Policymaking matters: The global impact of air pollution-related climate policies on annual exposure to PM2.5 air pollution

Air pollution is the deadliest environmental hazard factor worldwide (OurWorldinData, 2024b). Many climate policies have tangible air quality co-benefits, for example through emissions standards in the private transport sector, the phasing-out of coal-fired power plants, or the incentivisation of active travel (Karlsson et al., 2020). This report provides a study of the impact of climate policies on annual air pollution levels across the globe. It draws on the Climate Change Laws of the World (CCLW) data and computational text-as-data methods, specifically Structural Topic Models (STM) (Roberts et al., 2014) to measure the air-pollution focus of policies. Fixed-effects panel regression models show that the prevalence of such policies had a notable impact on peoples' annual exposure to PM2.5 air pollution levels at the country-year level between 1990 and 2020.

CONCEPTUALISATION OF AIR POLLUTION-RELATED CLIMATE POLICIES

The CCLW data provides information on national-level policymaking related to climate change across the globe. Every archived policy has been classified by the CCLW researchers in a number of categories (https://climate-laws.org/methodology) including a variable ('Family Summary') providing for a short text-based summary of the policies. I use this variable to assess the air pollution focus of policies in the database. The CCLW raw data contains 8,974 observations of executive and legislative policies, as well as country reports under the UNFCCC framework. As I focus on national-level climate policymaking, I do not consider the UNFCCC documents.

Topic models are computational methods designed to discover semantically coherent themes from such large text corpora. They enable researchers to understand documents in a corpus as a mixture of a pre-defined number of 'topics' based on commonly co-occurring words (Grimmer et al., 2022, Chapter 13). STM lends itself to the task of classifying short text summaries, which are particularly vexing for standards topic models (such as LDA) because they rely upon the correlation between words in documents to estimate topics (Grimmer et al., 2022, p. 154). By enabling researchers to predefine common document-level covariates (e.g. country groups according to the Human Development Index (HDI)), STM uses these document-level priors to borrow information from documents with similar values of the covariates rather than aggregating all the documents together into one prior, which helps the model identify better topics (Grimmer et al., 2022, p. 158). Because the text summaries of policies in the CCLW data vary in length and can be quite short, I draw on STM to inductively discover climate policy content related to air quality issues.

INDICATOR DEVELOPMENT

To conduct the computational and statistical analysis, I work in R. The first script in my github repository (01_text_indicators_development.R) provides the code for the computational text analysis. In step 1 of the script, I import the CCLW raw data and drop observations related to countries' reporting under the UNFCCC framework (see above). In step 2, I reduce the dataset to substantially interesting document-level variables (year of policy release, country, document title and text summary) and process the text contained in the text variable. Inspections of the text variable indicated some missing observations, html tags contained in the text as well as excess line breaks and whitespaces, which I clean away. Furthermore, I dropped very short policy summary texts with less than 6 words, as those contained mainly technical descriptions. In step 3, I extend the CCLW dataset by external country-level data obtained from the Varieties of Democracy (V-Dem) Project, the HDI, and the World Bank. I consider the following contextual-level variables as relevant to the objective of measuring the air pollution focus of climate policies and its relationship with public health outcomes:

- HDI groups (Very high, high, medium and low) as an indicator of socio-economic development across countries that is widely used in publications of the Lancet Countdown.
- GDP per capita, PPP constant 2021 international $ (from World Bank) as an indicator of cross-country levels of, and over-time changes in, economic prosperity
- Women political empowerment index (WPEI; V-DEM) as an indicator of how a participatory political culture, which has been linked to sustainable development (Lv & Deng, 2019)

- Political corruption index (PCI; V-Dem) as an indicator of the pervasiveness of corruption and quality of governance commonly linked to lapses in climate policy making and implementation (Rafaty, 2018).

These variables were chosen not just based on the concepts that they are measuring but also based on the breadth of data coverage that they are providing since 1990.

In step 4, I preprocess the text and estimate the STM. I use the quanteda package to generate a corpus object from the cleaned text including document-level covariates. I then preprocess the text before constructing a document-term matrix: I tokenise the text, remove punctuations and symbols, lowercase, remove stopwords and stem words. Finally, I further reduce dimensionality by deleting words that appear rarely (i.e. in less than 0,1% of documents) and very frequently (i.e. in more than 90% of documents). These steps follow a common text preprocessing recipe designed to reduce complexity and turn a corpus of text into numerical data for 'bag of words' models (Grimmer et al., 2022, Chapter 5).

I then fit a STM to the document-term matrix. Belonging to the family of 'unsupervised' methods, there are few parameters to control when fitting an STM. One is the document-level covariates to incorporate. Here, I use the contextual country-level variables listed above as well as the year of a policy release with a spline for non-linear over-time variations in topic prevalence. Another one is the number of topics to be estimated, which is a somewhat arbitrary decision affecting not only the number but also the meaningfulness of topics. By setting the number of topics k to '0', I instruct the STM to use the algorithm by Lee and Mimno (2014) to automatically select a meaningful number of topics (Roberts et al., 2019, p. 12). This results in a model differentiating 52 topics. I then inspect the highest FREX terms per topic, i.e. words weighted by their overall frequency and how exclusive they are to the topic (Roberts et al., 2019, p. 3), to identify topics with a discernible air pollution angle. Five topics were identified as such (see Table 1).

Table 1: Air pollution-related policy topics

Topic	Top.FREX.Terms	Label
18	air, pollut, limit, atmospher, coal-fir, dioxid, t	Air Pollution Standards
26	liquid, fuel, automobil, truck, fossil, pact, biomethan	Fuel and Transport Emissions
38	physic, nitrogen, deposit, leefomgev, netherland, besluit, valu	Nitrogen Pollution
43	tax, car, km, usd, hybrid, vehicl, eur	Carbon-Based Vehicle Taxation
47	cycl, walk, bicycl, mobil, advertis, bike, center	Active Travel Promotion

Based on these topics, I then coded policy documents as air pollution-related (=1), if any of those topics were estimated by the STM to be the most prevalent one, and 0 otherwise.

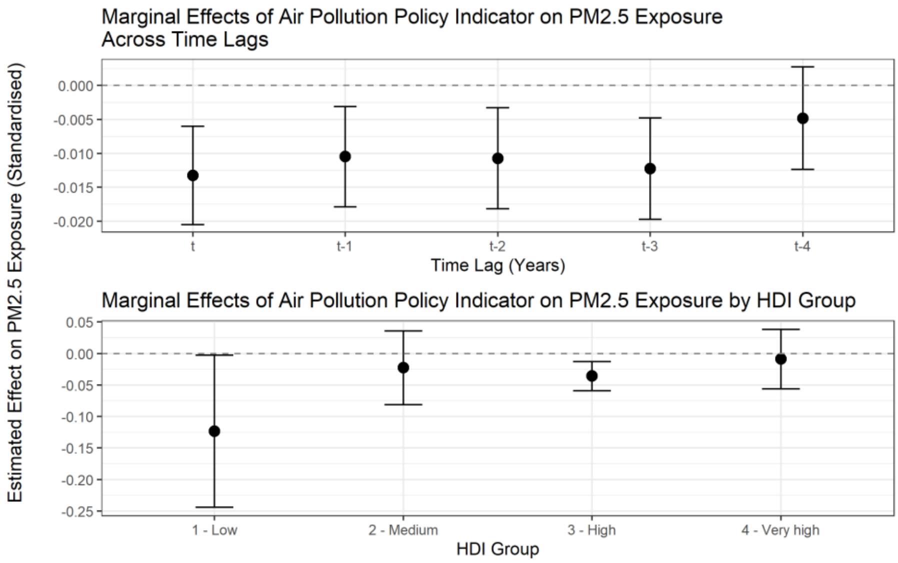
In step 5, I then aggregated that measure at the country-year level, counting the number of policies that were identified by the STM as air pollution related. Finally, in step 6, I saved the country-year level data as a new data file for subsequent statistical analysis.

STATISTICAL ANALYSIS

The second script in my github repository (02_statistical_analysis.R) provides the code for the statistical analysis examining the impact of air pollution-related policy activity on annual exposure to PM2.5 air pollution levels at the country-year between 1990 and 2020. Data on the latter flows from OurWorldInData (2024a), which provides a harmonised data file based on data from the Global Burden of Disease Study 2019, the Institute for Health Metrics and Evaluation (IHME) and the World Bank. I chose this data as it provides a 30-year coverage for a crucial indicator of air quality at the country level.

In step 1 of the statistical analysis script, I import the country-level dataset resulting from the computational text analysis. I am not only interested in the *immediate* effects of the air pollution policy indicator on actual air quality levels, but also in its *lagged* effects over time. Therefore, I prepare four duplicate datasets with one- to four-year lags for the air pollution policy indicator. In step 2, I import the country-level contextual data listed in the ‘indicator development’ section. In step 3, I import the data on the average annual exposure to PM2.5 air pollution. Step 4 merges the data files and z-standardises the outcome (air quality) and explanatory variables (air pollution policy indicator and control variables). In step 5, I run county-level fixed-effects panel regression models. I estimate 5 such models to estimate the immediate and lagged effect of the z-standardised policy indicator variable on the z-standardised air pollution levels, controlling for changes in GDP per capita, WPEI and PCI. The top panel of Figure 1 shows the marginal effects of this analysis, i.e. the effect of a one standard deviation increase in the air pollution policy variable on PM2.5 exposure. It indicates a negative effect which is not only significant in the year of the policy release but also up until 3 years after its release, while levelling off after 4 years.

Figure 1: The impact of air pollution policies on PM2.5 Exposure



In a final model, I also assessed whether this impact differed by HDI level by including an interaction term between the policy indicator variable (t0) and the assignment of countries to HDI groups. Results of this model are visualised in the bottom panel of Figure 1. They indicate that the impact of air pollution policies is significant at the 5% level in low and high HDI countries, but insignificant in medium and very high HDI countries. The most sizeable drop in air pollution levels caused by policymaking are, however, estimated to take place in low HDI countries.

VALIDATION AND ROBUSTNESS CHECKS

The third script in my github repository (03_validation_and_robustness.R) provides the code for the preliminary validation and robustness checks of the computational and statistical analysis.

REFERENCES

Grimmer, J., Roberts, M. E., & Stewart, B. M. (2022). *Text as data: A new framework for machine learning and the social sciences*. Princeton University Press.

Karlsson, M., Alfredsson, E., & Westling, N. (2020). Climate policy co-benefits: A review. *Climate Policy*, *20*(3), 292–316. https://doi.org/10.1080/14693062.2020.1724070

Lv, Z., & Deng, C. (2019). Does women’s political empowerment matter for improving the environment? A heterogeneous dynamic panel analysis. *Sustainable Development*, *27*(4), 603–612. https://doi.org/10.1002/sd.1926

Mimno, D., & Lee, M. (2014). Low-dimensional Embeddings for Interpretable Anchor-based Topic Inference. *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)*. Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP), Doha, Qatar. https://doi.org/10.3115/v1/d14-1138

OurWorldinData. (2024a). *Average annual exposure to PM2.5 air pollution*. https://ourworldindata.org/grapher/average-exposure-pm25-pollution?time=latest

OurWorldinData. (2024b). *Deaths by risk factor, World, 2021*. https://ourworldindata.org/grapher/number-of-deaths-by-risk-factor

Rafaty, R. (2018). Perceptions of Corruption, Political Distrust, and the Weakening of Climate Policy. *Global Environmental Politics*, *18*(3), 106–129. https://doi.org/10.1162/glep_a_00471

Roberts, M. E., Stewart, B. M., & Tingley, D. (2019). stm: An R Package for Structural Topic Models. *Journal of Statistical Software*, *91*(2). https://doi.org/10.18637/jss.v091.i02

Roberts, M. E., Stewart, B. M., Tingley, D., Lucas, C., Leder-Luis, J., Gadarian, S. K., Albertson, B., & Rand, D. G. (2014). Structural Topic Models for Open-Ended Survey Responses: STRUCTURAL TOPIC MODELS FOR SURVEY RESPONSES. *American Journal of Political Science*, *58*(4), 1064–1082. https://doi.org/10.1111/ajps.12103