On the Importance of Assurance in Carbon Accounting*

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Latest Version of this Working Paper

February 21, 2024

Abstract

Firms that obtain assurance for their carbon accounting report on average a 9.5% higher carbon intensity than their peers. When controlling for assurance, we do not find evidence that SBTi target-setters reduce their future emissions. Instead, firms that obtain assurance reduce their future carbon intensity by 3.3%. This has implications for portfolio managers and ESG raters as taking reported carbon emissions at face value would lead to penalizing firms that are more serious about their carbon reductions. It also calls for mandatory assurance when carbon reporting is mandatory and when reported emissions are generally relied upon in regulation.

Keywords: Auditing, Carbon Emission Targets, Carbon Accounting
JEL classification: Q54, Q56

*The authors would like to thank Clarity AI for access to their data. We are grateful to the Massachusetts Pension Reserves Investment Management Board, AQR Capital Management (Applied Quantitative Research), Qontigo, Capital One, and MFS Investment Management—members of the Aggregate Confusion Project Council—for their generous support of this research.

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1 Introduction

Firms are currently at various stages in their journey toward decarbonization. The reasons for reducing carbon emissions include benefiting from a lower cost of capital due to the increasing presence of ESG investors, mitigating transition risks, cost reductions from improved energy efficiency, or simply appealing to climate change-aware customers. The stages of decarbonization among firms differ largely. Some are taking the role of leaders by setting ambitious targets verified by organizations such as the Science Based Targets Initiative (SBTi). Others content themselves by merely issuing beautiful reports with little substance. Over 184 publicly listed firms have set SBTi targets until the end of 2021 and the pace of firms committing to targets has been accelerating in the past years as seen in Figure 1.

Two essential steps in evaluating decarbonization pathways involve on the one hand evaluating carbon accounting practices, i.e., if firms report emissions correctly, and on the other hand if firms indeed reduce future emissions as they claim. These two steps have three distinct challenges with the first being that most firms do not report CO_2 data at all. Hence, imputed data plays an essential role in the ESG industry, where data providers such as TruCost or Clarity AI impute up to 80% of the companies in their dataset. The imputed data is not only important for portfolio construction but also for fund reporting as some funds in Europe need to report carbon emissions at the fund level. Unfortunately, as Aswani, Raghunandan, and Rajgopal 2023 show, we cannot use these estimates to make any inference as they are in general based on financial and industry characteristics. The second challenge is that firms that do report their CO_2 data need to estimate the data themselves. For instance, firms usually take the amount of fuel they buy and multiply it by a coefficient to obtain the number of CO_2 emissions emitted by their fleet. Some firms might choose coefficients or procedures that go in their favor. Others might even simply omit parts of their emitted carbon emissions. Some firms pay for third-party assurance to sign off on their reported carbon emissions to signal reliable reporting. The process of obtaining assurance needs to be carried out by an independent external organization accredited and competent to perform GHG assurance. Third, just because a firm sets a target it does not mean it will reduce CO_2 emissions. These targets are often set at long horizons such as 2050. Firms might use them as a signal for future action while choosing not to reduce CO_2 emissions immediately.

To investigate these 3 challenges, we build a data set that combines reported and imputed carbon emissions from Clarity AI, the assurance status of the reported emissions from Clarity AI, and targets from SBTi. We choose SBTi targets as they, contrary to CDP, include a process of approval of the decarbonization pathway. Whenever a firm applies to adhere to an SBTi target, it needs to commit first, and then after a process of evaluation, a target might be accepted or rejected. We thus hypothesize that firms that set SBTi targets are more likely to reduce future carbon emissions than firms that just simply report targets through CDP.

We first establish that reported absolute CO_2 emissions are 14.9% higher than their imputed counterparts. We also find that when we control for reported data, the correlation between target setters and their respective CO_2 emissions changes. We thus use only reported data for our further analysis. Second, we initially show that firms that set a target have 32.7% lower absolute emissions and 27.1% lower carbon intensities. In this case, we do not control for the assurance status of the reported emissions. As we will see, the assurance status of a firm is an important omitted variable that, once included, changes our findings. Third, we find that firms that obtain assurance for their reported emissions have 13.7% higher absolute emissions and 9.5% higher carbon intensities. This indicates that firms that do not obtain assurance for their reporting might use more favorable assumptions or omit key parts in their estimation of carbon emissions. Fourth, when controlling for assurance practices, we find that target setters do not reduce their future CO_2 emissions. Surprisingly, only those firms that obtain assurance for their emission reporting have a significant and economically meaningful decline in their absolute emissions and carbon intensity. Total emissions decline by an economically meaningful 7.5% year-on-year, while the intensity declines by 3.3% percent a year. Overall, our findings show that firms without assurance set targets when they already have lower emissions but do not reduce them in the future. Instead, firms that obtain assurance reduce their future carbon emissions. This might indicate that firms pay for assurance as a signal to stakeholders to distinguish themselves from firms that do not have any intentions to reduce carbon emissions. These firms also accept that the signal comes at a cost, namely higher current carbon emissions.

We confirm previously found results that firms that set targets have on average lower emissions (Bolton and Kacperczyk 2021). We deviate from this literature by showing that targets are not associated with a future reduction in carbon emissions. Dahlmann, Branicki, and Brammer 2019 argue that the characteristics of these targets, such as their scope, duration, and specific goals, reveal much about a firm's genuine intentions towards environmental impact. Their analysis, based on data from the Carbon Disclosure Project (CDP) between 2010 and 2013, shows that ambitious, long-term, and absolute emission reduction targets are linked with significant emission reductions in firms. Complementing this, Ioannou, Li, and Serafeim 2016 finds a positive correlation between the ambition of decarbonization targets and the degree of target completion, highlighting the role of ambitious goal-setting in achieving environmental outcomes. Similarly, Freiberg, Grewal, and Serafeim 2021 demonstrates that firms with a history of setting and achieving ambitious carbon targets are more inclined to set science-based targets, indicating a pattern of escalating commitment to environmental responsibility.

Adding to this narrative, Ramadorai and Zeni 2023 employs dynamic micro models to suggest that firms' beliefs about climate regulation significantly shape their abatement plans and actions, pointing to the influence of regulatory expectations in corporate environmental behavior. Comello, J. Reichelstein, and S. Reichelstein 2023 introduces the concept of a time-consistent corporate carbon reporting (TCCR) standard, emphasizing the need for continuous monitoring and reporting for effective emission reduction. From a financial perspective, Lemma, Lulseged, and Tavakolifar 2021 reveals that firms with a stronger commitment to climate change actions issue a higher proportion of debt with longer terms to maturity, suggesting a reputational benefit and easier access to financial markets. This view is supported by Krueger, Sautner, and Starks 2020, who reports that long-term, large-scale investors favor engagement over divestment for managing climate risks, indicating a preference for active involvement in shaping corporate environmental strategies. Also, Cenci et al. 2023 find that there is an over-investment in risk mitigation actions as opposed to innovation and cooperation activities, which explains corporate misalignment with the Paris alignment targets. Lastly, Kacperczyk and Peydró 2022 underscores the financial sector's role in driving environmental performance, finding that firms with higher carbon footprints borrowing from environmentally committed banks receive less credit, linking financial incentives directly to environmental performance.

We contribute to the literature in three ways. First, we show that firms that verify their emissions report higher current emissions. Second, we show that target setters do not reduce future emissions when controlling for assurance. Third, we show that firms that obtain assurance reduce their future CO_2 emissions.

Our findings have implications for portfolio managers and ESG raters as taking disclosed carbon emissions at face value would lead to penalizing firms that are more serious about their carbon reductions. It also calls for mandatory auditing when carbon disclosure is mandatory and when disclosed emissions are generally relied upon in regulation.

2 CO_2 Data and Its Challenges

We build a data set that combines reported and imputed absolute carbon emissions as well as carbon intensities from Clarity AI and CDP, the assurance status of the reported emissions from Clarity AI, and targets from SBTi. In the following section, we explain these variables in more detail. Given both variables' importance, we include them both in our analysis.

2.1 Absolute Carbon Emissions and Carbon Intensities

We use Scope 1 emissions as our primary proxy for firm emissions. According to the Greenhouse Gas Protocol al (2022), Scope 1 emissions are direct greenhouse (GHG) emissions from sources controlled or owned by an organization. We also add carbon intensities. We include both as they are both important for a society's objective function.

At the overall level, if society would like to reduce worldwide carbon emissions it needs to focus on absolute emissions. But at the individual firm level, absolute emissions correlate mainly with production output or, put differently, the size of the firm. For example, Table 3 shows that absolute emissions correlate with revenue at 51%. Hence, reducing CO_2 at the firm level is about increasing carbon efficiency rather than focusing on absolute emissions. A simple example illustrates why. If investors or regulators focused on absolute emissions a firm could simply split into two halves to avoid pressure as each half would have lower absolute emissions. The absolute emissions on the societal level remain the same.

2.2 CO_2 Imputed Data

We use the Scope 1 dataset from Clarity AI. Clarity combines CDP data with their own. CDP is a global initiative that compiles comprehensive environmental data, including greenhouse gas emissions, from a diverse range of firms worldwide. They do so through a yearly questionnaire that firms voluntarily submit. Clarity AI completes the dataset by extracting Scope 1 data available in the firms' Corporate Sustainability Reports. In a similar way to other data providers, in case such information is not available, Clarity AI leverages proprietary machine-learning-based imputation methods to complete the missing information. These models exploit relationships between different firm features and reported emissions from other firms through machine learning techniques (Assael et al. 2023; Nguyen, Diaz-Rainey, and Kuruppuarachchi 2021; Serafeim and Velez Caicedo 2022). The imputation is based on firm size, business model, technology, and the business environment. Firm size is proxied by financial metrics like revenue, employees, assets, and capital intensity. The business model is represented by industry type, gross margin, and energy metrics. Technological aspects are gauged by capital expenditure and asset life expectancy. Business environment factors are determined by geographical data, including carbon tax schemes and/or carbon trading systems in the country.

The model's generalization capabilities are validated on a firm hold-out test set (see Figure 5 in the Appendix)—as well as by subject matter experts—and then used to infer the emissions of non-reporting firms. Similarly to other data providers in the industry, Clarity AI's imputation methods follow the precautionary principle, i.e., the imputed data is skewed towards higher values (see Figure 3). This minimizes the risk of strategic omissions, i.e., high emitters benefiting from not disclosing data.

In some cases, imputation might be useful for portfolio construction and aggregation, but as shown by Aswani, Raghunandan, and Rajgopal 2023, it shouldn't be used for studying the underlying emissions phenomena.

2.3 Assurance

There are two main types of ESG assurance: reasonable assurance and limited assurance. Reasonable assurance, known as examination in the U.S., provides a high level of certainty that reported information is materially correct. During this process, firms share their reporting methodology with the auditor, who in turn, assesses the risks of inaccuracies in the reporting. Based on this assessment, a sample of data is selected for detailed testing. The auditor evaluates the evidence against set criteria which may result in changes in the reported data. The process culminates in issuing an assurance statement. Limited assurance, referred to as review in the U.S., relies more on management's representations and involves less document verification and process understanding.

CDP acknowledges eight organizations as accredited assurance solutions providers, performing the validation under internationally recognized standards. This organization must be independent of the organizations that have gathered and/or provided the data and those that will use the data. This organization is also independent of the recognized standard used to perform the assurance (CDP accepts 43 accepted assurance standards such as ISO 14064).

2.4 Science Based Target Initiative

Furthermore, we add two variables that indicate the firms' status concerning the Science-Based Target Initiative (SBTI), namely *Commitment* and *Target*. The SBTI offers a structured target-setting process for firms. Firms begin by committing to set a target, which involves registering online and submitting a commitment letter. Following the letter, they develop their target, considering aspects such as emission scopes, base and target years, and sector-specific considerations. Once formulated, firms submit their target to the SBTI for validation, ensuring it meets the initiative's criteria. After validation, firms announce their targets and are subsequently required to disclose their progress regularly. In the context of this work, we build our *Target* variable with only the highest-stakes targets (Net-Zero targets or SBTi targets with targeted reductions of more than 75% of emissions). One important key problem is that disclosure of progress is not subject to verification. The SBTI also provides guidelines for recalculating targets if necessary. While the initiative promotes near-term science-based targets and longer-term net-zero ambitions, they are distinct commitments with different criteria and time frames.

3 Methodology

3.1 State of Reporting, Assurance, and Targets

We explore the propensities to report, obtain assurance, and adopt SBTI targets by estimating three logit models:

$$P(r_{i,t})=\sigma\left(\sum_c \gamma_c x_{i,t}^c+\mu_i+\nu_i+\theta_t+\epsilon_{i,t}\right), \tag{1}$$

$$P(v_{i,t})=\sigma\left(\sum_c \gamma_c x_{i,t}^c+\mu_i+\nu_i+\theta_t+\epsilon_{i,t}\right), \tag{2}$$

$$P(t_{i,t})=\sigma\left(\sum_c \gamma_c x_{i,t}^c+\mu_i+\nu_i+\theta_t+\epsilon_{i,t}\right), \tag{3}$$

where $r_{i,t}$ denotes the firm i's Scope 1 emissions (in levels or intensities) in year t, $v_{i,t}$ denotes assurance, and $t_{i,t}$ denotes having an active SBTI target. μ_i, ν_i and θ_t correspond to sector, continent, and year fixed effects. Finally, $x_{i,t}^c$ denotes control variable c for firm i at time t, and $\sigma(z)$ is the logistic function:

$$\sigma(z)=\frac{1}{1+e^{-z}} \tag{4}$$

The odds ratio of each feature across the three binary variables is shown in Figure 2.

3.2 Regression Model

Our baseline regression model is the following:

$$y_{i,t} = \alpha + \beta \cdot s_{i,t} + \sum_{c} \gamma_c x^c_{i,t} + \mu_i + \nu_i + \theta_t + \epsilon_{i,t} \tag{5}$$

$y_{i,t}$ denotes the firm i's Scope 1 emissions in year t. Depending on the regression model $y_{i,t}$ can be absolute carbon emissions or intensities. In further analysis, we also look at the year-on-year changes in $t+1$ of absolute carbon emissions and intensities. Throughout the paper, we use binary variables ($s_{i,t}$) that take the value of 1 if the firm has reported Scope 1 emissions, has set an SBTi target, has committed to set an SBTi target, or has obtained assurance. In the opposite case $s_{i,t}$ takes the value of 0.

The variables μ_i, ν_i and θ_t correspond to industry, country, and year fixed effects. We cluster standard errors by industry and year. Finally, $x^c_{i,t}$ denotes the control variables c for firm i at time t. The control variables are *Log Revenue*, *Log Market Cap*, *Log Employees*, and *Value Added* (gross margin relative to revenue). *Value Added* can be seen as a measure of vertical integration and is important in our context as Scope 1 emissions do not take into account the supply chain. If we did not control for this, we would penalize firms that integrate large parts of their supply chain.

4 Results

4.1 State of Reporting, Assurance, and Targets

In Figure 2, we show that the prevalence of reporting, assurance, and target setting varies significantly across geographies and sectors. There is a clear European leadership across the three dimensions, but the propensities show more heterogeneity across sectors. We also find that a 1%

increase in Revenue relates to a 2.5% odds of reporting increase.

4.2 Descriptive Statistics

Our dataset covers 30926 unique listed firms from 2016 to 2021, which is to our knowledge the most extensive dataset used in similar studies. In Tables 1, 2, and 3, we show descriptive statistics for the complete dataset used in our study.

4.3 Main Results

First, we use our full sample including imputed carbon data. Columns 1 and 2 in Table 4 show that firms that set an SBTi target have on average an impressive 36.7% lower absolute emissions as well as a 30% lower carbon intensity. Surprisingly, we do not find that firms that signed a commitment with SBTi have lower emissions. This is in line with previous literature that finds that firms with an SBTI target disclose lower emissions.

The control variables indicate that firms with higher *Log Revenue* and more *Log Employees* emit more $CO2$. *Log Market Cap* has an unexpected negative sign. Given we already control for revenue and employees it might be that *Log Market Cap* captures the fact that the firm can spend more on decarbonization. Causality might also go the other way, i.e., firms reduce their carbon footprint to attract investments and lower their cost of capital. Indeed, if we remove *Log Revenue* the sign of *Log Market Cap* flips and has a positive sign. *Value Added* is significant in the regression model with carbon intensities as the dependent variables.

In Columns 3 and 4 of Table 4, we control for imputed data as we expect these data points to behave differently (Aswani, Raghunandan, and Rajgopal 2023). We find that firms that report have on average 14.9% lower absolute emissions. There does not seem to be any difference between reported and imputed data of our carbon intensity variable. Put differently, this indicates that the imputed data is on average overestimating the absolute CO_2 emissions. We confirm Clarity AI's statement in its methodology description that it follows the precautionary principle. The rationale being that firms can choose not to disclose and in doing so might hide the fact that they are a high emitter. Controlling for reported data, SBTi targets are associated with 4% less absolute emissions. Regarding CO_2 intensity, the coefficient is similar to the case where we do not control for reported data. We established that there is a difference between reported and imputed data and we will thus focus on reported data only. This restricts our sample from previously 125377 to 19950 observations.

In Table 5 we add our binary variable for firms that obtain assurance of CO_2 emissions. In columns 1 and 2 we show that firms that verify their CO_2 emissions have substantially higher emissions. Assurance is associated with 11.9% higher absolute emissions and 7.9% higher carbon intensity. Columns 3 and 4 show the same regression specifications as in Table 4 with the difference that we use reported data only. This robustness check confirms our findings that targets are associated with lower emissions. Columns 5 and 6 show what happens when we add the assurance dummy to the regression model with targets. We also include an interaction term between targets and assurance as firms that set an SBTi target are not obliged to verify their emissions. The coefficients for the targets are in line with our previous findings. The coefficients for assurance are slightly higher. Absolute emissions are 13.7% higher and CO_2 intensity is 9.5% higher for firms that obtain assurance. The interaction term between target and assurance is not significant.

We now turn our focus on future changes in carbon emissions. Columns 1 and 2 in Table 6 show the correlation between targets and the year-on-year change in emissions a year ahead. We find that firms' future absolute emissions are correlated with SBTi targets but not commitments. Firms that set a target reduce future emissions by 5.1%. Changes in future carbon intensity is not correlated with targets. Firms that obtain assurance reduce their future absolute emissions by 7.6% and their carbon intensity by 3.3%. In columns 5 and 6 we combine assurance and target setting. Surprisingly, the coefficients for assurance remain similar but the coefficients for targets become insignificant. This indicates that the previous finding that firms reduce future emissions after having set a target might be explained by firms that obtain assurance. Put differently, assurance seems to be a signal that firms reduce future emissions but targets are not.

5 Conclusion

Firms that obtain assurance for their carbon emissions report on average a 9.5% higher carbon intensity than their peers without assurance. When controlling for assurance, we do not find evidence that SBTi target-setters reduce their future emissions. Instead, firms that audit reduce their future carbon intensity by 3.3%.

This has implications for portfolio managers and ESG raters as taking disclosed carbon emissions at face value would lead to penalizing firms that are more serious about their carbon reductions. It also calls for mandatory assurance when carbon disclosure is mandatory and when disclosed emissions are generally relied on in regulation.

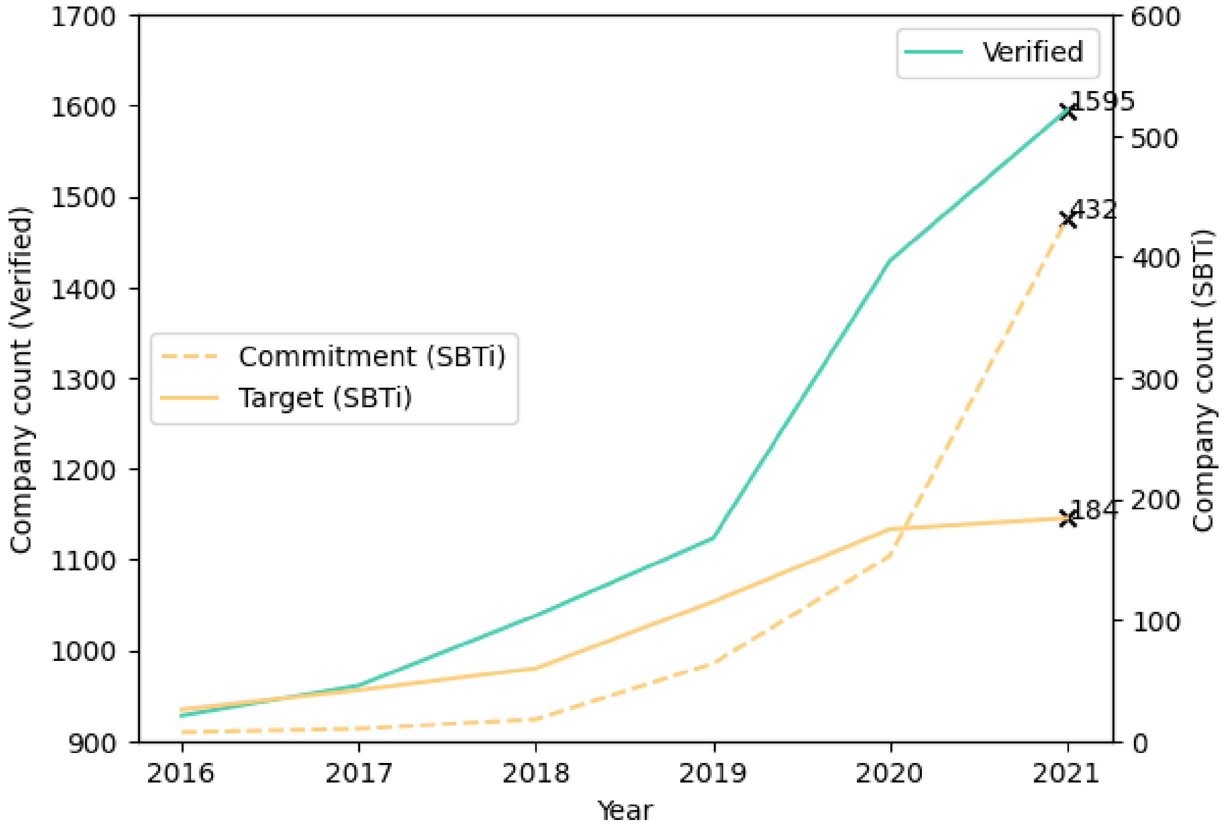

Figure 1: Amount of public firms' commitments and targets over time. Once a commitment is disclosed, the Science Based Targets initiative (SBTI) validates it and may promote it to the Target status, depending on the quality of the commitment. Only 182 public firms in our sample are considered to have a Science Based Target that classifies as Net-Zero as of 2023-11-31. On the contrary, many more firms reporting to CDP are verifying their emissions report with a third-party provider (the latest datapoint corresponds to the 2022 Carbon Disclosure Project questionnaire.)

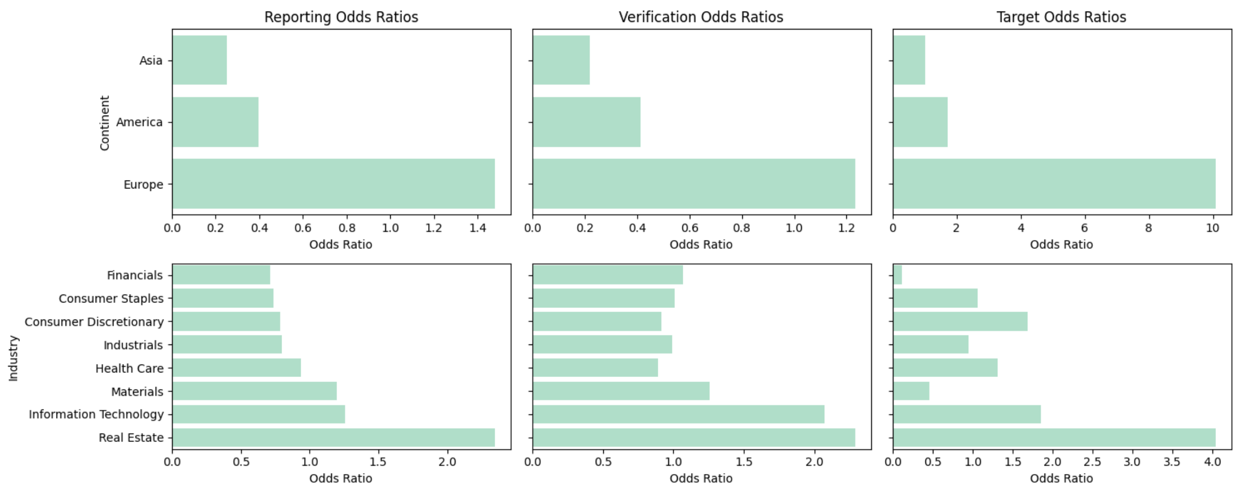

Figure 2: Odds ratios for reporting, assurance, and targets, by geography and sector, as calculated following Equation 4.

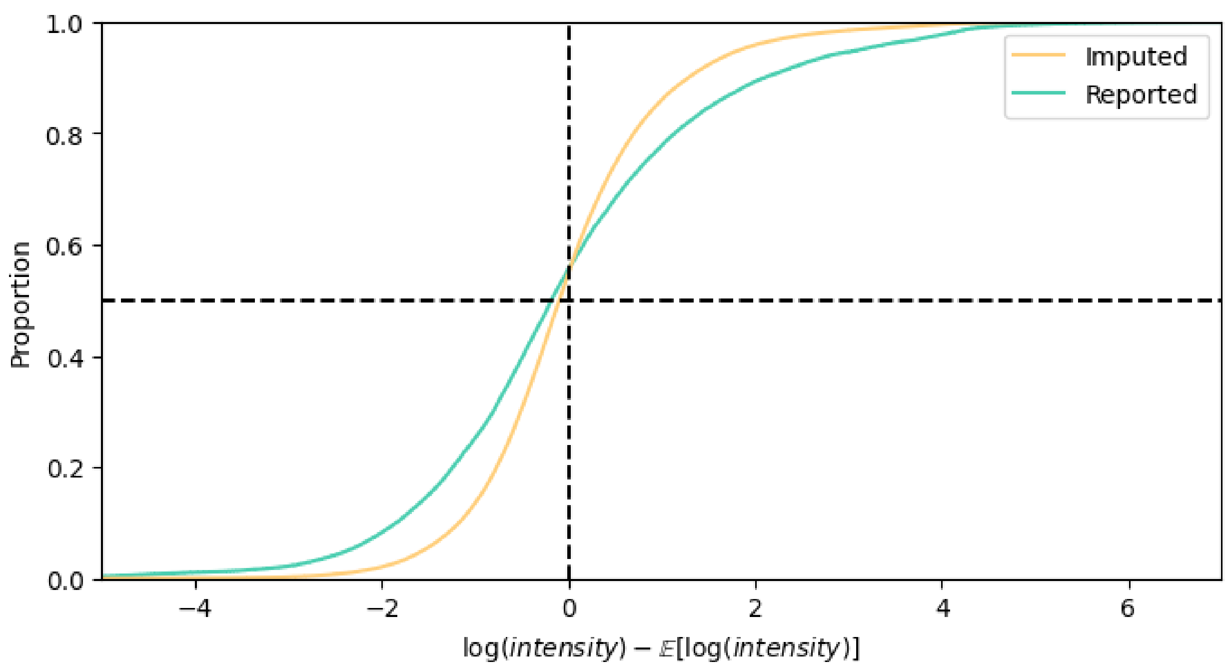

Figure 3: Distribution of CO_2 intensities comparing reported and imputed data. To make them comparable, the intensities are partialled-out using the same controls as in the rest of the analysis.

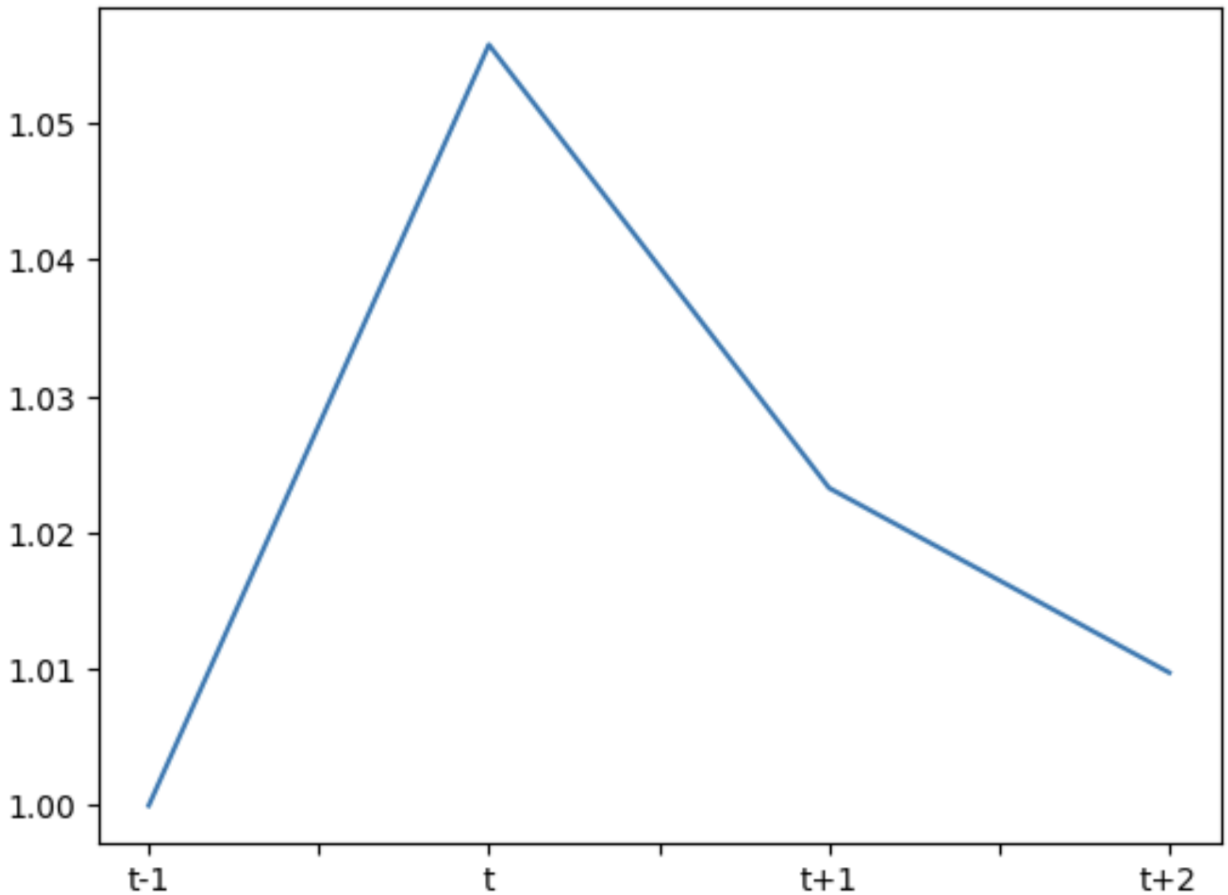

Figure 4: This figure shows the increase of the carbon intensity relative to t-1 where t is the year where firms obtain assurance for carbon data for the first time.

	Count	Mean	Std	Min	50%	Max
CO_2	129774	679735.04	50410209.80	0.00	3434.19	18054539100.00
Log CO_2	129774	8.42	2.81	0.00	8.14	23.62
CO_2 Intensity	129774	335.24	31392.00	0.00	13.88	10849529.44
Log CO_2 Intensity	129774	3.00	1.81	0.00	2.70	16.20
Market Cap	129774	3604.54	24551.32	0.00	367.72	2413420.00
Log Market Cap	129774	5.90	2.11	0.00	5.91	14.70
Revenue	129774	2456.31	11865.44	0.00	257.47	572754.00
Log Revenue	129774	5.65	2.00	0.00	5.55	13.26
Employees	129774	7226.38	32113.24	1.00	1007.00	2300000.00
Log Employees	129774	6.96	1.96	0.69	6.92	14.65
Value Added	129766	-0.17	43.76	-8108.00	0.33	3403.37

Table 1: Summary statistics for numeric variables.

Reported CO_2	Count Assurance	Total	Commitment	Target
False	False	107635	0	0
True	False	15065	200	148
	True	7074	484	454

Table 2: Summary statistics for dummy variables.

	Log CO_2	Log CO_2 Intensity	Log Revenue	Log Market Cap	Log Employees	Value Added
Log CO_2	1.00	0.84	0.51	0.32	0.41	0.00
Log CO_2 Intensity		1.00	-0.00	-0.08	-0.03	-0.03
Log Revenue			1.00	0.77	0.80	0.03
Log Market Cap				1.00	0.60	0.01
Log Employees					1.00	0.01
Value Added						1.00

Table 3: Pairwise correlations in the reported emissions set for emissions in levels, intensity, and explanatory variables.

	(1) Log $CO2_t$ b/se	(2) Log CO_2 Intensity_t b/se	(3) Log $CO2_t$ b/se	(4) Log CO_2 Intensity_t b/se
Target	-0.367***	-0.300***	-0.328***	-0.292***
	(0.11)	(0.08)	(0.11)	(0.08)
Commitment	-0.111	-0.038	-0.072	-0.030
	(0.07)	(0.06)	(0.07)	(0.06)
Reported CO_2			-0.149***	-0.031
			(0.03)	(0.02)
Log Market Cap	-0.028***	-0.011**	-0.021***	-0.010*
	(0.01)	(0.01)	(0.01)	(0.01)
Log Revenue	0.884***	-0.103***	0.888***	-0.102***
	(0.01)	(0.01)	(0.01)	(0.01)
Log Employees	0.082***	0.065***	0.085***	0.066***
	(0.01)	(0.01)	(0.01)	(0.01)
Value Added	-0.002	-0.005***	-0.002	-0.005***
	(0.00)	(0.00)	(0.00)	(0.00)
Constant	3.017***	3.156***	2.948***	3.142***
	c(0.03)	(0.03)	(0.03)	(0.03)
Observations	125377	125377	125377	125377
R2	0.782	0.589	0.783	0.589
Country, Industry, and Year F.E.	Yes	Yes	Yes	Yes

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 4: Emissions and SBTi, with and without controlling for imputed data: regression results for model specification from Equation 5. The estimation is performed on the whole dataset, and the observation unit is firm—year.

	(1) Log $CO2_t$ b/se	(2) Log CO2 $Intensity_t$ b/se	(3) Log $CO2_t$ b/se	(4) Log CO2 $Intensity_t$ b/se	(5) Log $CO2_t$ b/se	(6) Log CO2 $Intensity_t$ b/se
Assurance	0.119**	0.079*			0.137***	0.095**
	(0.05)	(0.04)			(0.05)	(0.05)
Target			-0.319***	-0.278***	-0.327*	-0.271*
			(0.11)	(0.09)	(0.18)	(0.15)
Assurance × Target					-0.033	-0.039
					(0.22)	(0.17)
Commitment			-0.062	-0.054	-0.089	-0.072
			(0.08)	(0.06)	(0.08)	(0.06)
Log Market Cap	-0.048**	-0.040**	-0.037*	-0.032*	-0.045**	-0.037*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Log Revenue	0.838***	-0.095***	0.847***	-0.088***	0.839***	-0.094***
	(0.04)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)
Log Employees	0.168***	0.100***	0.169***	0.101***	0.169***	0.101***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Value Added	-0.002**	-0.003***	-0.002**	-0.003***	-0.002**	-0.003***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	2.630***	2.970***	2.516***	2.886***	2.597***	2.942***
	(0.14)	(0.12)	(0.14)	(0.12)	(0.14)	(0.12)
Observations	19950	19950	19950	19950	19950	19950
R2	0.630	0.475	0.630	0.476	0.631	0.476
Country, Industry, and Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 5: Target and assurance interaction: regression results for model specification from Equation 5. The estimation is performed on the reported emissions dataset, and the observation unit is firm—year.

	(1) ΔLog $CO2_{t+1}$ b/se	(2) ΔLog CO2 $Intensity_{t+1}$ b/se	(3) ΔLog $CO2_{t+1}$ b/se	(4) ΔLog CO2 $Intensity_{t+1}$ b/se	(5) ΔLog $CO2_{t+1}$ b/se	(6) ΔLog CO2 $Intensity_{t+1}$ b/se
Assurance			-0.076***	-0.033***	-0.075***	-0.033***
			(0.01)	(0.01)	(0.01)	(0.01)
Target	-0.051**	-0.011			-0.034	-0.003
	(0.02)	(0.02)			(0.02)	(0.02)
Commitment	-0.046	-0.001			-0.028	0.007
	(0.03)	(0.02)			(0.03)	(0.02)
Log Market Cap	0.008	-0.017***	0.012	-0.015***	0.012	-0.015***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Log Revenue	0.013	0.031***	0.016	0.033***	0.017	0.033***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Log Employees	-0.017	-0.020**	-0.017	-0.019**	-0.017	-0.019**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Value Added	0.003***	0.001	0.003***	0.001	0.003***	0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	0.044	0.061	0.002	0.041	-0.001	0.041
	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)
Observations	15276	15276	15276	15276	15276	15276
R2	0.024	0.012	0.025	0.012	0.025	0.012
Country, Industry, and Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 6: Deltas on reported data including assurance: regression results for model specification from Equation 5, only now looking at forward-looking differences. The estimation is performed on the reported emissions dataset, and the observation unit is firm—year.

Appendix

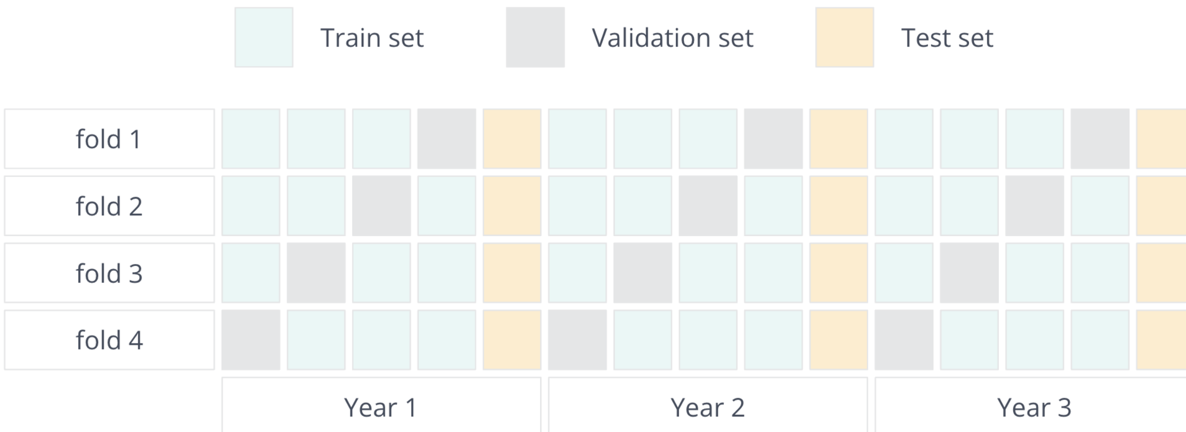

Figure 5: Schematic description of a firm hold out strategy for validating a machine-learning-based model for estimating corporate emissions. The data are split into k-folds (4 in this example). A standard train-valid-test strategy is performed over each split, ensuring that the firms in the test set are always the same.

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