A Comprehensive Analysis of Energy Policy Design and its Impact on Environmental Performance

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Introduction

Given the urgent need to decarbonise to combat climate change, it's essential to analyze energy policy design and its impact on environmental performance. This analysis will enable :

- the identification and potential application of effective strategies for decarbonisation
- inspiration to policymakers to accelerate transition towards cleaner and more sustainable energy sources,
- highlight areas where decarbonisation efforts are performing well
- presenting potential opportunities for enhanced clean energy efficiency - could also result in significant cost savings.

Therefore, our research explores:

1. **Current energy policy design**
2. **Relationship between energy policy design (diction and budget) and actual environmental performance (climate change related measures) by country**

Data

Our research is mainly based on two parts of data. One part consists of energy policy data from 26 countries spanning from 2020 to 2022, obtained from energypolicytracker.org.

We selected **six indicators** to investigate energy policy design:

1. Country: The country that has implemented the energy policy.
2. Policy Category: The categorised type of policy from the dataset, including Fossil unconditional, Fossil conditional, Clean unconditional, Clean conditional, and Other energy.
3. Name of Policy: The specific name of the policy that was implemented.
4. Energy Type: The energy type classified by the website, including solar, hydrogen, wind, and others.
5. Date of Entry into Force: The date when the policy was implemented.
6. Value Committed (USD): The allocated amount for the policy.

The second part of the data is the 2022 Environmental Performance Index (EPI) from Yale, which includes various indices such as Ecosystem Vitality, Environmental Health, and Climate Change Policy Objective for different countries.

Data Wrangling

First round of selection:
Energy policy aspect:
Based on the categorization of "Policy Category," classifications related to "Fossil" represented policies that support the production and consumption of fossil fuels. To investigate the decarbonization policies, we only selected policies classified as "Clean conditional" and "Clean unconditional." Additionally, we excluded policies with NA values for "Date of Entry into Force" or a value of 0 for "Value Committed(USD)." (However, it's worth noting that the exclusion of policies with unknown implementation dates and funding amounts is solely due to the lack of recorded data and to reduce variables in the study, not an indication that these policies have no impact on climate change.)

Environmental index aspect:
To study the impact of climate change, we selected only the "Climate Change" index as a measure of environmental conditions as it best aligns with the measures that would be affected by the energy policies.

Second round of filtering:
Separation of data:
Based on the energy policy and environmental index data, we divided them into three datasets. The first dataset includes the countries, policy names, and implementation years from the energy policy data. The second dataset represents the funding allocated based on countries and energy types in the energy policy data. The third dataset includes the climate change index from the environmental index data.

Text Mining

The purpose of text mining is to study the design of energy policy names in different countries. In R, we used the tidytext package to tokenize the policy names of each country. We cleaned the tokenized text by removing all numbers and eliminating common stop words such as "in," "of," and "with." Additionally, we utilised the SnowballC package to perform stemming on the words. For example, the stem of "energy" and "energies" is "energi," and the stem of "invests" and "investment" is "invest." This way, we obtained 951 keywords regarding energy policies. We also applied topic modelling to these keywords, aiming to discover and extract potential themes within different keywords.

In the exploratory data analysis, we calculated the frequency of occurrence for each policy keyword and created a bar chart showing the top 20 keywords. Additionally, we generated a word cloud using the top 100 keywords. We observed that, apart from some recurring terms related to energy policies such as "energy" and "investment," there were also other terms like "aid" and "electricity."

Figure 1

In the comparative exploratory analysis, we aimed to understand the changes in policy priorities between the years 2020, 2021, and 2022. We calculated the frequency of occurrence for the keywords in each of these years and examined the differences between them. Subsequently, we created word cloud visualisations to illustrate the variations in keywords over the three-year period. It can be observed that the impact of Covid on policy formulation gradually diminished, and instead, there was an increase in the emphasis on infrastructure development (such as transport and vehicles).

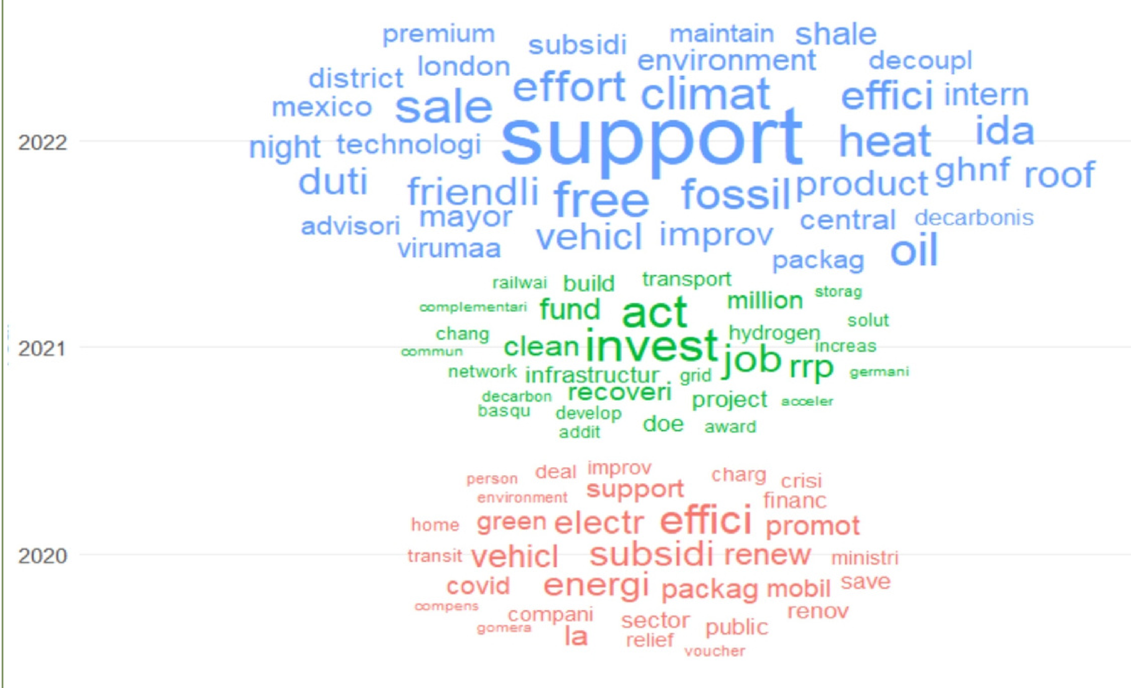

Figure 2

LASSO Regression & Findings

Furthermore, we conducted an analysis using LASSO regression using the glmnet package in R. Our aim was to find out if and which keywords significantly influence the performance on the Climate Change Index for each country. The lambda value was set at 2 for our model and we discovered that 12 keywords showed significant predictive power. See figure 3. The words 'decarbonis', 'walk', 'programm', 'scale', 'cycl', 'decreas', 'intern', and 'aerospac' are positive predictors i.e., associated with an increase in the Climate Change Index. Conversely, 'soe', 'hydro', and 'hydroelectr' act as negative predictors. It's clear from our findings that the language and focus of policies need to be thoughtfully considered to effectively combat climate change. In fact, our analysis suggests that policies related to hydro power (like hydropower and hydroelectric) may have a negative impact on the Climate Change Index.

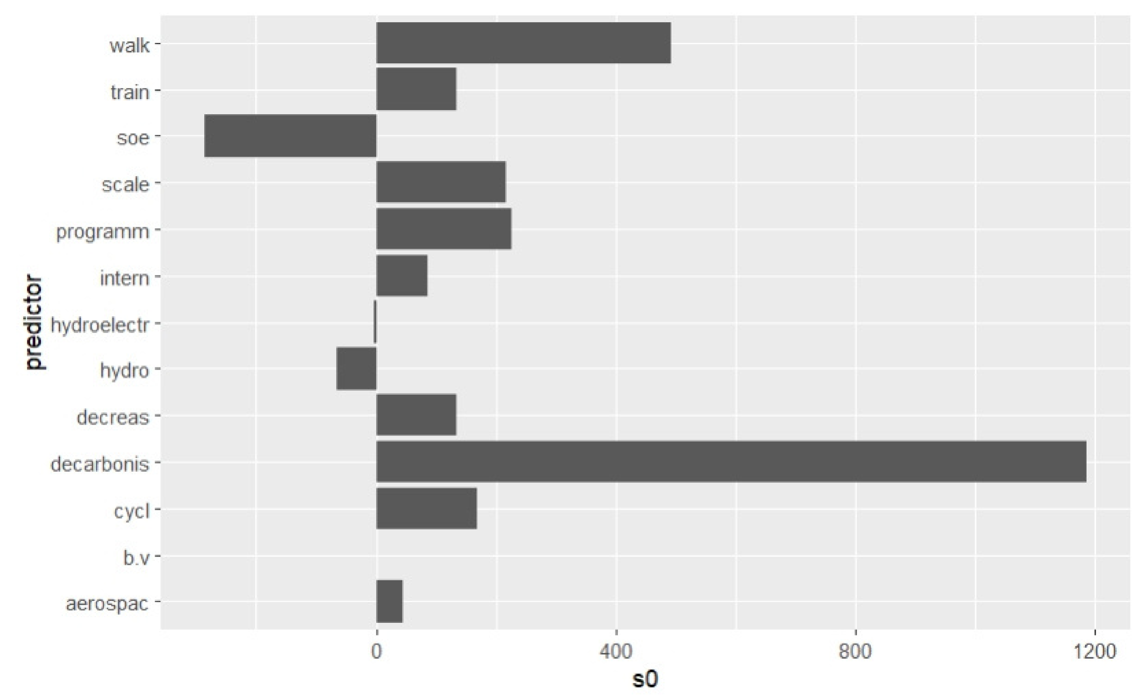

Figure 3

A similar LASSO regression analysis was conducted (lambda value = 0.01) to investigate the relationship between budget allocation (USD) for various energy types and the Climate Change Index performance by country. See figure 4. One notable finding was that the 'other renewable' category acted as a significant negative predictor, meaning an increase in budget for 'other renewable' sources was associated with a decrease in the Climate Change Index. Conversely, 'other energy type', 'oil and oil products', and 'active transport' displayed positive predictive correlation, indicating that increases in budget for these areas correlated with a marginally increased Climate Change Index. We recommend further research and possible policy changes in light of these findings.

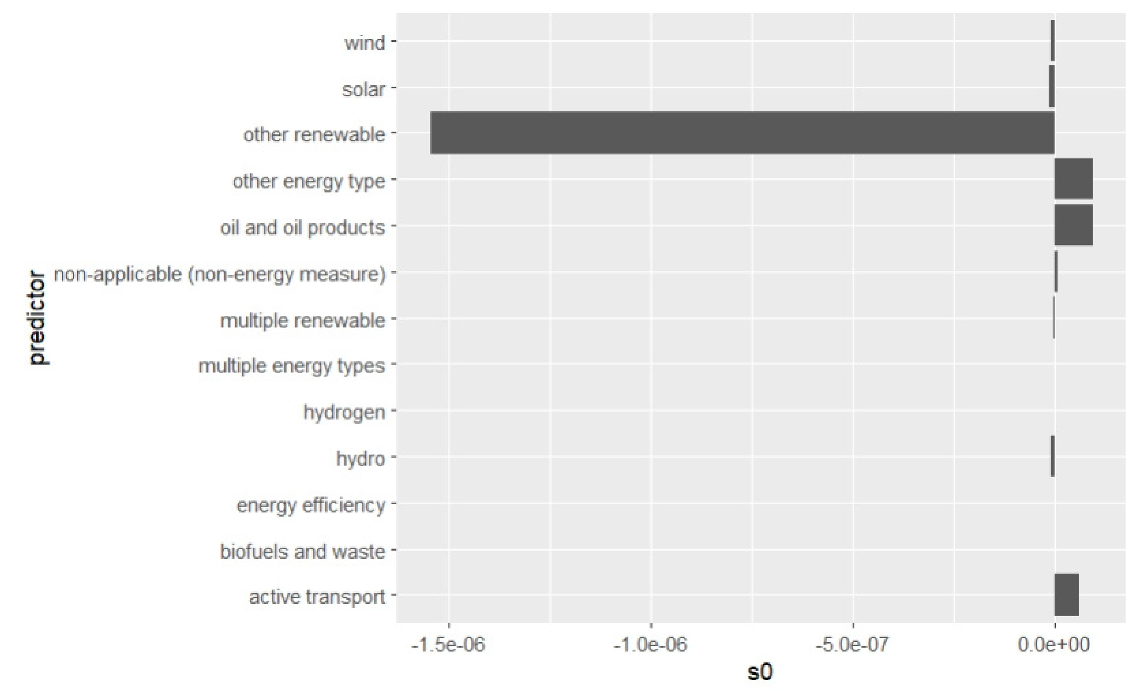

Figure 4

Limitations

1. Scope of policies: The jurisdiction of some policies is not the whole country, but some regions of the corresponding country. In our calculations, we classify them into the country, but their influence may not be the same as that of the country. Policies have different scales and scope. This affects the relevance of policy to performance.

2. Policy implementation effectiveness: First of all, the implementation of policies takes time, and the policies represented in the policy data set were first implemented in 2020. The performance data set represents the environmental effect in 2022. The general environment changes relatively slowly. We cannot ensure that the implemented policies will be fully implemented in 2022, which will affect the correlation between budget and performance to a certain extent.

3. Geographical layout of countries: It is impossible to analyze a country's climate change progress by isolating its own efforts as surrounding states could significantly impact other states' environment indirectly. This should be held into account when analyzing the implications of the results.

Conclusion

In conclusion, our study highlights the crucial role that thoughtfully designed policies play in the fight against climate change. By applying text mining and LASSO regression techniques, we were able to pinpoint key words and budget considerations that have a significant impact on a country's Climate Change Index performance. Our research emphasizes that policymakers need to be mindful of the language used and the areas of focus in their energy policies, particularly when it comes to hydro power. As we grapple with the pressing issue of climate change, our findings can offer valuable insights and greatly assist in shaping effective fiscal strategies for decarbonization and enhancing clean energy efficiency.

References

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