Media Bias and Democratic Backsliding

Evidence from U.S. Media Bias and Presidential Interventions

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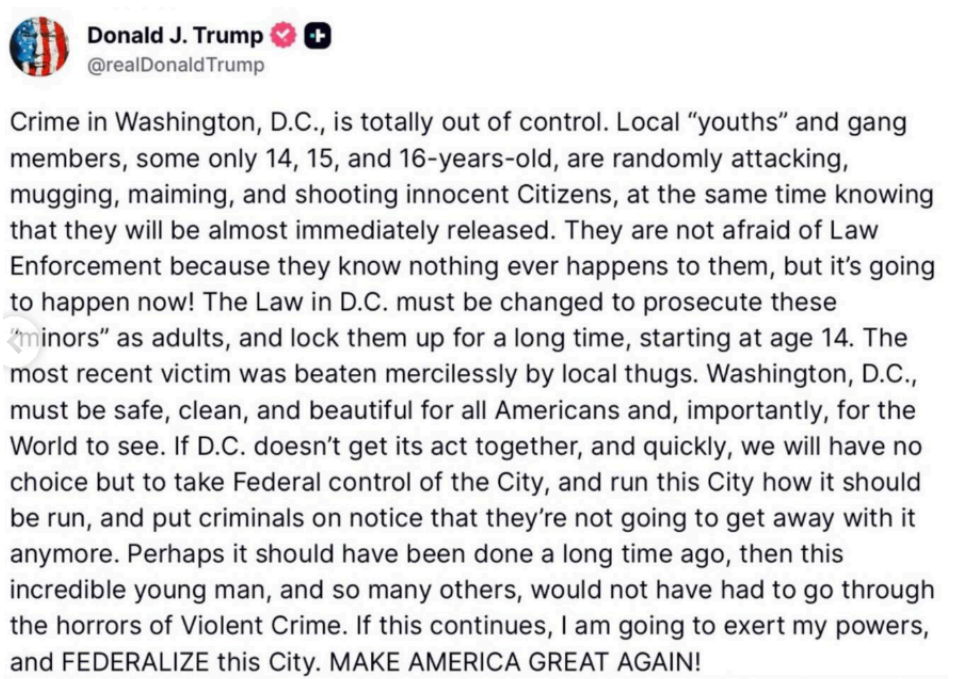
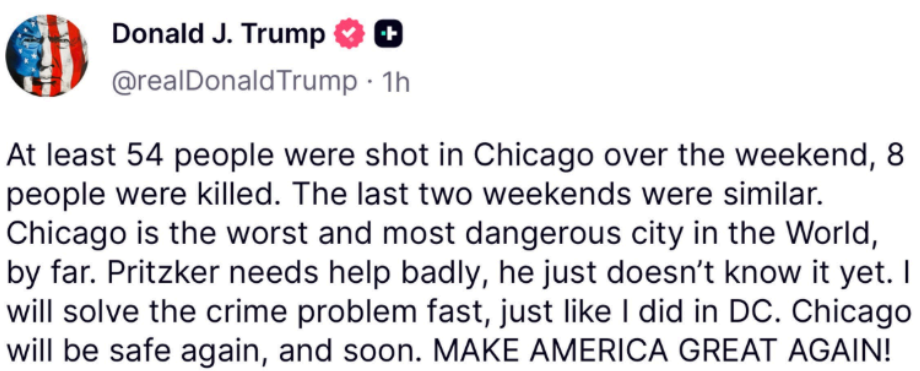
Research Question

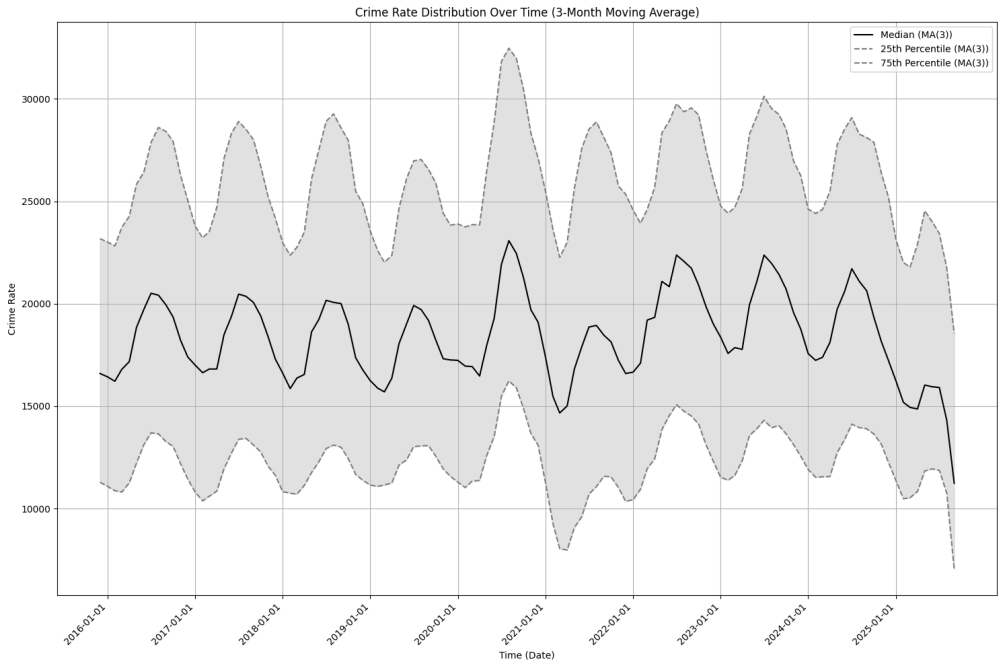
How does political leaders' messaging generate biased narratives to enable democratic backsliding?

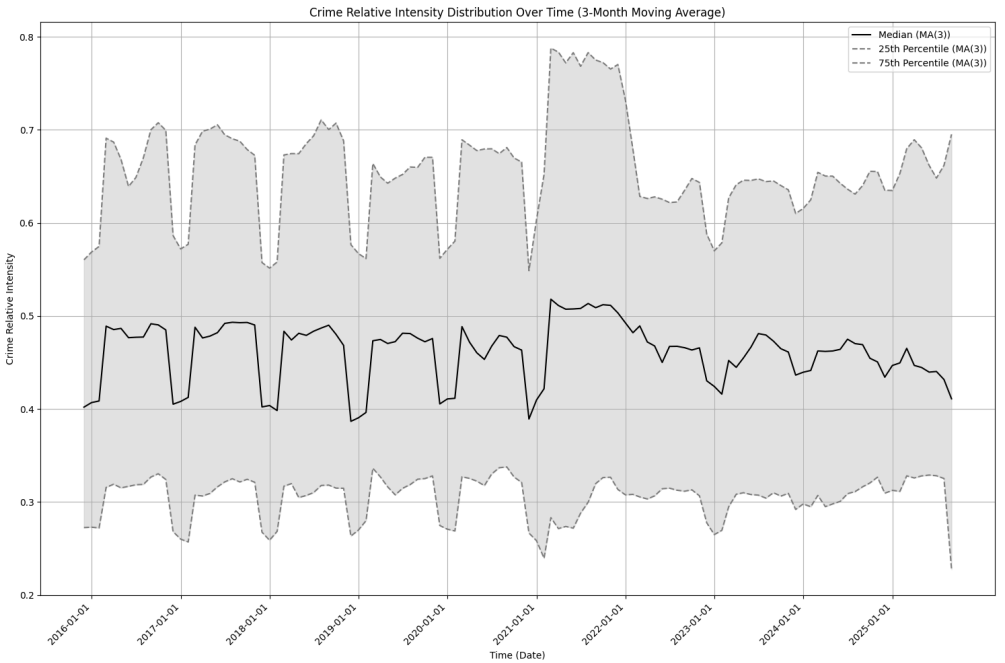
- Trump calling out Democratic cities for high crime

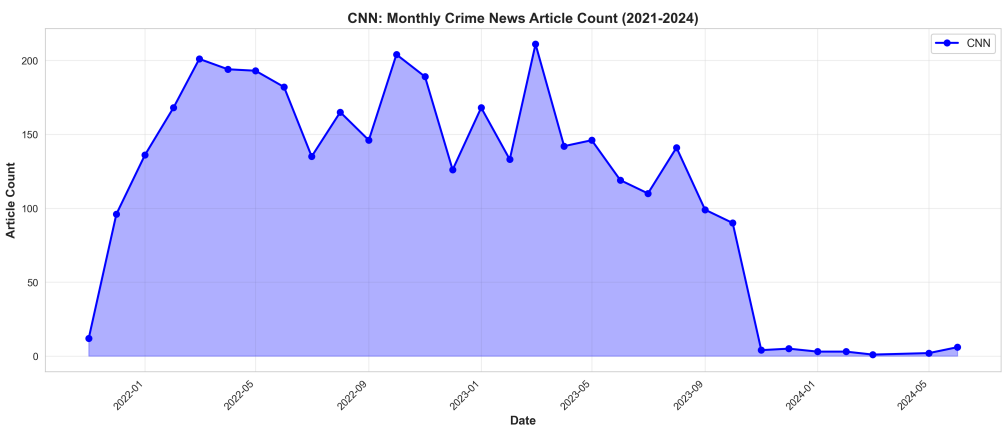


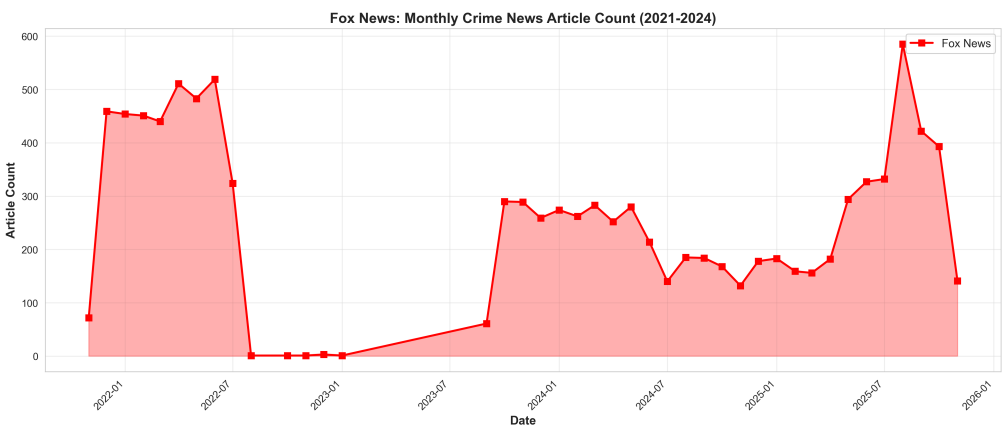


- Gaps between actual crime data and the narratives









Literature Review

Media Bias:

- Strong consensus on bias in “hard news” and politicized issues (Niven 1999; Niven 2001)
- Older research: less severe in “soft news” and objective topics (Niven 1999; Niven 2001)
- Partisan consumption patterns persist across all news types (Iyengar and Hahn 2009)
- Elites now directly contest objective data via social media (The White House 2025)

Democratic Backsliding & Performance:

- Better performance ⟶ more stable regimes (Carothers and Hartnett 2024)
- BUT: limited evidence that poor actual performance ⟶ democratic backsliding (Carothers and Hartnett 2024)
- Mixed cases: Brazil (Hunter and Power 2019), El Salvador (Economist 2019) vs. India (Sridharan 2014), Mexico (Sánchez-Talanquer and Greene 2021), Poland, Turkey (Carothers and Hartnett 2024)
- Voters embrace disruptive change promises (Carothers and Hartnett 2024)

Main Argument

Political leaders social media posts -> biased media coverage -> perceived performance -> support for drastic changes -> **democratic backsliding**

Contributions:

- Mechanism: elite rhetoric actively shapes information environments

Data Sources

Crime Data: - FBI Crime Data Explorer (actual crime rates across U.S. cities/states)

Population Data: - Federal Reserve Economic Data (state-level population for rate calculations)

Media Coverage: - The News APIs (systematic collection, partisan comparison)

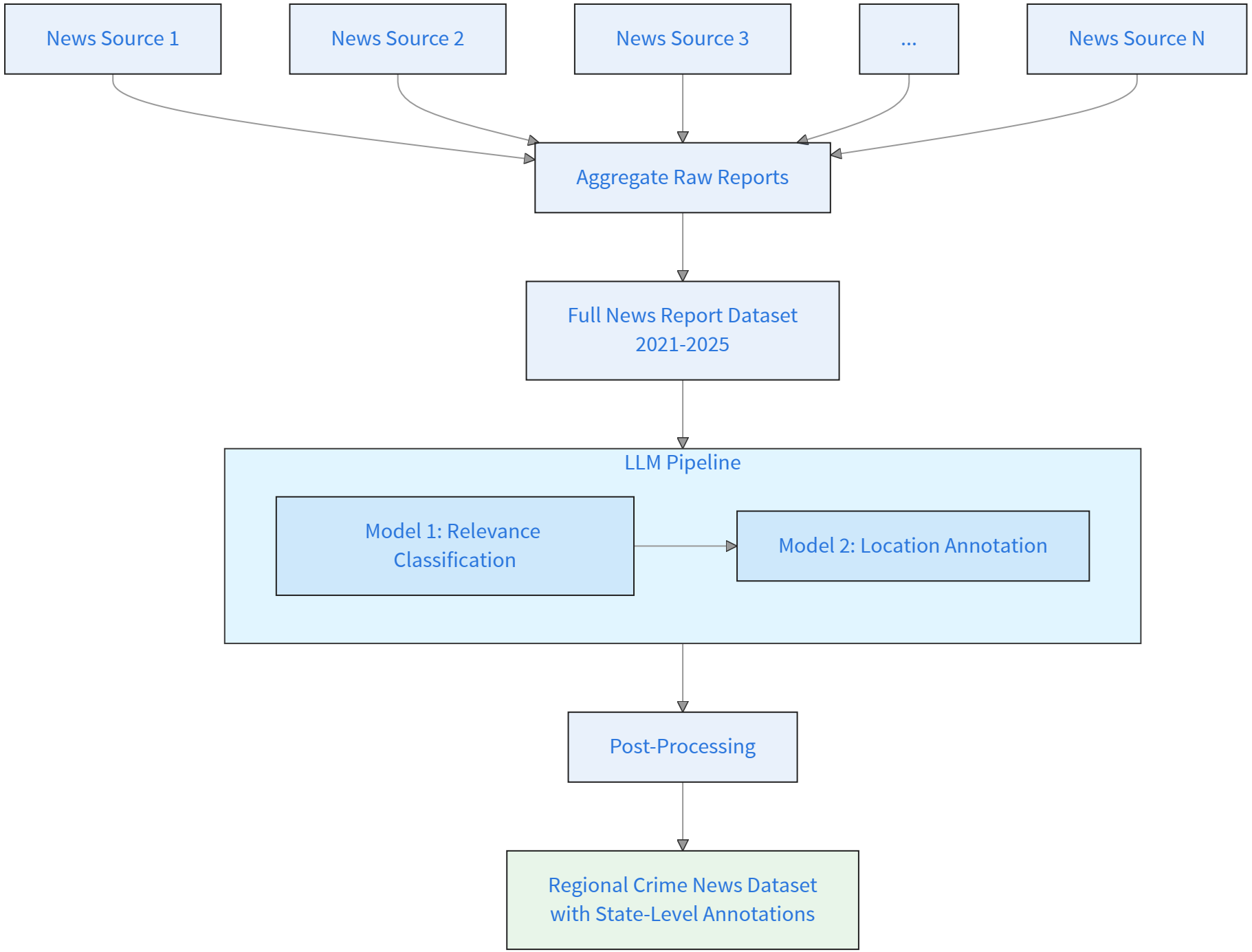
Presidential Communications: - Truth Social posts (intervention timing)

Data Generation

News Reports Processing:

- Scraped news reports from CNN and Fox News APIs.
- Used LLM (llama3.1:8b-instruct-q4_K_M) to classify filter,and annotate the news reports, created a regional crimenews reports dataset.

Architecture Design:


News Source 1
News Source 2
News Source 3
...
News Source N
Aggregate Raw Reports
Full News Report Dataset
2021-2025
LLM Pipeline
Model 1: Relevance
Classification
Model 2: Location Annotation
Post-Processing
Regional Crime News Dataset
with State-Level Annotations

Prompts Example:

Model 1 - Relevance Classification:

```
response_relevance = ollama.chat(
    model=model_name,
    messages=[{
        'role': 'user',
        'content': f'Is this text about crime in a US location?
                    Respond in JSON format:
                    {{"relevance": true}} or {{"relevance": false}}

                    Text: {text}'
    }],
    format='json'
)
```

Model 2 - Location Annotation:

```
response_location = ollama.chat(
    model=model_name,
    messages=[{
        'role': 'user',
        'content': f'Identify the exact US STATE mentioned in this text.
                    If no state is mentioned, respond with "None".
                    If the region is subnational, respond with the
                    two digit state code.
                    Respond in JSON format:
                    {{"location": "two digit state code"}}

                    Text: {text}'
    }],
    format='json'
)
```

Methodology

Doubly-Robust Difference-in-Differences (DRDID):

$$ATT_{DR} = \mathbb{E}\left[\left(\frac{G}{\mathbb{E}[G]} - \frac{\frac{p(X)(1-G)}{1-p(X)}}{\mathbb{E}\left[\frac{p(X)(1-G)}{1-p(X)}\right]}\right)(Y_1 - Y_0 - m(0,X))\right]$$

where G = treatment indicator, $p(X)$ = propensity score,
$m(0,X)$ = outcome model

Propensity Score Formula:

$$p(X) = P(G = 1|X) = \frac{\exp(\gamma_0 + \gamma X)}{1 + \exp(\gamma_0 + \gamma X)}$$

Outcome Model (Improved Estimator):

$$m(0, t, X) = \mathbb{E}[\Delta Y_{it}|D = 0, X_i] = \alpha_0 + \beta X$$

where $\Delta Y_{it} = Y_{it} - Y_{i,t-1}$ (change in outcome from pre to post)

Variables:

- Outcome (Y): News frequency (monthly article count)
- Treatment (G): Indicator for DC (treated 2025/08) or IL (treated 2025/09)
- Time periods: 2 periods, pre-treatment and post-treatment
- Covariates (X): Crime rate (in covariate-adjusted model)

Callaway & Sant'Anna Difference-in-Differences (CSDID):

$$ATT(g,t) = \mathbb{E}[Y_t - Y_{g-1} | G_g = 1] - \mathbb{E}[Y_t - Y_{g-1} | C = 1]$$

$$ATT_{dynamic}(e) = \sum_g \frac{P(G = g)}{\sum_g P(G = g)} \cdot ATT(g, g + e)$$

where $ATT(g,t)$ = average treatment effect for group first treated at time g in period t, e = event time, C = never-treated control group, $P(G = g)$ = proportion of units in treatment group g

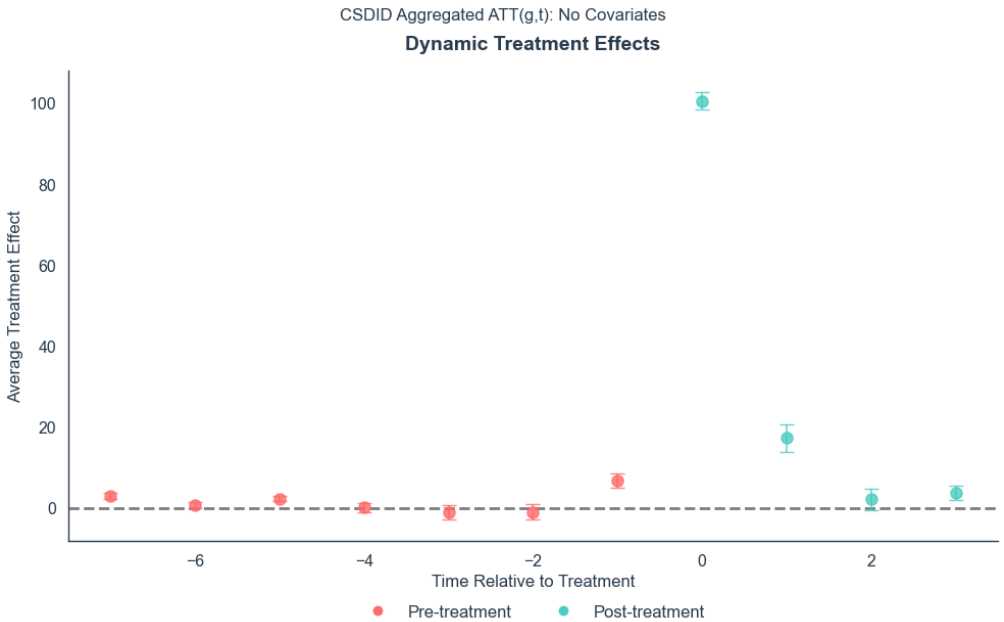
Variables:

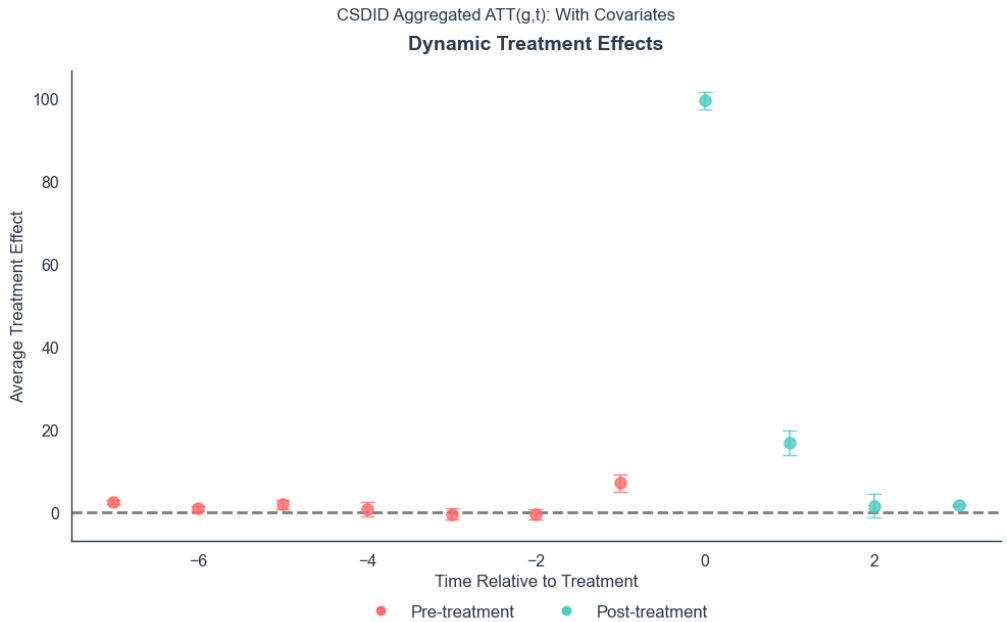
- Outcome (Y): Valid News frequency at region-time (monthly article count)
- Treatment groups (g): $g = 202508$ (DC), $g = 202509$ (IL)
- Control group (C): Never-treated states (49 states)
- Time periods (t): 2025/01-2025/10
- Covariates (X): Crime rate per 100,000 population (in covariate-adjusted model)
- ATT(g,t) Estimation method: drdid
- Aggregation: Dynamic event study ($e \in [-12, 10]$)

Results

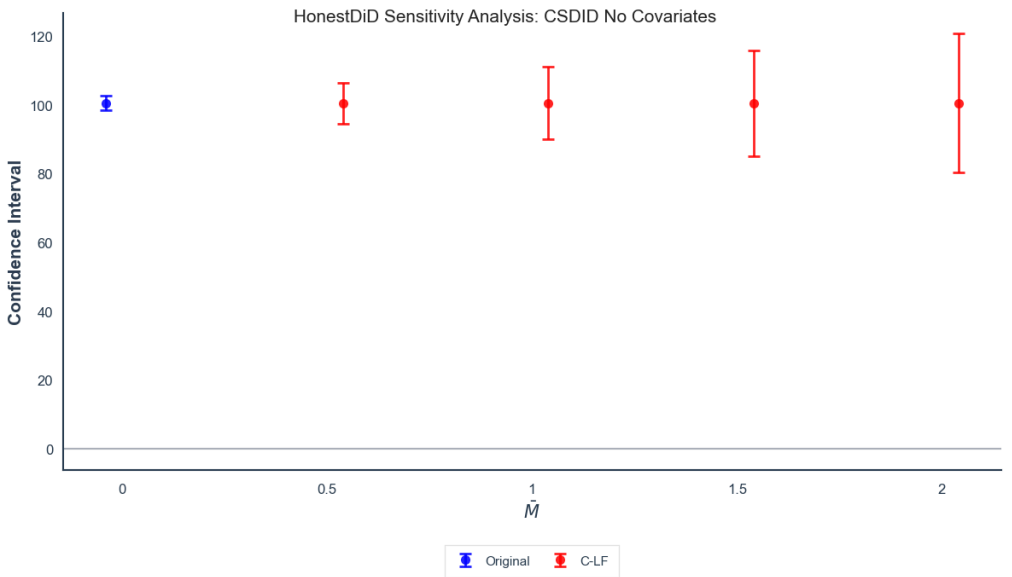

CSDID ATT(g,t): No Covariates
Group 202508
150
100
50
0
202502
202503
202504
202505
202506
202507
202508
202509
202510
202511
Time
Group 202509
ATT
20
10
0
−10
202502
202503
202504
202505
202506
202507
202508
202509
202510
202511
Time
Pre-treatment
Post-treatment

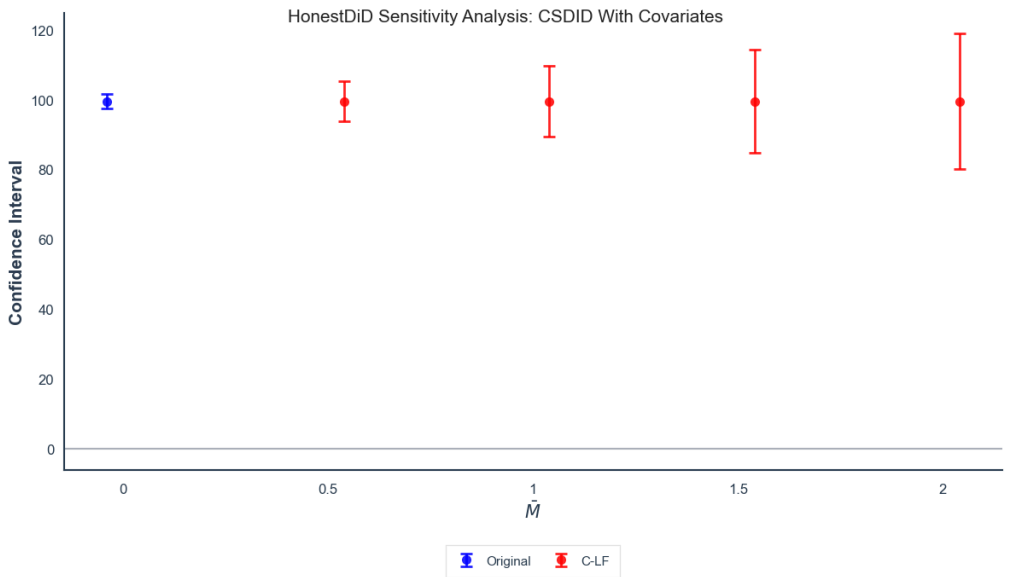

CSDID ATT(g,t): With Covariates
Group 202508
150
100
50
0
202502
202503
202504
202505
202506
202507
202508
202509
202510
202511
Time
Group 202509
ATT
20
10
0
−10
202502
202503
202504
202505
202506
202507
202508
202509
202510
202511
Time
Pre-treatment
Post-treatment


CSDID Aggregated ATT(g,t): No Covariates
Dynamic Treatment Effects
Average Treatment Effect
100
80
60
40
20
0
−6
−4
−2
0
2
Time Relative to Treatment
Pre-treatment
Post-treatment


CSDID Aggregated ATT(g,t): With Covariates
Dynamic Treatment Effects
Average Treatment Effect
100
80
60
40
20
0
−6
−4
−2
0
2
Time Relative to Treatment
Pre-treatment
Post-treatment

Robustness Check





Conclusion

- Presidential rhetoric significantly increased regional crime news coverage from aligned partisan media outlets:

DC (2025/08) and IL (2025/09) experienced 100+ additional monthly articles post-intervention

- HonestDiD sensitivity analysis confirms results remain robust to violations of parallel trends assumption up to twice the baseline magnitude.

Limitations

- Data collection is limited to CNN and Fox News, and the news reports are not comprehensive.
- The CNN news are not completely collected, due to the limited funding available.
- Treated states are too few, only 2 states, DC and IL, making csdid results less reliable.

Future Research

- Collect more news reports from more media outlets, and more states.
- Use more LLM pipelines to classify the support for the president’s rhetoric
- Use fine-tuned models to get the bias level of the news reports.
- add pre treatment parallel trends assumption test. (event study)
- investigage reverse causality: media bias -> political leaders’ messaging