Cheap talk in corporate climate commitments

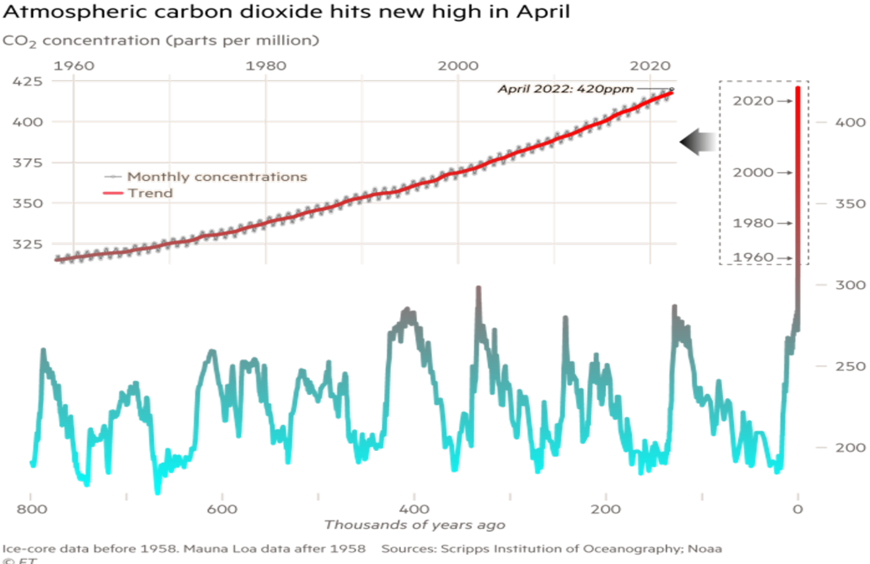
The role of climate initiatives

Julia Anna Bingler* Mathias Kraus** Markus Leippold***
Nicolas Webersinke**

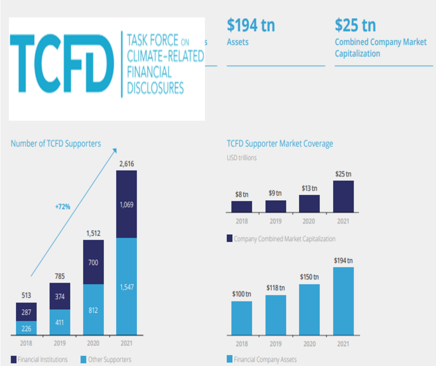
* ETH Zurich and Council on Economic Policies **FAU Erlangen-Nuremberg ***University of Zurich and Swiss Finance Institute (SFI)

Emissions rise

Record carbon dioxide levels alarm scientists (May 13, 2022, Financial Times)



Not only emissions rise but also the amount of climate-related disclosures!



Climate Action 100+

SCIENCE BASED TARGETS
DRIVING AMBITIOUS CORPORATE CLIMATE ACTION

Science Based Targets initiative accused of providing a ‘platform for greenwashing’

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Nestlé, Ikea and Unilever are among brands the New Climate Institute found did not live up to the 1.5C-compatible label they’d been awarded

Greenpeace activist protest at a pension fund in Luxembourg (Photo: Sara Poza Alvarez/Flickr)

We need decision-useful climate risk information

Previous literature

- **Climate-related risks are priced**, particularly transition risk:
  - Bolton and Kacperczyk (2021a); Monasterolo and De Angelis (2020); Engle et al. (2020); Kölbel et al. (2022)
- However, **full risk may not be captured**, e.g., for physical climate risk:
  - Hong et al. (2019); Baldauf et al. (2020); Bakkensen and Barrage (2021).
- Growing body of literature argues that **climate-related disclosures are an essential prerequisite** to managing and mitigating climate-related financial risks
  - Grewal et al. (2019); Hong et al. (2019); Krueger et al. (2020); Bolton and Kacperczyk (2021a); Deng et al. (2022).
- **Disclosures tend to suffer from greenwashing and severe inaccuracies**
  - Kim and Lyon (2015); Marquis et al. (2016); Fabrizio and Kim (2019).

Do climate initiatives improve the quality of climate-related disclosures?

Data

Using **annual reports** of all the MSCI World constituents from 2010 to 2020, extract with ClimateBert the dependent variables:

- **Commitments and actions** related to climate mitigation measures.
- **Specificity** of commitments.
- Define ratio of non-specific to all commitments as the **Cheap Talk Index (CTI)**.

Research Questions

1. Ownership and Engagement

Hypothesis 1: Active Engagement

Being part of the **Climate Action 100+** active ownership and engagement target companies is **negatively associated with cheap talk**.

- Previous literature on ESG:
  1. **Institutional ownwership** is associated with higher ESG transparency.
  2. **Targeted engagement** strategies and active ownership enhance corporate sustainability performance and transparency.

Research Questions

2. Signaling

Hypothesis 2: Signaling

A firms' public support for the **TCFD** recommendations is **negatively associated with cheap talk**.

- Pre-commitment mechanism might explain the public TCFD support. Pre-commitment to disclosures maximizes value ex-ante and improves risk-sharing (Diamond, 1985).
- Signaling (and credibility) is an attempt to reduce information costs for investors and to reduce climate risk uncertainty premium Bolton and Kacperczyk (2021b); Chen et al. (2020).

Research Questions

3. Credibility

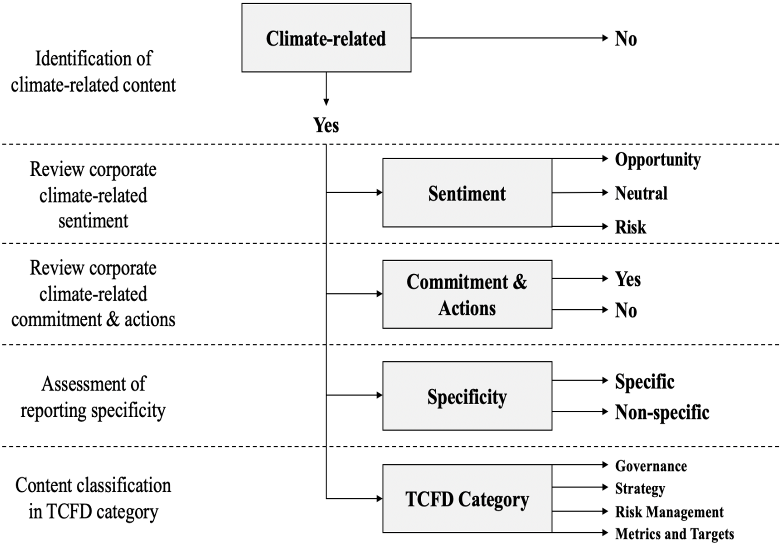
Hypothesis 3: Credibility

A firms' public announcement to set a third party verified **science-based target (SBTi)** is **negatively associated with cheap talk**.

- Firms might be better off if they work towards third-party verification to differentiate themselves from firms that apply managerial "cheap talk" (Almazan et al., 2008; Bingler et al., 2022).

Classification hierarchy

Task setup for analyzing climate-related disclosures



Data and Analysis

- Sample: 14,584 annual reports of the **1,500 MSCI World index firms** for the fiscal years 2010-2020
- ClimateBert-based dependent variable: **Cheap talk index**

$$CTI_{i,t} = \frac{COMMIT \cap NONSPEC_{i,t}}{COMMIT_{i,t}},$$

- Panel regression setup:

$$\begin{aligned} CTI_{i,t} = \alpha &+ \beta_T TCFD_{i,t} + \beta_S SBT_{i,t} + \beta_C ClimAct100_{i,t} + \beta_{OR} Opp \\ &+ \beta_{GHG} GHG_{i,t} + \beta_M Material_i \\ &+ \beta_X X_{i,t} + \eta_i + \delta_i \times \nu_t + \epsilon_{i,t}, \end{aligned}$$

with different financial controls X_t.

Cheap Talk Index

Across different industries

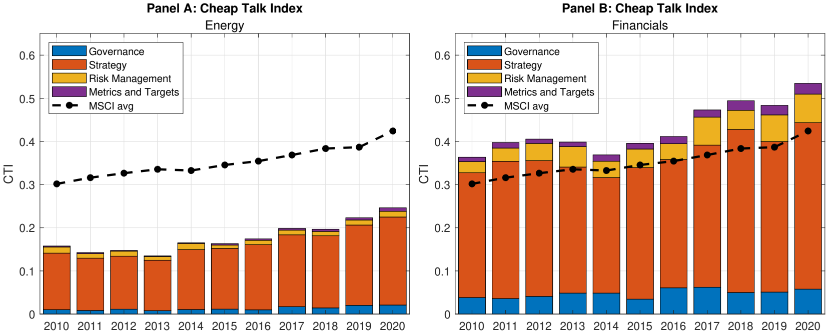


Figure: Evolution of the Cheap Talk Index (CTI) for the Energy (Panel A) and the Financials (Panel B) using the companies that are part of the MSCI World index. We decompose the CTI into the cheap talk in the four different TCFD categories, i.e., governance, strategy, risk management, and metrics and targets.

Cheap Talk Index

Across different countries

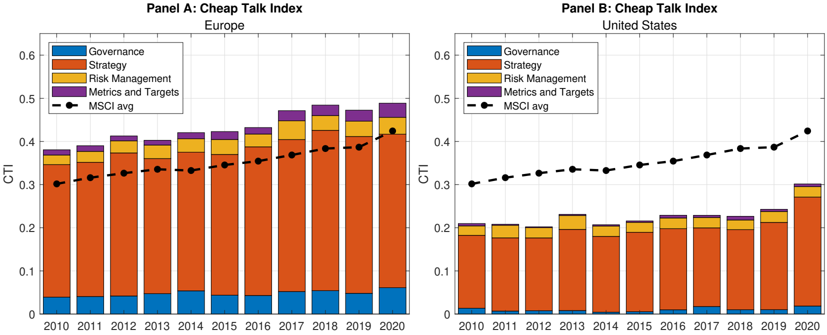


Figure: Evolution of the Cheap Talk Index (CTI) for Europe (Panel A) and the US (Panel B) using the companies that are part of the MSCI World index. We decompose the CTI into the cheap talk in the four different TCFD categories, i.e., governance, strategy, risk management, and metrics and targets.

Panel Regression Results

Full Sample

	Main	Main with controls	Main lagged	Mandatory
ClimAct100	-0.0641***	-0.0271**		-0.0380***
SBT	-0.0014	-0.0101		0.0023
TCFD	0.0336**	0.0371**		0.0745***
Age		-0.0002*	-0.0002*	0.0001
EDS		0.1293***	0.1317***	0.2187***
GHG		-0.0170***	-0.0168***	-0.0174***
IOwn		0.0493**	0.0499**	-0.1386***
Material		-0.0050	-0.0051	-0.0132
OppRisk		-0.0164***	-0.0164***	0.0143***
$ClimAct100_{lag1}$			-0.0300***	
SBT_{lag1}			-0.0186*	
$TCFD_{lag1}$			0.0234**	
Mandatory				0.0001
ClimatePolicyGrade				-0.0009
Country FE	Yes	Yes	Yes	No
Sector × Year FE	Yes	Yes	Yes	Yes
No. Observations	12915	9849	9849	9407
R-squared	0.2572	0.3006	0.3000	0.2197

Panel Regression Results

After 2017

	Main	Main with controls	Main lagged	Mandatory
*ClimAct*100	-0.0643***	-0.0313**		-0.0348**
SBT	0.0017	-0.0088		-0.0033
TCFD	0.0184	0.0218**		0.0653***
Age		-0.0002	-0.0002	0.0003*
EDS		0.1554***	0.1613***	0.2038***
GHG		-0.0144***	-0.0144***	-0.0128***
IOwn		0.0367	0.0367	-0.1268***
Material		-0.0045	-0.0047	-0.0153
OppRisk		-0.0131**	-0.0132**	0.0176***
$ClimAct100_{lag1}$			-0.0349***	
SBT_{lag1}			-0.0212**	
$TCFD_{lag1}$			0.0118	
Mandatory				0.0438*
ClimatePolicyGrade				0.0437***
Country FE	Yes	Yes	Yes	No
Sector × Year FE	Yes	Yes	Yes	Yes
No. Observations	3891	3231	3231	3063
R-squared	0.2932	0.3152	0.3147	0.2423

Conclusion

- Setting of a **science-based target is associated with less cheap talk** only when the variable is lagged.
- Publicly supporting the **TCFD is associated with more cheap talk**.
- Active institutional ownership with targeted engagement strategies through **Climate Action 100+ is associated with less cheap talk**.

Creating a climate-specific language model

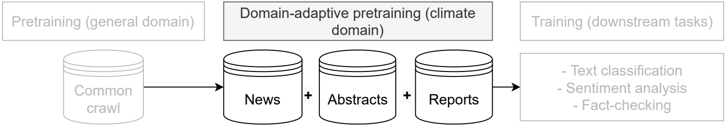
Pretrained language models in NLP

- Why not use a keyword-based approach?
  - Cao et al. (2021) show how corporations adjust their wording to "AI"-based algorithms.
  - Climate-related wording could vary substantially by source (Kim and Kang, 2018).
  - Deep learning techniques that promise higher accuracy are gradually replacing these approaches (e.g., Kölbel et al., 2022; Bingler et al., 2022; Callaghan et al., 2021; Wang et al., 2021).
  - Deep learning in NLP allows for impressive results, outperforming traditional methods by large margins (Varini et al., 2020).
- We go one step further:
  - We train climateBERT (Webersinke et al., 2021) on a large corpus of climate-relevant text (we use DistillRoberta, see Hershcovich et al. (2022) on efficient NLP methods).

Collecting climate-specific text data

Pretraining requires a large corpus of data

- Sequence of training phases:



- Corpus used for pretraining:

Dataset	**Num. of paragraphs**	**Avg. num. of words**		
		Q1	**Mean**	**Q3**
News	641,095	30	48	57
Abstracts	530,819	165	218	260
Reports	490,292	34	65	79
Total	1,662,206	36	107	168

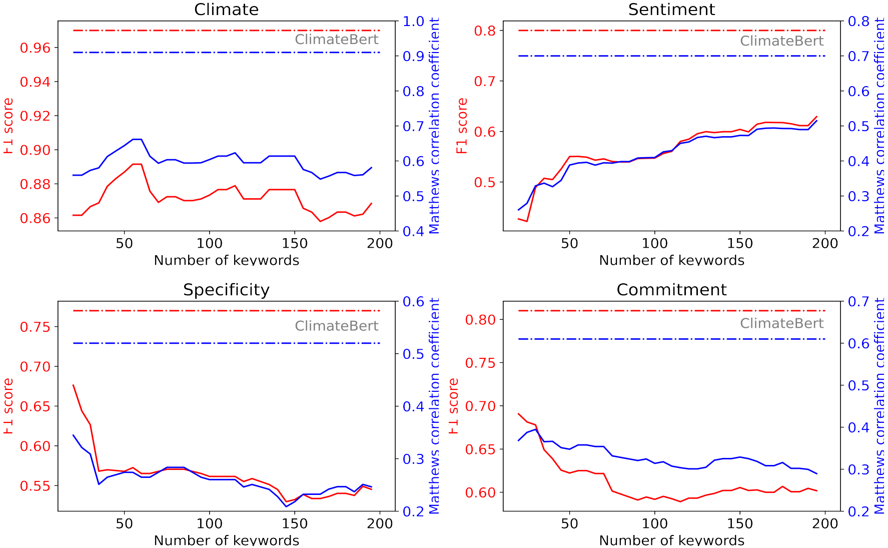
How well does ClimateBERT perform?

A comparison with alternative approaches

- Using our annotated data, we create a keyword list for our different classification tasks, following Liu et al. (2019).
    - To improve the results from a keyword based approach, we use a weighted dictionary based on a LASSO model.
    - For each classification task, we generate such a weighted dictionary.
- Instead of rule-based approaches, we also implement some machine learning approaches:
    - Naïve Bayes (e.g., Huang et al., 2014; Li, 2010; Das and Chen, 2007).
    - Support Vector Machine (SVM) with BoW and ELMo (Embeddings from Language Model) embeddings.

How well does ClimateBERT perform?

A comparison with keyword-based approaches



How well does ClimateBERT perform?

Comparison with other machine-learning approaches

- Evaluation results for climate-related classification task:

Approach	Precision	Recall	F1	AUROC	Support
Naïve Bayes	0.89	0.86	0.87	0.66	400
SVM + BoW	0.88	0.87	0.87	0.76	400
SVM + ELMo	0.91	0.88	0.89	0.70	400
climateBERT	0.97	0.97	0.97	0.91	400

- Evaluation results for cross-validation:

Approach	Climate-related	Sentiment	Commitments & actions	Specificity	TCFD
Naïve Bayes	0.04***	0.05***	0.07***	0.08***	0.07***
SVM + BoW	0.05***	0.08***	0.11***	0.12***	0.08***
SVM + ELMo	0.03***	0.05***	0.06***	0.06***	0.04***

The table shows mean improvement of climateBERT's F1 scores over baseline models for different downstream tasks for $n = 30$ runs on 800 samples for training and 400 samples for testing. By *, **, and *** we denote p-levels below 10%, 5%, and 1%, respectively.

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