Analysis of Climate Campaigns on Social Media using Bayesian Model Averaging

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PURDUE UNIVERSITY

Climate Change

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Social Media *Influence* Public Opinion

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- International Energy Agency: **net zero by 2050**.
- United Nations campaign for individual action on climate change and sustainability called **ActNow**.
- **Lagging** from climate goals.
  - **Negative influence** of fossil fuel companies (*Nosek 2020*).
- Interest groups, social movement organizations, and individuals **engage** in **collective action** on **climate issue** on **social media**.

Online Advertising

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Goal

- **Climate actions**.
- **Climate misinformation**.
- **Climate change-denial ads** continue to be approved.
- Facebook allows advertisers to **adapt** their messaging to **target** audiences.
    - **Microtargeting**.
- **Analyze** the landscape of **climate campaigns**.
    - **Our experiments**: Analyze content supporting either the pro-energy or the clean-energy campaigns in USA.

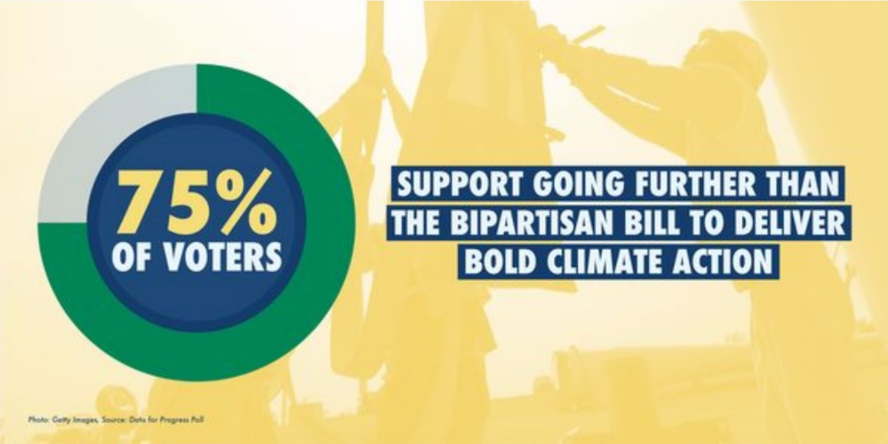
Climate Campaigns on Facebook

ExxonMobil
Sponsored • Paid for by **EXXON MOBIL CORPORATION**

The oil and gas industry supports millions of local jobs. Unnecessary regulations can stand in the way. Support local jobs by taking action today!

Climate Power
Sponsored • Paid for by **Climate Power**

New polling shows widespread support for the full Build Back Better reconciliation package that includes investments in clean energy and environmental justice.



CLIMATEPOWER.US
NEW POLL: 3 in 4 Voters Support Build Back Better
Congress Must Act

Learn more

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Stance: *Pro-energy*
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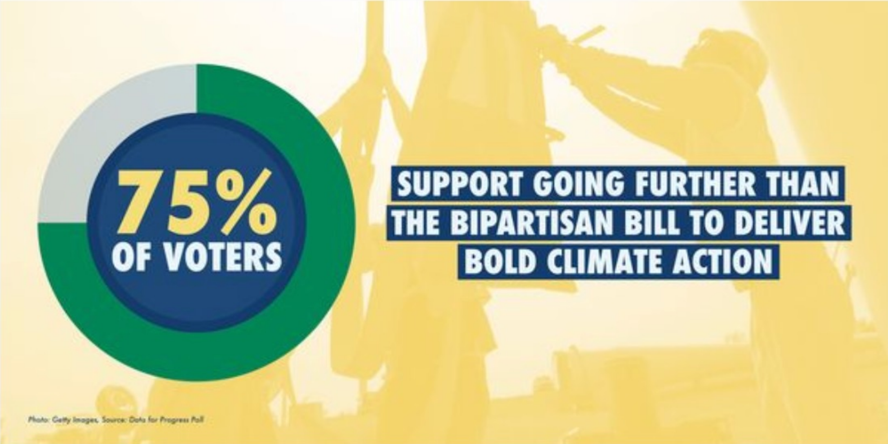

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Stance: *Pro-energy*
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Stance: *Clean-energy*
Theme: *SupportClimatePolicy*

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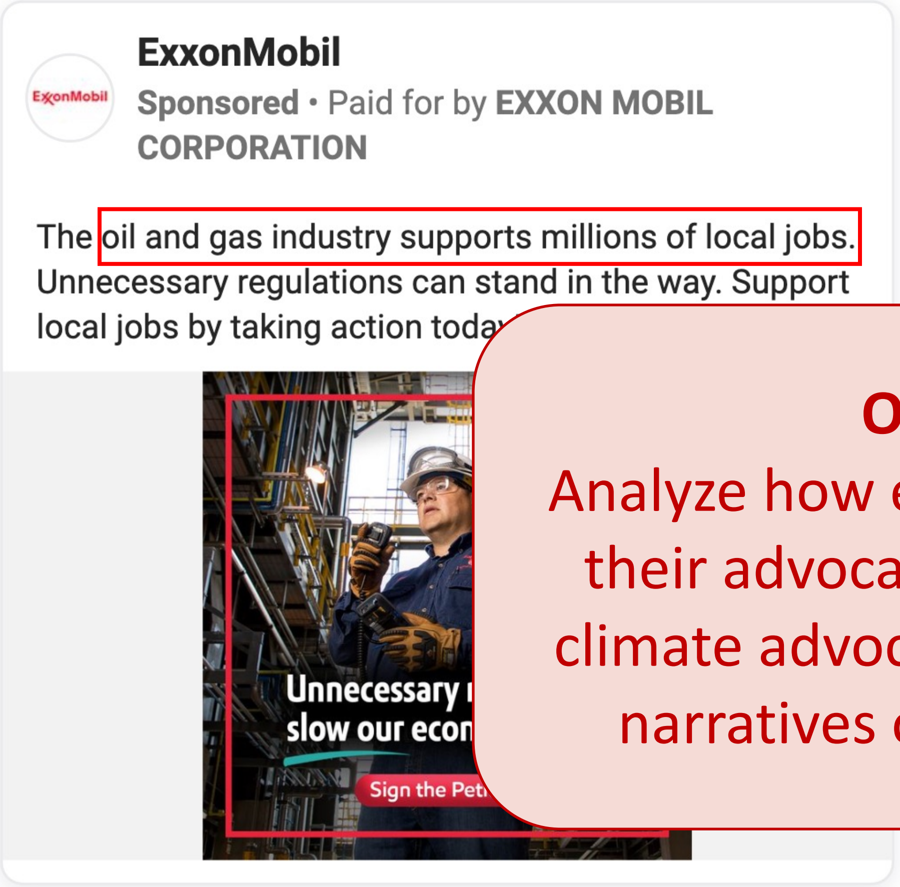

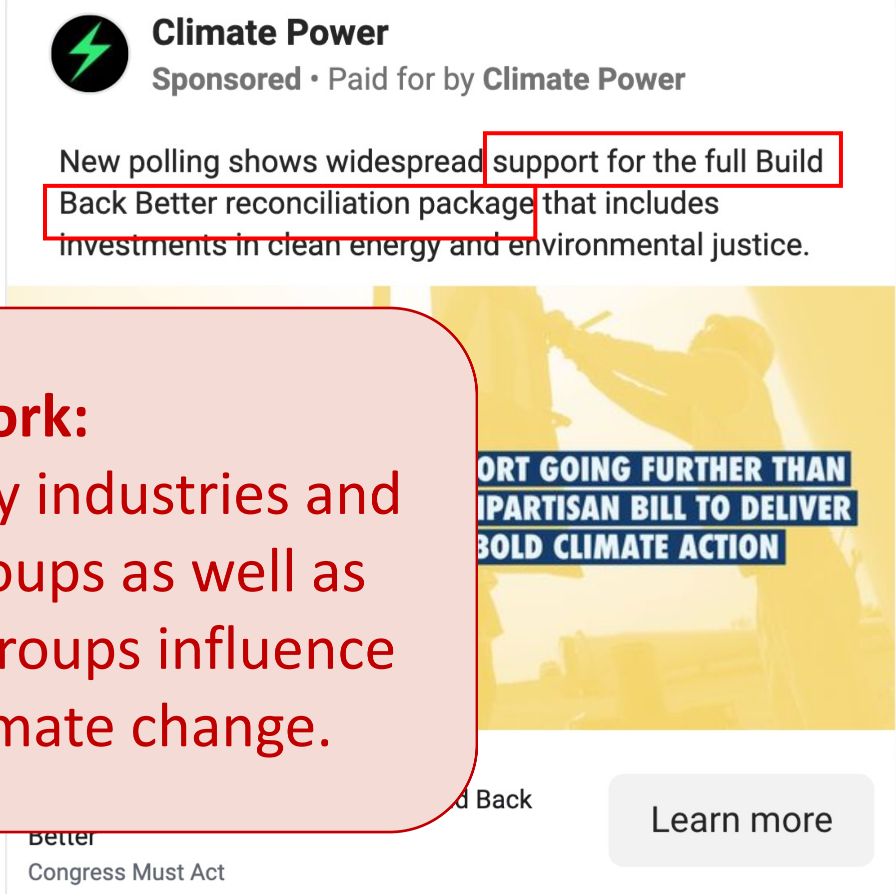

Our Work:
Analyze how energy industries and their advocacy groups as well as climate advocacy groups influence narratives on climate change.

Stance: *Pro-energy*
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Theme: *SupportClimatePolicy*

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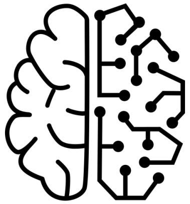	Methodology
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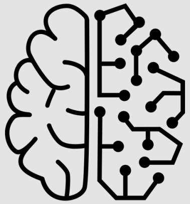	Methodology
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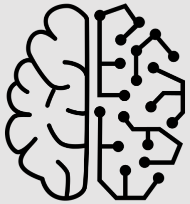	Methodology
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1. Uniform soup
2. Greedy soup

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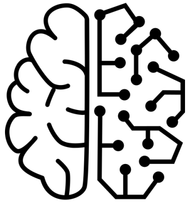	Methodology
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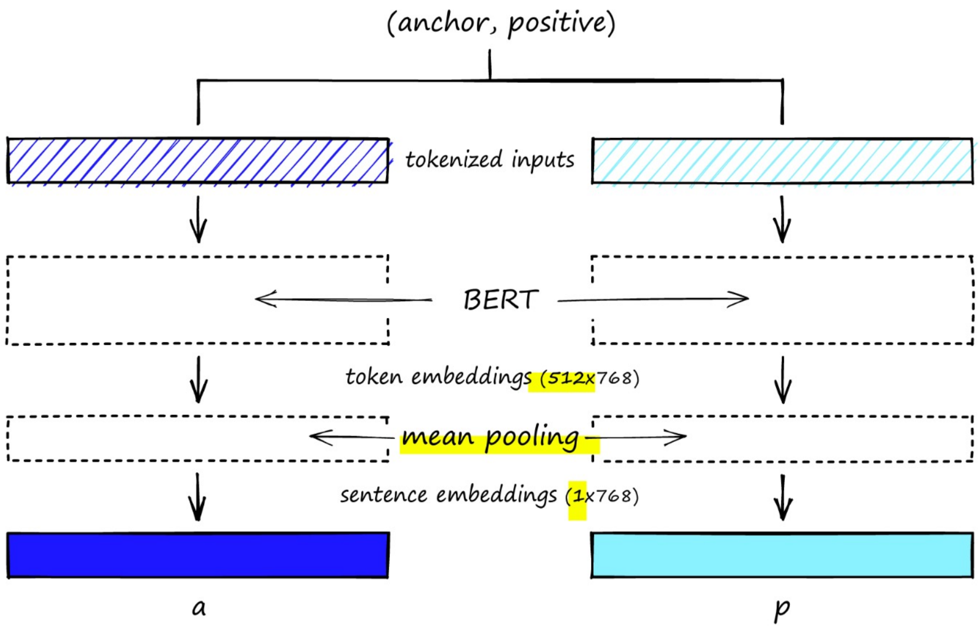

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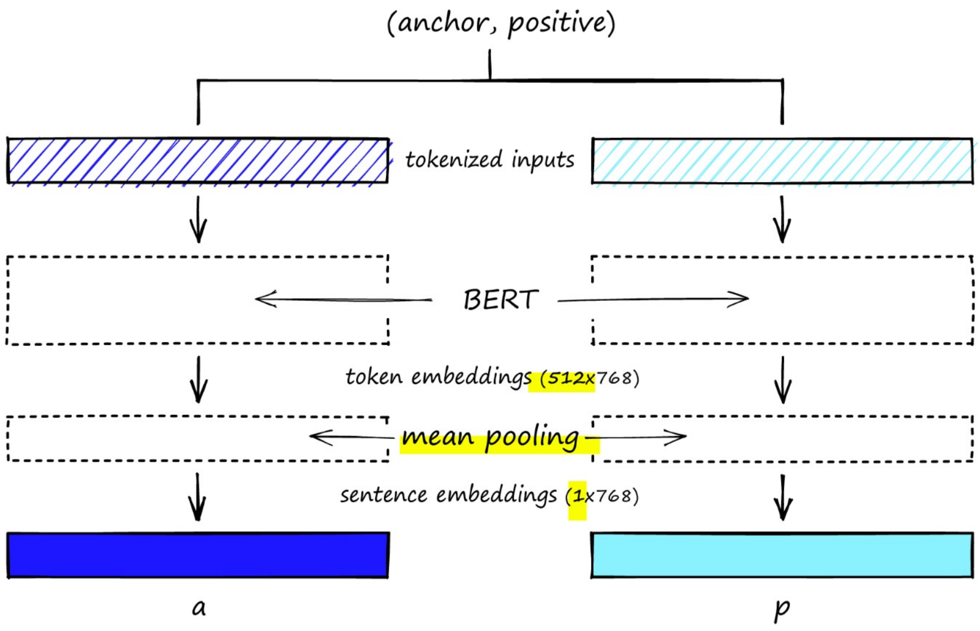

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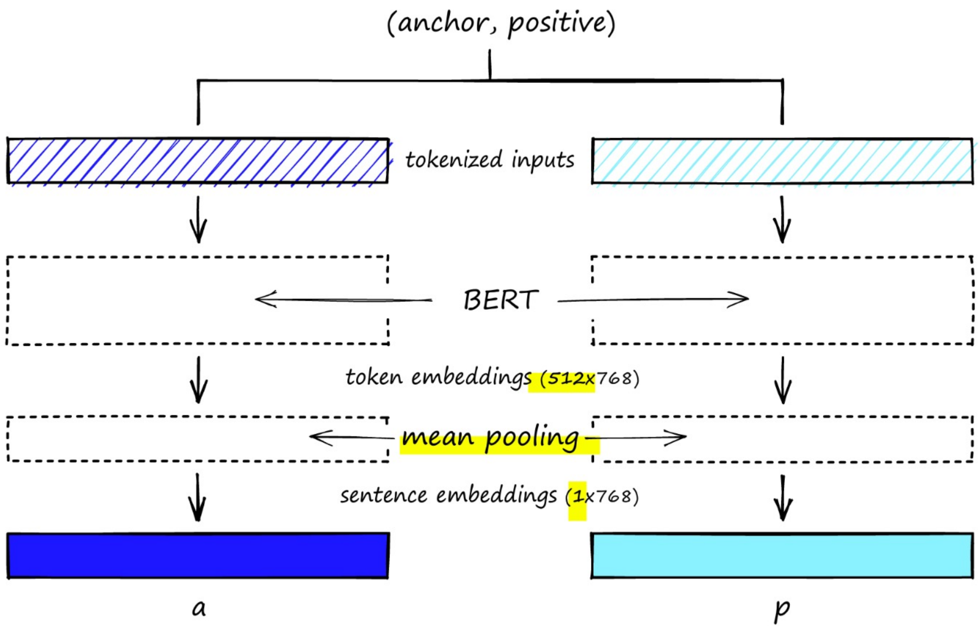

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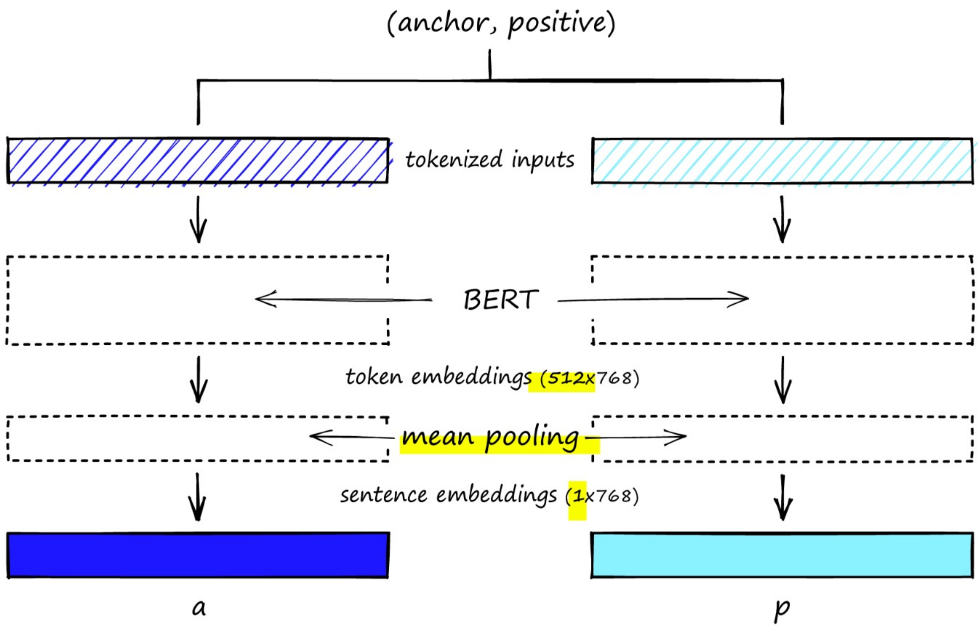

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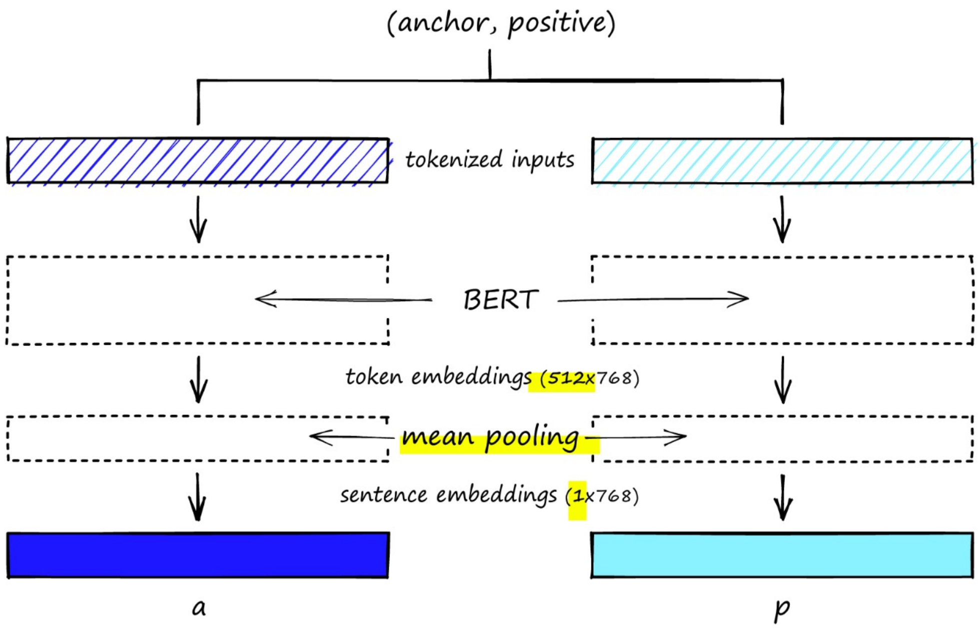

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- **7 pro-energy** and **8 clean-energy** themes.

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- **Ground the phrases** in a set of climate ads and **match similarity** between their **fine-tuned Sentence BERT** embeddings.
- Quality of theme label (**300** ground truth):
  - Accuracy: **38.4%**
  - Macro-avg F1: **40.2%**
  - Significantly better than random (**6.6%**)

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- Greedy soup:

Recipe 1 GreedySoup

Input: Potential soup ingredients $\{\theta_1, \ldots, \theta_k\}$ (sorted in decreasing order of $\mathsf{ValAcc}(\theta_i)$).
ingredients $\leftarrow \{\}$
for $i = 1$ **to** k **do**
  if ValAcc(average(ingredients $\cup \{\theta_i\}$)) $\geq$
      ValAcc(average(ingredients)) **then**
    ingredients $\leftarrow$ ingredients $\cup \{\theta_i\}$
return average(ingredients)

Greedy soup recipe borrowed from *wortsman et al 2022*

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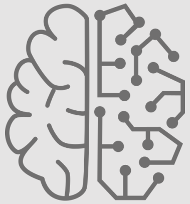	Methodology
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Model	**Method**	**Accuracy**	**Macro-avg F1**
LR_tf-idf	Best individual model	0.810	0.506
RoBERTa-base	Best individual model	0.943	0.879
T5-small	Best individual model	0.874	0.8743
BERT-base	Best individual model	0.921	0.854
	Uniform Model soup	0.944	**0.888**
	Greedy Model soup	**0.945**	0.884

Ablation Study

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- **Uniform model soup (text + theme)** gives **better performance** than the uniform model soup (text), greedy model soup (text), and the best single text only models.

Model	Accuracy	Macro-avg F1	Learning rate	Weight decay
FBERT_Hyper1 (text)	0.897	0.833	2.00E-05	0.01
FBERT_Hyper2 (text)	0.909	0.866	1.00E-05	0.01
FBERT_Hyper3 (text)	0.899	0.687	1.00E-04	0.001
FBERT_Hyper4 (text)	0.895	0.774	1.00E-04	0.01
FBERT_Hyper5 (text)	0.905	0.856	1.00E-05	0.001
FBERT_Hyper6 (text)	0.898	0.813	3.00E-05	0.001
FBERT_Hyper7 (text)	0.896	0.825	3.00E-05	0.01
FBERT_Hyper8 (text)	0.892	0.833	2.00E-05	0.1
FBERT_Hyper9 (text)	0.885	0.813	1.00E-04	0.0001
FBERT_Hyper10 (text)	0.906	0.861	1.00E-05	0.1
Uniform Model soup (text)	*0.943*	*0.880*	-	-
Greedy Model soup (text)	*0.933*	*0.872*	-	-
Point_est_Hyper1 (text + thm)	0.921	0.854	2.00E-05	0.01
Point_est_Hyper2 (text + thm)	0.883	0.835	1.00E-05	0.01
Point_est_Hyper3 (text + thm)	0.916	0.695	1.00E-04	0.001
Point_est_Hyper4 (text + thm)	0.874	0.845	1.00E-04	0.01
Point_est_Hyper5 (text + thm)	0.897	0.826	1.00E-05	0.001
Point_est_Hyper6 (text + thm)	0.902	0.825	3.00E-05	0.001
Point_est_Hyper7 (text + thm)	0.894	0.830	3.00E-05	0.01
Point_est_Hyper8 (text + thm)	0.894	0.829	2.00E-05	0.1
Point_est_Hyper9 (text + thm)	0.888	0.781	1.00E-04	0.0001
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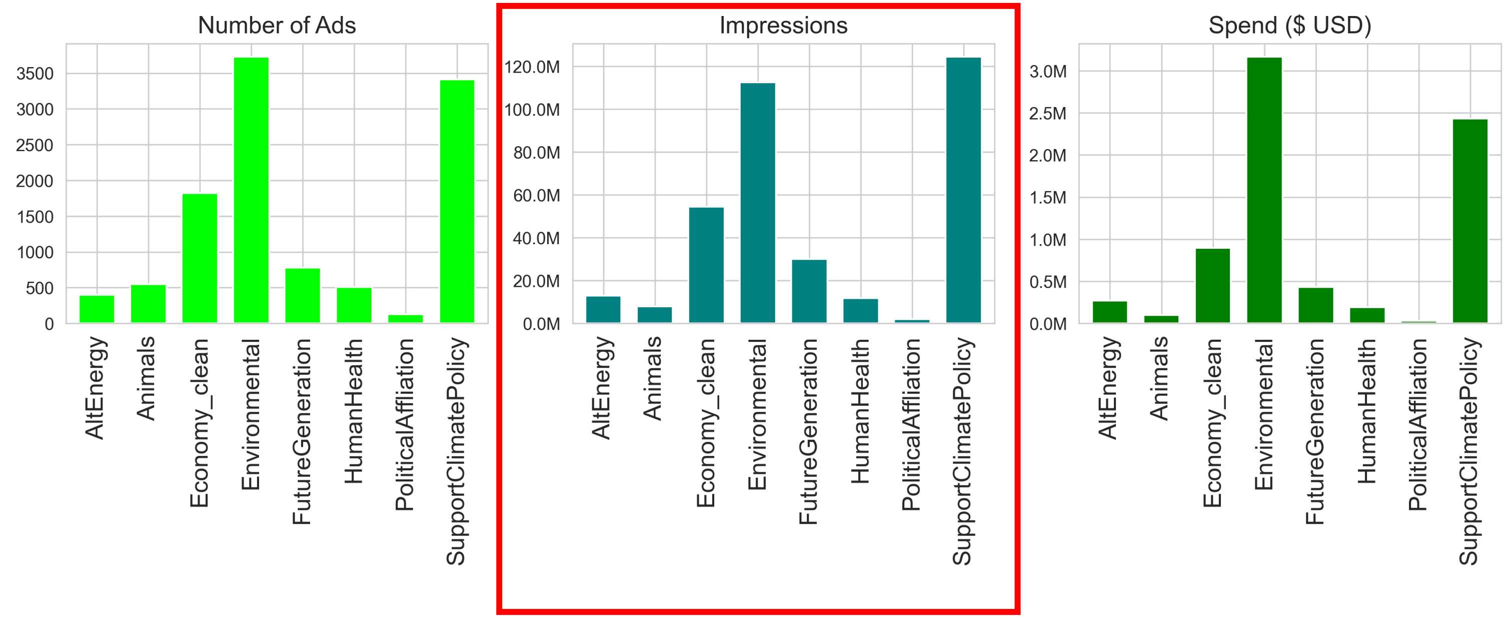
What are the intersecting themes of the messaging?

- Most popular theme for **clean-energy** ads is **Support Climate Policy**.



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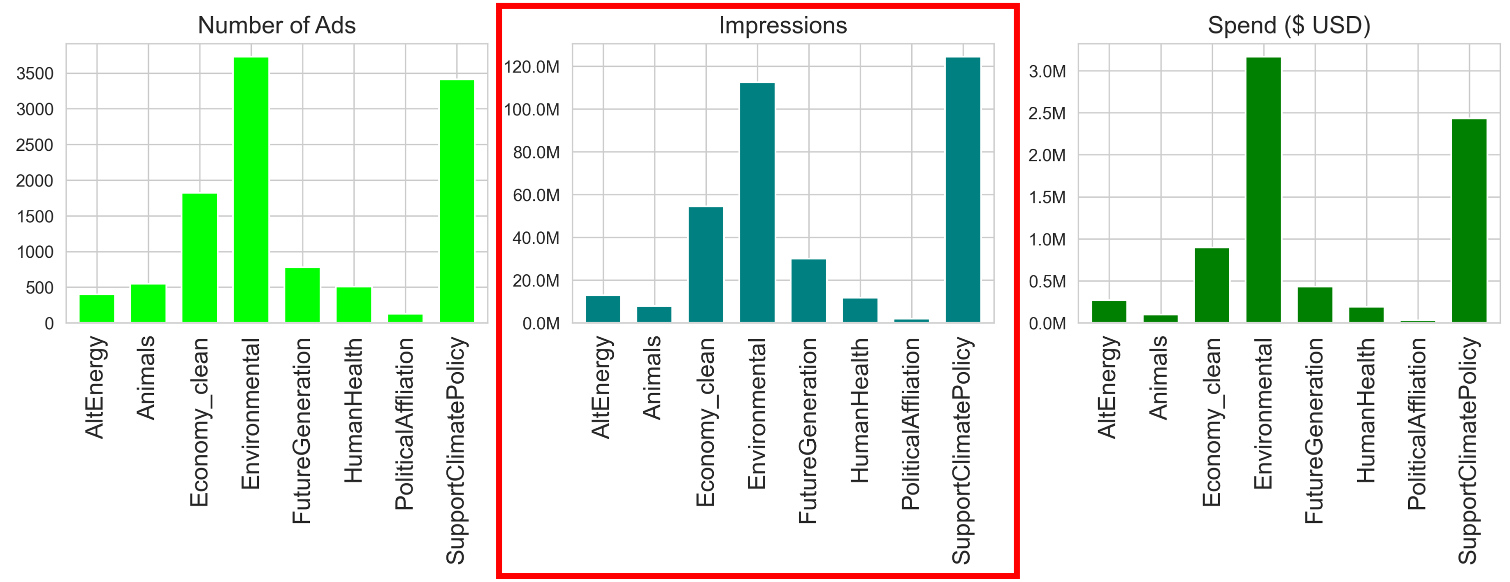

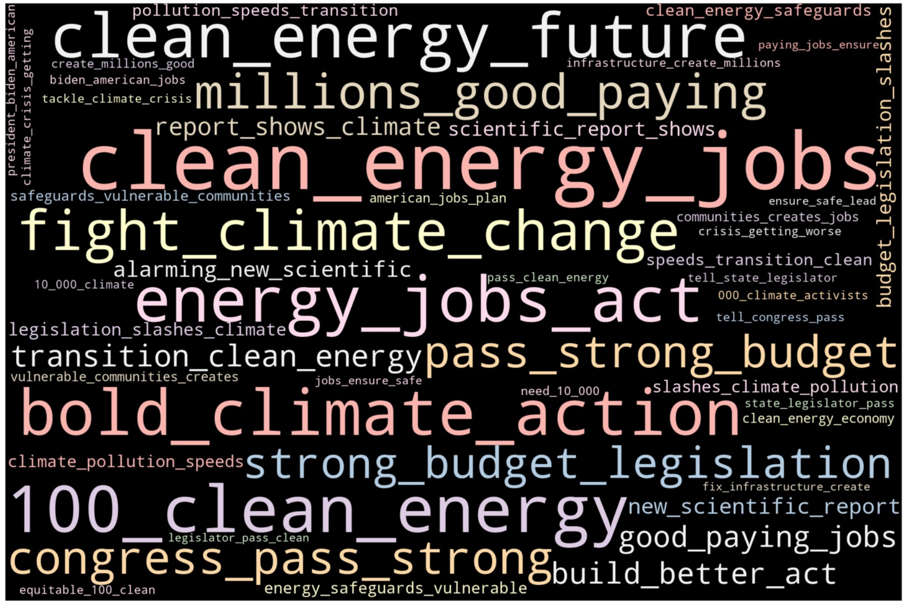

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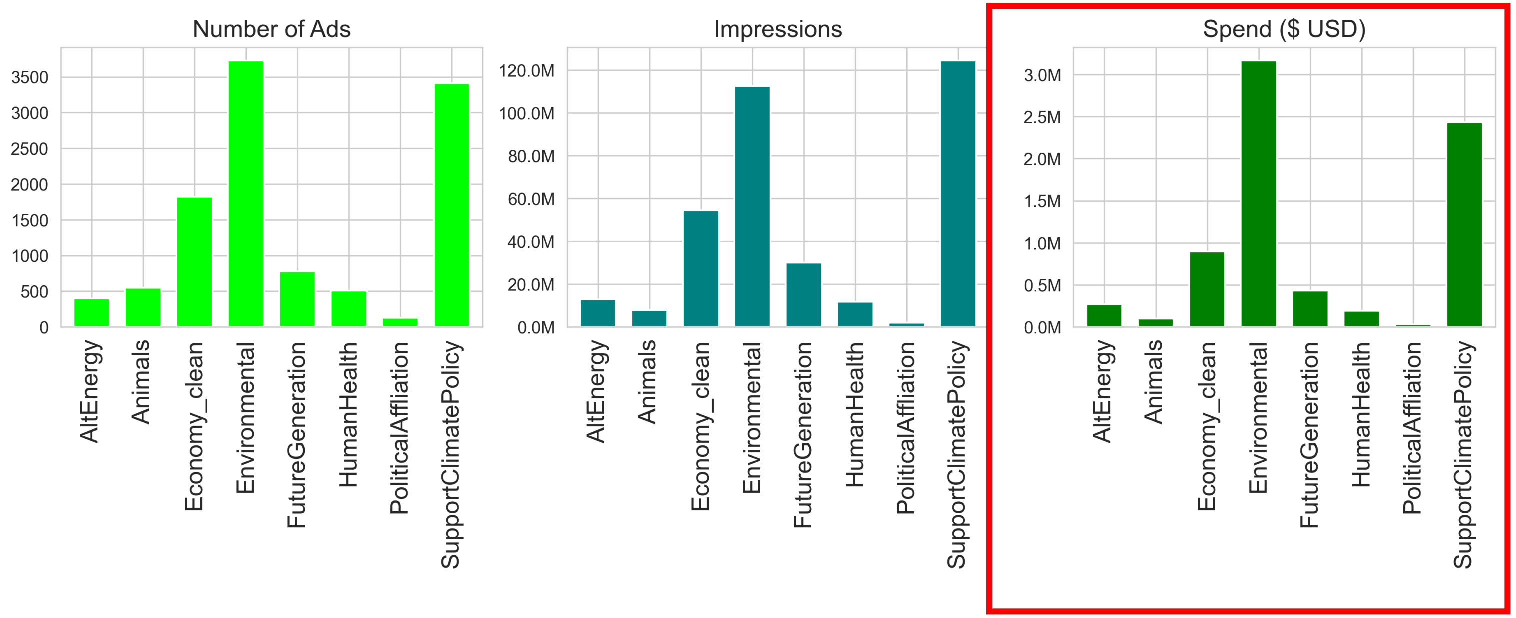

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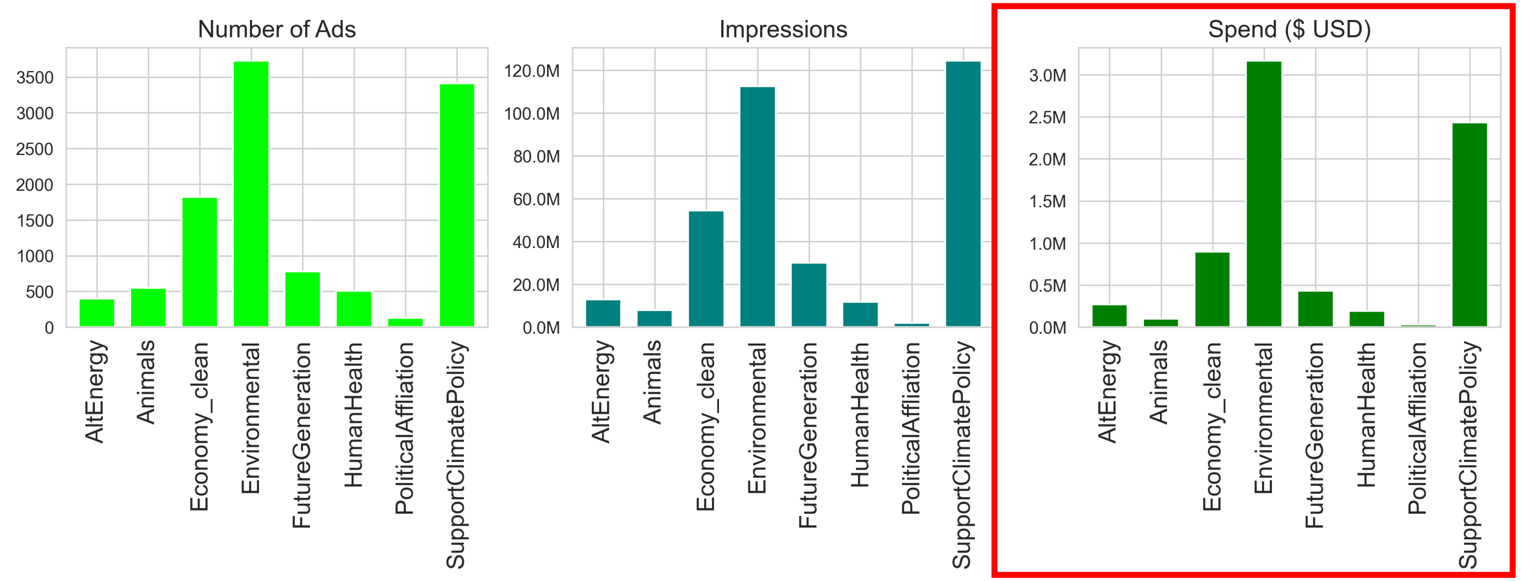
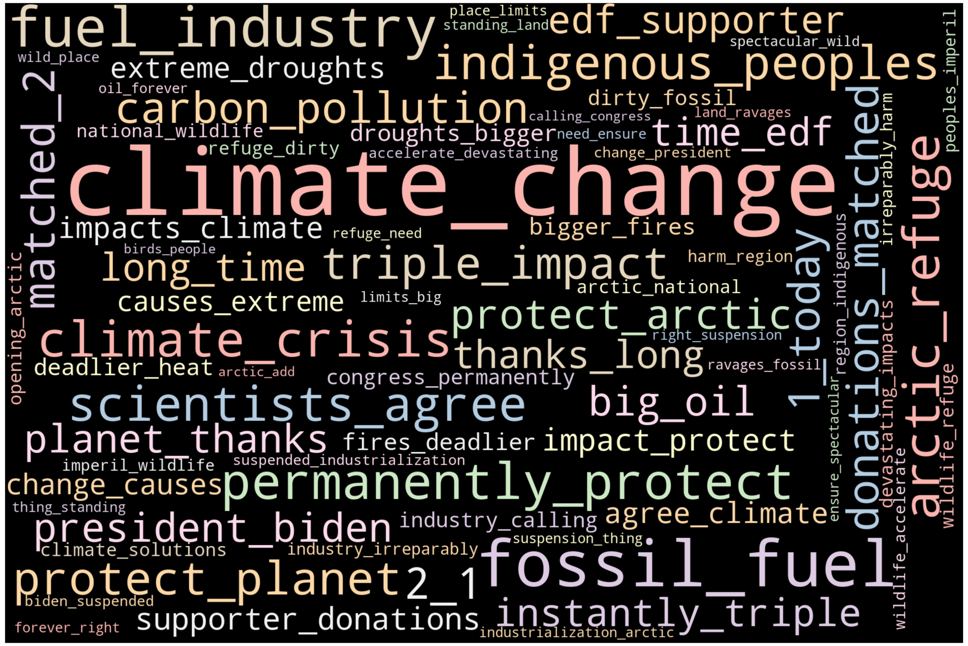
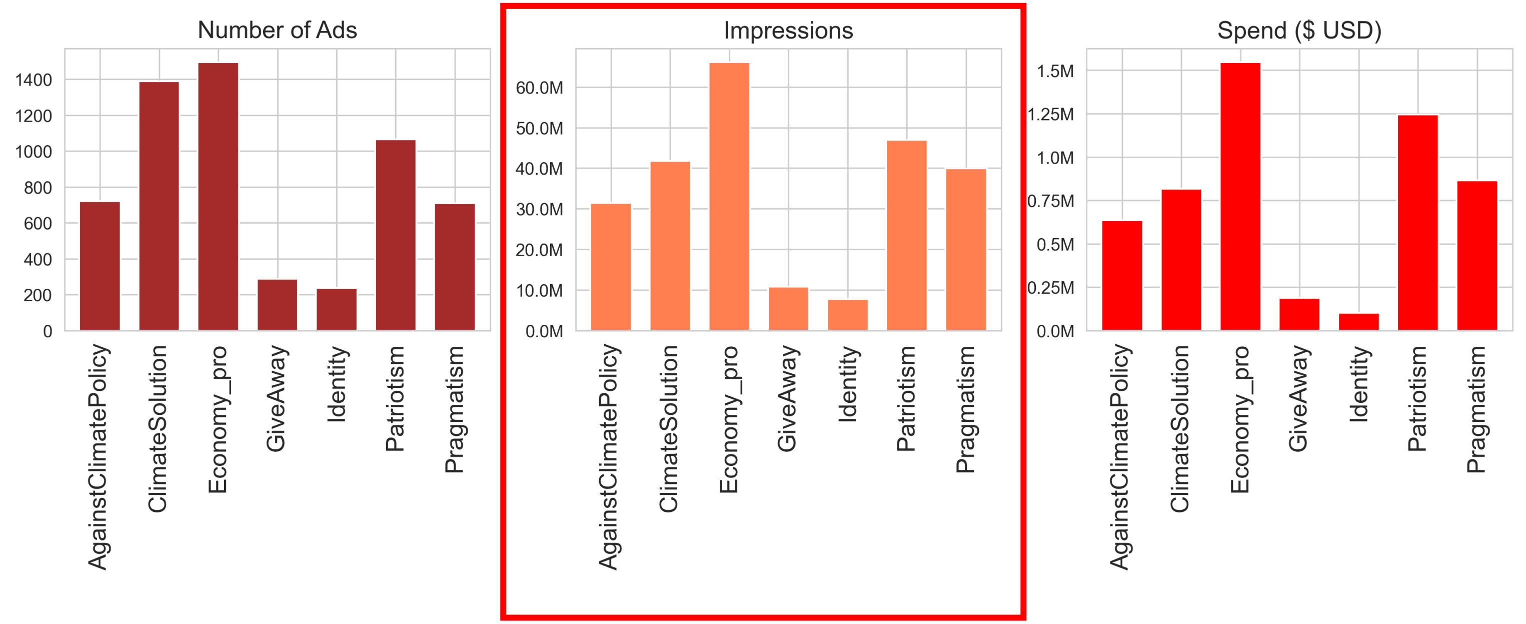
  - Focuses on narratives about '*how dirty fossil fuel industries would harm the indigenous peoples and wildlife*', '*why climate scientists agree that climate change causes more extreme droughts, bigger fires and deadlier heat*', '*effects of carbon pollution on climate crisis*' etc.





What are the intersecting themes of the messaging?

- Most popular theme for **pro-energy** ads is **Economy_pro**.



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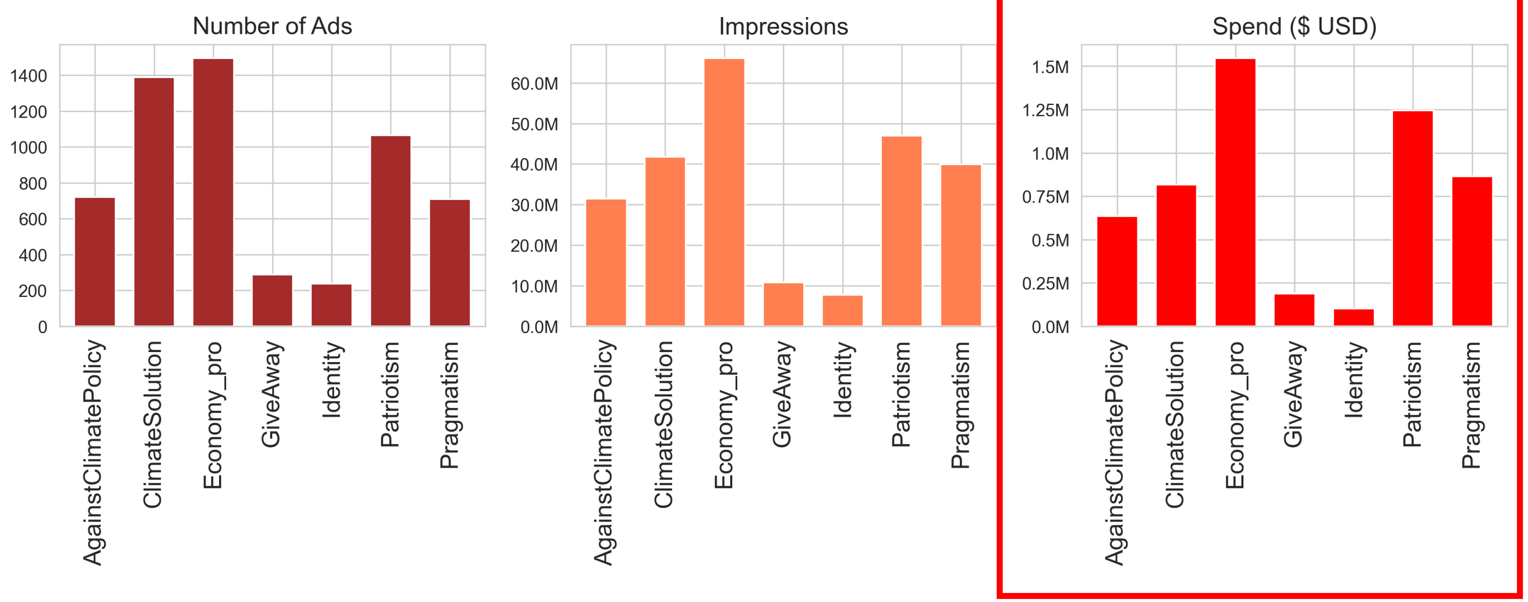

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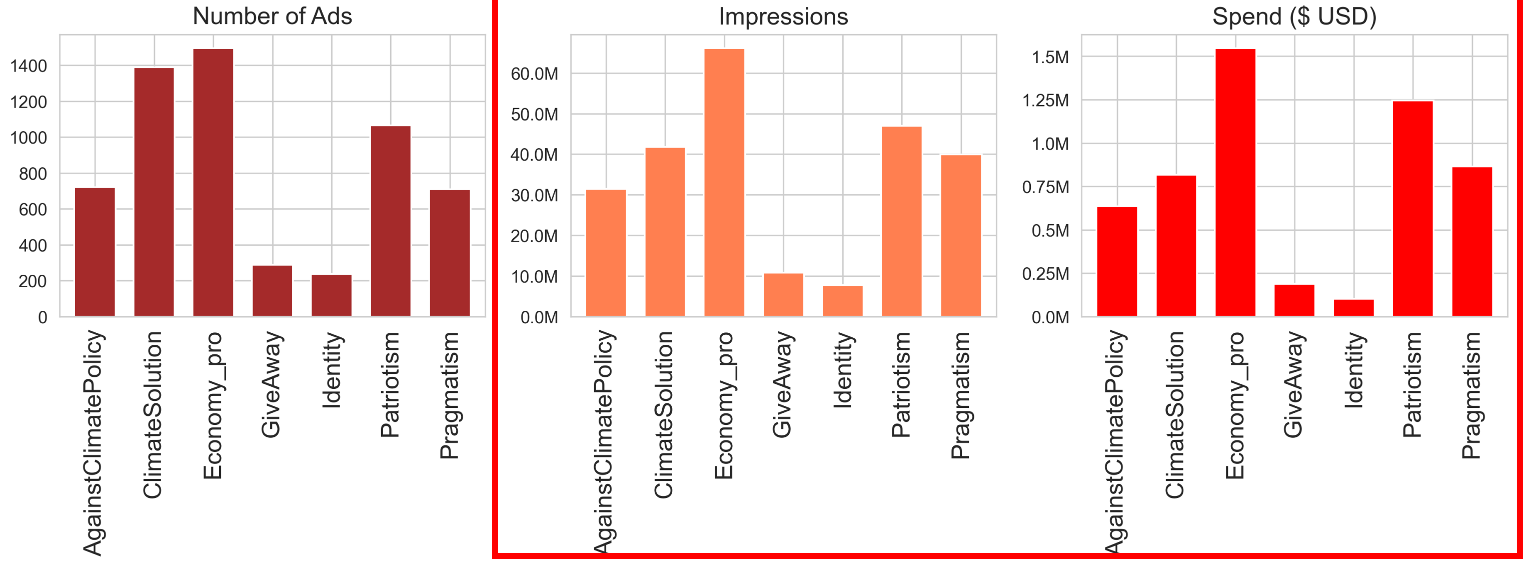
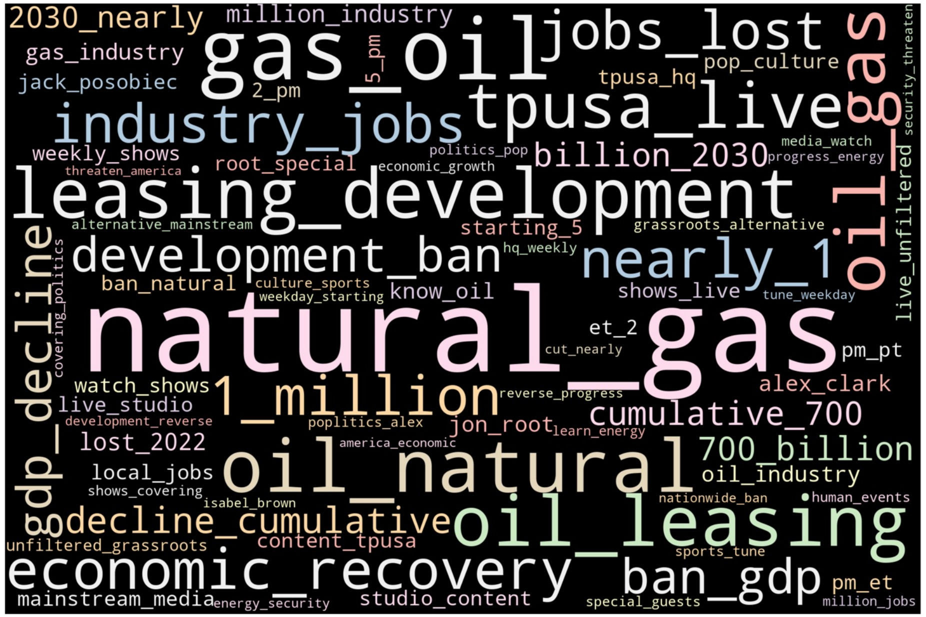
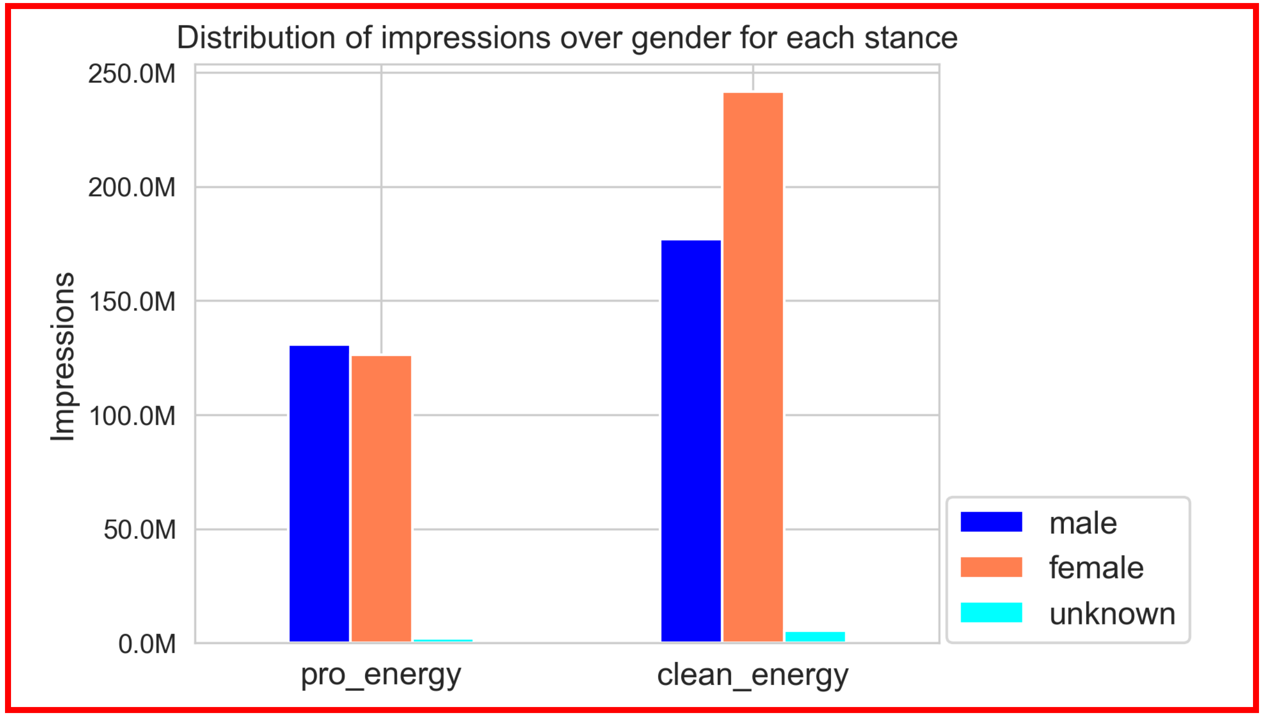
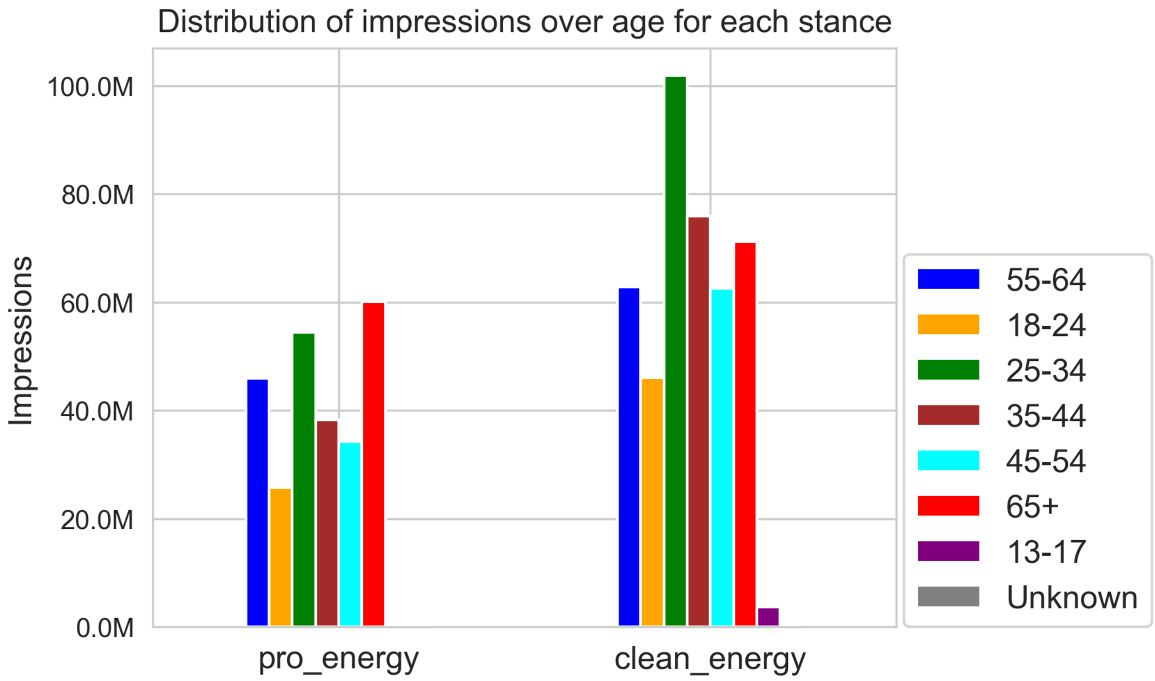
- Sponsors spend more on **Economy_pro** themed ads.
  - Narratives promote how *'natural gas and oil industry will drive economic recovery', 'GDP would decline by a cumulative 700 billion through 2030 and 1 million industry jobs would be lost by 2022 under natural gas and oil leasing and development ban'*.





What demographics are targeted by the advertisers?





- More males than females view pro-energy ads.
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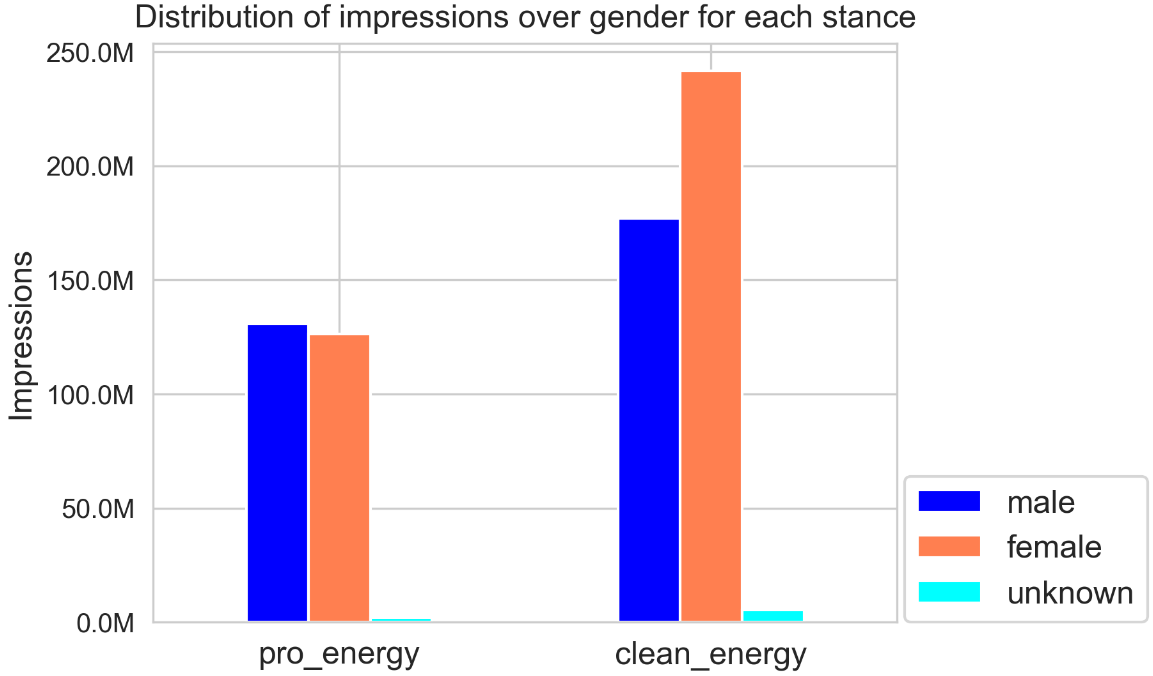

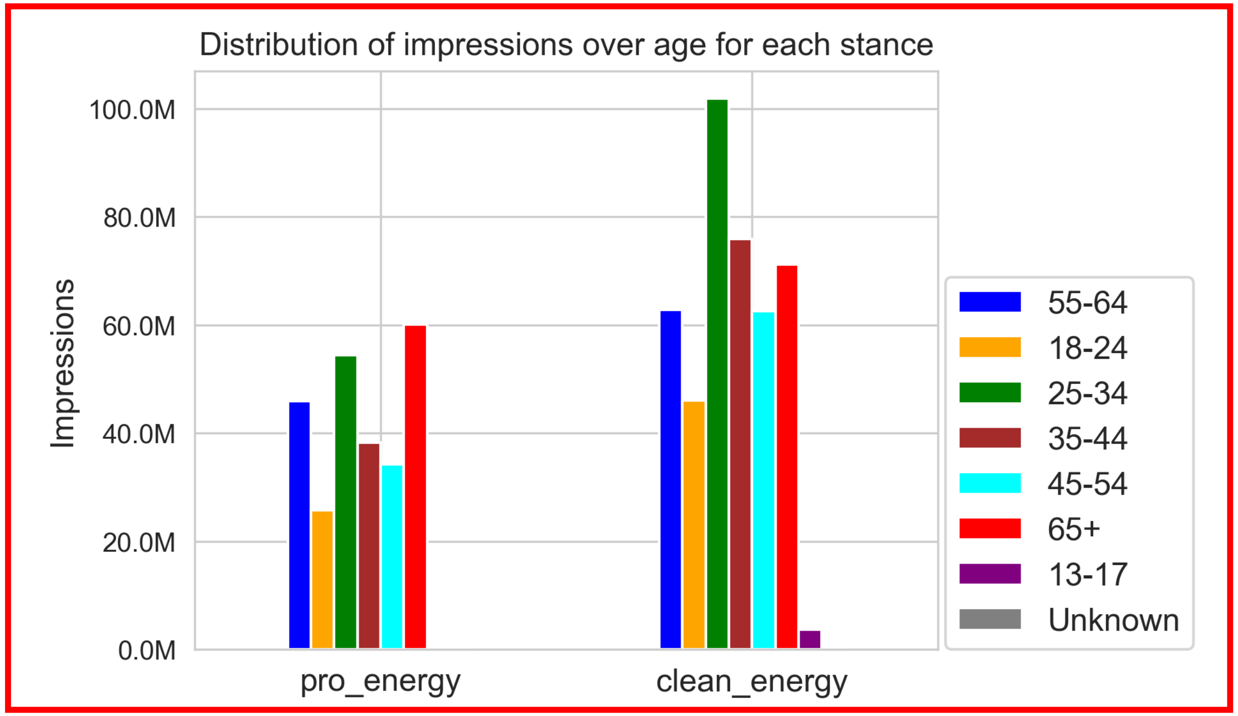

- **More males** than females view pro-energy ads.
- **More females** than males view clean-energy ads.
- The **older** population (65+) watches the pro-energy ads.
- The **younger** population (25 – 34) watches clean-energy ads.

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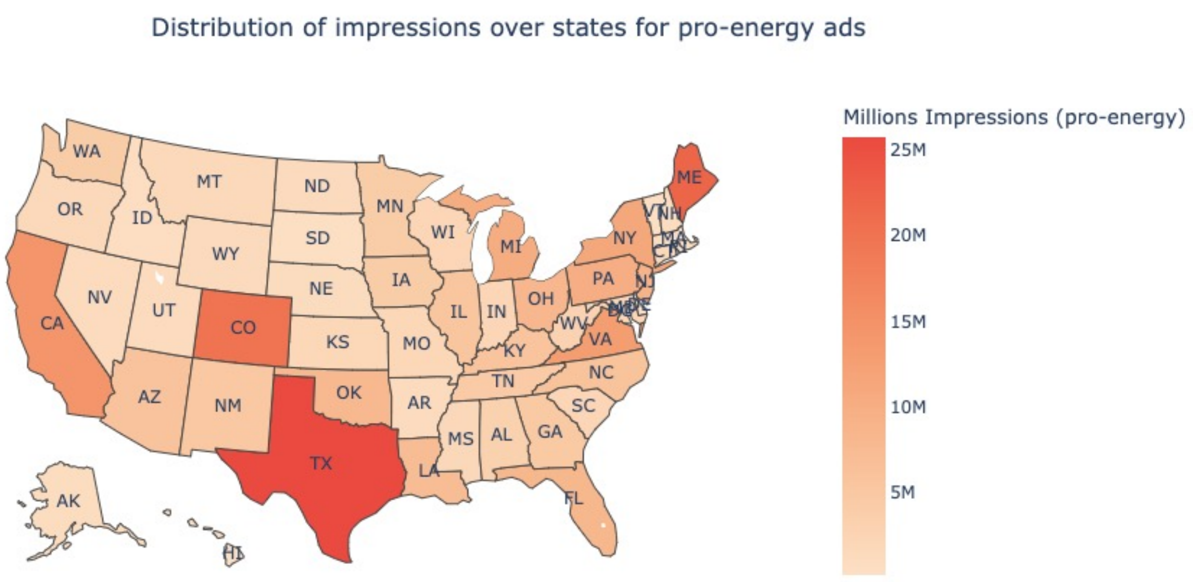

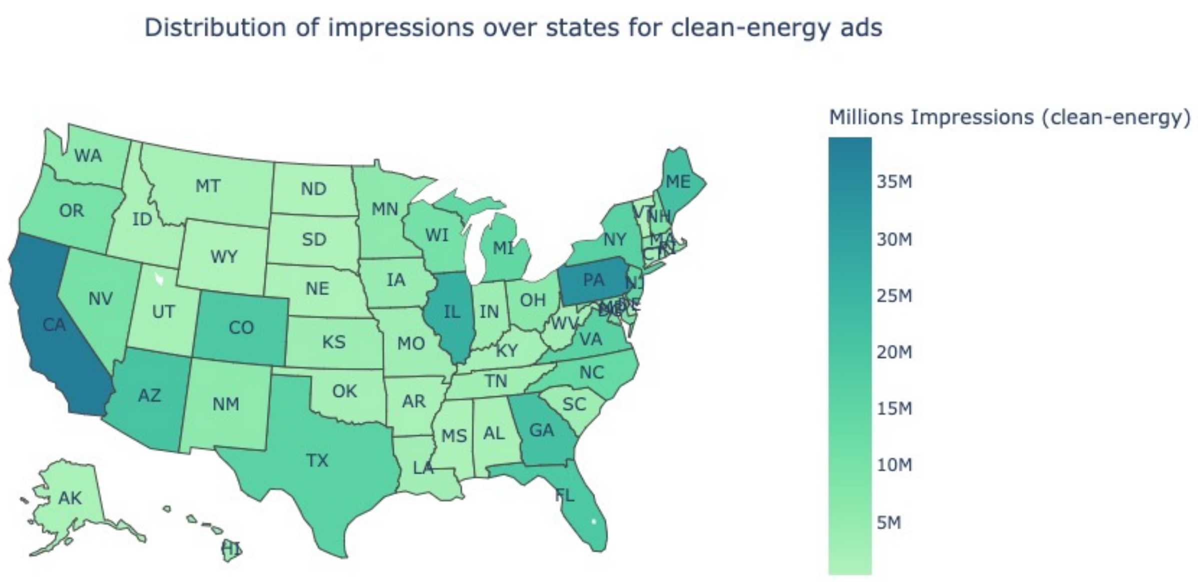

- Pro-energy ads receive the most views from **Texas**.

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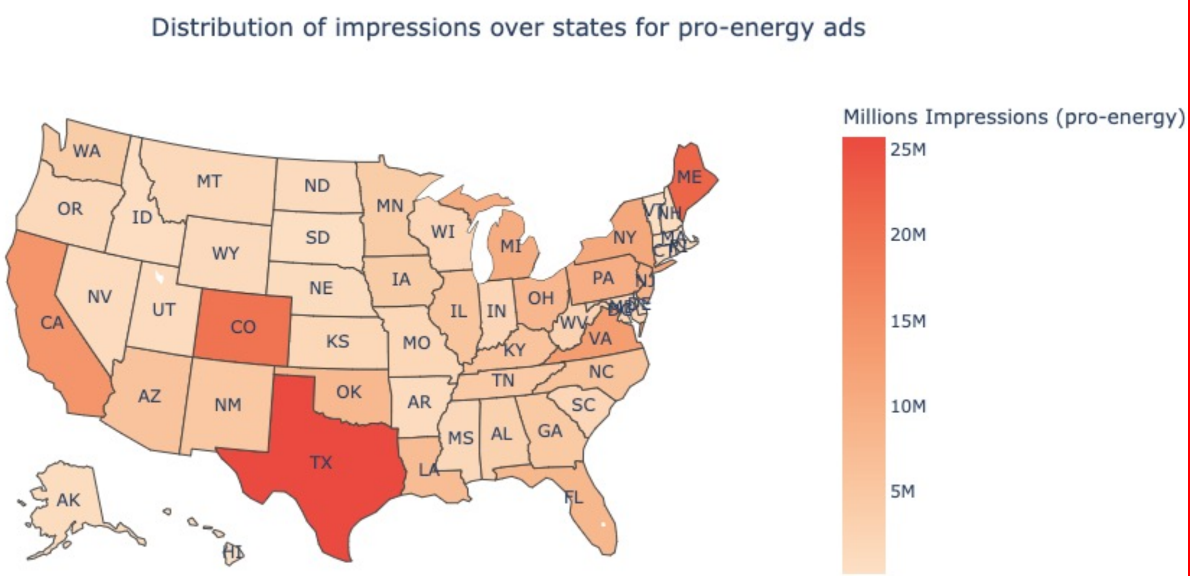

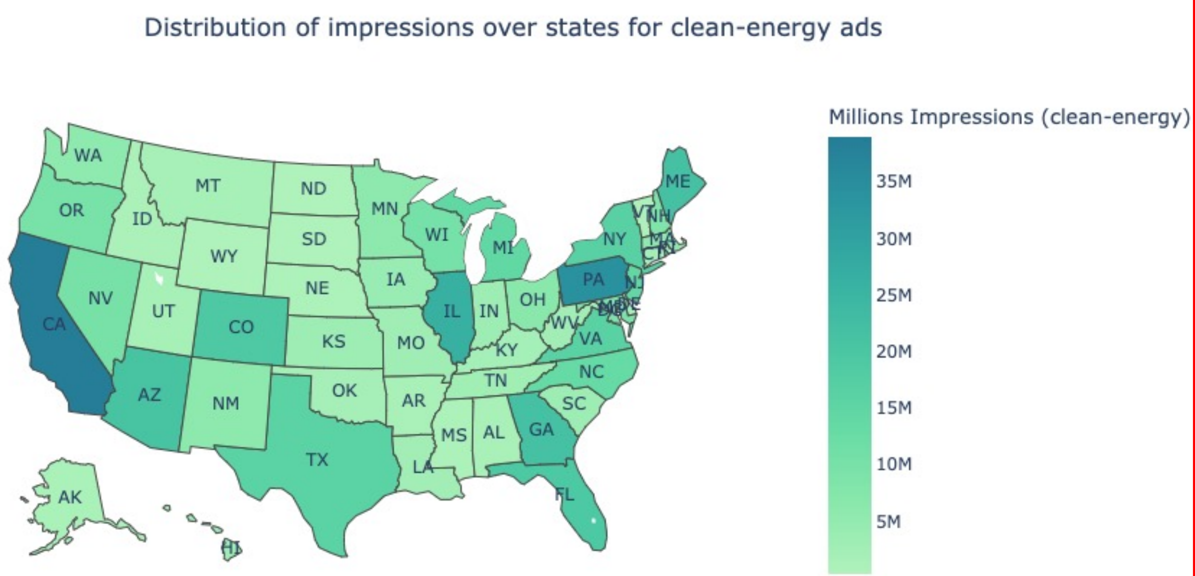

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- Clean-energy ads are mostly viewed from **California**.

Do the messages differ based on entity type?

- Categorize pro-energy funding entities into **three** types based on their **expenditure**.

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  - Corporations,
  - Industry Associations
  - Advocacy Groups

Type	Entity
Corporation	EXXON MOBIL CORPORATION
Corporation	Shell
Corporation	BP CORPORATION NORTH AMERICA INC.
Corporation	Twin Metals Minnesota
Corporation	Wink to Webster Pipeline LLC
Industry Association	AMERICAN PETROLEUM INSTITUTE
Industry Association	New York Propane Gas Association
Industry Association	Texas Oil & Gas Association
Industry Association	New Mexico Oil and Gas Association
Industry Association	National Propane Gas Association
Advocacy Group	Coloradans for Responsible Energy Development
Advocacy Group	Grow Louisiana Coalition
Advocacy Group	Voices for Cooperative Power
Advocacy Group	Consumer Energy Alliance
Advocacy Group	Maine Affordable Energy

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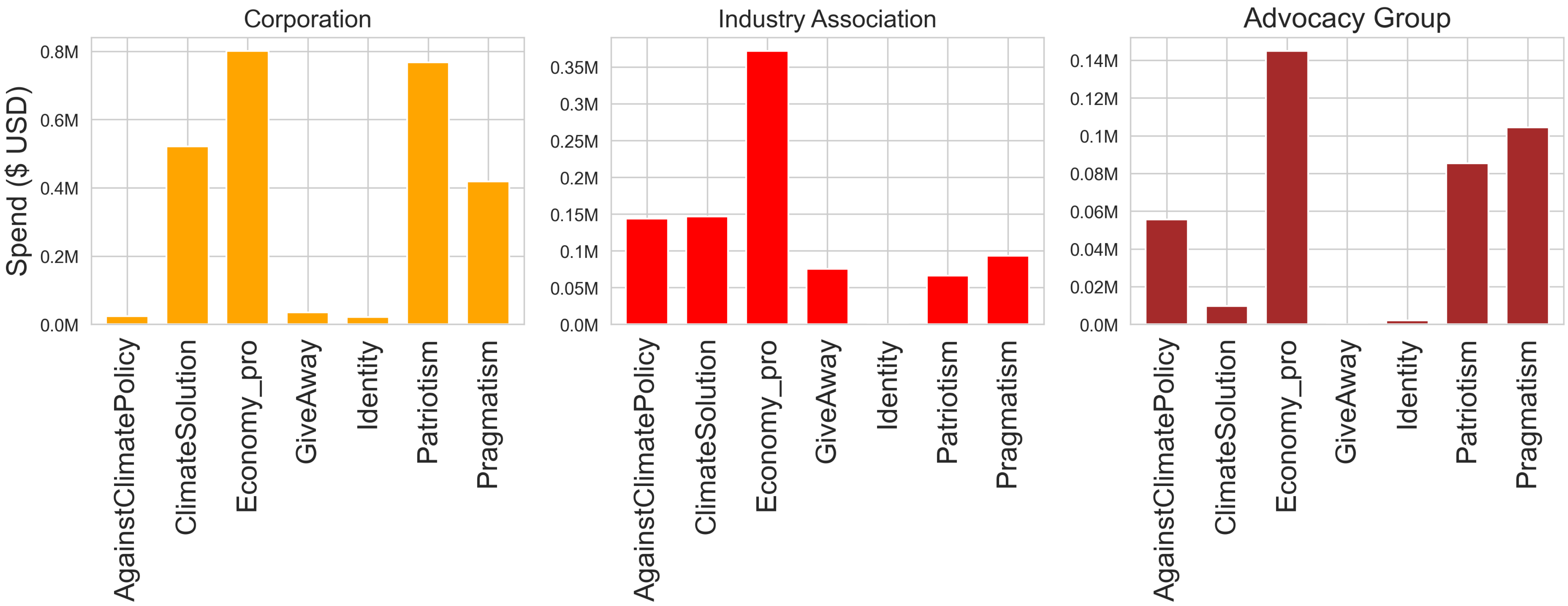

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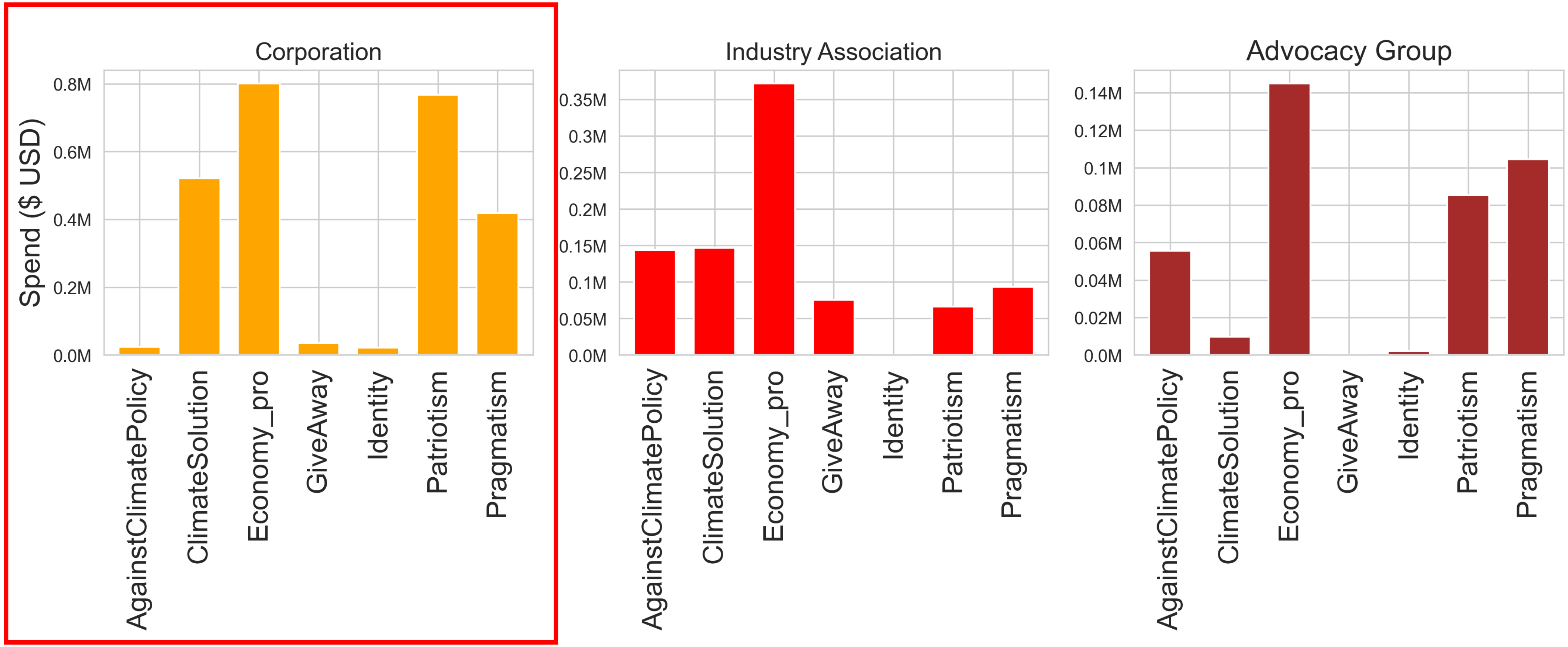

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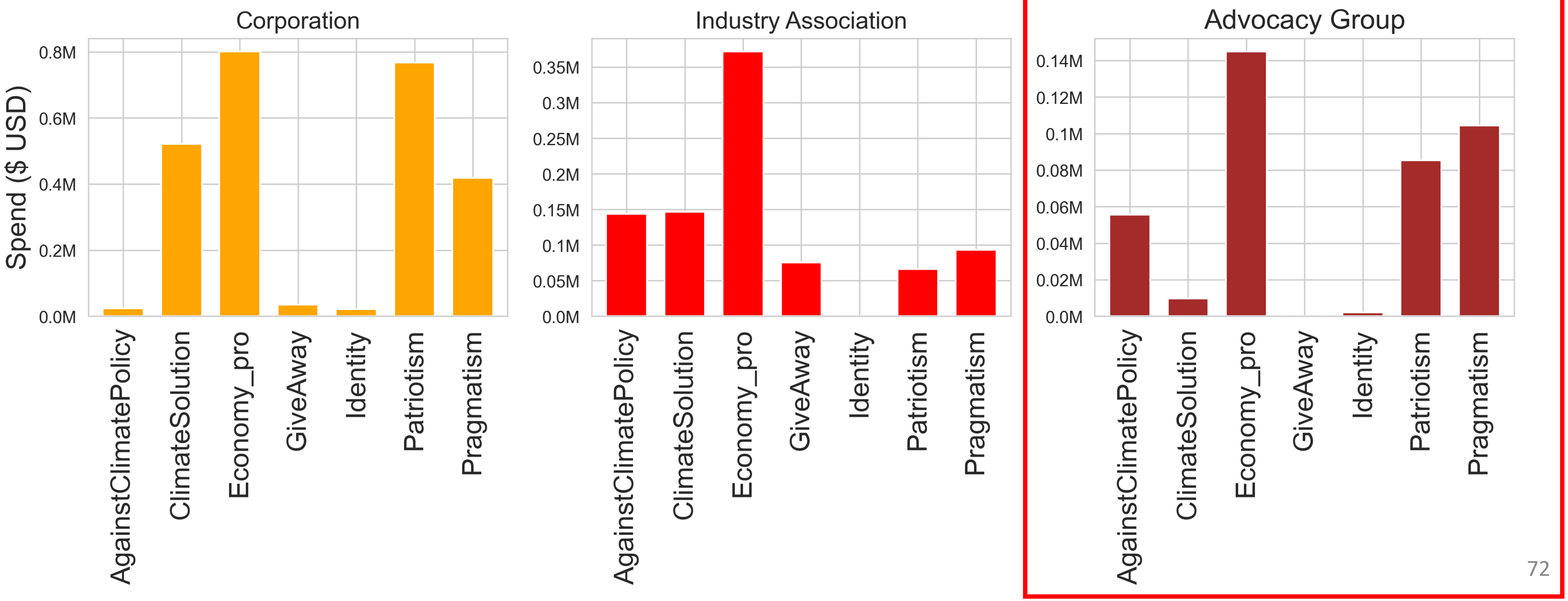

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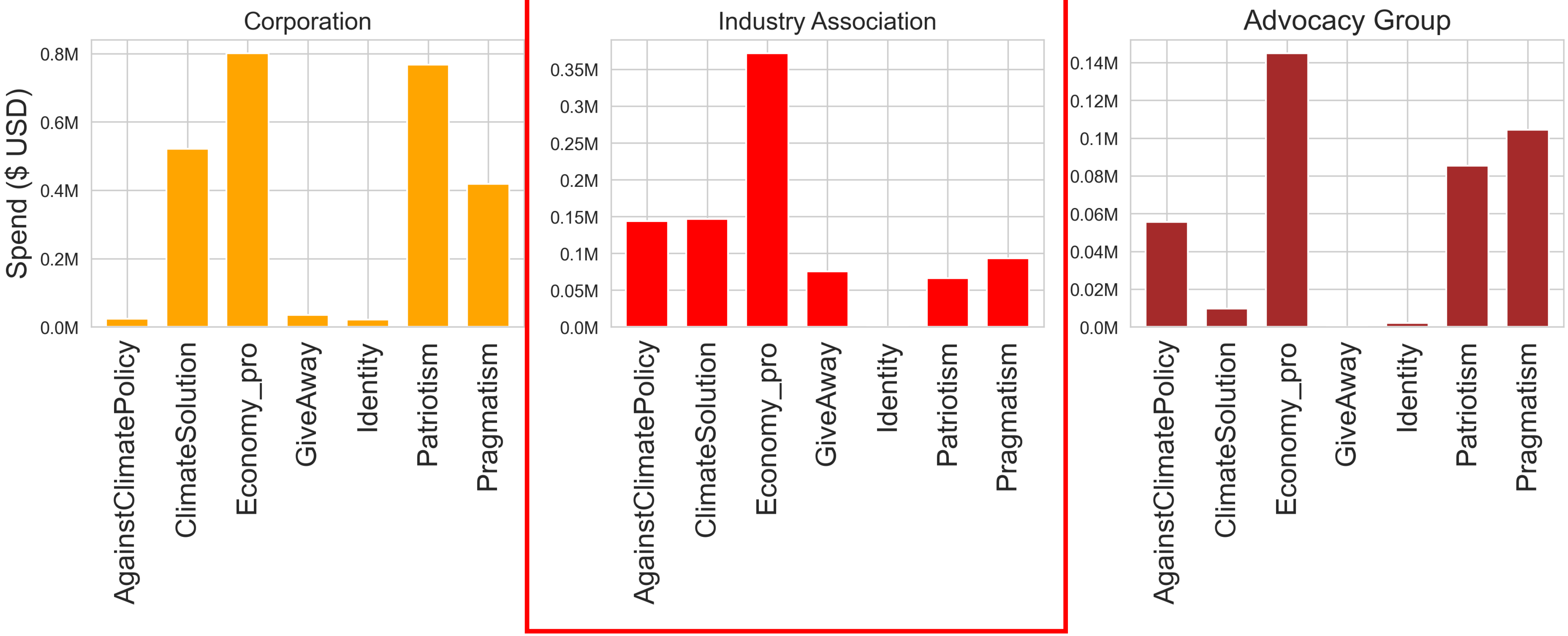
- **Industry associations** spend almost equally on ClimateSolution and AgainstClimatePolicy narratives.



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- Conduct **quantitative** and **qualitative** analysis on real world dataset to demonstrate the effectiveness of our proposed model.
- Our code and dataset are **publicly available** at https://github.com/tunazislam/BMA-FB-ad-Climate.

THANK YOU ☺

Slide: https://tunazislam.github.io/files/climateFbAd.pdf

Questions?

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