatory variables, a non-linear model (random forest regressor) has been tested (Breiman, 2001; Nguyen et al., 2021). The random forest regressor is an ensemble of decision trees, where the training process selects the variables by splitting the entire dataset into nodes, and the reduction in the sum of the squared error is used for estimating the average relative importance for each variable (Breiman, 2001; Nguyen et al., 2021). To do so, the dataset has been split to train the model, and parameters tuned such as the number of splits and nodes to avoid overfitting (Probst et al., 2019; Segal, 2004).

Since some results may be inferred by a low number of appearances of a variable value in the dataset, bootstrapping techniques have been applied to the three models (the main and the two alterative models) to test the robustness and the stability of the variable selection process (Austin and Tu, 2004; Heinze et al., 2018; Hesterberg, 2011). The original dataset has been resampled 1000 times to an identical size with randomly replaced data for a whole row, i.e., target progress with its corresponding explanatory variable information (Austin and Tu, 2004; Efron and Tibshirani, 1994; Hesterberg, 2011). The variables are selected based on a minimum of 60% of appearances on the 1000 resampling of each model.

3. Results

3.1. Final sample

The total number of companies reporting in the 2020 CDP climate change questionnaires is 4524 of which 2975 disclosed a climate mitigation target (66%). The total number of targets reported by those companies is 6,058, involving 4341 scope 1 and/or 2 targets (72%) and 1717 scope 3 related targets (28%).

After compiling all required information for the target progress calculation and determinants, 2734 targets were deemed 'complete'. However, 1206 targets did not pass the data consistency test (see Section 2.1), reducing the final sample to 1528 targets from 1030 companies. The number of targets exceeds the number of companies as some report multiple targets, e.g., absolute and intensity targets, different scope coverage, or short-term and long-term targets. The total scope 1 and 2 emissions of the 1030 companies represents 4.7 GTCO2e, which corresponds to 80% of United States annual emissions in 2021 (Friedlingstein et al., 2022). The expected reduced emissions from the 1528 targets are 1.8 GTCO2e.

Table 2 presents the number of companies and targets by sector contained in the final sample, including the scope covered by the targets. Information per country and region is available in the SI. For the 1528 targets, 45% cover combined scope 1 and 2 location-based, and 31% cover combined scope 1 and 2 market-based. Targets covering only scope 1 represent 13%, scope 2 location-based, 8%, and scope 2 market-based, 3%.

3.2. Target progress

Fig. 2 shows the distribution of the target progress indicator for the 1528 targets ($P_{k,t}$). The average target progress is 0.97, corresponding to being slightly behind a linear reduction pathway, see Fig. 1. The variability in target progress is relatively high, with a standard deviation of 0.5, a first quartile of 0.67, a median of 1, and a third quartile of 1.3. No outliers are present in the progress results using an interquartile range approach for identification, as the target progress indicator is bounded from 0 to 2 by construction. In contrast, other progress indicators show outliers due to targets being over- or underachieved, resulting in values exceeding 100% or falling below 0%. These are included in the targets represented by white bars with dots or hatching in Fig. 2, respectively.

As displayed in Figs. 2 and 844 targets (55% of the sample) are achieved or on track to be achieved ($P_{k,t} \geq 1$). Of those 844 targets, 475 (31% of the sample) are achieved, while 108 of them (7%) also reached their target year ($P_{k,t} = 1$; grey parts with dots in Fig. 2). The remaining 369 of the 844 targets with $P_{k,t} \geq 1$ (24% of the sample) correspond to companies reducing faster than their target linear trajectory, without having reached their target year or their targeted emissions reduction (white bars with values over 1 and no dots in Fig. 2). Furthermore, 684 targets (45% of the sample) correspond to companies that are running late against their target linear reduction trajectory ($P_{k,t} < 1$). Of those 684 targets, 457 (30%) correspond to companies that increased emissions after the base year (hatching parts in Fig. 2), of which 96 companies' targets (6%) reached their target year ($P_{k,t} = 0$; grey hatch parts in Fig. 2). The remaining 227 targets out of the 684 (15%) pertain to companies reducing their emissions after the base year but are behind their target linear reduction trajectory (white bars with values under 1

Table 2
Number of companies and targets by sector included in the final sample. The scopes covered by the targets are represented in the last five columns. Abbreviations: SC1 = scope 1; SC2 LB = scope 2 location-based; SC2 MB = scope 2 market-based.

Sector	Number of companies	Number of targets	SC1 & 2 LB	SC1 & 2 MB	SC1	SC2 LB	SC2 MB
Apparel	25	31	15	11	2	2	1
Biotech, health care & pharma	53	76	23	37	6	7	3
Food, beverage & agriculture	56	73	32	28	7	5	1
Fossil Fuels	26	36	18	6	9	2	1
Hospitality	17	25	13	10	1	0	1
Infrastructure	63	100	50	28	17	5	0
International bodies	1	1	1	0	0	0	0
Manufacturing	348	483	239	132	52	48	12
Materials	111	155	70	55	19	6	5
Power generation	30	57	25	2	28	0	2
Retail	58	91	32	42	6	10	1
Services	208	350	156	118	28	34	14
Transportation services	34	50	18	11	19	2	0
Total	1030	1528	692	480	194	121	41

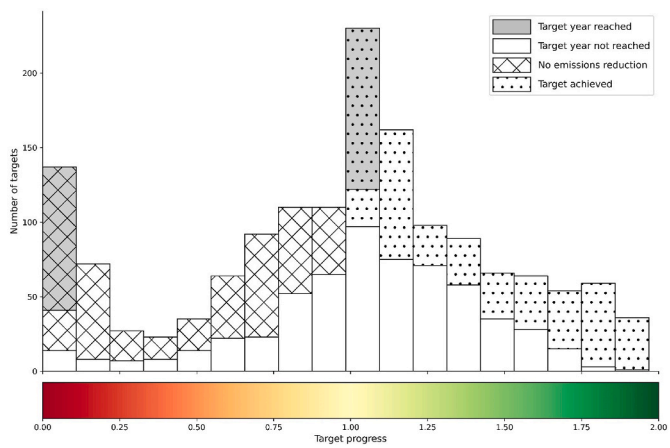

Fig. 2. Distribution of target progress indicator $P_{k,t}$. The color bar ranging from orange to red indicates targets behind linear reduction trajectory, while the range from yellow to green indicates targets ahead of that trajectory (see Fig. 1). Targets that have reached their target year are shown in grey (% time elapsed = 100%), while targets that have not reached their target year in white (% time elapsed <100%). Among the targets that have not reached their target year, those with no emissions reduction are indicated with hatching (% target achieved = 0%), and those with 100% of their target achieved are indicated with dots.

and no hatching in Fig. 2).

Some sectors were found to progress better than others. The power generation sector has a median target progress above other sectors, while the transportation services and fossil fuels sectors are lagging the most. Companies with headquarters in Southern Europe and Northern Europe have median target progress values ahead of all other regions. A deeper analysis of the target progress results per sector and region is available in the SI.

3.3. Key determinants of target progress

Using the backward stepwise OLS regression with a p-value threshold of 0.05 (the main model), 19 key determinants were identified, as listed in Fig. 3. Of the 120 explanatory variables analyzed, 34 have been disregarded due to multicollinearity (correlation between explanatory variables). The remaining 86 have a variance inflation factor under 5, implying no major multicollinearity left in the model (Akinwande et al., 2015; Daoud, 2017; Shrestha, 2020).

The main model, including the 19 selected determinants, is highly significant with a p-value far below 0.01 (F-statistic probability) and explains 35.4% of target progress variance in the sample (R-squared). The 19 key determinants in Fig. 3 are ranked from most to least significant p-value. The three most significant determinants are linked to the 'Target parameters' category, followed by determinants of the categories 'Region', 'Risks and opportunities', 'Governance', 'Emissions reporting and other targets', and 'Carbon price'. No determinants have been selected for the categories 'Strategy', 'Verification', 'Engagement', 'Sector', and 'Additional reporting elsewhere' (see Table 1).

Regarding the coefficients presented in Fig. 3, a positive value means that an increase of one standard deviation of the determinant value will increase the average value of the target progress by the coefficient value (positive association), while a negative coefficient implies a decrease in target progress values (negative association) (Siegel and Wagner, 2016). The coefficient interpretation arises from the determinant units associated with the z-score standardization (standard deviation; see Section 2.4). The coefficients and p-values for each key determinant are available in the SI.

The determinant *Percentage of the target achieved at the year the target was set* is the most significant and positively associated with target progress. These results can be explained by 19% of the sample having targets already being achieved by the year the target was set. On average, 32% of the targeted emission reductions are realized by the year the target was set.

The determinant *Number of years between the base year and the target year* is the second most significant determinant. Since positively associated, companies progress better against targets with longer timeframe than shorter ones. On the other hand, the *Number of years between the base year and the year the target was set* is negatively associated. Accordingly, progress is worse for targets with many years between the base year and the year the target was set (first key determinant). Indeed, some targets announced in 2015 or later have base years extending back to 1990.

Regarding the other key determinants linked to the 'Target parameters' category, *Absolute target (not intensity target)* is positively associated with target progress, meaning that companies progress better towards absolute targets than intensity targets. *Annualized target ambition* is negatively associated with target progress, suggesting firms setting more ambitious targets are less likely to attain them compared to firms setting less ambitious targets. The overall median annualized ambition for the sample is 2%, which is higher than the 1.4% median annualized ambition for targets already achieved (31% of the sample). Furthermore, targets that were achieved at the year the target was set have a 1% median annualized ambition. However, companies reporting ambitious targets as approved by the Science-Based Target Initiative (SBTi) progress better towards their targets than companies with other ambitious targets, hence *Approved by the SBTi* being identified as a positively associated determinant. These targets represent 17% of the sample, with a 2.5% median annualized ambition.

Of the 19 key determinants, 8 are linked to the region of company

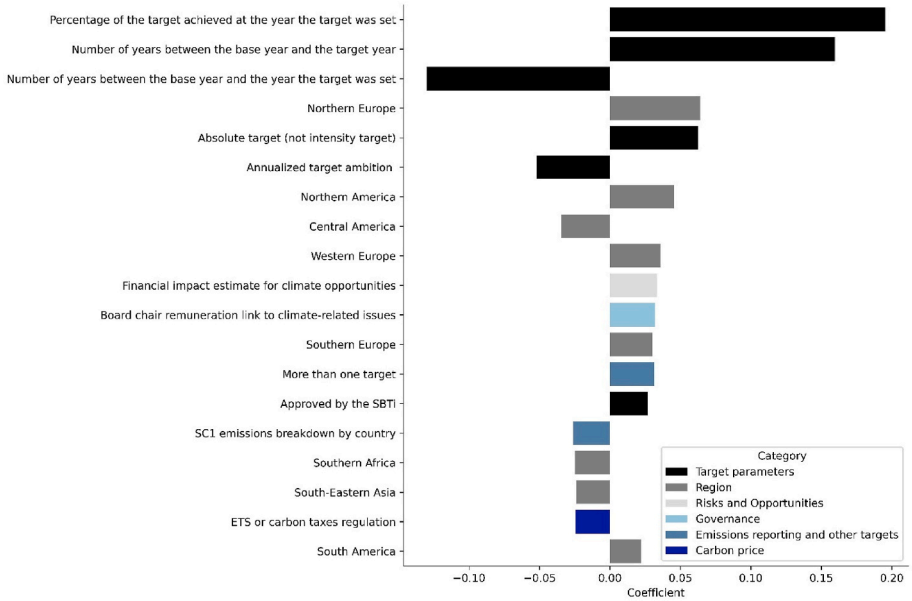

Fig. 3. Coefficient values for the 19 key determinants selected with the backward stepwise OLS regression model. Determinants are ordered from the most to least significant p-value (under 0.05). Abbreviations: SBTi = Science-Based Target Initiative; SC1 = scope 1; ETS = Emissions Trading System.

headquarters. Some regions (generally hosting developed economies) are positively associated with target progression, i.e., *Northern Europe, Northern America, Western Europe, Southern Europe*, and *South America*. However, *Central America, Southern Africa*, and *South-Eastern Asia* are negatively associated. Note that we could not identify key determinants related to sectors, suggesting that the type of product or service offered by a company does not influence its target progress.

Regarding the 'Risks and Opportunities' category, companies that have identified opportunities leading to a substantive financial impact, e.g., resource or production efficiency and development of new products or services, are positively associated with target progress. However, CO_2 savings, monetary annual savings and investment required for mandatory or voluntary initiatives implemented were, perhaps surprisingly, not identified as being significant ('Strategy' category). Concerning the 'Governance' category, progress was found to be better when the board chair remuneration is linked to climate-related issues, while CEO and manager remunerations were not significantly associated with target progress.

Regarding the 'Emissions reporting' category and other targets, companies disclosing more than one target, i.e., short-term and long-term targets, absolute and intensity targets, or multiple targets covering different scopes, progress better against their targets than companies only disclosing a single target. However, companies specifically reporting an energy target were not significantly associated with target progress. The determinant *SC1 emissions breakdown by country* is negatively associated with target progress, as with companies operating under an *ETS or carbon taxes regulation*. However, these determinants are less significant with p-values between 0.01 and 0.05, and less robust, as

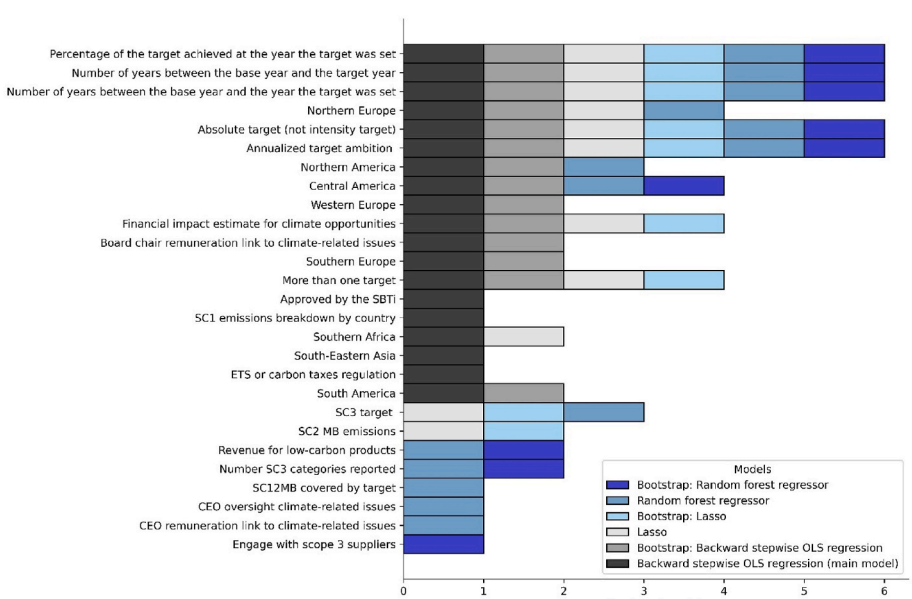

Fig. 4. Determinant selection for the main model (dark grey) and the five other models used to analyse the results robustness. Determinants are in the same order as in Fig. 3 if selected by the main model. Abbreviations: SBTi = Science-Based Target Initiative; SC1 = scope 1; ETS = Emissions Trading System, SC3; scope 3, SC2 MB; scope 2 market-based, SC12MB; scope 1 and scope 2 market-based.

discussed in the following section.

3.4. Robustness of key determinants

Fig. 4 presents the results of robustness analysis performed on the main model selection, as well as additional determinants selected by the other models, i.e., lasso (selection by coefficient constrained), random forest regressor (selection by average relative importance), and three bootstrap models (selection by 60% appearance threshold in its model). Five of the most significant determinants in the main model (see Fig. 3) are also selected by the other five models, confirming a strong robustness throughout, i.e., *Percentage of the target achieved at the year the target was set, Number of years between the base year and the target, Number of years between the base year and the year the target was set, Absolute target (not intensity target), and Annualized target ambition.* The determinants linked to the category 'Region' are not as strongly selected by the other models. Four determinants identified as significant by the main model have not been selected by any of the other models, i.e., *Approved by the SBTi, SC1 emissions breakdown by country, South-Eastern Asia, and ETS or carbon taxes regulation.* Those determinants have a p-value significance greater than 0.01 in the main model.

Eight additional determinants are selected by the other models with some from the 'Strategy' and 'Engagement' categories (bottom rows of Fig. 4). In contrast to the main model, three of the other models (random forest regressor, lasso and its bootstrap model) found a relationship between the disclosure of scope 3 targets and progress on scope 1 and 2 targets. The use of a different variable selection method with a linear regression model (lasso and its bootstrap) identified one supplementary determinant, i.e., *Company reporting their SC2 MB emissions* (positive association). Nevertheless, six supplementary determinants have been selected by non-linear models (random forest regressor and its bootstrap), i.e., companies reporting their SC3 emissions, the percentage of revenue for low-carbon products, target covering SC12 MB, CEO oversight and remuneration link to climate-related issues, and company engaging with their scope 3 suppliers. Determinants selected by the random forest regressor or its bootstrap model have no positive or negative association, since no coefficient is estimated in contrast to other models (Breiman, 2001; Nguyen et al., 2021).

4. Discussion

The present study contributes to the scientific literature on corporate climate mitigation targets. This has been established through assessing the progression of 1528 targets from 1030 companies, considering 120 explanatory variables grouped in 11 categories (see Section 2.3). This represents a substantial increase in variables and categories compared to existing studies (Dahlmann et al., 2019; Giesekam et al., 2021; Ioannou et al., 2016; Wang, 2017; Yeo et al., 2022). Through the development of a new target progress indicator, the results obtained shed new light on ambitious targets compared to existing literature and identify some best practices, but also poor ones (Section 4.1). Furthermore, the findings reveal the significance of certain target characteristics and identify future research orientation to be further examined (Section 4.2). The study's limitations are addressed in Section 4.3 and recommendations to stakeholders are given in Section 4.4.

4.1. Comparison with existing literature

The findings suggest that companies with absolute targets and longer timeframes progress better than others. Furthermore, companies with more ambitious targets generally progress less, except when these ambitious targets are approved by the SBTi. Previous studies have stated that firms with higher ambition are more likely to be attained (Dahlmann et al., 2019; Ioannou et al., 2016; Yeo et al., 2022). While our results support Dahlmann et al. (2019) findings regarding absolute targets with longer timeframes and Ioannou et al. (2016) findings regarding monetary incentives, our findings suggests the opposite of their statement for companies with higher ambition. Recent studies by Dragomir (2023) and Aldy et al. (2023), however, support our findings that companies with less ambitious targets generally progress better, although our results differ from Dragomir (2023) findings on targets with shorter timeframes progressing more.

The differences observed with previous studies might be partly explained by the progress indicators used (see SI), reducing the comparability of study results. Additionally, earlier study did not annualize target ambitions (Ioannou et al., 2016), while recent studies from Dragomir (2023) and Aldy et al. (2023) included companies with extremely high or low target achievements. In contrast, Yeo et al. (2022) did not include such extremes, further increasing the differences from our current study sample.

Another possible reason for these discrepancies could be the evolution of corporate target disclosures. Earlier studies by Dahlmann et al. (2019) and Ioannou et al. (2016) with companies disclosing targets over 10 years ago might have included a higher proportion of early adopters genuinely committed to reducing their emissions (leaders). In contrast, more recent studies have larger sample sizes, and may include a higher proportion of companies reporting targets as a disclosure exercise rather than genuine commitment (Dragomir, 2023; Montgomery et al., 2023). These cases might involve low ambition targets that were easily (and overly) achieved, including those achieved at the year the target was set (related to the first key determinants, see Section 3.3), showing the importance of considering extreme values in the analysis. As suggested by Aldy et al. (2023), companies with ambitious targets might not have properly accounted for future sales growth when setting their targets, potentially indicating these targets were more about disclosure than genuine commitment. However, Freiberg et al. (2021) determined that firms committing to SBTi targets are associated with increased investment in initiatives towards emission reductions, perhaps explaining why progress is better for targets approved by the SBTi than other ambitious targets. In this regard, our study found an association between the target progress and companies that have identified opportunities leading to substantive financial impacts as well as the percentage of revenue generated from low-carbon products (other models, see Fig. 4).

Giesekam et al. (2021) results have shown that firms with SBTi approved targets covering scope 3 emissions progress significantly less than companies only including scope 1 and 2 emissions and later progress reports by SBTi confirm this pattern (SBTi, 2023). Our study's sample exclude scope 3 targets due to accounting and reporting issues (Section 2.1). However, results obtained indicate that companies reporting scope 3 targets progress better on their targets covering a scope 1 and 2 (selected by three of the other models, see Fig. 4). Furthermore, the number of scope 3 category reported and engaging with suppliers appear to impact the progression of scope 1 and 2 targets (non-linear relationship with target progress). Further research should investigate why scope 3 disclosure, including targets and initiatives, may influence the progress of scope 1 and 2 targets. Moreover, different models should be tested to capture non-linear relationships between target progress and key determinants (six additional determinants, see Fig. 4).

Regarding executive remuneration, our results support the findings of Ioannou et al. (2016) concerning a link with target progress. Ioannou et al. (2016) found a positive association between monetary incentives to the management which combined the board, CEO, COO, directors, and managers. Results from the main model suggest board remuneration is specifically associated with target progress. Nevertheless, CEO remuneration and corresponding oversight of climate-related issues is selected by one other model (see Fig. 4) but does not include the managers remuneration. Companies having headquarters located in Northern Europe or North America progress better than others while in Central America, less than others. To a certain extent, this is inconsistent with the findings of Wang (2017), since the present study identifies European firms as being more significantly associated to target progress

than North American firms. However, Wang (2017) only assessed US and European firms without including other North American firms.

4.2. Future research orientation

The findings highlight that the 'Target Parameters' category is of most significance for determining target progress (see Fig. 3). Moreover, the five most robust determinants, across statistical models, belong to this category (see Fig. 4). The key relevant determinants are combined into three main target characteristics needing further investigation: the choice of base year, target trajectory, and target ambition.

The choice of base year from companies is mainly implied in the first and third key determinants which led to opposite target progression directions, i.e., respectively, *Percentage of the target achieved at the year the target was set* and *Number of years between the base year and the year the target was set*. While in some cases a high percentage of target achieved at the year the target was set may indicate genuinely impressive emission reductions, it may also reflect poor practices by a company, i.e., low target ambition (targeting a low percentage reduction), and base year 'cherry-picking' (selecting a base year with unusually high emissions) (Bjørn et al., 2023; Bolton and Kacperczyk, 2023; Callery and Kim, 2021; Dragomir, 2023). Further research is needed to better understand the base year choice and its implications for target progress. For example, what types of companies 'cherry-pick' a base year with unusually high emissions? Are companies with approved SBTs less likely to 'cherry--pick' base years than companies with other type of targets?

While the choice of base year may have some implications, the emission trajectory and its timeframe may also explain some findings for the first three key determinants. The trajectory of emission towards long-term targets may not be linear (second key determinant; *Number of years between the base year and the target year*), with a higher progress achieved in the beginning, where companies are picking low-hanging fruits (first key determinant), and lower later when easy options have been depleted (third key determinant). An inverse 's-shaped' curve may potentially apply in some cases, when initial investments take years to yield their potential for emission reductions. Future investigation is deeply needed to understand the different trajectories and the target characteristics related to them. Such crucial research would provide the basis required to use non-linear trajectories when assessing the progression of companies toward their targets. For example, what types of company and targets relate to slower initial progress? Are companies with longer timeframes and interim targets more likely to reduce rapidly in the beginning than companies with no interim targets?

The findings regarding target ambition underpin the relevance of continuing to assess companies based on their ambition, i.e., *Percentage of the target achieved at the year the target was set, Annualized target ambition,* and *Approved by the SBTi*. For example, future research could assess a sub-group of firms with ambitious targets, like approved SBTs as previously done by Giesekam et al. (2021), or compare firms with ambitious targets and different characteristics, such as approved SBTs versus other ambitious targets. Additional scrutiny is needed to understand why companies with approved SBTs appear to progress better than other companies with ambitious targets (see Section 4.1). Similarly, the type of targets, i.e., *Absolute target (not intensity target)* could be used to determine subgroups since it is one of the important key determinants and include additional components such as *More than one target*, e.g., net-zero targets with absolute interim targets vs net-zero targets with intensity interim targets.

Furthermore, the contrasting results regarding target ambitious between our study and earlier studies suggest the need for closer investigation into target progress indicators, the evolution of target disclosures over time, and the impact of extreme values in study samples (see Section 4.1). For example, future research could compare progress using different indicators for the same disclosure year and varying sample restraint (including or excluding extreme values) to better understand their effect on study results, particularly for ambitious targets.

4.3. Limitations

The main limitations of this study are the accuracy of the information reported by companies, the exclusion of scope 3 targets in the dependent variable, the assumption of a linear reduction trajectory, and the choice of explanatory variables (see Table 1). Since this study relies on the use of self-reported information by companies, one issue concerns the potential lack of reliability of the data, particularly for emissions data used to calculate the progression of companies' targets. Companies may have over- or understated their emissions (and misreported information related to determinants assessed), either unintentionally or intentionally (Callery and Perkins, 2021; Garcia-Vega et al., 2023), leading to potential distortions in the analysis. To minimize this issue, our study implemented a set of criteria to filter out inconsistencies (see Section 2.1), mainly found in base year emissions of companies' targets. These inconsistencies resulted in the exclusion of 44% of targets that had all the input data required for our analysis (see Section 3.1). This indicates a pervasive issue around reliability of self-reported climate data, at large. Our findings should therefore be interpreted with caution, although we emphasize that a study of this size (number of companies and target progress determinants) could not have been realized without voluntarily reported information. Indeed, disclosures are not mandatory in every country and mandatory disclosures do not include the extent of information used in this study (Busch et al., 2022; He et al., 2020; World Bank, 2023).

As previously mentioned in Section 2.1, targets covering scope 3 have been excluded since consistency assessment of their base year emissions was not possible in the CDP year assessed. Many studies stated that companies often struggle with scope 3 emissions accounting (Dahlmann et al., 2023; Patchell, 2018; Puschmann and Quattrocchi, 2023), making their disclosures relatively uncertain despite recent improvements (Blanco, 2021; Busch et al., 2022; Hansen et al., 2022; Klaaβen and Stoll, 2021). Including scope 3 targets without cross-validation of related emission disclosures could bias results, as their inconsistencies would likely exceed the 44% exclusion rate observed with scope 1 and 2 targets. However, scope 3 emissions could represent more than 75% of the total company emissions (CDP, 2024a; Huang et al., 2009; Mejia and Kajikawa, 2024; Schmidt et al., 2022), meaning that excluding scope 3 targets risks overlooking an important corporate lever for reducing global emissions. To mitigate this limitation, determinants with scope 3 perspective were incorporated into our analysis. Future research could extend to scope 3 target progress and their determinants; CDP has recently introduced more extensive scope 3 content (CDP, 2024b). Using our criteria for filtering inconsistencies, these studies could provide rich insights for future assessments and stakeholders.

Since companies did not provide information on the expected reduction trajectory of their targets, the target progress indicator assumes a linear reduction trajectory, as commonly done in previous studies (Aldy et al., 2023; Dietz et al., 2021; Giesekam et al., 2021; Hale et al., 2021; Hsu et al., 2020; Kuramochi et al., 2021). Our findings suggest that mitigation efforts may not always follow a linear path, particularly for targets with longer timeframes (see Section 4.2). The target progress indicator can be adapted for non-linear reduction trajectories. Applying an exponent on the percentage of time elapsed results in higher progress initially and slower later (mitigation efforts already started, exponent >1), or slower progress initially and faster later, (mitigation efforts starting later due to time to initiate them, exponent between 0 and 1). Without further investigation or specific information from companies regarding their planned reduction trajectories, assuming these alternative trajectories currently lacks basis and risks mislabeling targets with minimal initial reductions as 'on track'.

Different determinants or a higher number of determinants may lead to different results. Increasing the number of determinants, disaggregating more CDP questions, or including data outside CDP are new avenues for future research. For example, CDP does not include

variables related to company size or financial information. Such variables may lead to a higher variance of the target progress explained. However, not all companies assessed are public, which implies a lack of financial information for the full sample of this study.

4.4. Implications of findings

The findings of this study have generated valuable insights leading to future research orientation (see Section 4.2), as well as recommendations for companies, policymakers, and investors. Companies need to improve the quality and completeness of their target disclosure. Inconsistencies, such as those found with target base year emissions (1206 targets disregarded out of 2734 initially judged complete), can be viewed as poor practice and damage a company's reputation. Furthermore, companies should provide additional information regarding their target reduction trajectory (Bjørn et al., 2023; Bolay et al., 2022). This would facilitate non-linear trajectory assumptions and prevent companies from being assessed as 'not on track' if their reduction plans involve slower initial reductions followed by accelerated reductions due to scheduled investments.

Understanding companies' behaviors and how they are progressing towards their targets can help policymakers identify areas needing increased efforts and regulation. In addition to poor corporate behaviors, such as inconsistencies, and disparities in target parameters, our findings suggest that ambitious targets from some firms may only be symbolic due to their lower progression. Governments should implement regulations to prevent misleading information for investors and other stakeholders and provide clear guidance on appropriate target parameters and disclosures. The CDP should require companies to specify the expected reduction trajectory in their questionnaire.

The key determinants leading to lower or higher progression of companies' targets can be useful for investors to inform their market-value assessment of firms, such as with ambitious targets. Investors should exercise caution and conduct deeper investigations before increasing a firm's market value based on ambitious targets. Following target progression should be integrated into investment assessments, given that 30% of firm targets have increased their emissions compared to their base year and another 19% achieved at the year the target was set. Investors could use the poor practices identified in this study to inform their engagement strategies. Meanwhile, companies should be account for the key determinants by carefully choosing their target parameters, favoring absolute targets over intensity, setting more than one target such as those covering scope 3 emissions, linking remuneration to climate-related issues, and getting their ambitious targets approved by the SBTi.

5. Conclusion

This study contributes to the understanding of corporate climate mitigation targets and is the most comprehensive study of the determinants influencing their progress, with the analysis of 120 determinants applied to a final sample of 1528 targets from 1030 companies. Using a new indicator to evaluate progress in a comparable way, this study identifies 19 key determinants that explain why companies progress better or worse than others towards their targets. These determinants provide valuable insights by revealing future research directions and recommendations for companies, policymakers, and investors.

The findings highlight that companies with absolute targets, longer timeframes, disclosing additional targets, and remuneration associated with climate-related issues tend to progress better. The results reveal that companies with ambitious targets progress less, except when these targets are approved by the SBTi. This suggests that some ambitious targets may be more symbolic than genuine. Investors should investigate the progression and ambition of corporate targets when assessing companies, and policymakers should provide clear guidance and regulations to prevent misleading information target information.

The progression of companies' targets shows that 19% of targets were achieved in the year they were set. Furthermore, 30% had increased their emissions compared to their base year, with an additional 15% of targets 'not on track' and the remaining 55% being on track (or already achieved).

Despite its valuable contributions, this study is not without limitations, including the reliance on self-reported data by companies and the exclusion of scope 3 emissions targets. Future research should address these limitations and explore the implications of target progress indicators, non-linear reduction trajectories, base year choices, and target ambitions to provide a more comprehensive understanding of corporate target progression.

CRediT authorship contribution statement

Anne-France Bolay: Conceptualization, Formal analysis, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Anders Bjørn:** Supervision, Writing – review & editing. **Laure Patouillard:** Supervision, Writing – review & editing. **Olaf Weber:** Supervision, Writing – review & editing. **Manuele Margni:** Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2024.143124.

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