Strategic Alignment and Social Media Behavior of U.S. Congress Members

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Outline

Motivation: Politicians' Strategic Behavior Under a National Signal

- **Fenno foundation:** Members pursue reelection, power in the chamber, and policy goals. We focus on **reelection** as the primary objective in this project.
- **Optimization logic:** Representatives choose communication and positioning strategies that maximize their probability of being reelected.
- **Context:** Trump's Truth Social posts are high-salience national signals that rapidly structure elite attention and partisan messaging.
- **Strategic problem:** Representatives balance two incentives:
  - **National-party loyalty:** signal alignment with a nationally popular party leader.
  - **Local accountability:** represent district preferences that may diverge from the national party line.
- **Dominant-strategy possibility:** As Trump became highly popular with a solid Republican base, alignment may become the dominant strategy for many Republican representatives.
- **Core trade-off:** Alignment can help with partisan coordination and base signaling, but can increase electoral risk when district opinion is misaligned.
- **Strategic opacity channel:** On controversial topics, representatives may soften or hide extreme positions in public text while taking clearer positions in roll-call votes, where voter monitoring costs are higher.

Theory Foundation: Strategy vs. Electoral Consequences

Strand 1: Strategic behavior

- Legislators use presidential cues strategically in rhetoric (Noble 2023).
- Members follow supporter issue attention more than they lead it (Barberá et al. 2019).
- Electoral incentives shape effort, activity, and visibility (Fouirnaies & Hall 2022).
- Reelection remains the primary organizing goal (Fenno; Aldrich, Perry & Rohde).

Strand 2: Electoral accountability

- Misalignment with district preferences can reduce vote share (Canes-Wrone, Brady & Cogan).
- Excessive party loyalty can be electorally costly, especially in cross-pressured districts (Carson et al.).
- Ideological extremism often hurts in generals and shows limited primary benefit (Hirano et al.; Brady, Han & Pope).

Key conceptual tension

If politicians are forward-looking, observed behavior may already be an equilibrium strategy. Then estimated costs identify constrained choices, heterogeneous trade-offs, or strategic mistakes.

Behavioral Predictions by Party

Republicans — cue-following with a silence escape valve

- Under Strand 1, Republicans are expected to *follow* Trump's signal: publicly align with his position when it is clear and uncontroversial.
- However, on a **controversial stance switch** (e.g. blaming Ukraine), Republicans in cross-pressured districts face a dilemma:
  - *Align publicly* $\Rightarrow$ risk alienating pro-Ukraine constituents.
  - *Openly oppose* $\Rightarrow$ risk primary blowback.
  - **Optimal: strategic silence** on social media.

Democrats — counter-cueing, intensified under pressure

- Under Strand 1 (presidential cue argument), the *opposing* party reacts consistently counter-positioning against the president's signal (Cohen 1995; Eshbaugh-Soha & Peake).

Key asymmetry

Republicans absorb controversial signals silently; Democrats counter-signal forcefully.

The Two Signals: Trump's Ukraine Stance Shift

Event 1 — Blame `ukraine_blame_01` Feb 19 2025, 15:47 UTC

"Think of it, a modestly successful comedian, Volodymyr Zelenskyy, talked the United States of America into spending $350 Billion Dollars, to go into a War that couldn't be won, that never had to start, but a War that he, without the U.S. and 'TRUMP,' will never be able to settle. The United States has been SCAMMED, just like it has been SCAMMED by so many other Countries and 'Partners' for years. Zelenskyy, with no cards to play, is not the innocent man he portrays himself to be..."

Trump's position: **blame Ukraine / Zelensky** for prolonging the war; anti-Ukraine framing.

Event 2 — Reversal `ukraine_reversal_01` Sep 23 2025, 18:55 UTC

"After getting to know and fully understand the Ukraine/Russia Military and Economic situation and, after seeing the Economic trouble it is causing Russia, I think Ukraine, with the support of the European Union, is in a position to fight and WIN all of Ukraine back in its original form. With time, patience, and U.S. support, it can ALL be gotten back!"

Trump's position: **pro-Ukraine reversal** — endorses Ukraine's ability to win with EU + U.S. support.

Both posts constitute sharp, unanticipated changes in Trump's publicly stated position on Ukraine.

Research Setting and Identification

- **Research setting:** We treat Trump's high-salience posts as observable coordination shocks and study how members adjust messaging and text–vote consistency in response.

Two sources of variation

- **Long-run persistent topics** $\Rightarrow$ panel VAR.
- **Discrete Trump stance switches** (timing randomness assumption) $\Rightarrow$ difference-in-differences or Regression Discontinuity.

Behavioral margins

- **Extensive margin:** does the legislator engage with the topic at all?
- **Intensive margin:** conditional on engagement, what stance does the legislator take?

Measurement implication

Silence is a strategic choice — ignoring it biases estimates toward understating local pressure.

Link to accountability: Are tweets a cheap signal of the same preference that drives votes, or a distinct strategic device?

Research Questions

RQ1: Strategic response

When Trump issues a high-salience national signal, how do members of Congress adjust issue attention and rhetorical stance?

RQ2: National loyalty vs. local pressure

Do politicians follow presidential/party cues even when those cues conflict with local constituency opinion?

RQ3: Electoral accountability under strong signals

When the national signal is very strong, does partisan loyalty still carry electoral punishment, or does it become electorally safer?

This Paper

What we do

- The Two Signals: Trump's Ukraine Stance Shift
- Define $\pm$7-day windows around each T_e; query all congressional tweets
- Classify all candidate tweets for *relevance* and *stance* using Qwen LLMs
- Construct a daily member $\times$ event panel; estimate RD in time at T_e
- Examine heterogeneous effects by party, district Trump vote, and local issue sentiment

Contribution (Ongoing)

- Scalable LLM pipeline for measuring elite rhetorical attention and stance across $>$2M candidate tweets
- **Causal identification** via RD and DID.
- politican's tradeoff between national loyalty and local accountability.

Data Sources (1/2): Social Media & Signal Corpus

Congressional social-media panel

- All original tweets from sitting MCs, 2022–Jan 2026
- Full text + engagement (likes, RTs, replies, quotes, views)
- Linked to member via Bioguide crosswalk

Tweet filters applied:

- No retweets, replies, or quote-tweets
- English only; >20 characters

Trump signal corpus

- Truth Social (Feb 2022–Jan 2026)
- Original posts only; HTML stripped
- T_e identified per event via keyword search + researcher review

Stance classification

- Relevance: Qwen2.5-7B-Instruct (4-bit)
- Stance: Qwen2.5-14B-Instruct (4-bit)
- Robustness: GPT-4o validator + DeBERTaV3-NLI

Data Sources (2/2): District Covariates, CES & Roll-Call Votes

District-level covariates

- 2020 Trump / Biden vote share (district preference proxy)
- CES policy-preference estimates at district level (Ansolabehere & Kuriwaki 2022)
- Demographics: income, density, education, race

Member identity

- Bioguide crosswalk: party, state, chamber, district

Roll-call votes (for RQ4: rhetoric vs. votes)

- Congressional Record parser (Judd et al. 2017)
- Matched to CES decision agenda (Ansolabehere & Kuriwaki 2022)
- Links each vote to a policy topic j for text–vote comparison

Topic definition

- Topics defined *ex ante* from CES + Westwood, Grimmer & Hall (2025)
- Query expansion: King, Lam & Roberts (2017) keyword procedure

Two Identification Strategies & Behavioral Margins

Two behavioral margins

- **Extensive:** does the legislator engage with the topic at all? (e_{ijt})
- **Intensive:** conditional on engagement, what stance? (s_{ijt})

Empirical Setup: Notation & Definitions

Indices

- i — individual legislator (unique time series)
- $d(i)$ — congressional district of legislator i
- j — policy topic/issue
- t — day

Signals & preferences

- $s^T_{jt} \in [-1, +1]$ — Trump's daily stance on topic j (LLM-scored from Truth Social)
- $\mathrm{TrumpShare}_{d(i)}$ — 2020 Trump vote share in district $d(i)$; proxy for district-level favor toward the national Trump agenda
- $\theta_{d(i),j}$ — CES-based district preference on issue j; local opinion on specific issues

Alignment gap:

$$\mathrm{Gap}_{ijt} \equiv \left| s^T_{jt} - \theta_{d(i),j} \right|$$

Legislator outcomes

- $D_{ijt} \in \{0, 1\}$ — engagement indicator *(extensive margin)*
- $s_{ijt} \in [-1, +1]$ — expressed stance *(intensive margin)*
- A_{ijt} — daily attention share on topic j

Event-level outcomes (DiD)

For Trump event e with timestamp T_e:

- Window: $[T_e - 30\text{d},\ T_e + 30\text{d}]$
- $\mathrm{Post}_{jt} = \mathbf{1}[t \geq T_e]$ — Trump raises or repositions on topic j
- $y^S_{ite} = \mathbf{1}[s_{it} = s^T_{jt}]$ (stance alignment)

FE structure: legislator α_i + day γ_t
Key assumption: timing of T_e is quasi-random conditional on FE; pre-trend test $\hat{\beta}_k \approx 0$ for $k < 0$.

Strategy 1: Panel VAR Setup

Units (actors)

- **Trump** — single sender; Truth Social posts
- **Each legislator** i — individual MC time series
- **20 media figures** — journalists from CNN, Fox News, and individual broadcasters

Two outcome series per actor $\times$ topic j $\times$ day t:

- A_{ijt} — daily attention share on topic j
  log-odds: $Z^A_{ijt} = \log\left(\frac{A_{ijt}}{1-A_{ijt}}\right)$
- $s_{ijt} \in [-1, +1]$ — daily expressed stance on topic j (Trump's series: s^T_{jt}, scored from Truth Social via LLM)
- $D_{ijt} \in \{0, 1\}$ — engagement on topic j (feeds A_{ijt})

Bivariate VAR with $p = 7$ lags, topic FE α_j:

$$\begin{pmatrix} Z^A_{ijt} \\ s_{ijt} \end{pmatrix} = \alpha_j + \sum_{k=1}^{7} \mathbf{B}_{ik} \begin{pmatrix} Z^A_{ijt-k} \\ s_{ijt-k} \end{pmatrix} + \varepsilon_{ijt}$$

Key IRF questions:

- Trump attention $\to$ legislator i attention: how fast, how large?
- Trump stance $\to$ legislator i stance: does s_{ijt} shift toward s^T_{jt}?
- Heterogeneity: split into Quartiles based on $\mathrm{TrumpShare}_{d(i)}$, $\theta_{d(i),j}$, and party

Empirical Strategy: Regression Discontinuity in Time

Running variable: $\tilde{d}_t = t - T_e$ (event-relative day) **Cutoff:** T_e (Trump's Truth Social post)

Estimating equation

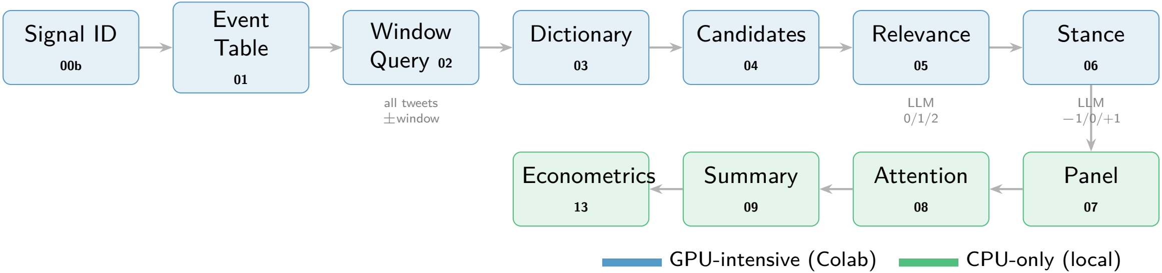
$$Y_{it} = \underbrace{\alpha_i}_{\text{member FE}} + \underbrace{\beta \cdot \mathbf{1}[t \geq T_e]}_{\text{within-member RD jump at } T_e} + \underbrace{\gamma\, \tilde{d}_t + \delta \left(\mathbf{1}[t \geq T_e] \cdot \tilde{d}_t\right)}_{\text{local-linear trend (each side)}} + \varepsilon_{it}$$

- **Two outcomes** estimated separately:
  - Y_{it}^{attn}: Ukraine-tweet share of all tweets (defined $\forall$ member-days)
  - Y_{it}^{stance}: mean Qwen stance score (*conditional* on $\geq$1 Ukraine tweet)
- β: within-member discontinuous jump at T_e — causal effect of the Trump signal
- Member FE α_i absorbed; window $\pm$7 days; SE clustered by `member_id`

Identification assumption

Potential outcomes $Y_{it}(0)$ are *continuous* through T_e absent the Trump post. The $\pm$7-day window minimizes the risk of confounding events producing a concurrent discontinuity.

Data Pipeline Overview



Stages 00b–01: Signal Identification & Event Registration

Stage 00b — Signal identification

1. Researcher defines seed keywords per event (*e.g.* "ukraine", "zelensky", "peace deal")
2. Script searches Truth Social archive; ranks candidates by keyword match
3. Researcher reviews candidates; commits one post as T_e
4. Audit JSON written: `*_te_selection.json`

Stage 01 — Event registration

- T_e timestamp, window parameters, event type → `events/events.parquet`
- `event_description` and `trump_position` populated

Example: `ukraine_blame_01`

- T_e: 2025-02-19 15:47 UTC   Type: `stance_shift`   Pre/Post: 90/30 days
- Seed keywords: `ukraine`, `zelensky`, `kyiv`, `peace`, `war`, `russia`, `dictator`
- Selected post: *"Think of it, a modestly successful comedian, Volodymyr Zelenskyy, talked the United States of America into spending $350 Billion Dollars, to go into a War that couldn't be won, that never had to start..."*

Stages 02–03: Window Query & Dictionary Building

Stage 02 — Window query

- DuckDB query over Twitter Parquet archive
- Retrieves all original English tweets from member accounts in $[T_e - \text{pre}, T_e + \text{post}]$
- Typical yield: 90,000–120,000 tweets per event
- Output: `candidates/{eid}_window.parquet`

Stage 03 — LLM dictionary (GPU)

- Qwen2.5-7B-Instruct generates keyword dictionary from seed terms + event description
- Outputs: keywords, phrases, entities, hashtags, anchor context map
- Output: `events/dictionaries/{eid}.json`

Example: `ukraine_blame_01` dictionary (excerpt)

Field	Terms
Keywords	ukraine, zelensky, kyiv, russia, peace, war, dictator, blame
Phrases	"peace deal", "end the war", "zelensky dictator", "proxy war"
Hashtags	#Ukraine, #Zelensky, #StandWithUkraine
Entities	Kyiv, Zelenskyy, Putin, NATO, EU
Anchor	ukraine: [war, peace, russia, blame, support, negotiate]

Stages 04–05: Candidate Retrieval & Relevance Classification

Stage 04 — Candidate retrieval

- Window tweets matched against dictionary using anchor-aware contextual matching
- Typical yield: 2,000–25,000 candidates per event
- Output: `candidates/{eid}_candidates.parquet`

Stage 05 — Relevance (GPU)

- Qwen2.5-7B-Instruct, 4-bit, with checkpoint/resume
- Labels: 0 = not relevant, 1 = indirectly relevant, 2 = clearly about event
- Confidence via constrained single-token generation; checkpoint every 100 rows
- Output: `classified/{eid}_classified.parquet`

Relevance distribution: `ukraine_blame_01`

Label	Count	%
0 — not relevant	6,546	84.7%
1 — indirectly relevant	864	11.2%
2 — clearly relevant	326	4.2%
Total classified	7,736	
Relevant (1+2)	1,190	15.4%

Classified Tweets: Label 0 — Not Relevant (ukraine_blame_01, $n = 6{,}546$)

Interpretation

These tweets matched the Ukraine keyword dictionary but are *not* about Trump's blame-shift event — general foreign policy, domestic issues, MAGA messaging, etc. Retained in panel for attention-share denominator; excluded from stance analysis.

Handle	Conf	Tweet (excerpt)
@RepMcCaul	1.00	Biden's weakness invited Russian aggression. We need strong leadership to deter China next.
@GregoryMeeks	1.00	We must continue to support our allies. America's credibility is on the line worldwide.
@RepTonyGonzales	0.98	The border crisis is a national security threat. We have to stop the flow right now.

Classified Tweets: Label 1 — Indirectly Relevant (`ukraine_blame_01`, $n = 864$)

Interpretation

These tweets address U.S.–Ukraine policy, NATO support, or the Russia–Ukraine war in ways *tangentially* connected to Trump's blame-shift — without explicitly referencing his Truth Social post.

Handle	Conf	Tweet (excerpt)
@RepMikeQuigley	0.84	We cannot abandon our allies. Cutting aid to Ukraine is a gift to Putin.
@BrianMast	0.79	The American people are tired of writing blank checks to foreign wars with no strategy.
@RepGregoryMeeks	0.71	The United States must remain a reliable partner to democracies fighting for their survival.

Classified Tweets: Label 2 — Clearly Relevant (ukraine_blame_01, $n = 326$)

Interpretation

These tweets explicitly respond to Trump blaming Ukraine/Zelensky for the war. They form the core sample for stance classification (Stage 06).

Handle	Conf	Tweet (excerpt)
@RepAdamSmith	0.97	Trump calling Zelensky a dictator is an insult to every democracy. Putin is the aggressor here.
@RepMariaSalazar	0.91	President Zelensky is fighting for freedom. America must stand with Ukraine, not blame the victim.
@RepScottPerry	0.88	Zelensky has refused every reasonable peace offer. The U.S. shouldn't keep funding a stalemate.

Stage 06: Stance Classification

Model & setup

- Qwen2.5-14B-Instruct (larger model for nuanced stance), 4-bit
- Input: all classified tweets (labels 0, 1, 2) from Stage 05 — every tweet has a stance score
- Constrained generation over {A, B, C, D} tokens

Label mapping

Token	Meaning	Numeric
A	Oppose Trump's position (pro-Ukraine)	-1
B	Neutral / no clear stance	0
C	Support Trump's position (anti-Ukraine)	$+1$
D	Unclear	99

Example: `ukraine_blame_01` Output: `classified/{eid}_classified.parquet`

	Dem	Rep
Oppose — pro-Ukraine (-1)	majority	minority
Neutral (0)		
Support — anti-Ukraine ($+1$)	minority	majority

Mean stance (all labels): -0.60 (std 0.61); strong partisan divergence in DiD estimates.

Stages 07–09: Panel, Attention Metrics & Event Summary

Stage 07 — Daily panel

- Unit: member i × event e × day t
- `ukraine_share`: keyword-tweet share of all tweets that day
- `mean_stance_all`: daily mean stance across all classified tweets
- Output: `panel/panel.parquet`

Stages 08–09 — Attention metrics & summary

- Pre/post daily means, attention ratio, aggregate counts
- Output: `panel/attention_metrics.parquet`, `panel/event_summary.parquet`

Pipeline completion: 22 events

Stage	n Done	GPU
02 Window	22/22	No
03 Dictionary	21/22	Yes
04 Candidates	22/22	No
05 Relevance	22/22	Yes
06 Stance	22/22	Yes
07–09 Panel	22/22	No

Stance: Overview

Key descriptive findings

- Democrats oppose Trump's position in **58–97%** of relevant tweets across all events
- Republicans support Trump in **23–84%** of tweets, with notable within-party variation
- Partisan gap is large and consistent — parties rarely converge
- **Ukraine** (Rep: 49% support) and **NATO threat** (Rep: 43% support) are clearest exceptions to GOP alignment
- **Tariffs** shows highest GOP support at 83.7%

Average stance across all 22 events

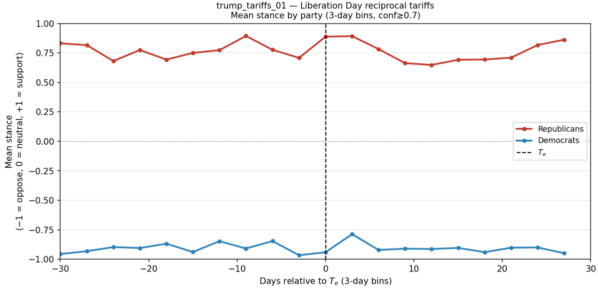
Metric	Democrats	Republicans
Avg % oppose	$>$80%	$\sim$18%
Avg % neutral	$\sim$12%	$\sim$15%
Avg % support	$<$5%	$\sim$65%
Highest support	7.3%	83.7%
Lowest support	0.0%	22.6%

Sample: $\sim$60,000 classified tweets (conf $\geq$ 0.70), 22 events.

Stance: trump_tariffs_01 (Mar 3 2025 — Liberation Day)

Partisan distribution

	Dem	Rep
% Oppose	91.3	4.8
% Neutral	5.9	8.6
% Support	2.3	83.7



takeaway

Tariffs: highest GOP alignment in the sample (83.7% support).

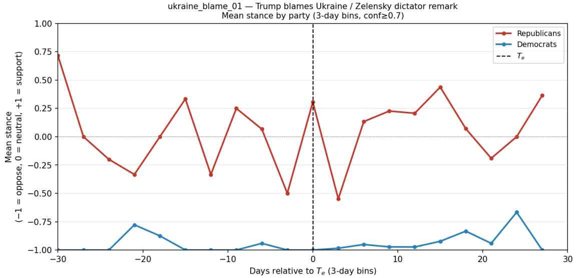
Contrast with Ukraine (49% R support): tariffs are a *consolidated* Republican position, where the national-party loyalty trade-off imposes minimal electoral cost.

Democrats near-unanimously opposed (91.3%), consistent with counter-cueing.

Stance: ukraine_blame_01 (Feb 19 2025)

Partisan distribution

	Dem	Rep
% Oppose	96.3	41.7
% Neutral	2.3	9.0
% Support	0.6	48.9

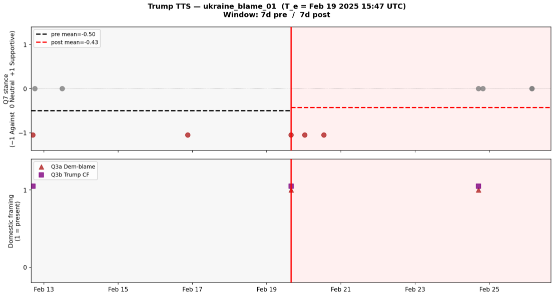


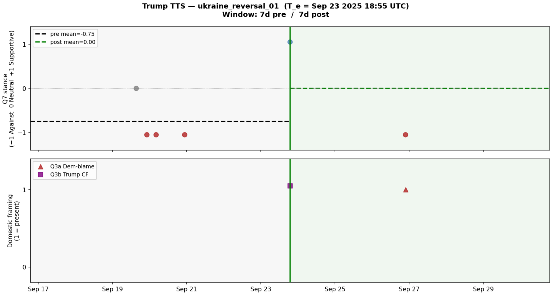
takeaway

Republican support (49%) is the lowest in the sample — nearly split. Ukraine is *not* a fully consolidated GOP position;

Democrats are near-unanimously opposed (96%); the lowest Democrat support of any event.

Stance Validation: Ukraine Events





Left: `ukraine_blame_01` (Feb 19 2025) **Right:** `ukraine_reversal_01` (Sep 23 2025)
Distribution of Qwen stance scores (-1 = oppose/pro-Ukraine, 0 = neutral, $+1$ = support/anti-Ukraine) by party.

RD Results: Discontinuity at T_e (Member FE)

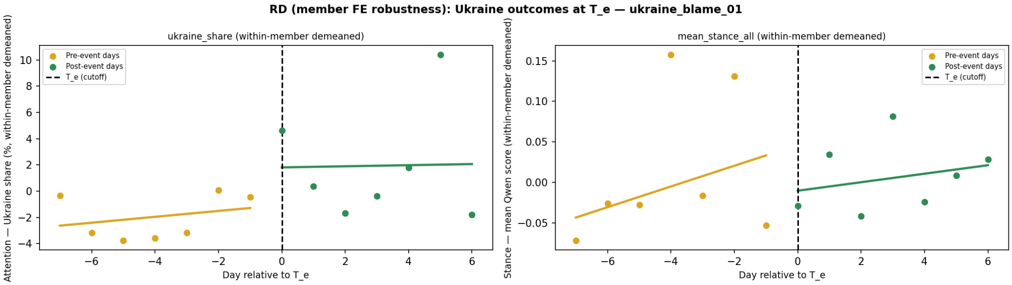
Spec: $Y_{it} = \alpha_i + \beta\, \mathbf{1}[t \geq T_e] + \gamma\, \tilde{d}_t + \delta\, (\mathbf{1}[t \geq T_e] \cdot \tilde{d}_t) + \varepsilon_{it}$
Member FE absorbed; SE clustered by member. $^{**}p < 0.05$, $^{***}p < 0.01$

Event / Outcome	$\hat{\beta}$	SE	p	N
***ukraine_blame_01** — Trump blames Ukraine/Zelensky (Feb 19 2025)*				
Attention share	$+0.030$	0.014	0.037^{**}	3,922
Stance (Qwen)	-0.075	0.083	0.370	803
***ukraine_reversal_01** — Trump shifts pro-Ukraine (Sep 23 2025)*				
Attention share	$+0.030$	0.011	0.007^{***}	3,911
Stance (Qwen)	$+0.252$	0.153	0.102	589

Takeaway

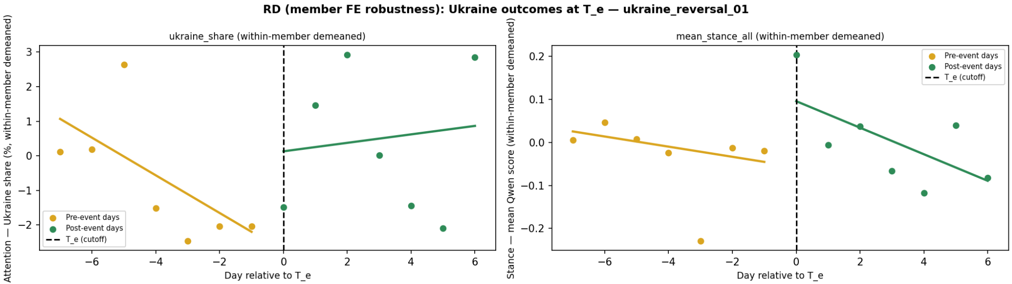
Both events produce a significant within-member jump in Ukraine *attention share* at T_e. Stance RD is in the expected direction but underpowered — improving LLM accuracy is the priority.

RD Visual: `ukraine_blame_01` (Feb 19 2025)



Scatter = within-member demeaned daily means. Lines = local-linear fit on demeaned outcomes (pre: ● gold; post: ● green). Within-member jump at T_e: $\hat{\beta} = +0.030$, $se = 0.014$, $p = 0.037$.

RD Visual: `ukraine_reversal_01` (Sep 23 2025)



Scatter = within-member demeaned daily means. Lines = local-linear fit on demeaned outcomes (pre: ● gold; post: ● green). Within-member jump at T_e: $\hat{\beta} = +0.030$, $se = 0.011$, $p = 0.007$.

RD Heterogeneous Effects: Attention by Party & Local Issue

Outcome: Ukraine attention share. Member FE absorbed; SE clustered by member.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Subgroup	RD jump	SE	p	N
ukraine_blame_01 *(Feb 19 2025)*				
Republican (all)	+0.020	0.019	0.315	1,893
Democrat (all)	+0.042	0.021	0.051*	2,029
D | Low Trump	+0.040	0.021	0.059*	1,985
ukraine_reversal_01 *(Sep 23 2025)*				
Republican (all)	+0.011	0.015	0.463	1,873
Democrat (all)	+0.047	0.016	0.004***	2,038
D | Low Trump	+0.054	0.016	0.001***	1,997
D | (Low T, High Local)	+0.060	0.019	0.002***	1,286

Pattern

Democrats drive both RD jumps; Republicans show no response (strategic silence). On reversal, effect is strongest in Low-Trump, High-Local (pro-Ukraine constituency) districts (+6.0pp, $p = 0.002$). High-Trump Democrat cells too sparse for reliable estimation.

RD Heterogeneous Effects: Stance by Party & Local Issue

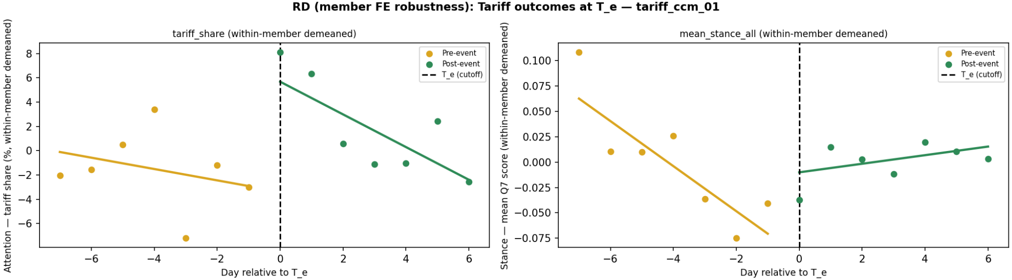
Outcome: mean Qwen stance score (-1 = pro-Ukraine/oppose Trump; $+1$ = anti-Ukraine/support Trump).
Member FE absorbed; SE clustered by member. $^{*}p < 0.10$, $^{**}p < 0.05$

Subgroup	RD jump	SE	p	N
ukraine_blame_01 *(Feb 19 2025)*				
R (all)	-0.208	0.097	0.035**	386
R | High Trump	-0.186	0.099	0.065*	365
R | (High Trump, Low Local)	-0.279	0.144	0.058*	235
D (all)	$+0.104$	0.130	0.425	417
ukraine_reversal_01 *(Sep 23 2025)*				
R (all)	$+0.463$	0.226	0.045**	244
R | High Trump	$+0.327$	0.203	0.111	224
R | (High Trump, Low Local)	$+0.366$	0.300	0.230	138
D (all)	$+0.087$	0.200	0.663	345

Takeaway

Engaged Republicans *do* align with Trump when they tweet. High-Trump, Low-Local R districts amplify his blame framing (-0.21, $p = 0.035$) and follow his pro-Ukraine reversal ($+0.46$, $p = 0.045$). Democrats hold their pro-Ukraine stance throughout. Improving LLM accuracy is needed before drawing strong conclusions.

RD Visual: `tariff_ccm_01` (Feb 1 2025)



Scatter = within-member demeaned daily means (tariff-topic tweet share). Lines = local-linear fit on demeaned outcomes (pre: ● gold; post: ● green). Vertical line = T_e (CCM tariff announcement, Feb 1 2025). Both parties show a clear upward jump at T_e.

RD Heterogeneous Effects: Attention — `tariff_ccm_01`

Outcome: tariff-topic tweet share. Member FE absorbed; SE clustered by member. $^{**}p < 0.05$, $^{***}p < 0.01$

Subgroup	RD jump	SE	p	N
Republican (all)	+0.130	0.030	0.000***	2,026
R | High Trump	+0.132	0.032	0.000***	1,868
R | High Trump + Pro-Tariff Local	+0.118	0.042	0.006***	1,115
R | High Trump + Anti-Tariff Local	+0.131	0.052	0.014**	701
R | Low Trump	+0.119	0.076	0.162	97
Democrat (all)	+0.074	0.020	0.000***	3,255
D | Low Trump	+0.098	0.025	0.000***	2,094
D | Low Trump + Anti-Tariff Local	+0.115	0.029	0.000***	1,261
D | Low Trump + Pro-Tariff Local	+0.064	0.046	0.168	808

Pattern

Both parties significantly increase engagement. Republicans in High-Trump districts respond uniformly regardless of local tariff sentiment (+13pp either way). Anti-Tariff Democrats also spike (+11.5pp) — amplifying opposition.

RD Heterogeneous Effects: Stance — `tariff_ccm_01`

Outcome: mean Qwen stance score (-1 = anti-tariff/oppose Trump; $+1$ = pro-tariff/support Trump). Member FE absorbed; SE clustered by member. $^{***}p < 0.01$

Subgroup	RD jump	SE	p	N
Republican (all)	+0.179	0.059	0.003***	714
R | High Trump	+0.179	0.062	0.005***	665
R | High Trump + Pro-Tariff Local	+0.227	0.069	0.002***	421
R | High Trump + Anti-Tariff Local	+0.105	0.138	0.450	218
R | Low Trump	+0.147	0.163	0.401	32
Democrat (all)	+0.067	0.078	0.387	800
D | Low Trump	+0.049	0.121	0.685	432
D | Low Trump + Anti-Tariff Local	+0.068	0.164	0.682	248

Takeaway

Republicans align with Trump's pro-tariff stance ($+0.18$, $p = 0.003$); strongest in High-Trump, Pro-Tariff districts ($+0.23$, $p = 0.002$). **Democrats show no significant stance shift** — they increase engagement to oppose, but their mean stance does not move (remains firmly anti-tariff throughout).

Contrasting Issues (1/2): Ukraine — Controversial

Ukraine — **Controversial signal** 49% Republican support

GOP trade-off: R districts are split 49/41 for/against Ukraine ⇒ engaging publicly imposes electoral risk.

Attention RD

- Democrats: significant jump (+4.2pp, $p = 0.051$) on Blame; (+4.7pp, $p = 0.004$) on Reversal — counter-cue to raise salience
- Republicans: no significant response in either event
- Low-Trump D districts lead; High-Trump D cells sparse

Stance RD

- Engaged R (High-Trump, Low-Local) *do* shift toward Trump's frame: Blame -0.21 ($p = 0.035$); Reversal $+0.46$ ($p = 0.045$)
- D hold pro-Ukraine stance throughout — no shift in either event

Takeaway

Many Republicans stay silent to avoid local backlash. Those who *do* tweet align with Trump.

Contrasting Issues (2/2): Tariffs — Consolidated

Tariffs — Consolidated party agenda 84% Republican support (highest in sample)

No GOP trade-off: Tariffs = MAGA/America First core agenda ⇒ small local-accountability penalty for engaging.

Attention RD

- Republicans: large, uniform jump (+13pp, $p < 0.001$) — party agenda-setting; effect holds regardless of local tariff sentiment (+11.8pp pro-local, +13.1pp anti-local)
- Democrats: also jump significantly (+7.4pp, $p < 0.001$) to amplify opposition and raise counter-salience

Stance RD

- R shift pro-tariff (+0.18, $p = 0.003$); strongest in High-Trump, Pro-Tariff districts (+0.23, $p = 0.002$)
- D: engage more but stance does not shift — remains firmly anti-tariff

takeaway

Republicans mobilize fully on consolidated agenda items (engagement *and* stance follow Trump). Democrats consistently counter-cue.

Summary of Findings (1/2): Attention & Engagement

Pattern

On a consolidated party agenda item, **both parties mobilize** at T_e. On a controversial topic, only the **opposing party** mobilizes; the in-party goes quiet.

Summary of Findings (2/2): Stance Alignment

Ukraine (controversial) — Stance

- *Interpretation:* Silence filters out cross-pressured Republicans; those who engage are the least locally constrained

Tariffs (consolidated) — Stance

- **Republicans**: significant pro-tariff shift; strongest in High-Trump, Pro-Tariff districts
- **Democrats**: increased engagement and remain firmly anti-tariff

Core interpretation

Strategic silence is issue-specific. The national-loyalty vs. local-accountability trade-off suppresses Republican engagement *only* on controversial topics. When the party agenda is consolidated, Republicans engage and align freely.
Democrats consistently counter-cue regardless of issue type.

Stance Validation: Qwen vs. GPT-4o (100 tweets each)

Method: Stratified random sample of 100 relevant tweets per event; GPT-4o labels same A/B/C scheme; errors excluded.

`ukraine_blame_01`

Metric	Value
% agreement	*TBD*
Cohen κ	*TBD*
Qwen=A GPT agree	*TBD*
Qwen=B GPT agree	*TBD*
Qwen=C GPT agree	*TBD*

Confusion matrix (rows=Qwen, cols=GPT):

	A	B	C
Qwen=A	–	–	–
Qwen=B	–	–	–
Qwen=C	–	–	–

`tariff_ccm_01`

Metric	Value
% agreement	*TBD*
Cohen κ	*TBD*
Qwen=A GPT agree	*TBD*
Qwen=B GPT agree	*TBD*
Qwen=C GPT agree	*TBD*

Confusion matrix (rows=Qwen, cols=GPT):

	A	B	C
Qwen=A	–	–	–
Qwen=B	–	–	–
Qwen=C	–	–	–

Interpretation

A=oppose Trump, B=neutral, C=support Trump. $\kappa > 0.6$ = substantial agreement; $\kappa > 0.8$ = near-perfect.

Stance Validation: Ukraine `ukraine_blame_01` — Inconsistent

[05] `B001301` Qwen=A (oppose) GPT=B (neutral)

American foreign policy should always be America First. I've been saying for years on record, we need to have an exit strategy, a plan for peace, and have accountability for every dollar spent that the U.S. has provided for the Ukrainian conflict with Russia.

[06] `L000596` Qwen=A (oppose) GPT=C (support Trump)

The American taxpayer should not be burdened with the cost of Zelensky's war. They must pay back every cent they owe. It is billions and billions of dollars!

[09] `K000367` Qwen=A (oppose) GPT=B (neutral)

So if Zelenskyy had just emblazoned "tech support" on his black shirt and donned a MAGA hat, would that have been up to standard under White House dress code? *(nyt photo)*

Stance Validation: Ukraine `ukraine_blame_01` — Consistent

[01] `S000510` Qwen=A GPT=A

The U.S. vote alongside Russia, North Korea, Belarus & Hungary to block a UN resolution condemning Putin's unprovoked attack on Ukraine is deeply concerning. Trump has made it clear: he wants to walk away from our European allies, including Ukraine.

[02] `G000599` Qwen=A GPT=A

I took an oath to support and defend the Constitution, just like every single one of my Republican colleagues. We must hold Republicans' feet to the fire – history will judge them for either siding with our democracy or with Donald Trump.

Stance Validation: Tariff `tariff_ccm_01` — Inconsistent

[01] `S001195` Qwen=C (support Trump) GPT=B (neutral)

The Trump tax cuts gave American workers and businesses the tools they needed to compete against global adversaries like China. When our tax code puts America first, America wins.

[06] `G000590` Qwen=B (neutral) GPT=C (support Trump)

It's no secret that the CCP seeks to outpace the United States, repress its own citizens, and sever America's global alliances. My Bring American Companies Home Act is critical to protect our supply chain from the Chinese Communist Party's influence.

Pattern

Both cases involve **adjacent-topic framing** (tax cuts, supply-chain decoupling) that is thematically pro-America-First but does not explicitly address the CCM tariffs. Qwen and GPT diverge on whether to infer latent tariff support from ideological context.

Stance Validation: Tariff `tariff_ccm_01` — Consistent

[04] T000468 Qwen=A (oppose Trump) GPT=A (oppose Trump)

These tariffs will increase prices and hurt U.S. businesses and families. My colleagues and I are demanding @POTUS, @secrubio, @USTradeRep, and @CommerceGov Acting Secretary Pelter reverse this decision.

[05] G000590 Qwen=C (support Trump) GPT=C (support Trump)

The American people elected President Trump to stop the fentanyl that was pouring into our country from our northern and southern borders. Tariffs send a strong message to get countries like Communist China, Mexico, and Canada to act.

[08] H001082 Qwen=B (neutral) GPT=B (neutral)

The American people are fed up. They outright rejected Joe Biden's failed America Last agenda. But instead of listening, Biden doubled down. He's not just ignoring the crisis — he's selling off pieces of the border wall. When President Trump returns, that border wall will be back.

Next Steps

Local Stance Benchmark

1. Identify controversial issues and party agenda
2. Start with CES survey benchmark

Causal Identification

1. Event study DiD with pre-trend falsification
2. Argue plausibility of quasi-random T_e timing

Heterogeneity

1. MAGA vs. Establishment Republicans
2. Electoral vulnerability (2024 vote share)
3. State-level constituency alignment

Data expansion

1. Additional events

Validation

1. Human coding of event dates
2. ...

Limitations & Will-Do List

Current limitations

- **Stance classifier accuracy ≈70%** — Qwen2.5-14B (4-bit) was chosen for cost and pipeline reproducibility, but off-the-shelf accuracy is limited; noisy labels attenuate estimates toward zero.

Will-do: upgrade stance labeling

- Replace Qwen stance labels with **GPT-4o** or **PoliBERTweet** or **manual (validation set)** annotations on the full classified sample.

Thank you

Questions & Comments Welcome

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Appendix: Full Data Funnel I

Pipeline data funnel: window → candidates → classified. `pre_days` *and* `post_days` *give window half-widths around* T_e.

event_id	type	Te	pre_days	post_days	window_start	wind
biden_dropout_01	novel_shock	2024-06-21	90	30	2024-03-23	2024
charlie_kirk_assassination_01	novel_shock	2025-08-27	90	30	2025-05-29	2025
dei_executive_order_01	stance_shift	2025-01-19	90	30	2024-10-21	2025
doge_disbanded_01	stance_shift	2025-11-20	90	30	2025-08-22	2025
doge_establish_01	novel_shock	2024-12-04	90	30	2024-09-05	2025
government_shutdown_01	stance_shift	2025-03-13	90	30	2024-12-13	2025
greenland_01	novel_shock	2024-12-22	30	30	2024-11-22	2025
greenland_02	novel_shock	2026-01-14	30	30	2025-12-15	2026
haitian_pets_01	novel_shock	2024-08-15	90	30	2024-05-17	2024
minneapolis_ice_shooting_01	novel_shock	2025-12-11	90	30	2025-09-12	2026
nato_threat_01	stance_shift	2025-03-08	90	30	2024-12-08	2025
roe_wade_01	stance_shift	2022-06-24	90	30	2022-03-26	2022
trump_assassination_attempt_01	novel_shock	2024-07-01	90	30	2024-04-02	2024
trump_convicted_01	novel_shock	2024-05-31	90	30	2024-03-02	2024
trump_musk_feud_01	stance_shift	2025-06-05	90	30	2025-03-07	2025
trump_tariffs_01	novel_shock	2025-03-03	90	30	2024-12-03	2025

Appendix: Full Attention Metrics I

Attention metrics: pre- and post-T_e daily tweet means and ratio.

Event	Pre mean	Post mean	Ratio	Confirmed	Pre flat
greenland_01	0.833000	2.581000	3.097000	1	0
greenland_02	4.300000	6.581000	1.530000	0	0
biden_dropout_01	18.789000	48.194000	2.565000	1	0
charlie_kirk_assassination_01	11.900000	65.839000	5.533000	1	0
dei_executive_order_01	2.711000	17.936000	6.616000	1	0
doge_disbanded_01	15.700000	13.387000	0.853000	0	0
doge_establish_01	6.522000	23.548000	3.610000	1	0
government_shutdown_01	47.122000	50.161000	1.064000	0	0
haitian_pets_01	2.267000	1.871000	0.825000	0	0
minneapolis_ice_shooting_01	54.267000	49.194000	0.906000	0	0
nato_threat_01	4.367000	3.936000	0.901000	0	0
roe_wade_01	1.911000	4.516000	2.363000	1	0
trump_assassination_attempt_01	5.844000	16.677000	2.854000	1	0
trump_convicted_01	7.578000	11.323000	1.494000	0	0
trump_musk_feud_01	24.467000	40.484000	1.655000	0	0
trump_tariffs_01	56.144000	110.871000	1.975000	0	0

Appendix: Event Summary (Stage 09) I

Event-level summary statistics for all events (Stage 09 output). $\mathit{attention\_confirmed}$ = *True when post-T_e mean $\geq 2\times$ pre-T_e mean.*

event_id	event_type	event_date	issue_domain	confounds_noted	attention_ratio	attention_c
greenland_01	novel_shock	2024-12-22	foreign_policy	—	3.259300	
greenland_02	novel_shock	2026-01-14	foreign_policy	—	0.741600	