How Cheap Talk in Climate Disclosures Relates to Climate Initiatives, Corporate Emissions, and Reputation Risk

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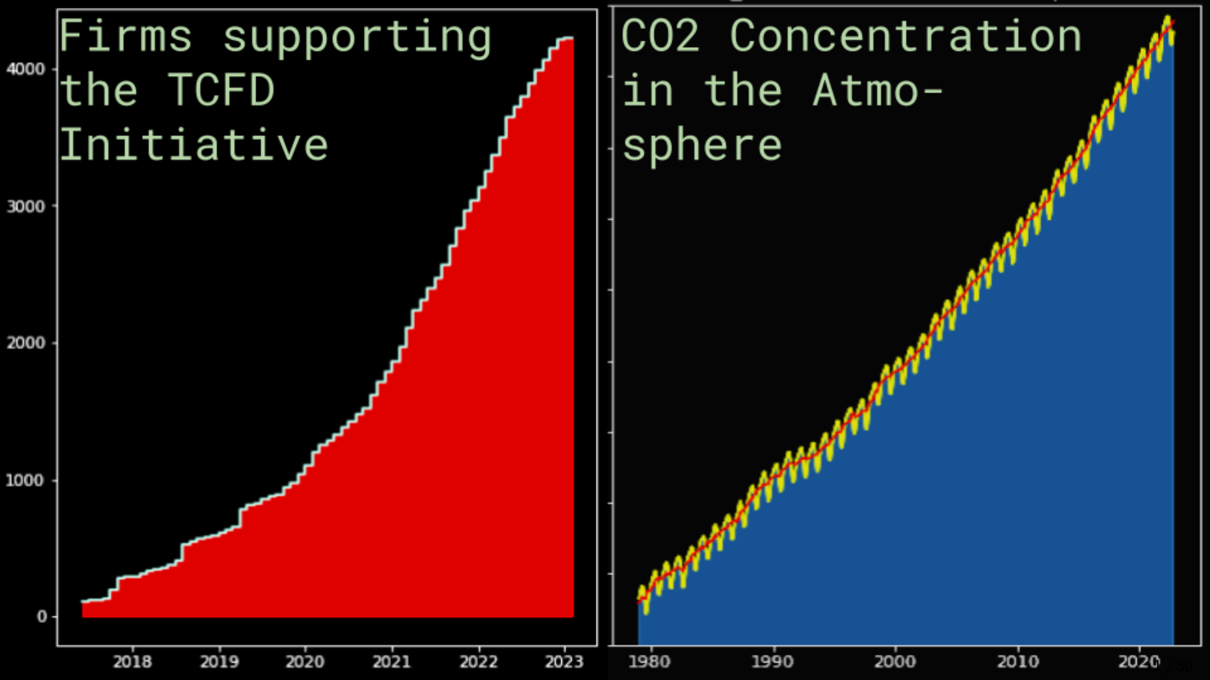


Firms supporting the TCFD Initiative
4000
3000
2000
1000
0
2018
2019
2020
2021
2022
2023
CO2 Concentration in the Atmo- sphere
1980
1990
2000
2010
2020

We need transparent information on climate risk exposure

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); Sautner 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); Gostlow (2022).
- 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).
- Supporters of the **Principles of Responsible Investing** (PRI) **do not necessarily have better ESG ratings**.
  - Gibson et al. (2021); Kim and Yoon (2022).

What our paper does

- Can we rely on ESG ratings?

> We construct a measure, the Cheap Talk Index (CTI), that may more accurately capture the quality of climate-related disclosure.

- Can we avoid cheap talk and improve availability of decision-useful information?

> We ask whether initiatives like the TCFD, SBTi, or Climate Action 100+ help to alleviate this problem.

- Does cheap talk have some real effects?

> We ask whether cheap talk relates to emissions and negative news coverage (reputation risk).

Dataset

Using **annual reports** of all the MSCI World constituents from 2010 to 2020:

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

Using **emission data** from Urgentem/ICE:

- Includes Scope 1, 2, and 3 emissions.
- Differentiates between reported and estimated emissions.

Using **environmental news incidents** from RepRisk:

- Creating a controversy index out of severity, novelty, and reach.

Research Questions

1. Signaling

Hypothesis 1: 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

2. Credibility

Hypothesis 2: 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).

Research Questions

3. Ownership and Engagement

Hypothesis 3: 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.
- But what about active engagement on climate-related matters?

Research Questions

4. Cheap talk and emission reduction

- Many companies may promise to address climate change to improve their public image but often fail to take concrete action to reduce their greenhouse gas emissions.
- Does a company's cheap talk imply that it takes fewer climate actions relative to their peers?

Hypothesis 4: Emission

A high level of cheap talk in climate commitments indicates that companies **are not genuinely committed** to significantly reducing greenhouse gas emissions. .

Research Questions

5. Cheap talk and negative media coverage

Hypothesis 5: Restoring reputation

Heightened controversial news coverage concerning environmental incidents **prompts an increase in cheap talk** about a company's climate commitments.

- Cheap talk may potentially serve as a way to restore their reputation and legitimacy.

Hypothesis 6: Reputation risk

A high level of cheap talk in climate commitments **leads to more** controversial news coverage.

- Cheap talk in climate commitments may signify inadequate management and inconsistent climate strategies.

1. Creating ClimateBERT
2. Measuring Firm-Level Cheap Talk and Sentiment
3. Results
4. Conclusion

Creating a climate-specific language model

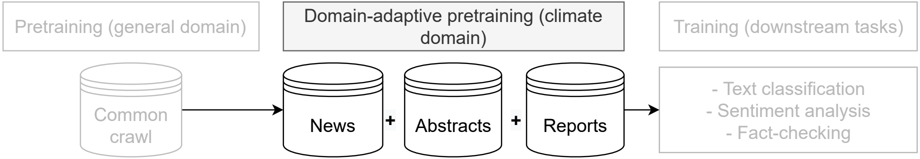
Pretrained language models in NLP

- 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., 2022) 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:

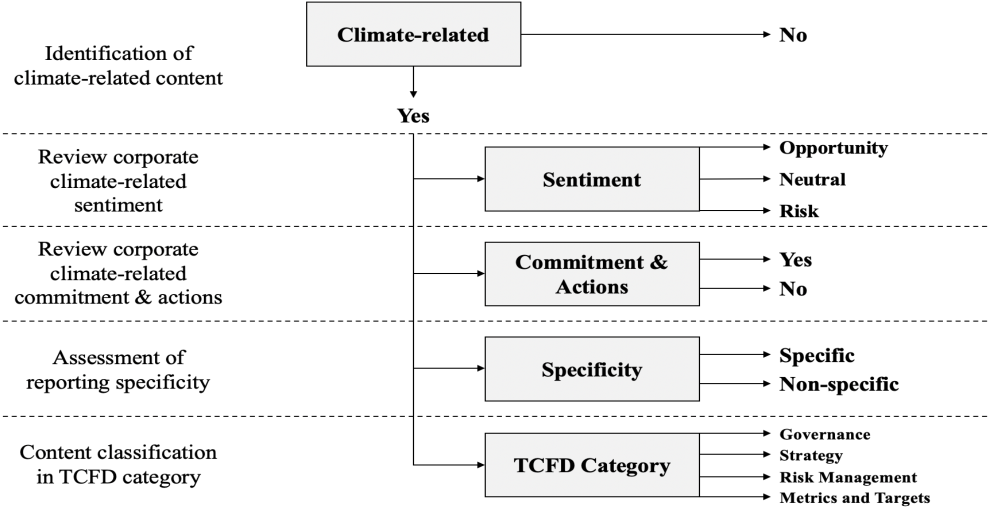


- Corpus used for pretraining (Proceedings, AAAI 2022, Fall Symposium):

Dataset	**Num. of paragraphs**	**Avg. num. of words**		
		Q1	**Mean**	**Q3**
News	1,025,412	34	56	65
Abstracts	530,819	165	218	260
Reports	490,292	34	65	79
Total	2,046,523	36	107	168

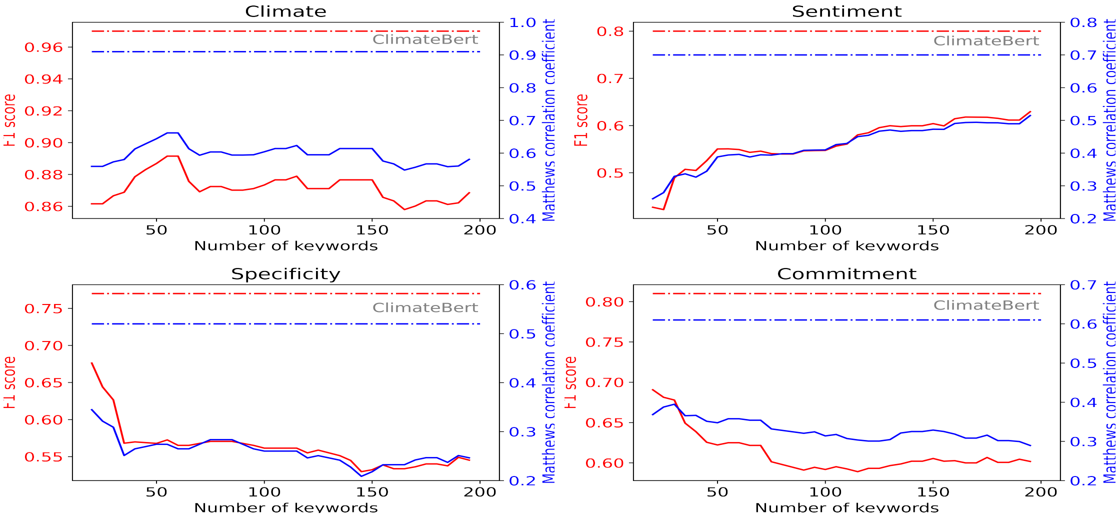
Classification hierarchy

Task setup for analyzing climate-related disclosures



How well does ClimateBERT perform?

A comparison with keyword-based approaches



Data and Methodology

- 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**

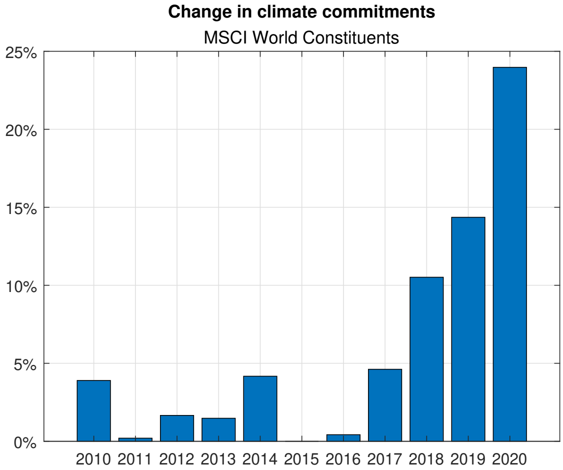
$$CTI_{i,t} = \frac{COMMIT \cap NONSPEC_{i,t}}{COMMIT_{i,t}},$$

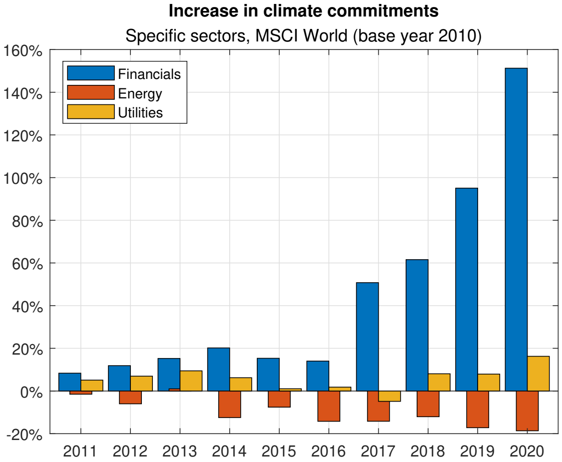
- Panel regression setup for Hypotheses 1 to 3:

$$CTI_{i,t} = \alpha + \beta_T TCFD_{i,t} + \beta_S SBT_{i,t} + \beta_C ClimAct100_{i,t} + \beta_X X_{i,t} + \eta_i + \delta_i \times \nu_t + \epsilon_{i,t},$$

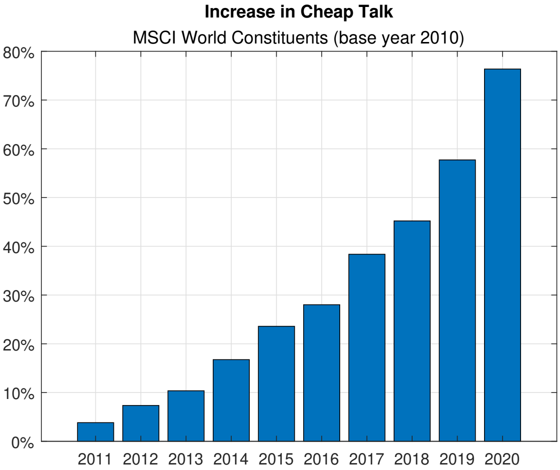
with different financial controls X_t.

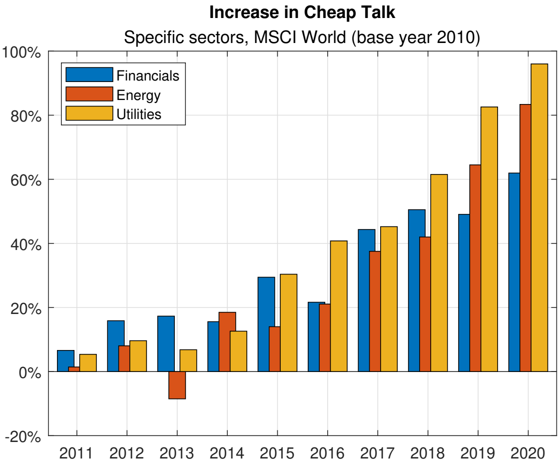
Preliminary Analysis I: Changes in Commitments





Preliminary Analysis II: Changes in Commitments (Financials)





Panel Regression Results

Full Sample

	(I) Main	(II) Main with controls	(III) Main lagged	(IV) Mandatory	(V) Mandatory lagged
ClimAct100	-0.0633***	-0.0357***		-0.0569***	
	(0.0000)	(0.0033)		(0.0000)	
SBT	-0.0092	0.0009		0.0150	
	(0.4071)	(0.9407)		(0.2306)	
TCFD	0.0347**	0.0390**		0.0847***	
	(0.0274)	(0.0175)		(0.0000)	
ClimAct100lag1			-0.0398***		-0.0641***
			(0.0000)		(0.0000)
SBTlag1			-0.0031		0.0180
			(0.7938)		(0.2359)
TCFDlag1			0.0250*		0.0662***
			(0.0630)		(0.0000)
Country FE	Yes	Yes	Yes	No	No
Sector $\times$ Year FE	Yes	Yes	Yes	Yes	Yes
R-squared	0.2575	0.2825	0.2819	0.1893	0.1865
No. Observations	12,943	11,044	11,044	10,543	10,543

Panel Regression Results

Subsample, reporting years 2017 to 2020

	(I) Main	(II) Main with controls	(III) Main lagged	(IV) Mandatory	(V) Mandatory lagged
ClimAct100	-0.0640***	-0.0408***		-0.0492***	
	(0.0000)	(0.0014)		(0.0002)	
SBT	-0.0086	0.0008		0.0128	
	(0.4511)	(0.9464)		(0.2810)	
TCFD	0.0212	0.0254*		0.0755***	
	(0.1261)	(0.0836)		(0.0000)	
ClimAct100lag1			-0.0455***		-0.0571***
			(0.0000)		(0.0000)
SBTlag1			-0.0039		0.0128
			(0.7358)		(0.3580)
TCFDlag1			0.0134		0.0594***
			(0.3143)		(0.0000)
Country FE	Yes	Yes	Yes	No	No
Sector $\times$ Year FE	Yes	Yes	Yes	Yes	Yes
R-squared	0.2893	0.3063	0.3055	0.2155	0.2104
No. Observations	5,140	4,603	4,603	4,390	4,390

Panel Regression Results

Hypothesis 4: Cheap talkers increase their emissions more

Regression equation:

$$\Delta GHG_{i,t} = \alpha + \beta_{CTI} CTI_{i,t} + \eta_i + \delta_i \times \nu_t + \epsilon_{i,t}.$$

	2010-2020		2017-2020			
	(I) Scope 1+2	(II) Total	(III) Scope 1+2	(IV) Total	(V) Scope 1+2	(VI) Total
CTI	-0.0984	-0.0166	0.0733	0.3197***	0.1348**	0.3230***
	(0.3773)	(0.8599)	(0.2816)	(0.0003)	(0.0115)	(0.0005)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector $\times$ Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.0150	0.0481	0.0222	0.0721	0.0253	0.0725
No. Observations	11,237	11,237	4,690	4,690	4,690	4,690

Panel Regression Results

Hypothesis 5: Increased negative news leads to more cheap talk

$$CTI_{i,t} = \alpha + \beta_{Controv} Controv_{i,t} + \beta_X X_{i,t} + \eta_i + \delta_i \times \nu_t + \epsilon_{i,t},$$

	2010-2020		2017-2020	
	(I) Main with controls	(II) Mandatory	(III) Main with controls	(IV) Mandatory
controversy	0.1510**	0.1538*	0.1908**	0.2144**
	(0.0237)	(0.0637)	(0.0271)	(0.0281)
Country FE	Yes	No	Yes	No
Sector × Year FE	Yes	Yes	Yes	Yes
R-squared	0.3130	0.2265	0.3208	0.2347
No. Observations	6,954	6,719	3,056	2,955

Panel Regression Results

Hypothesis 6: High level of cheap talk leads to controversies

$$Controv_{i,t} = \alpha + \beta_{CTI} CTI_{i,t-1} + \beta_{OR} OppRisk_{i,t-1} + \beta_{GHG} GHG_{i,t} + \beta_M Material_i + \beta_X X_{i,t} + \eta_i + \delta_i \times \nu_t + \epsilon_{i,t},$$

	(I) Main with controls	(II) Mandatory	(III) Main with controls	(IV) Mandatory
CTIlag1	0.0058*	0.0062*	0.0110**	0.0122***
	(0.0799)	(0.0764)	(0.0110)	(0.0080)
ClimateSharelag1	0.0295**	0.0213	0.0230**	0.0180*
	(0.0446)	(0.1357)	(0.0461)	(0.0701)
R-squared	0.3512	0.3316	0.3585	0.3420
No. Observations	7,667	7,425	3,358	3,256

Conclusion

- Publicly supporting the **TCFD is not at all or even positively associated** with an **increase in cheap talk**.
- **Active institutional ownership** with targeted engagement strategies through Climate Action 100+ is associated with **less cheap talk**, more robust when the variable is lagged.
- **SBTi** does not lead to more decision-useful information in disclosures.
- Cheap talkers **increase emissions more**, particularly total emissions.
- Cheap talkers **are more involved in controversies**.

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