

# GenAI-Powered Inference

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## Motivation

- Generative AI is transforming medicine, education, marketing, etc.
- Can methodologists get some help from GenAI too?

How can a methodologist use LLM to help improve research? Give me a short answer.



A methodologist can use large language models (LLMs) to enhance research by automating literature reviews, generating hypotheses, designing study frameworks, and analyzing data. LLMs can also assist in drafting and refining research papers, coding qualitative data, and even suggesting relevant methodologies or statistical approaches, making the research process faster and more rigorous.

# Using GenAI to Improve Causal Inference

- GenAI-Powered Inference (GPI)
- GenAI-assisted causal inference with unstructured data
  - ① generate new unstructured data at scale  
regenerate existing unstructured data at scale
  - ② obtain true internal representation from GenAI
  - ③ use it directly for machine learning without fine tuning GenAI
- Advantages:
  - no need to estimate representation
  - avoid functional form assumptions
- Better empirical performance

# Generative AI: Definition and Assumption

- Deep generative model:

$$\mathbb{P}(\mathbf{X}_i \mid \mathbf{h}_\gamma(\mathbf{R}_i)),$$

$$\mathbb{P}(\mathbf{R}_i \mid \mathbf{P}_i).$$

- $\mathbf{P}_i$ : prompt
  - $\mathbf{X}_i$ : unstructured, generated object
  - $\mathbf{R}_i$ : hidden states or internal representations
  - $\mathbf{h}_\gamma(\mathbf{R}_i)$ : deterministic function from hidden states to the last layer
- **Deterministic decoding:**

$\mathbb{P}(\mathbf{X}_i \mid \mathbf{h}_\gamma(\mathbf{R}_i))$  is degenerate

- can be achieved by setting a hyperparameter
- use of open-source GenAI and deterministic encoding for replicability

# Motivating Application: Texts-as-Treatments

- Candidate Biography Experiment (Fong and Grimmer, 2016)
  - 1246 biographies of American politicians scraped from Wikipedia
  - 1,886 voters as respondents
  - randomly assign biographies to voters
  - feeling thermometer  $[0, 100]$  as the outcome
- Analysis
  - supervised topic model to discover 10 treatment features
  - estimate the average treatment effects of estimated topic proportions
- Existing approaches for texts-as-treatments:
  - 1 model-based approach (e.g., Egami *et al.* 2022; Fong and Grimmer, 2023)
  - 2 causal representation learning based on fine-tuned BERT embedding (e.g., Veitch *et al.* 2020; Pryzant *et al.* 2021; Gui and Veitch, 2023)

## Example Biographies

### **Candidate biography with military background**

Anthony Higgins was born in Red Lion Hundred in New Castle County, Delaware. He attended Newark Academy and Delaware College, and graduated from Yale College in 1861, where he was a member of Skull and Bones. After studying law at the Harvard Law School, he was admitted to the bar in 1864 and began practice in Wilmington, Delaware. He also served for a time in the United States Army in 1864.

### **Candidate biography without military background**

Benjamin Tappan was born in Northampton, Massachusetts, the second child and oldest son of Benjamin Tappan and Sarah (Homes) Tappan, who was a grandniece of Benjamin Franklin. Two of his younger brothers were abolitionists Arthur Tappan and Lewis Tappan. He attended the public schools in Northampton and traveled to the West Indies in his youth. He apprenticed as a printer and engraver, also studying painting with Gilbert Stuart. He read law to be admitted to the bar in Hartford, Connecticut, in 1799. Later that year, he moved to the Connecticut Western Reserve and founded what is now Ravenna, Ohio, laying out the original village in 1808. He married, March 20, 1801, Nancy Wright, sister of John C. Wright (congressman), afterwards a United States House of Representatives from Ohio. They had one son, Benjamin, born in 1812.

# Setup

- Notation

- $Y_i(\mathbf{x})$ : Potential outcome when exposed to treatment object  $\mathbf{x}$
- $Y_i = Y_i(\mathbf{X}_i)$ : Outcome (collected from the survey respondents)
- $T_i$ : Binary treatment feature (e.g., military experiences)
- $\mathbf{U}_i$ : Confounding features (e.g., college education)

- Assumptions

- ① Treatment Feature:

$$T_i = g_T(\mathbf{X}_i)$$

- ② Confounding Features:

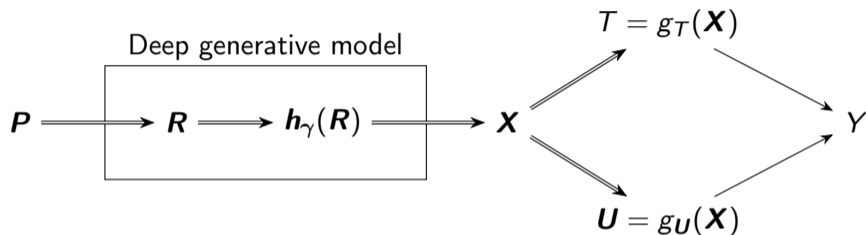
$$\mathbf{U}_i = \mathbf{g}_U(\mathbf{X}_i) \quad \text{where } \dim(\mathbf{U}_i) \ll \dim(\mathbf{X}_i)$$

- ③ Separability:

$$Y_i(\mathbf{x}) = Y_i(g_T(\mathbf{x}), \mathbf{g}_U(\mathbf{x})),$$

- $T$  is not a function of  $\mathbf{U}$
    - $\mathbf{U}$  is not a function of  $T$

## Summary of Assumptions



- Assumptions:
- **Overlap:** The above assumptions imply that for any  $t \in \{0, 1\}$  and  $\mathbf{u} \in \mathcal{U}$ , there exists  $\epsilon > 0$  such that

$$\mathbb{P}(T_i = t \mid \mathbf{U}_i = \mathbf{u}) > \epsilon.$$

# Nonparametric Identification

- Average treatment effect (ATE):

$$\tau := \mathbb{E}[Y_i(1, \mathbf{U}_i) - Y_i(0, \mathbf{U}_i)]$$

- Under these assumptions, there exists a **Deconfounder**  $\mathbf{f} : \mathbb{R}^r \rightarrow \mathbb{R}^q$  with  $q \ll r$  such that

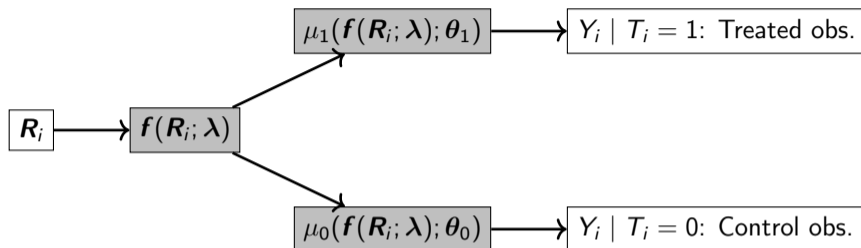
$$Y_i \perp\!\!\!\perp \mathbf{R}_i \mid T_i = t, \mathbf{f}(\mathbf{R}_i), \quad t \in \{0, 1\}$$

- Deconfounder does not have to be unique
- Example: Confounding Features  $\mathbf{U}_i$  (deterministic function of  $\mathbf{R}_i$ )
- By adjusting for this Deconfounder, we can identify

$$\mathbb{E}[Y_i(t, \mathbf{U}_i)] = \sum_{\mathbf{f}' \in \mathbb{R}^q} \mathbb{E}[Y_i \mid T_i = t, \mathbf{f}(\mathbf{R}_i) = \mathbf{f}'] \mathbb{P}(\mathbf{f}(\mathbf{R}_i) = \mathbf{f}'),$$

- Direct adjustment for  $\mathbf{R}_i$  leads to the lack of overlap

## Estimation and Inference



- 1 Estimate the outcome models and deconfounder via TarNet (Shalit et al. 2017):

$$\{\hat{\lambda}, \hat{\theta}_0, \hat{\theta}_1\} = \underset{\lambda, \theta_0, \theta_1}{\operatorname{argmin}} \frac{1}{n} \sum_{i=1}^n \{Y_i - \mu_{T_i}(f(R_i; \lambda); \theta_{T_i})\}^2$$

- 2 Estimate the propensity score using the estimated Deconfounder

$$\pi(f(R_i; \hat{\lambda})) = \mathbb{P}(T_i = 1 | f(R_i; \hat{\lambda}))$$

- 3 Estimate ATE and its standard error by Double Machine Learning (Chernozhukov et al. 2018)

## Practical Implementation Details

- Internal representation extracted from LLM is still high-dimensional:

$$\dim(\mathbf{R}) = \text{number of tokens} \times 4096 \quad \text{for Llama 3 (8 billion parameters)}$$

- Pooling strategy: the hidden states of the last token for Llama!3
- TarNet requires hyperparameter tuning
  - size and depth of layers
  - learning rate
  - maximum epoch size
- Use of automatic hyperparameter optimization methods (Optuna)

# Simulation Study Setup

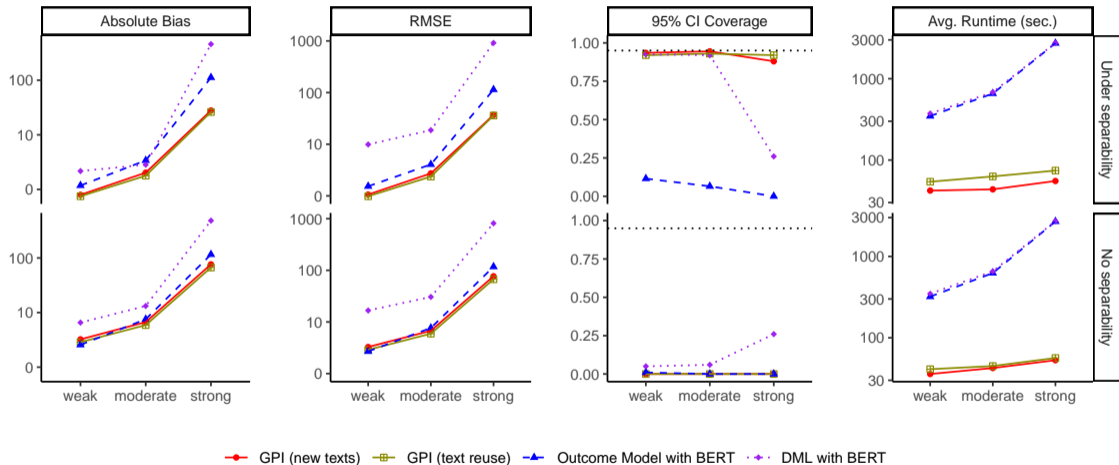
- A simulation based on the candidate biography experiment
  - Create 4,000 sets of the first, middle, and last names of political candidates via randomly sampling from the Fong and Grimmer data
  - Use Llama 3 to generate a biography for each US political candidate's
  - Instruct LLM to repeat the same texts for reuse
- The data generating process:

$$Y_i = \alpha_1 T_i + \alpha_2 T_i h_1(\mathbf{X}_i) - \alpha_3 h_1(\mathbf{X}_i) - \alpha_4 h_2(\mathbf{X}_i) + \epsilon_i$$

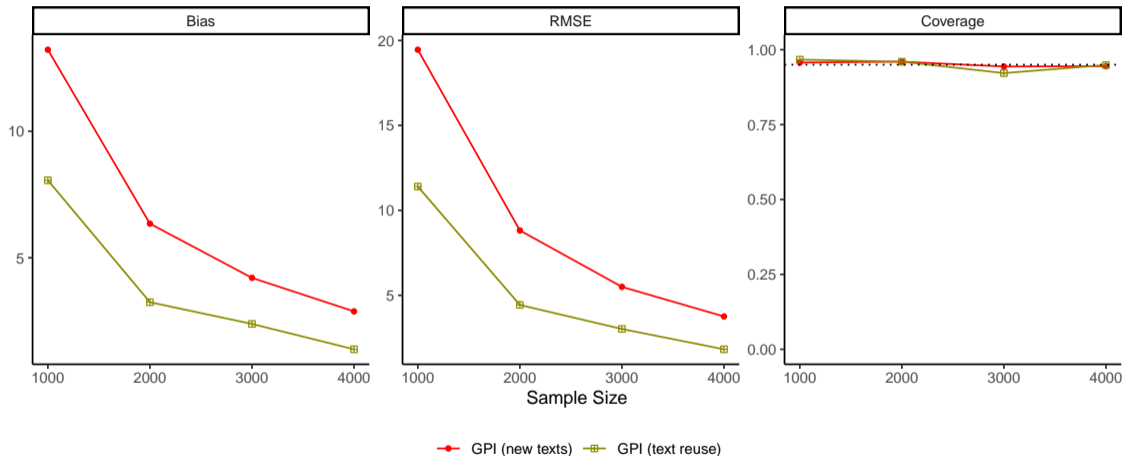
where  $\epsilon_i \sim \mathcal{N}(\mu_i, 1)$  and

- $T_i$ : military background (binary)
  - $h_1(\mathbf{X}_i)$ : topic-model based confounder
  - $h_2(\mathbf{X}_i)$ : sentiment-analysis based confounder
- $2 \times 3 = 6$  scenarios:
    - ① separability holds or does not hold (separate or overlapping topics)
    - ② weak, medium, or strong confounding

# Simulation Results



# Performance across Different Sample Sizes



# Empirical Analysis

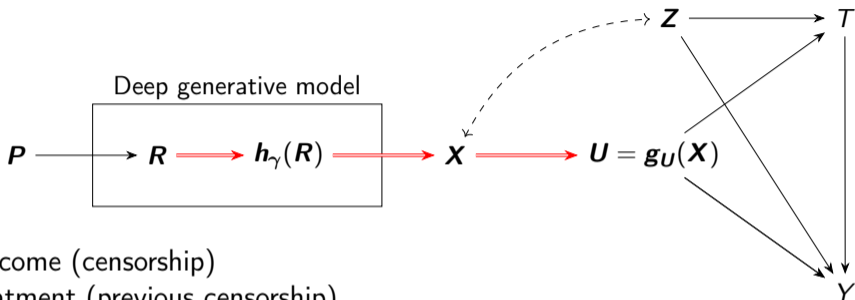
- Analyze the original survey by Fong and Grimmer (2016)
  - 1,246 Congressional candidate biographies from Wikipedia
  - 1,886 survey participants with a total of 5,291 observations
  - evaluate a biography using the feeling thermometer [0, 100]
  - Keyword-based treatment coding: “military”, “war”, “veteran”, or “army”
  - use text-reuse approach with Llama 3

Methods	ATE	95% Conf. Int.	Runtime
Proposed method (reuse)	5.462	[2.790, 8.135]	28.9 sec.
Outcome model with BERT	-2.557	[-2.608, -2.505]	6139.7
DML with BERT	-67.777	[-109.967, -25.587]	6210.3

## Text as Confounder: Chinese Censorship (Roberts et al. 2020)

- Do Chinese social media users who had their post censored become more likely to be censored for later posts or self-censor themselves?
  - Treatment: whether or not a post was censored
  - Outcomes: censorship during four weeks after a censored post
    - 1 number of posts
    - 2 proportion of censored posts
    - 3 proportion of missing posts
  - structural confounders: lagged outcomes, date of the post (dummies)
  - text-as-confounder: contents of posts
- Original analysis: Matching (CEM) with topic proportions (STM) and propensity score (inverse regression)
- Our reanalysis:
  - Text reuse with Llama 3
  - Apply the proposed method:
    - 1 entire sample (4155 users; 75324 Weibo posts)
    - 2 matched sample (628 users; 879 posts)

# Assumptions

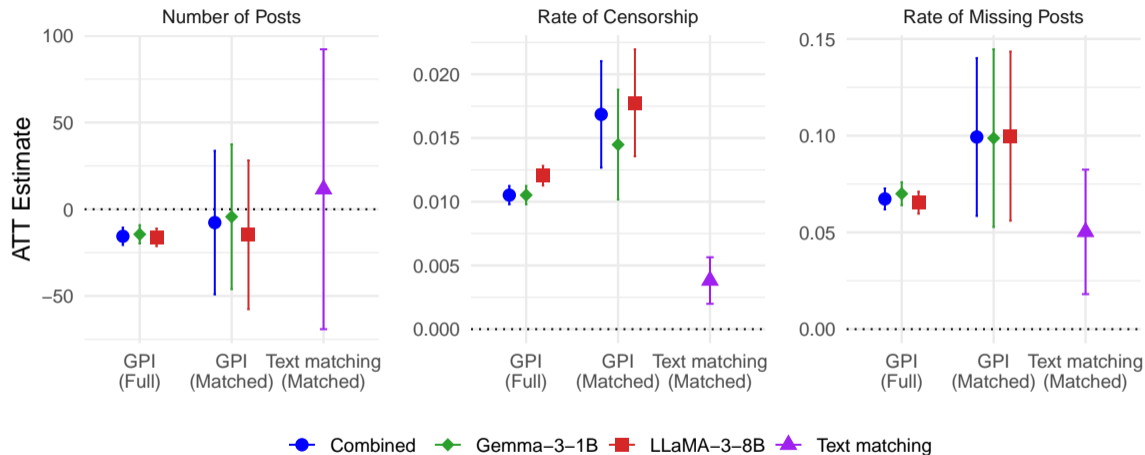


- $Y$ : outcome (censorship)
- $T$ : treatment (previous censorship)
- $\mathbf{Z}$ : observed structured confounding variables
- $\mathbf{X}$ : unstructured confounding object
- $\mathbf{U} = g_U(\mathbf{X})$ : unknown and unstructured confounding variables
- **Strong latent ignorability:**

$$\{Y_i(t)\}_{t \in \mathcal{T}} \perp\!\!\!\perp T_i \mid \mathbf{Z}_i = \mathbf{z}, \mathbf{U}_i = \mathbf{u}, \quad \text{for all } \mathbf{z} \in \mathcal{Z}, \mathbf{u} \in \mathcal{U}$$

$$\mathbb{P}(T_i = t \mid \mathbf{Z}_i = \mathbf{z}, \mathbf{U}_i = \mathbf{u}) > \epsilon \quad \text{for all } t \in \mathcal{T}, \mathbf{z} \in \mathcal{Z}, \mathbf{u} \in \mathcal{U}$$

# Empirical Results



- Our analysis shows higher rates of censorship and self-censorship
- Full sample analysis is much more efficient

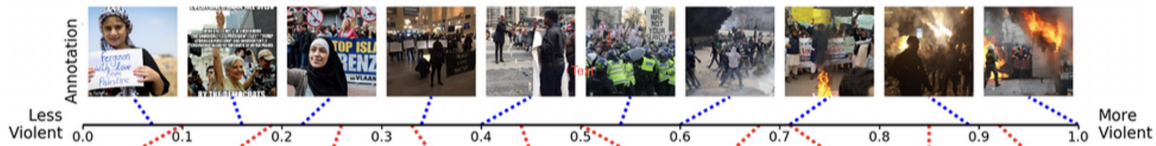
## Sensitivity to Candidate Textual Confounders

- Candidate textual confounder: proportion of 60 keywords related to censorship and self-censorship (Fu et al. 2013)
- Include these confounders and see how much the estimates change relative to the original estimates

<b>Outcome</b>	<b>GPI (LLaMA3-8B)</b>		<b>GPI (Gemma3-1B)</b>		<b>Text matching</b>
	Full	Matched	Full	Matched	Matched
Number of posts	0.084 (0.068)	0.242 (0.682)	0.062 (0.067)	0.370 (3.638)	2.507
Rate of censorship	0.007 (0.003)	0.196 (0.140)	0.037 (0.033)	0.132 (0.097)	0.323
Rate of missing posts	0.040 (0.049)	0.279 (0.346)	0.124 (0.042)	0.142 (0.212)	0.209

# Image as Treatment

- Data: 9,316 protest images with human annotations of visual attributes and perceived violence levels (Won et al. 2017)
- Empirical validation of GPI:
  - Treatment: nighttime vs. daytime
  - Outcome: perceived violence



- Nighttime images are associated with higher levels of perceived violence (correlation = 0.21)
- Changing an image from nighttime to daytime should not alter other aspects of the image (though perception may slightly change)
- Adjusting for confounding features of images should reduce association

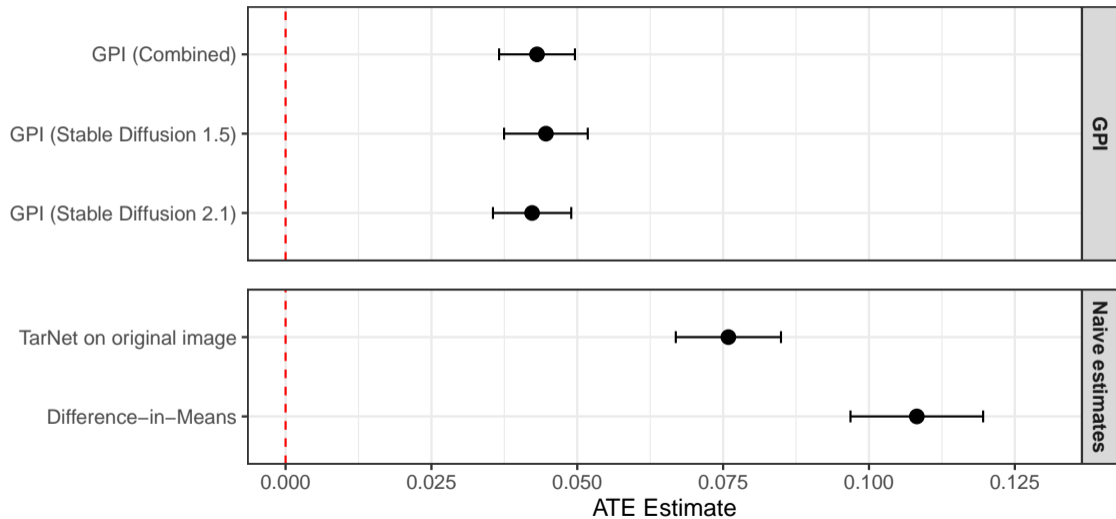
# Empirical Analysis

- Reproduce all images using **Stable diffusion** (ver. 1.5 and 2.1)
- Original images (smaller images are padded):

$$\dim(\mathbf{X}) = 512(\text{width}) \times 512(\text{height}) \times 3(\text{RGB}) = 786,432$$

- Internal representation:  $\dim(\mathbf{R}) = 16,384$
  
- Neural network architecture:
  - convolutional neural network encoding layer
  - $\dim(\mathbf{f}(\mathbf{R}))$ : 256 for version 1.5 and 128 for version 2.1

# Empirical Results



## Concluding Remarks

- Generative AI can be used to improve causal inference
  - can generate treatments at scale
  - enables the extraction of true internal representation
  - better causal inference with unstructured data

- Open-source software **GPI** is available at

<https://gpi-pack.github.io/>

- Ongoing projects

- dynamic causal inference
- causal inference with multimodal data (e.g., videos)
- interpretation of estimated deconfounder
- discovery of treatment features
- policy learning with unstructured treatments

- Papers are available at <https://imai.fas.harvard.edu>

# Structural Model of Texts: Persuasion and Rhetoric

(Blumenau and Lauderdale, 2022)

- Which types of political rhetorics are most persuasive?
- Forced choice conjoint experiment with texts
- Total of 336 political arguments
  - 12 policy issues: tuition fees, fracking, etc.
  - 14 rhetorical elements: cost and benefit, morality, etc.
  - for or against
- Outcome: Persuasiveness of arguments
  - one argument is more persuasive than the other
  - equally persuasive

## Example Text Pair

- Policy topic: building a third runway at Heathrow:

### Appeal to authority / For

The Airports Commission, an independent body established to study the issue, have argued that expanding Heathrow is the most effective option to address the UK's aviation capacity challenge

### Appeal to history / Against

History show us that most large infrastructure projects do not lead to significant economic growth, which suggests that the expansion of Heathrow will fail to pay for itself

- Can we adjust for the unstructured confounding features of texts?

# The Structural Model

- The original **Bradley-Terry** type model:

$$\log \left[ \frac{\mathbb{P}(Y_{jj'(i)} \leq k)}{\mathbb{P}(Y_{jj'(i)} > k)} \right] = \delta_k + (\alpha_{P_j} S_j + \beta_{T_j} + \gamma_j) - (\alpha_{P_{j'}} S_{j'} + \beta_{T_{j'}} + \gamma_{j'})$$

where  $i$  indexes respondents,  $j$  indexes arguments,  $P_j$  denotes policy area,  $S_j$  denotes for/against, and  $T_j$  denotes rhetoric

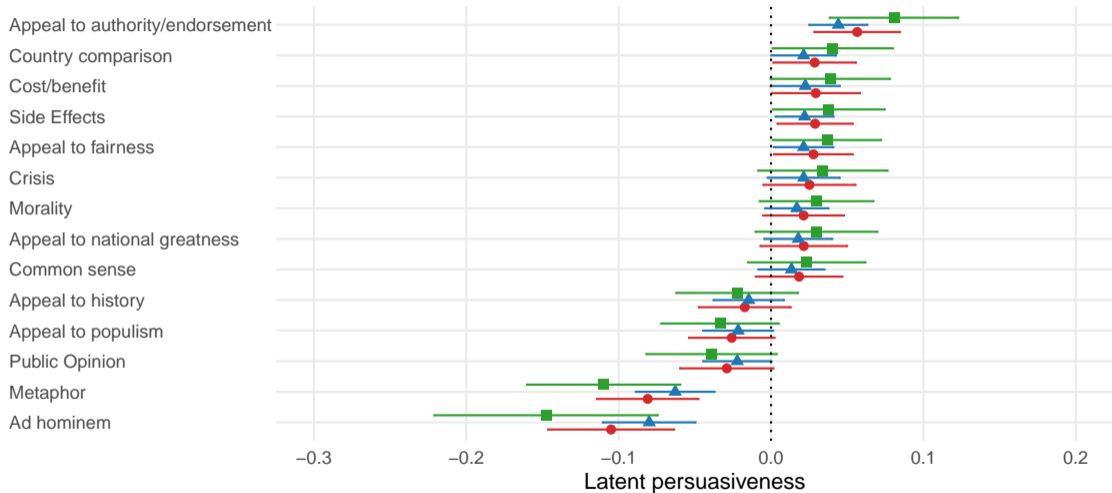
- Our **semiparametric model**:

$$\log \left[ \frac{\mathbb{P}(Y_{j(i)j'(i)} \leq k)}{\mathbb{P}(Y_{j(i)j'(i)} > k)} \right] = \delta_k + \beta_{T_j} - \beta_{T_{j'}} + h(\mathbf{U}_j) - h(\mathbf{U}_{j'})$$

where  $h(\mathbf{U}_j)$  is the latent confounder

- We estimate this model using the internal representation and GPI

# Empirical Findings



Model ● LLaMA-3-8B ▲ LLaMA-3.3-70B ■ Gemma-3-1B