Where the Cloud Hits the Ground: Multi-Tier Measurement of Resource Salience, Public Pressure, and Institutional Bargaining Over AI Infrastructure (2023-2026)

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Abstract

While national policy debates over artificial intelligence frequently center on frontier model capabilities or macroeconomic competitiveness, a major political fault line over AI in the United States is forming where physical compute infrastructure—hyperscale data centers, high-voltage substations, transmission corridors, water-cooling systems, and gigawatt power generation—meets local communities, utility ratepayers, municipal councils, county boards, public utility commissions, and state legislatures. We introduce a reproducible multi-tier measurement framework and panel dataset monitoring public, regulatory, and legislative responses to AI infrastructure across a baseline panel of 364 dated, URL-verified records (2023–2026) spanning 48 jurisdictions (251 Tier 1 Local records, 50 Tier 2 State records, and 63 Tier 3 Federal dockets), alongside a cleaned, deduplicated, event-dated, 100%-live-scored on-topic panel of 243 records across 44 jurisdictions (`data/ai_infrastructure_observatory_panel_v1_2.csv`, pairing 192 on-topic Local and State records with 51 relevance-ranked and phrase-matched 2023–2026 Federal Register dockets).

Evaluating both panels across live open-weight large language model (LLM) judges and deterministic non-LLM documentary benchmarks—where all continuous and ordinal construct scores are explicitly interpreted as LLM-ensemble text representations and lexical indicators rather than human-annotated ground truth—yields four principal findings: 1. **Live-Ballot Inter-Rater Reliability:** In the baseline 4-judge annotation run, concurrent rate limits and reasoning-token truncation (`max_tokens = 500`) caused 824 of 1,456 ballot slots (`56.59%`) on the three secondary cloud judges to fall back to a deterministic keyword rule, whereas `meta-llama/llama-3.3-70b-instruct` completed `364 / 364` (`100.0%`) live ballots. Restricting Shrout-Fleiss [1] inter-rater reliability strictly to live LLM ballots (`n = 169` records where both `deepseek-v4.1-flash` and `llama-3.3-70b-instruct` ran live; `n = 68` where three judges ran live), two-judge live `ICC(2,2)` / single-rater `ICC(2,1)` are `0.9361` / `0.8799` (`r = 0.9045`) on `public_pressure_index`, `0.9196` / `0.8511` (`r = 0.8521`) on `policy_posture_code`, `0.8391` / `0.7228` (`r = 0.7415`) on `frame_labor_civil_rights`, `0.7845` / `0.6454` (`r = 0.6541`) on `frame_water_land_env`, `0.7302` / `0.5750` (`r = 0.6529`) on `frame_grid_ratepayer`, `0.6707` / `0.5045` (`r = 0.6769`) on `frame_natsec_competitiveness`, `0.6459` / `0.4770` (`r = 0.6036`) on `frame_fiscal_tax`, and `0.6308` / `0.4607` (`r = 0.5998`) on `resource_ratepayer_salience` (`0.7320` / `0.4766` across three live judges on `n = 68`, and `0.7442` / `0.5926` on the rebuilt 51-record federal sample where fallback usage is `0%`). 2. **Resource-Ratepayer Salience Strongly Predicts Public Pressure and Institutional Friction Within Observed Empirical Support (Proposition P2):** On the cleaned, deduplicated, event-dated, 100%-live-scored on-topic panel (`data/ai_infrastructure_observatory_panel_v1_2.csv`, $N = 243, G = 44$), controlling for `frame_labor_civil_rights`, lexical `word_tone`, standardized excerpt length `excerpt_char_len_z`, region fixed effects `C(region)`, and calendar-year fixed effects `C(event_year)`, the unstandard-

ized ordinary least squares (OLS) slope on `resource_ratepayer_salience` predicting `public_pressure_index` is `48.1730` (`48.173` per `[0, 1]` index unit, jurisdiction-clustered SE = 12.5497, $t = 3.8386$, $p = 0.0001$, restricted Rademacher wild-cluster bootstrap $p_{\text{wcb}} = 0.0028$, Holm-Bonferroni adjusted $p_{\text{Holm}} = 0.0006$), and `61.3411` in an unadjusted bivariate regression (SE = 13.0849, $t = 4.6879$, $p < 0.0001$). Because the observed empirical support of `resource_ratepayer_salience` on $N = 243$ is `[0.0000, 0.6183]` (SD = 0.1290, IQR = 0.2000), a hypothetical 1-unit shift ($\Delta X = 1.0$) extrapolates beyond the support of the data; evaluated over realistic within-sample shifts, a **1-SD increase (`+0.1290`) predicts a `+6.2144`-point (`+6.21`) increase in `public_pressure_index`** (**SE** = 1.6189, 95% **CI** [3.0413, 9.3875]), an **IQR increase (`+0.2000`) predicts a `+9.6346`-point (`+9.63`) increase** (**SE** = 2.5099, 95% **CI** [4.7151, 14.5541]), and a **bounded-outcome Fractional Logit Generalized Linear Model (`sm.GLM` Binomial logit on `public_pressure_index / 100` $\in [0, 1]$)** yields a log-odds coefficient of `2.5620` (SE = 0.6986, $z = 3.6674$, $p = 0.0002$), corresponding to an average marginal effect (AME) of **`+6.4688` percentage points per 1-SD shift** (**SE** = 1.7638), **`+10.0291` percentage points per IQR shift** (**SE** = 2.7346), and `+50.1454` percentage points per index unit (SE = 13.6731). Across the full 364-record baseline panel (`data/ai_infrastructure_observatory_panel.csv`), the controlled OLS coefficient is `55.0318` on live-ballot-only scores (SE = 10.7657, $t = 5.1118$, $p < 0.0001$, $p_{\text{wcb}} = 0.0004$), `30.0137` on the 225-record on-topic subset of the baseline panel using live ballots (SE = 14.2031, $t = 2.1132$, $p = 0.0346$), and `26.2713` on the baseline 4-slot pooled scores (full-rank SE = 9.8013, $t = 2.6804$, $p = 0.0074$, $p_{\text{wcb}} = 0.0282$). The positive association persists under classical errors-in-variables disattenuation (`+10.4831` points per 1-SD, $\text{SE}_{\text{full}} = 2.8148$, 95% $\text{CI}_{\text{full}} = [4.9661, 16.0001]$, and `+16.2527` points per IQR, $\text{SE}_{\text{full}} = 4.3640$, 95% $\text{CI}_{\text{full}} = [7.6993, 24.8061]$, corresponding to an unstandardized slope of `81.2636` at observation-weighted predictor reliability $\bar{\rho}_{\bar{x}\bar{x}} = 0.5928$ with full bivariate delta-method $\text{SE}_{\text{EIV, full}} = 21.8198$ and 95% $\text{CI}_{\text{full}} = [38.4967, 124.0302]$ propagating the bootstrap sampling variance $\text{SE}(\bar{\rho}_{\bar{x}\bar{x}}) = 0.0385$, and `64.7313` to `76.3681` at $\rho = 0.7442$ and $\rho = 0.6308$), cross-rater rater-noise calibration (`77.6145`, SE = 17.8421, first-stage $F = 109.13$; `71.3410` under inverse probability weighting for live-ballot availability—strictly a calibration for idiosyncratic rater noise that does not satisfy the instrumental-variable exclusion restriction for shared text features), 44-jurisdiction within-cluster fixed effects (`48.8726`, SE = 19.7230, $p = 0.0132$ on all 44 clusters and `49.4768`, SE = 20.9810, $p = 0.0184$ on the 28 clusters with $N_g \geq 5$), individual-rater models across each live LLM judge separately (`58.6188` on $N = 243$ and `36.7412` on $N = 364$ for `llama-3.3-70b-instruct`; `51.3151` on $N = 135$ secondary live judges; `75.3325` on $N = 169$ live `deepseek-v4.1-flash`; `77.0910` on $N = 89$ live `minimax-m3.1-flash`), non-LLM physical-resource term benchmarks (`33.6515` capped density, `3.3010` uncapped count, `3.2320` uncapped rate per 100 words, and `2.8448` strict technical rate per 100 words, all $p \leq 0.0073$), and restriction strictly to the 171 primary `.gov`/OData government records (`68.5533`, SE = 13.1039, $p < 0.0001$). Disaggregating the pre-registered three-frame formative index (Cronbach's $\alpha = -0.1374$ across the three sub-frames; $\alpha = 0.0806$ across the two physical sub-frames) shows that its positive effect is driven by physical electricity grid (`+12.3683`, $p = 0.0133$) and water/land/environmental (`+32.7564`, $p < 0.0001$) salience, whereas `frame_fiscal_tax` (`-7.7359` conditional, $p = 0.2003$; `-17.7727` standalone, $p = 0.0045$) does not contribute positively. 3. **Null Aggregate Cross-Tier Salience Difference (Proposition P1 Not Supported) vs. Exploratory Agency Decomposition:** Proposition P1—which hypothesized higher aggregate `resource_ratepayer_salience` in Local and State proceedings than in Federal dockets—**is not supported**. While conventional asymptotic cluster-robust standard errors on the baseline panel ($N = 364, G = 48$) suggested a positive difference (`0.0769`, SE = 0.0347, $p = 0.0268$), `tier_local_or_state` is invariant within clusters with only $G_{\text{fed}} = 4$ federal agency clusters; applying a restricted Rademacher wild-cluster bootstrap [2] [3] yields $p_{\text{wcb}} = 0.1740$. Moreover, when we replace the baseline 2026-only federal slice with 51 relevance-ranked and phrase-matched 2023–2026 Federal Register dockets in `data/ai_infrastructure_observatory_panel_v1_2.csv` ($N = 243, G = 44$), the controlled OLS coefficient on `tier_local_or_state` predicting `resource_ratepayer_salience` is statistically indistinguishable from zero at `0.0502` (SE = 0.0650, 95% CI $[-0.0772, +0.1777]$, $t = 0.7721$, $p = 0.4401$, $p_{\text{wcb}} = 0.6264$; bivariate `0.0519`, SE =

0.0574, $p = 0.3653$, with 80%-power minimum detectable effect $\text{MDE}_{80\%} = 2.8 \times \text{SE} = 0.1821$). In an exploratory, non-pre-registered post-hoc subgroup decomposition disaggregating the four federal clusters into energy/environmental dockets (`US_EPA_Env` `0.2974` and `US_FERC_DOE_Grid` `0.2343`) versus AI-governance dockets (`US_DOE_WhiteHouse_AI` `0.0642` and `US_NTIA_Commerce_OMB` `0.0385`), the contrast between Local/State records and EPA/FERC (`-0.0750`, SE = 0.0381, unadjusted $p = 0.0489$, Bonferroni-adjusted $p_{\text{Bonf}} = 0.0978$ across $M = 2$ subgroup contrasts) is not statistically significant after multiplicity correction, whereas Local/State records score higher than DOE/NTIA AI-governance dockets (`+0.1331`, SE = 0.0307, unadjusted $p < 0.0001$, Bonferroni-adjusted $p_{\text{Bonf}} = 0.000029$). Across tiers as a whole, Local and State actions exhibit higher `public_pressure_index` (`36.6803` vs. `19.4618`) and `frame_fiscal_tax` (`0.2095` vs. `0.0711`), whereas Federal dockets emphasize `frame_natsec_competitiveness` (`0.3330` or `0.333` in Federal vs. `0.0627` in Local/State). 4. **Institutional Bargaining vs. Direct Denials Under High Local Pressure:** Deriving ordinal policy posture from the median or mode of live LLM ballots shows that across the cleaned on-topic panel ($N = 243$), **conditional bargaining (`Code 2: 31.69%` median / `28.40%` mode) and procedural pauses or moratoria (`Code 3: 20.58%`) together constitute the majority of institutional responses at `52.26%` (`127 / 243` on live median; `48.97%` or `119 / 243` on live mode and standalone `llama-3.3-70b-instruct`)**, while **direct denials, project cancellations, and judicial blockades (`Code 5`) account for `7.00%` (`17 / 243`, live median) to `9.88%` (`24 / 243`, live mode and standalone `llama-3.3-70b-instruct`)**. Within high-pressure conflicts (`public_pressure_index >= 40`, `>= 50`, and `>= 60`), responses divide across three tracks: at `PPI >= 50` ($N = 70$), conditional bargaining and procedural pauses represent `42.86%` (median) to `45.71%` (mode), direct denials represent `24.29%` (median) to `31.43%` (mode), and targeted restrictions represent `22.86%` to `32.86%`. Finally, within-corpus temporal shifts between 2023–2024 and 2025–2026 (`period_2025_2026`, Proposition P3) are statistically indistinguishable from zero (`-3.1579`, SE = 3.5529, $p = 0.3741$ on the cleaned panel; `-0.3349`, SE = 4.9131, $p = 0.9457$ on unmodified municipal Legistar OData records).

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1. Introduction and Theoretical Motivation

Engineering and resource-systems studies have quantified the electricity, water, and carbon footprints of data centers and artificial intelligence hardware across distinct analytical scopes. Masanet et al. [4] recalibrated global data-center electricity-use estimates between 2010 and 2018, showing that hardware and cooling efficiency gains moderated global data-center energy-use growth over that decade despite rapidly rising compute instances. Examining the United States specifically, Siddik et al. [5] constructed spatially detailed estimates of the water, energy, and carbon footprints of U.S. data centers and documented that a substantial share of U.S. data-center water consumption is drawn from water-stressed watersheds. Focusing on generative artificial intelligence servers, de Vries [6] projected the growing electricity and water footprint of AI training and inference workloads as deployment scales.

In parallel, scholarship on facility siting and energy politics has investigated how host communities perceive and respond to locally sited infrastructure. Dear [7] analyzed community opposition to locally unwanted facility siting and strategies for addressing "not-in-my-backyard" (NIMBY) conflict. Critiquing simplistic NIMBY explanations of wind-energy perceptions, Devine-Wright [8] reviewed six strands of empirical literature—levels of public support or opposition, specific turbine attributes, the impact of physical proximity, changes in public acceptance over time, critical evaluations of the "NIMBY" concept, and the role of local involvement—to propose an integrated framework for understanding public perceptions of wind energy. Empirical evidence on whether geographic proximity alone drives opposition is mixed: Stokes [9] demonstrated that spatial proximity to wind turbines in Ontario generated significant retrospective electoral backlash and local resistance against the governing party's climate policy, whereas Konisky, Ansolabehere, and Llewelyn [10] found little evidence in U.S. survey data that residential proximity or narrow NIMBY objections alone determine public support for energy infrastructure projects.

That divergence in the siting literature directly motivates our empirical inquiry. If geographic proximity or generic anti-infrastructure sentiment alone does not automatically explain public friction [10], what specific issue frames and institutional mechanisms shape conflict over physical AI infrastructure? In local council chambers, county zoning hearings, state public utility commissions (PUCs), and state legislatures across the United States, debates over hyperscale data centers and power facilities center on concrete distributional and regulatory questions: whether residential ratepayers will cross-subsidize gigawatt transmission and substation upgrades through monthly electric bills, how evaporative cooling affects local water supplies, whether sales-tax exemptions yield commensurate local fiscal returns, and whether projects are negotiated under municipal nondisclosure agreements (NDAs). Rather than reducing to a binary between unconditional approval (`Code 1`) and outright rejection (`Code 5`), institutional responses frequently take the form of conditional bargaining (`Code 2`: large-load tariff ring-fencing, closed-loop cooling mandates, acoustic setbacks) and procedural pauses or audits (`Code 3`), alongside targeted zoning or tax restrictions (`Code 4`) and, in roughly one-quarter to one-third of high-pressure proceedings, direct denials or lawsuits (`Code 5`).

To measure this landscape reproducibly, we construct and analyze two linked multi-tier panels spanning 2023–2026: 1. **The Pre-Registered Baseline Panel (`data/ai_infrastructure_observatory_panel.csv`, $N = 364$ records across $G = 48$ jurisdictions):** Combines 186 municipal records from direct Granicus Legistar OData APIs (`Legistar_Municipal_API`), 63 Federal Register dockets (`Federal_Register_API`), and 115 county, state legislative, and PUC records (`State_County_PUC_Primary_Search`, explicitly partitioned via `source_provenance_type` into 18 primary `.gov/.us` records and 97 secondary news, public-radio, legal, and policy-tracker reports). 2. **The Cleaned, Deduplicated, Event-Dated, 100%-Live-Scored On-Topic Panel (`data/ai_infrastructure_observatory_panel_v1_2.csv`, $N = 243$ records across $G = 44$ jurisdictions):** Removes one pre-2023 clerk budget artifact (`AII-2023-013`), deduplicates 28 multi-outlet secondary articles covering the same local vote, corrects 17 web-page modification dates to their underlying 2023–2025 policy event dates, filters out 80 routine municipal utility easements lacking AI, data-center, or large-load content (`is_on_topic_ai_dc == 1`), and pairs the resulting 192 on-topic Local/State records with 51 relevance-ranked and phrase-matched 2023–2026 Federal Register dockets scored `100%` live with zero rule fallbacks.

2. Corpus Construction, Provenance Auditing, and Sample Attrition

2.1 Multi-Tier Sampling Architecture

Our data collection spans three institutional tiers across the United States between 2023 and 2026: - **Tier 1 Local — Municipal and County Governments** ($N = 251$ **baseline;** $N = 159$ **in cleaned on-topic panel):** - *Tier 1A Municipal Legistar OData API* (*N = 186 baseline; N = 107 in cleaned on-topic panel*)*:* Retrieved from 24 municipal and county Granicus Legistar OData portals (`https://webapi.legistar.com/v1/{client}/matters`). Because the initial OData query matched general electrical-utility terms (`Substation`, `Electric Utility`, `Transmission Line`) without requiring co-occurrence with `data center` or `AI`, `56 / 186` (`30.11%`) baseline Legistar records contain explicit AI, data-center, or large-load markers (`is_on_topic_ai_dc == 1`), whereas `129` are routine municipal power/substation easements and `1` (`AII-2023-013`, Richmond `ORD. 1984-088-102`, uploaded to Legistar on `2023-08-24`) is a clerk-digitized FY1984–85 Electric Utility Budget. In `data/ai_infrastructure_observatory_panel_v1_2.csv`, `AII-2023-013` and all `80` off-topic municipal utility easements are excluded prior to analysis. - *Tier 1B County Board, Municipal Hearing, and Public Radio Records* (*N = 65 baseline, State_County_PUC_Primary_Search*)*:* Covers 12 county and local clusters experiencing intense data-center siting activity (`VA_Loudoun`, `VA_PrinceWilliam`, `VA_Fairfax`, `VA_Fauquier_Henrico`, `GA_Atlanta`, `GA_Metro_Counties`, `AZ_Chandler`, `OH_NewAlbany_Licking`, `TX_Local_Counties`, `WA_GrantCounty_Quincy`, `MW_Local_Counties`, and `US_PublicRadio_LocalBeat`). - **Tier 2 State — State Legislatures and Public Utility Commissions** ($N = 50$ **baseline;** $N = 33$ **in cleaned on-topic panel):** - Covers state legislative bills, joint legislative audit reports, and state PUC large-load tariff proceedings across 10 state clusters (`VA_State_Leg_SCC`, `GA_State_Leg_PSC`, `AZ_State_ACC_Water`, `OH_State_PUCO`, `TX_State_ERCOT`, `OR_Hillsboro_State`, `IL_State_ElkGrove`, `CA_State_Leg_CPUC`, `NC_State_NCUC`, `PA_State_PJM`). Across all 115 `State_County_PUC_Primary_Search` records (`65` Tier 1B + `50` Tier 2), `18` (`15.65%`) come from `.gov` or `.us` domains and `97` (`84.35%`) come from secondary news, public-radio, legal, and tracker domains (`source_provenance_type`). In the cleaned 243-record panel, `171 / 243` (`70.37%`) records are primary government records (`107` municipal Legistar OData + `13` `.gov`/`.us` state/county records + `51` Federal Register dockets) and `72 / 243` (`29.63%`) are deduplicated secondary reports. - **Tier 3 Federal — National Regulatory and Executive Dockets (**$N = 63$ **baseline;** $N = 51$ **rebuilt 2023–2026 in cleaned panel):** - *Baseline Federal Sample* (*N = 63*)*:* Sampled the newest Federal Register documents per query (`order="newest"`), which restricted baseline federal dates to `2026-04-09` through `2026-11-03`, omitted Presidential Documents (`abstract: null`), and drew off-topic general agency notices into `US_DOE_WhiteHouse_AI` (`0.0789` resource salience) and `US_NTIA_Commerce_OMB` (`0.0623`). - *Rebuilt 2023–2026 Federal Sample* (*N = 51, 2023-03-29 to 2026-10-27*)*:* Queries the Federal Register API with `order="relevance"` and phrase matching across 2023–2026 (`5` dockets in `2023`, `13` in `2024`, `14` in `2025`, `19` in `2026`) and ingests full verbatim text from `raw_text_url/body_html_url` for Presidential Documents. The 51 dockets span four federal clusters (`US_FERC_DOE_Grid` $N = 14$, `US_DOE_WhiteHouse_AI` $N = 14$, `US_EPA_Env` $N = 14$, `US_NTIA_Commerce_OMB` $N = 9$), including Executive Order `14318` (`FR-2025-14212`, `2025-07-28`), Executive Order `14141` (`FR-2025-01395`, `2025-01-17`), Executive Order `14110` (`FR-2023-24283`, `2023-11-01`), Executive Order `14365` (`FR-2025-23092`, `2025-12-16`), the Department of Energy's *Request for Information on Artificial Intelligence Infrastructure on DOE Lands* (`FR-2025-05936`, `2025-04-07`) and *Accelerating Speed to Power* (`FR-2025-18058`, `2025-09-18`), NTIA's *Request for Comments on Bolstering Data Center Growth, Resilience, and Security* (`FR-2024-19524`, `2024-09-04`), BIS's *Data Center Validated End User Authorization* (`FR-2024-22587`, `2024-10-02`) and *Framework for Artificial Intelligence Diffusion* (`FR-2025-00636`, `2025-01-15`), FERC Order `1920` (`FR-2024-10872`, `2024-`

06-11), and EPA power-plant and stationary-turbine rules.

2.2 Step-by-Step Sample Attrition from Baseline ($N = 364$) to Cleaned On-Topic Panel ($N = 243$)

Table 1 documents the exact sample attrition between the baseline panel (data/ai_infrastructure_observatory_panel.csv, $N = 364, G = 48$) and the cleaned on-topic panel (data/ai_infrastructure_observatory_panel_v1_2.csv, $N = 243, G = 44$), and reports how the controlled live-ballot P2 slope behaves at each intermediate step so that sample-composition changes and rule-fallback removal are never conflated.

Attrition Step	Scope / Tier	Record Count (N)	Jurisdictions (G)	Intermediate Controlled Live P2 Slope ($\hat{\beta}$, SE, p)	Exact Attrition Accounting
1. Baseline Pre-Registered Panel	Tier 1 (251) + Tier 2 (50) + Tier 3 (63)	364	48	55.0318 (SE = 10.7657, $p <$ 0.0001)	186 Legistar OData + 115 County/State search (18 .gov/.us + 97 secondary) + 63 Federal Register (2026-04-09 to 2026-11-03).
2. Remove Pre-2023 Clerk Budget Artifact	Local/State (301 to 300)	363 (300 Local/State)	48	54.7011 (SE = 10.7810, $p <$ 0.0001)	Removed AII-2023-013 (VA_Richmond ORD. 1984-088-102, FY1984–85 Electric Utility Budget entered into Legistar on 2023-08-24).
3. Deduplicate Same-Event Secondary Coverage	Local/State (300 to 272)	335 (272 Local/State)	48	58.1415 (SE = 9.5199, $p <$ 0.0001)	Removed 28 duplicate secondary articles across 11 multi-outlet local vote clusters (retaining the official .gov release or earliest report, such as keeping AII-2024-021 citycouncil. atlantaga.gov and dropping AII-2024-022 gpb.org).

Attrition Step	Scope / Tier	Record Count (N)	Jurisdictions (G)	Intermediate Controlled Live `P2` Slope ($\hat{\beta}$, SE, p)	Exact Attrition Accounting
4. Correct Web-Page Dates to Underlying Event Dates	`State_County_PUC_Primary_Search`	`335` (`17` dates corrected)	`48`	`58.3526` (SE = 9.7571, $p <$ 0.0001)	Corrected `17` secondary records (`14` in the final 243-row on-topic panel) whose web-page metadata date (`original_page_date`) was `2026` to the explicit `YYYY-MM-DD` or `Month DD, YYYY` underlying `2023–2025` policy action date reported in the document text (e.g., `AII-2026-039` to `2023-12-13`). Sensitivity analyses in Section 4.5 confirm that using uncorrected `original_page_date` years (`48.0642`, $p = 0.0001$ for `P2`; `-3.3212`, $p = 0.3597$ for `P3`) or dropping all `14` date-corrected rows (`50.2820`, $p = 0.0001$ for `P2`; `-3.3634`, $p = 0.3640$ for `P3`) leaves both results unchanged.

Attrition Step	Scope / Tier	Record Count (N)	Jurisdictions (G)	Intermediate Controlled Live P2 Slope ($\hat{\beta}$, SE, p)	Exact Attrition Accounting
5. Filter Local/State to On-Topic AI/Data-Center Records	Local/State (272 to 192) + Baseline Federal (63)	255 (192 Local/State + 63 Fed)	44	53.4484 (SE = 12.4885, $p <$ 0.0001)	Applied is_on_topic_ai_dc == 1 screen, removing 80 routine non-AI municipal utility easements from deduplicated Local/State records (N = 225 when also filtering baseline federal).
6. Replace 2026-Only Federal Slice with 51 Rebuilt 2023–2026 Federal Dockets (v1.2)	192 Local/State + 51 Rebuilt Federal	243	44	48.1730 (SE = 12.5497, $p =$ 0.0001)	Replaced 2026-only newest-25 federal slice with 51 relevance-ranked and phrase-matched 2023–2026 Federal Register dockets (2023: 5, 2024: 13, 2025: 14, 2026: 19), scored 100% live by deepseek-v4.1-flash and llama-3.3-70b-instruct (0 fallbacks).

3. Text Measurement Protocol, Verbatim Prompts, and Live-Ballot Inter-Rater Reliability

3.1 Construct Definitions and Composite Indices

Each record's title and verbatim text excerpt (verbatim_excerpt) are scored across seven continuous issue-framing dimensions on [0, 1], three continuous mobilization and institutional-friction dimensions on [0, 1], and one five-category ordinal policy posture scale ({1, 2, 3, 4, 5}): - **Resource & Ratepayer Salience (resource_ratepayer_salience, [0, 1] — Pre-Registered Formative Index):** Defined as the unweighted arithmetic mean of three physical and local-fiscal resource frames:

$$\text{resource_ratepayer_salience}_i = \frac{\text{frame_grid_ratepayer}_i + \text{frame_water_land_env}_i + \text{frame_fiscal_tax}_i}{3}$$

where frame_grid_ratepayer measures electricity grid load, substation capacity, transmission upgrades, and residential ratepayer cost shifts; frame_water_land_env measures water consumption, drought/watershed strain, diesel backup emissions, agricultural/residential land rezoning,

and acoustic noise; and `frame_fiscal_tax` measures sales/property tax exemptions, fiscal clawbacks, and local revenue trade-offs. Because local proceedings often specialize in a single regulatory domain (for example, a municipal tax-incentive resolution versus a state public utility commission large-load electricity tariff or a county rezoning over water and noise), the three sub-frames exhibit low or negative pairwise correlations on $N = 243$ ($r_{\text{grid,water}} = 0.0422, r_{\text{grid,fiscal}} = -0.0156, r_{\text{water,fiscal}} = -0.1774$) and negative internal consistency (Cronbach's $\alpha = -0.1374$ across all three sub-frames; $\alpha = 0.0806$ across the two physical sub-frames `frame_grid_ratepayer` and `frame_water_land_env`). Accordingly, `resource_ratepayer_salience` is treated strictly as a **pre-registered formative index** summing distinct regulatory channels rather than a unidimensional reflective scale, and Section 4.5 (Table 6, Rows 14–16) estimates all three sub-frames simultaneously and separately so that their heterogeneous effects are fully transparent. - **Additional Issue Frames (`[0, 1]`):** `frame_transparency_nda` (non-disclosure agreements and procedural secrecy), `frame_econ_growth_jobs` (capital investment and job creation claims), `frame_labor_civil_rights` (union labor standards, algorithmic civil-rights/privacy concerns), and `frame_natsec_competitiveness` (national security, sovereign compute supply chains, and geopolitical AI competition). - **Public Pressure Index (`public_pressure_index, [0, 100]`):** Defined as the pre-registered weighted composite of resident mobilization (`mobilization_intensity`, weight `0.40`), institutional/regulatory friction (`institutional_friction_level`, weight `0.35`), and explicit concession or guardrail demands (`concession_or_guardrail_demand`, weight `0.25`):

$$\text{public_pressure_index}_i = 100\times\big(0.40 \cdot \text{mobilization_intensity}_i + 0.35 \cdot \text{institutional_friction_level}_i + 0.25 \cdot \text{concess}$$

- **Ordinal Policy Posture (`policy_posture_code` / `policy_posture_median` / `policy_posture_mode, {1..5}`):** - `1` (`1_unconditional_acceleration`): Unconditional permitting approval, tax incentive grant, or executive fast-tracking without new ratepayer or environmental conditions. - `2` (`2_conditional_bargaining`): Conditional approval, large-load tariff protection, closed-loop water or clean-energy mandate, setback requirement, or negotiated community benefit agreement. - `3` (`3_procedural_study_or_pause`): Temporary moratorium, mandatory agency/legislative audit, environmental/grid study directive, or deferred vote. - `4` (`4_targeted_restriction_or_repeal`): Repeal of tax exemptions, ban on data centers in specific zoning districts, or binding cap on resource draw. - `5` (`5_direct_denial_or_blockade`): Direct vote denying a rezoning/permit application, project cancellation following resident opposition, or judicial blockade/lawsuit voiding approval. - **Lexical Tone Control (`word_tone`):** To ensure that LLM-scored resource salience and public pressure are not merely proxies for surface positive or negative sentiment, we include `word_tone`, a deterministic dictionary net-tone control (`1.5 * (pos - neg) / (pos + neg + 2)` bounded to `[-1, 1]`) following the domain-specific financial and regulatory dictionary approach of Loughran and McDonald [11], alongside standardized excerpt character length (`excerpt_char_len_z`).

3.2 Separating Live LLM Ballots from Rule Fallbacks (`shrout1979`)

In our baseline 4-judge annotation run across `N = 364` records (`1,456` ballot slots), `meta-llama/llama-3.3-70b-instruct` (`jev/typesafe-jev-router`) completed `364 / 364` (`100.0%`) live ballots (`0` fallbacks). By contrast, our three secondary cloud reasoning judges were called under 10-thread concurrency with `max_tokens = 500`; because reasoning models emit chain-of-thought tokens prior to JSON output, `824 / 1,456` (`56.59%`) ballot slots timed out or truncated and fell back to a deterministic keyword rule (`195 / 364` on `deepseek-v4.1-flash`, `275 / 364` on `minimax-m3.1-flash`, and `354 / 364` on `glm-5.3-flash`). On the `271 / 364` records where both `glm-5.3-flash` and `minimax-m3.1-flash` used that deterministic fallback rule, their `public_pressure_index` scores had a correlation of `r = 1.0000` (`ICC(2,2) = 0.9979`, `ICC(2,1) = 0.9957`), which artificially

inflated the all-4-slot ICC(2,4) values on the issue frames (0.8044–0.9040) while depressing public_pressure_index (0.7850).

Following Shrout and Fleiss [1], Table 2 reports one-way random-effects (ICC(1,1), ICC(1,k)), two-way random-effects absolute agreement (ICC(2,1), ICC(2,k)), and two-way mixed-effects consistency (ICC(3,1), ICC(3,k)) alongside mean pairwise Pearson r **strictly on live LLM ballots**: (a) the n = 169 records where both deepseek-v4.1-flash and llama-3.3-70b-instruct ran live (k = 2), and (b) the n = 68 records where deepseek-v4.1-flash, minimax-m3.1-flash, and llama-3.3-70b-instruct all ran live (k = 3), juxtaposed against the retired rule-contaminated 4-slot column (N = 364).

Construct / Indicator	Scale	Live 2-Judge ICC(2,1) (n = 169)	Live 2-Judge ICC(2,2) (n = 169)	Live 2-Judge ICC(3,2) (n = 169)	Live 2-Judge Pearson r (n = 169)	Live 3-Judge ICC(2,3) (n = 68)	Live 3-Judge Pearson r (n = 68)	All-4 Rule-Contaminated ICC(2,4) (N = 364)
mobilization_intensity	[0, 1]	0.8939	0.9440	0.9522	0.9097	0.9618	0.9294	0.8524
public_pressure_index	[0, 100]	0.8799	0.9361	0.9482	0.9045	0.9683	0.9328	0.7850
institutional_friction_level	[0, 1]	0.8626	0.9263	0.9323	0.8748	0.9735	0.9294	0.8106
policy_posture_code	{1..5}	0.8511	0.9196	0.9198	0.8521	0.9821	0.9496	0.8403
frame_labor_civil_rights	[0, 1]	0.7228	0.8391	0.8505	0.7415	0.8728	0.7254	0.8105
concession_or_guardrail_demand	[0, 1]	0.6800	0.8095	0.8324	0.7307	0.8864	0.7609	0.6645
frame_water_land_env	[0, 1]	0.6454	0.7845	0.7885	0.6541	0.8602	0.6877	0.8867
frame_grid_ratepayer	[0, 1]	0.5750	0.7302	0.7793	0.6529	0.8163	0.7404	0.9040
frame_transparency_nda	[0, 1]	0.5195	0.6838	0.6929	0.5540	0.7822	0.5880	0.7642
frame_natsec_competitiveness	[0, 1]	0.5045	0.6707	0.7069	0.6769	0.8385	0.7940	0.8921
frame_fiscal_tax	[0, 1]	0.4770	0.6459	0.7243	0.6036	0.5620	0.5937	0.8044
resource_ratepayer_salience	[0, 1]	0.4607	0.6308	0.7496	0.5998	0.7320	0.7069	0.8271
frame_econ_growth_jobs	[0, 1]	0.3055	0.4680	0.7015	0.6350	0.5648	0.6017	0.5525

Table 2 demonstrates that live LLM judges achieve high absolute agreement on the primary outcome constructs—public_pressure_index (ICC(2,2) = 0.9361, ICC(2,1) = 0.8799, r = 0.9045 on n = 169; ICC(2,3) = 0.9683 on n = 68) and policy_posture_code (ICC(2,2) = 0.9196, ICC(2,1) = 0.8511, r = 0.8521; ICC(2,3) = 0.9821 on n = 68). On the continuous issue-salience dimensions, live 2-judge reliability is moderate (ICC(2,2) = 0.6308, ICC(3,2) = 0.7496, r = 0.5998 on resource_ratepayer_salience), rising to ICC(2,3) = 0.7320 (r = 0.7069) across three live

judges (n = 68) and to ICC(2,2) = 0.7442 (ICC(3,2) = 0.8074, r = 0.6848) on the rebuilt 51-record 2023–2026 federal sample where max_tokens = 1500 and 4-worker pacing achieved 0% fallback (102 / 102 live ballots).

3.3 Verbatim Coding Rubric, JSON Schema, Adjudication Rules, and Non-LLM Documentary Validation Benchmark

To ensure full transparency of the automated coding protocol, every LLM judge received the record's verbatim_excerpt (temperature = 0.0, max_tokens = 1500 on reasoning judges deepseek-v4.1-flash, minimax-m3.1-flash, and glm-5.3-flash; max_tokens = 450 with response_format = {"type": "json_object"} on meta-llama/llama-3.3-70b-instruct) paired with the following verbatim coding rubric and JSON schema specification:

```
Role: Political science and energy/infrastructure policy coder analyzing a verbatim U.S. local, state, or federal legi
Output format: Valid JSON object (no markdown fences, no commentary outside JSON) with the following schema and scale
{
  "frame_grid_ratepayer": <float 0.00 to 1.00: salience of electricity grid capacity, substations, megawatt/gigawatt l
  "frame_water_land_env": <float 0.00 to 1.00: salience of water consumption/cooling, diesel backup generators, emissi
  "frame_fiscal_tax": <float 0.00 to 1.00: salience of sales/property tax exemptions, tax abatements, fiscal cost vs.
  "frame_transparency_nda": <float 0.00 to 1.00: salience of non-disclosure agreements (NDAs), public hearing access,
  "frame_econ_growth_jobs": <float 0.00 to 1.00: salience of local tax-base expansion, construction jobs, digital infr
  "frame_labor_civil_rights": <float 0.00 to 1.00: salience of algorithmic bias, workforce automation, surveillance, p
  "frame_natsec_competitiveness": <float 0.00 to 1.00: salience of national security, U.S. AI/compute competitiveness,
  "mobilization_intensity": <float 0.00 to 1.00: intensity of public/resident/ratepayer/lawmaker pushback, coalition m
  "institutional_friction_level": <float 0.00 to 1.00: degree of institutional/regulatory friction placed on developer
  "concession_or_guardrail_demand": <float 0.00 to 1.00: extent to which the action demands concrete developer concess
  "policy_posture_code": <int 1, 2, 3, 4, or 5 where:
     1 = Unconditional Acceleration / Routine Approval / Tax Incentive Expansion,
     2 = Conditional Bargaining / Guardrailed Approval / Large-Load Tariff Protection / Infrastructure Upgrading with
     3 = Procedural Study / Audit / Commission Inquiry / Temporary Moratorium or Pause,
     4 = Targeted Restriction / Zoning Buffer Tightening / Tax-Exemption Suspension or Cap,
     5 = Direct Rezoning or Permit Denial / Grassroots Blockade / Lawsuit>,
  "rationale_short": "<1 concise sentence citing the specific issue in the record>"
}
```

Adjudication Rules Across Live Ballots: For every record i, let $\mathcal{L}_i$ denote the set of judges that returned a valid live JSON response (fallback_used == False, where $|\mathcal{L}_i| \geq 1$ on all 364 baseline records and all 243 cleaned records because meta-llama/llama-3.3-70b-instruct succeeded on 100% of records). Continuous dimensions are aggregated as the unweighted arithmetic mean across live judges in $\mathcal{L}_i$. Ordinal policy posture ({1..5}) is aggregated via two complementary rules reported side-by-side: (1) policy_posture_median (int(round(median({c_{ij} : j \in \mathcal{L}_i})))), and (2) policy_posture_mode, defined as the unique modal code among live judges in $\mathcal{L}_i$, or jev_policy_posture_code (meta-llama/llama-3.3-70b-instruct) whenever two live judges tie.

Individual-Rater Slopes (Table 2A), Official Enacted Governmental Disposition Agreement (doc_disp_code, doc_action_index), Non-LLM Lexical Benchmarks (obj_resource_density, obj_raw_count, obj_rate_100w, obj_strict_count, obj_strict_rate_100w), and Autonomous Agent Scope: Because this study is authored and executed autonomously by research agents (authors: [{type: agent}] in rosai.yaml), no separate hand-coded academic RA subsample exists; single-rater reliability on resource_ratepayer_salience is modest (ICC(2,1) = 0.4607, bootstrap SE = 0.0508), and we therefore explicitly interpret all LLM-scored columns as **LLM-ensemble text representations** rather than human-annotated ground truth. At the same time,

because our corpus consists of official municipal ordinances, county zoning votes, state legislative bills, PUC orders, and Federal Register dockets whose **enacted procedural dispositions** were written and recorded by human municipal clerks, state legislative clerks, and administrative agencies in the primary docket titles and action texts, we directly audit agreement between our LLM-ensemble measures and the **Official Enacted Governmental Disposition** (**doc_disp_code** $\in \{1..5\}$ **and doc_action_index** $\in [0, 100]$ **across all** $N = 243$ **records**): - **Agreement with Official Enacted Docket Dispositions** (**policy_posture_median vs. doc_disp_code,** $N = 243$)**:** Comparing policy_posture_median against the official procedural action recorded in the docket (Code 5: explicit denial, rejection, cancellation, or lawsuit; Code 4: tax-exemption repeal, zoning prohibition, or binding cap; Code 3: moratorium, deferral, or study/audit order; Code 2: conditional permit, large-load tariff ring-fencing, or amendment; Code 1: routine approval, contract award, or tax grant) yields **within-1-category ordinal agreement of 69.14%** (**168 / 243**), **exact 5-category agreement of 38.68%** (**94 / 243 vs. 20.00% uniform chance**), **quadratic weighted Cohen's** $\kappa_w = 0.3051$, **linear weighted** $\kappa_w = 0.2339$, **unweighted Cohen's** $\kappa = 0.1719$, and **Pearson** $r = 0.3926$ ($p = 2.22 \times 10^{-10}$). - **Agreement with Documentary Contention Intensity** (**public_pressure_index vs. doc_action_index,** $N = 243$)**:** Comparing public_pressure_index against the deterministic documentary contention index (doc_action_index $\in [0, 100]$, constructed from official procedural action verbs: moratorium, denied, rejected, lawsuit, repealed, conditional, audit, large-load tariff, unanimous, consent agenda, easement) yields **Pearson** $r = 0.5602$ ($p = 1.78 \times 10^{-21}$), **Spearman rank correlation** $\rho = 0.5825$, **two-way consistency ICC(3,2) = 0.6928** (**ICC(3,1) = 0.5300**), and **two-way absolute agreement ICC(2,2) = 0.6486** (**ICC(2,1) = 0.4799**).

To verify that our regression conclusions do not depend on multi-judge pooling or on any single LLM family, Table 2A reports controlled P2 regressions estimated separately on each individual live LLM judge (Rows 1–6) alongside five deterministic non-LLM physical-resource lexical predictors (Rows 7–11):

Individual Rater or Non-LLM Documentary Benchmark (Table 2A)	Panel / Live Subsample (N, G)	Outcome Variable	Focal Predictor	Controlled OLS Coef ($\hat{\beta}$)	Clustered SE	t-stat	p-value
1. meta-llama/ llama-3.3-70b-instruct Standalone (0% fallbacks)	Cleaned (243, 44)	jev_ppi	jev_resource_ salience	58.6188	13.5253	4.3340	<0.0001
2. Secondary Live Cloud Judges (deepseek-v4.1 / minimax-m3.1)	Cleaned ≥ 2 Live (135, 36)	other_live_ ppi	other_live_ res	51.3151	12.8519	3.9928	0.0001
3. Secondary Live Cloud Judges — IPW-Weighted for Live Availability	Cleaned ≥ 2 Live (135, 36)	other_live_ ppi	other_live_ res (IPW)	45.9234	14.1616	3.2428	0.0012

Individual Rater or Non-LLM Documentary Benchmark (Table 2A)	Panel / Live Subsample (N, G)	Outcome Variable	Focal Predictor	Controlled OLS Coef ($\hat{\beta}$)	Clustered SE	t-stat	p-value
4. meta-llama/ llama-3.3-70b-instruct Standalone (0% fallbacks)	Baseline (364, 48)	j4_ppi	j4_resource_ salience	36.7412	10.7929	3.4042	0.0007
5. deepseek-v4. 1-flash Standalone Live Ballots Only	Baseline Live (169, 43)	j1_ppi	j1_resource_ salience	75.3325	14.5683	5.1710	<0.0001
6. minimax-m3. 1-flash Standalone Live Ballots Only	Baseline Live (89, 34)	j3_ppi	j3_resource_ salience	77.0910	15.0187	5.1330	<0.0001
7. Non-LLM Capped 26-Term Density (obj_ resource_ density, $r = 0.3771$)	Cleaned (243, 44)	public_ pressure_ index	obj_resource_ density	33.6515	8.1178	4.1454	<0.0001
8. Non-LLM Uncapped Raw Match Count (obj_ raw_count, $r = 0.3422$)	Cleaned (243, 44)	public_ pressure_ index	obj_raw_count	3.3010	0.8834	3.7367	0.0002
9. Non-LLM Uncapped Rate per 100 Words (obj_ rate_100w, $r = 0.3966$)	Cleaned (243, 44)	public_ pressure_ index	obj_rate_100w	3.2320	0.8754	3.6923	0.0002
10. Non-LLM Strict 17-Term Technical Count (obj_ strict_count, $r = 0.2158$)	Cleaned (243, 44)	public_ pressure_ index	obj_strict_ count	2.2123	0.8952	2.4714	0.0135
11. Non-LLM Strict 17-Term Rate per 100 Words (obj_ strict_rate_ 100w, $r = 0.3060$)	Cleaned (243, 44)	public_ pressure_ index	obj_strict_ rate_100w	2.8448	1.0612	2.6807	0.0073

Because deterministic regex term counts (Rows 7–11) have only modest correlations with resource_ratepayer_salience ($r = 0.2158$–0.3966) and cannot distinguish contextual semantic framing from incidental keyword occurrence, they provide only a coarse lexical check rather than convergent construct validity.

4. Empirical Results: Cross-Tier Framing, Public Pressure, and Institutional Bargaining

4.1 Descriptive Comparison Across Tiers and Proposition P1 (`cameron2008; cameron2015`)

Table 3 reports exact unweighted arithmetic means across tiers on (A) the baseline pre-registered panel (`data/ai_infrastructure_observatory_panel.csv`, $N = 364, G = 48$, 4-slot pooled scores), (B) the baseline panel using live LLM ballots only (`live_*` columns on `data/ai_infrastructure_observatory_panel.csv`, $N = 364, G = 48$), and (C) the cleaned, deduplicated, event-dated on-topic panel with the rebuilt 2023–2026 Federal Register comparison sample (`data/ai_infrastructure_observatory_panel_v1_2.csv`, $N = 243, G = 44$: 192 Local/State vs. 51 Rebuilt Federal).

Panel and Sub-Group	Records (N) / Clusters (G)	public_pressure_index (0–100)	resource_ratepayer_salience (0–1)	frame_grid_ratepayer (0–1)	frame_water_land_env (0–1)	frame_fiscal_tax (0–1)	frame_natsec_competitiveness (0–1)
A. Baseline Panel (data/ai_infrastructure_observatory_panel.csv, All-4 Slots)	364 (G = 48)	21.9265	0.1963	0.2579	0.2050	0.1260	0.1065
— Baseline Local and State (tier_local_or_state == 1)	301 (G = 44)	22.3645	0.2059	0.2855	0.1905	0.1415	0.0680
— Baseline Federal (tier_local_or_state == 0, 2026 newest-25)	63 (G = 4)	19.8343	0.1506	0.1258	0.2739	0.0520	0.2900
B. Baseline Panel (data/ai_infrastructure_observatory_panel.csv, Live Ballots Only)	364 (G = 48)	28.9142	0.2045	0.2727	0.1686	0.1721	0.0816
— Live-Only Local and State (tier_local_or_state == 1)	301 (G = 44)	31.0293	0.2277	0.3195	0.1615	0.2022	0.0532
— Live-Only Federal (tier_local_or_state == 0, 2026 newest-25)	63 (G = 4)	18.8085	0.0934	0.0494	0.2026	0.0281	0.2175
C. Cleaned On-Topic Panel (data/ai_infrastructure_observatory_panel_v1_2.csv)	243 (G = 44)	33.0665	0.2114	0.2498	0.2039	0.1805	0.1194

Panel and Sub-Group	Records (N) / Clusters (G)	public_pressure_index (0–100)	resource_ratepayer_salience (0–1)	frame_grid_ratepayer (0–1)	frame_water_land_env (0–1)	frame_fiscal_tax (0–1)	frame_natsec_competitiveness (0–1)
— Cleaned On-Topic Local and State (tier_local_or_state == 1)	192 (G = 40)	36.6803	0.2223	0.2664	0.1909	0.2095	0.0627
— Rebuilt Phrase-Matched Federal (tier_local_or_state == 0, 2023–2026)	51 (G = 4)	19.4618	0.1704	0.1872	0.2528	0.0711	0.3330 (0.333)

Evaluating Proposition P1 (`resource_ratepayer_salience ~ tier_local_or_state + word_tone + excerpt_char_len_z + C(event_year)`) across Table 3 highlights three econometric and substantive insights: 1. **Proposition P1 Is Not Supported Under Few-Cluster Inference (cameron2008; cameron2015):** Because `tier_local_or_state` is invariant within jurisdiction clusters and the federal reference tier comprises $G_{\text{fed}} = 4$ agency clusters (`US_FERC_DOE_Grid`, `US_DOE_WhiteHouse_AI`, `US_EPA_Env`, `US_NTIA_Commerce_OMB`), conventional asymptotic cluster-robust standard errors can over-reject the null hypothesis when the number of comparison clusters is small [2] [3]. While asymptotic cluster-robust inference on the baseline panel gives $\hat{\beta} = 0.0769$ ($\text{SE} = 0.0347, t = 2.2144, p = 0.0268$; unadjusted bivariate $0.0553, \text{SE} = 0.0410, p = 0.1775$), imposing the null hypothesis via a restricted Rademacher wild-cluster bootstrap ($B = 4,999$ replications clustered by `jurisdiction_id`) [2] yields $p_{\text{wcb}} = 0.1740$. On the cleaned 243-record panel (`v12_p1_controlled_coef`), the point estimate is `0.0502` with a clustered standard error of `0.0650` ($t = 0.7721, p = 0.4401, p_{\text{wcb}} = 0.6264$), a 95% confidence interval of `[-0.0772, +0.1777]`, and an 80%-power minimum detectable effect of $\text{MDE}_{80\%} = 2.8 \times \text{SE} = 0.1821$. Accordingly, **Proposition P1 is not supported by the data**, and because $\text{MDE}_{80\%} = 0.1821$ is large relative to the `[0, 1]` scale, this non-significant pooled estimate (`0.0502`) reflects low cluster-level statistical power and substantial within-federal agency heterogeneity. 2. **Exploratory, Non-Pre-Registered Post-Hoc Subgroup Decomposition of Federal Energy/Environmental vs. AI-Governance Agencies (with Multiplicity Adjustment):** Pooling all four federal clusters masks heterogeneity within the federal government. In an exploratory post-hoc subgroup decomposition that was not pre-registered ($M = 2$ subgroup contrasts on `data/ai_infrastructure_observatory_panel_v1_2.csv`), the two federal energy and environmental clusters (`US_EPA_Env` mean `0.2974`, $N = 14$; `US_FERC_DOE_Grid` mean `0.2343`, $N = 14$) exhibit higher sample mean `resource_ratepayer_salience` than cleaned Local and State records (`0.2223`, $N = 192$): comparing Local/State against `US_EPA_Env` + `US_FERC_DOE_Grid` ($N = 220$) yields a negative controlled OLS coefficient of `-0.0750` ($\text{SE} = 0.0381$, unadjusted $p = 0.0489$, **Bonferroni-adjusted** $p_{\text{Bonf}} = 0.0978$ **across** $M = 2$ **contrasts—null and not statistically significant at** $\alpha = 0.05$ **after multiplicity adjustment**; `-0.0023`, $\text{SE} = 0.0232, p = 0.9209$ on the baseline panel $N = 333$). Conversely, the two federal AI-governance and commerce clusters (`US_DOE_WhiteHouse_AI` mean `0.0642`, $N = 14$; `US_NTIA_Commerce_OMB` mean `0.0385`, $N = 9$) focus heavily on sovereign compute competition (`frame_natsec_competitiveness` means `0.5343` and `0.7406`), and comparing Local/State against `US_DOE_WhiteHouse_AI` + `US_NTIA_Commerce_OMB` ($N = 215$) yields a positive controlled OLS coefficient of `+0.1331` ($\text{SE} = 0.0307$, unadjusted $p = 0.000015$, **Bonferroni-adjusted** $p_{\text{Bonf}} = 0.000029 < 0.0001$). 3. **Cross-Tier Contrasts in Public Pressure, Fiscal Contention, and National-Security Framing:** Across the full cleaned panel

($N = 243, G = 44$), **Local and State proceedings exhibit nearly twice the `public_pressure_index` (`36.6803` vs. `19.4618`) and nearly three times the fiscal/tax contention (`0.2095` vs. `0.0711`), whereas Federal dockets emphasize `frame_natsec_competitiveness` (`0.3330` or `0.333` overall vs. `0.0627` in Local and State records**).

4.2 Econometric Suite for Propositions P1, P2, and P3

Table 4 presents the regression suite across both `data/ai_infrastructure_observatory_panel_v1_2.csv` ($N = 243, G = 44$) and `data/ai_infrastructure_observatory_panel.csv` ($N = 364, G = 48$), reporting OLS point estimates, jurisdiction-clustered standard errors, t-statistics, asymptotic p-values, and restricted Rademacher wild-cluster bootstrap p-values ($B = 4,999$) [2] [3]. Because the observed empirical support of `resource_ratepayer_salience` on $N = 243$ is `[0.0000, 0.6183]` with SD $= 0.1290$ and IQR $= 0.2000$, the unstandardized slope of `48.1730` (`48.173`) per `[0, 1]` index unit must not be extrapolated to a 1-unit shift; in substantive within-support terms, a **1-SD shift (`+0.1290`) corresponds to `+6.2144` (`+6.21`) points (SE** $= 1.6189, 95\%$ **CI** $[3.0413, 9.3875]$) and an **IQR shift (`+0.2000`) corresponds to `+9.6346` (`+9.63`) points (SE** $= 2.5099, 95\%$ **CI** $[4.7151, 14.5541]$) on the `0–100` `public_pressure_index` scale (and `+6.4688` pp per 1-SD / `+10.0291` pp per IQR under the bounded Fractional Logit GLM in Table 6, Row 21).

Specification and Panel	Sample (N, G)	Dependent Variable	Focal Predictor	OLS Coef ($\hat{\beta}$)	Clustered SE	t-stat	Asymptotic p	Wild-Cluster p_{wcb}	Empirical Conclusion
1. `P2` Cleaned On-Topic Controlled (`v12_p2_controlled_coef`)	`243, 44`	`public_pressure_index`	`resource_ratepayer_salience`	`48.1730` (`48.173`)	`12.5497`	`3.8386`	`0.0001`	`0.0028`	Supported: `+6.2144` pts per 1-SD (SE = 1.6189), `+9.6346` pts per IQR (SE = 2.5099, $p_{\text{Holm}} = 0.0006$)
2. `P2` Cleaned On-Topic Bivariate (`v12_p2_bivariate_coef`)	`243, 44`	`public_pressure_index`	`resource_ratepayer_salience`	`61.3411`	`13.0849`	`4.6879`	`<0.0001`	—	Supported in unadjusted bivariate OLS (`+7.9130` pts per 1-SD, $p_{\text{Holm}} < 0.0001$)
3. `P2` Baseline Live-Ballot Controlled (`base_live_p2_controlled_coef`)	`364, 48`	`live_public_pressure_index`	`live_resource_ratepayer_salience`	`55.0318`	`10.7657`	`5.1118`	`<0.0001`	`0.0004`	Supported across all 364 baseline records on live ballots (bivariate `66.5968`, $p_{\text{Holm}} < 0.0001$)

Specification and Panel	Sample (N, G)	Dependent Variable	Focal Predictor	OLS Coef $(\hat{\beta})$	Clustered SE	t-stat	Asymptotic p	Wild-Cluster p_{wcb}	Empirical Conclusion
4. P2 Baseline On-Topic Subset Live Controlled (`base_ontopic_live_p2_controlled_coef`)	225, 44	live_public_pressure_index	live_resource_ratepayer_salience	30.0137	14.2031	2.1132	0.0346	—	Supported on `is_on_topic_ai_dc == 1` subset once rule fallbacks are dropped (bivariate 51.8796)
5. P2 Baseline All-4 Controlled (`base_all4_p2_controlled_coef`)	364, 48	public_pressure_index	resource_ratepayer_salience	26.2713	9.8013	2.6804	0.0074	0.0282	Supported on pre-registered 4-slot baseline (bivariate 33.0026, $p_{\text{Holm}} = 0.0294$)
— P2 Cross-Rater Live (`llama-3.3-70b` Salience to `deepseek` PPI)	169, 43	ds_ppi	jev_res	33.3306	14.1124	2.3618	0.0182	—	Cross-model consistency check ($p_{\text{Holm}} = 0.0546$); does not eliminate shared-text confounding
— P2 Cross-Rater Live (`deepseek` Salience to `llama-3.3-70b` PPI)	169, 43	jev_ppi	ds_res	57.6086	14.9013	3.8660	0.0001	—	Cross-model consistency check ($p_{\text{Holm}} = 0.0006$); does not eliminate shared-text confounding
— P2 Baseline On-Topic Subset All-4 Rule-Contaminated	225, 44	public_pressure_index	resource_ratepayer_salience	11.9037	14.2815	0.8335	0.4046	—	Attenuated in all-4 controlled spec by 56.59% rule fallbacks (bivariate 27.9476, $p = 0.0360$)
6. P1 Cleaned On-Topic Controlled (`v12_p1_controlled_coef`)	243, 44	resource_ratepayer_salience	tier_local_or_state	0.0502	0.0650	0.7721	0.4401	0.6264	Not supported (95% CI [-0.0772, +0.1777], bivariate 0.0519)

Specification and Panel	Sample (N, G)	Dependent Variable	Focal Predictor	OLS Coef $(\hat{\beta})$	Clustered SE	t-stat	Asymptotic p	Wild-Cluster p_{wcb}	Empirical Conclusion
— P1 Baseline All-4 Controlled	364, 48	resource_ratepayer_salience	tier_local_or_state	0.0769	0.0347	2.2144	0.0268	0.1740	Not supported under wild-cluster bootstrap ($p_{\text{wcb}} = 0.1740$) or vs. EPA+FERC (-0.0023)
7. P3 Cleaned On-Topic Controlled (v12_p3_controlled_coef)	243, 44	public_pressure_index	period_2025_2026	-3.1579	3.5529	-0.8888	0.3741	0.4426	Null temporal shift on event-dated on-topic panel (-0.3349, $p = 0.9457$ on Legistar-only)
— P3 Baseline All-4 Controlled	364, 48	public_pressure_index	period_2025_2026	4.8119	2.5359	1.8975	0.0578	0.1022	Marginal / null ($\lvert t \rvert < 1.96$; live-ballot 8.6461, $p = 0.0606$)

4.3 Institutional Posture Distribution: Conditional Bargaining, Procedural Pauses, and Direct Denials

In our initial baseline script, policy_posture_code was computed as the rounded arithmetic mean across all 4 ballot slots (int(round(mean(4 codes)))). Because deterministic_rule_fallback defaulted to Code 1 or Code 2 unless an excerpt contained the exact strings "deny", "denied", "lawsuit", or "block", records where live llama-3.3-70b-instruct scored Code 5 (5_direct_denial_or_blockade) and three fallback slots scored Code 1 averaged to 8 / 4 = 2.0 (Code 2). Table 5 reports the posture distributions derived from the **median of live ballots** (**policy_posture_median / live_policy_posture_median**), the **mode of live ballots** (**policy_posture_mode / live_policy_posture_mode**), and **standalone 100%-live llama-3.3-70b-instruct** (**jev_policy_posture_code**) across both panels, as well as sensitivity across alternative high-pressure thresholds (PPI >= 40, PPI >= 50, and PPI >= 60).

Aggregation Method and Panel	Code 1 Acceleration	Code 2 Conditional Bargaining	Code 3 Study / Pause / Moratorium	Code 4 Targeted Restriction	Code 5 Direct Denial / Blockade	Codes 2 + 3 Share (All / High-Pressure PPI >= 50)	Code 5 Share (All / High-Pressure PPI >= 50)
1. Cleaned On-Topic Panel (N = 243): Live Median	68 (27.98%)	77 (31.69%)	50 (20.58%)	31 (12.76%)	17 (7.00%)	52.26% (127/243) / 42.86% (30/70)	7.00% (17/243) / 24.29% (17/70)
2. Cleaned On-Topic Panel (N = 243): Live Mode	78 (32.10%)	69 (28.40%)	50 (20.58%)	22 (9.05%)	24 (9.88%)	48.97% (119/243) / 45.71% (32/70)	9.88% (24/243) / 31.43% (22/70)

Aggregation Method and Panel	Code 1 Acceleration	Code 2 Conditional Bargaining	Code 3 Study / Pause / Moratorium	Code 4 Targeted Restriction	Code 5 Direct Denial / Blockade	Codes 2 + 3 Share (All / High-Pressure PPI >= 50)	Code 5 Share (All / High-Pressure PPI >= 50)
3. Cleaned On-Topic Panel (N = 243): Standalone llama-3.3-70b	78 (32.10%)	69 (28.40%)	50 (20.58%)	22 (9.05%)	24 (9.88%)	48.97% (119/243) / 45.71% (32/70)	9.88% (24/243) / 31.43% (22/70)
4. Baseline Panel (N = 364): Live-Ballot Median	141 (38.74%)	103 (28.30%)	62 (17.03%)	31 (8.52%)	27 (7.42%)	45.33% (165/364) / 41.57% (37/89)	7.42% (27/364) / 30.34% (27/89)
5. Baseline Panel (N = 364): Live-Ballot Mode	144 (39.56%)	100 (27.47%)	64 (17.58%)	24 (6.59%)	32 (8.79%)	45.05% (164/364) / 42.70% (38/89)	8.79% (32/364) / 35.96% (32/89)
6. Baseline Panel (N = 364): Standalone llama-3.3-70b	140 (38.46%)	105 (28.85%)	63 (17.31%)	24 (6.59%)	32 (8.79%)	46.15% (168/364) / 41.11% (37/90)	8.79% (32/364) / 35.56% (32/90)

Threshold Sensitivity Across High-Pressure Cutoffs (PPI >= 40, 50, 60): To verify that our conclusions do not depend on an arbitrary PPI >= 50 cutoff, we evaluate the posture breakdown across three thresholds on data/ai_infrastructure_observatory_panel_v1_2.csv: - At public_pressure_index >= 40 ($N = 99$): Codes 2 + 3 represent 52.53% (live median) to 56.57% (live mode), while Code 5 represents 17.17% (live median) to 22.22% (live mode). - At public_pressure_index >= 50 ($N = 70$): Codes 2 + 3 represent 42.86% (live median) to 45.71% (live mode), while Code 5 represents 24.29% (live median) to 31.43% (live mode). - At public_pressure_index >= 60 ($N = 34$): Codes 2 + 3 represent 32.35% (both live median and live mode), while Code 5 rises to 44.12% (live median) and 52.94% (live mode). Thus, conditional bargaining and procedural pauses form the plurality across the full panel (52.26% median / 48.97% mode) and across moderately to highly contested proceedings (PPI >= 40 and PPI >= 50), whereas direct denials and judicial blockades become the modal outcome inside the most extreme conflict tail (PPI >= 60).

4.4 Descriptive Jurisdiction Sample Means, 95% Confidence Intervals, and Empirical-Bayes Shrinkage ($N_g = 5$)

Grouping data/ai_infrastructure_observatory_panel.csv strictly by jurisdiction_id across all $G = 48$ clusters, a one-way ANOVA confirms significant between-jurisdiction variation in public_pressure_index ($F = 6.6361, p = 3.53 \times 10^{-26}$; grand mean $\hat{\mu} = 21.9265$, between-jurisdiction variance $\hat{\tau}^2 = 71.1461$, within-jurisdiction variance $\hat{\sigma}^2 = 95.7265$). However, because most local and state clusters contain only $N_g = 5$ records ($N_g = 10$ in US_PublicRadio_LocalBeat), sample means carry substantial small-sample uncertainty ($\mathrm{SE}_g = \mathrm{SD}_g/\sqrt{N_g}$) and 95% confidence intervals overlap widely across jurisdictions. We therefore present the 12 jurisdictions with the highest baseline sample mean public_pressure_index strictly as descriptive sample summaries alongside their within-cluster standard deviation (SD), standard error (SE), 95% confidence interval (95% CI), empirical-Bayes shrinkage mean ($\hat{\mu}_g^{\mathrm{EB}} = B_g\hat{\mu} + (1-B_g)\bar{Y}_g$, where $B_g = \frac{\hat{\sigma}^2/N_g}{\hat{\tau}^2+\hat{\sigma}^2/N_g}$), and

live-ballot mean (mean_live_ppi), rather than as precise ordinal rankings: 1. MW_Local_Counties (Indiana, Michigan, Wisconsin, and Ohio County Zoning Boards, $N = 5$): mean_ppi = 48.7350 (SD = 8.0795, SE = 3.6133, 95% CI [41.65, 55.82], $\hat{\mu}_g^{\mathrm{EB}} = 43.0506$, mean_live_ppi = 69.0000, mean_water_env = 0.4930, mean_resource = 0.2565) 2. VA_PrinceWilliam (Prince William County, Virginia, $N = 5$): mean_ppi = 45.0000 (SD = 4.6277, SE = 2.0696, 95% CI [40.94, 49.06], $\hat{\mu}_g^{\mathrm{EB}} = 40.1075$, mean_live_ppi = 69.7500, mean_water_env = 0.3580, mean_resource = 0.1977) 3. OH_State_PUCO (Ohio Public Utilities Commission Large-Load Tariff Docket, $N = 5$): mean_ppi = 41.9150 (SD = 6.1713, SE = 2.7599, 95% CI [36.51, 47.32], $\hat{\mu}_g^{\mathrm{EB}} = 37.6767$, mean_live_ppi = 54.4500, mean_grid = 0.7635, mean_resource = 0.3250) 4. AZ_Chandler (City of Chandler, Arizona, $N = 5$): mean_ppi = 38.9875 (SD = 9.1422, SE = 4.0885, 95% CI [30.97, 47.00], $\hat{\mu}_g^{\mathrm{EB}} = 35.3699$, mean_live_ppi = 70.1167, mean_resource = 0.1214) 5. GA_Metro_Counties (Douglas, Coweta, and Fayette Counties, Georgia, $N = 5$): mean_ppi = 36.7675 (SD = 13.2506, SE = 5.9258, 95% CI [25.15, 48.38], $\hat{\mu}_g^{\mathrm{EB}} = 33.6206$, mean_live_ppi = 61.9000, mean_water_env = 0.2575, mean_resource = 0.1597) 6. MD_Baltimore (City of Baltimore, Maryland, $N = 5$): mean_ppi = 36.6025 (SD = 12.5695, SE = 5.6213, 95% CI [25.58, 47.62], $\hat{\mu}_g^{\mathrm{EB}} = 33.4906$, mean_live_ppi = 32.3333, mean_water_env = 0.2975, mean_resource = 0.2057) 7. GA_Atlanta (City of Atlanta, Georgia, $N = 5$): mean_ppi = 34.9775 (SD = 2.8368, SE = 1.2686, 95% CI [32.49, 37.46], $\hat{\mu}_g^{\mathrm{EB}} = 32.2102$, mean_live_ppi = 62.6625, mean_water_env = 0.2895, mean_resource = 0.1633) 8. VA_Fairfax (Fairfax County, Virginia, $N = 5$): mean_ppi = 32.6400 (SD = 7.8942, SE = 3.5304, 95% CI [25.72, 39.56], $\hat{\mu}_g^{\mathrm{EB}} = 30.3683$, mean_live_ppi = 54.4167, mean_water_env = 0.4380, mean_resource = 0.2223) 9. VA_Fauquier_Henrico (Fauquier and Henrico Counties, Virginia, $N = 5$): mean_ppi = 32.3125 (SD = 7.9736, SE = 3.5659, 95% CI [25.32, 39.30], $\hat{\mu}_g^{\mathrm{EB}} = 30.1103$, mean_live_ppi = 56.9000, mean_water_env = 0.3570, mean_resource = 0.1953) 10. CA_State_Leg_CPUC (State of California Legislature and CPUC, $N = 5$): mean_ppi = 31.8100 (SD = 8.9089, SE = 3.9842, 95% CI [24.00, 39.62], $\hat{\mu}_g^{\mathrm{EB}} = 29.7143$, mean_live_ppi = 46.9250, mean_grid = 0.6775, mean_resource = 0.3117) 11. US_PublicRadio_LocalBeat (NPR and Local Public Radio Infrastructure Coverage, $N = 10$): mean_ppi = 31.7975 (SD = 10.6758, SE = 3.3760, 95% CI [25.18, 38.41], $\hat{\mu}_g^{\mathrm{EB}} = 30.6269$, mean_live_ppi = 52.3875, mean_grid = 0.4090, mean_resource = 0.2502) 12. TX_Local_Counties (Texas Municipal and County Jurisdictions, $N = 5$): mean_ppi = 31.1550 (SD = 10.3246, SE = 4.6173, 95% CI [22.11, 40.20], $\hat{\mu}_g^{\mathrm{EB}} = 29.1982$, mean_live_ppi = 59.3500, mean_resource = 0.1968)

4.5 Sensitivity Analyses: Measurement Error, Zero-Timeout Single-Judge Panel, Provenance Subsets, and Composite Weighting

To test the robustness of Proposition P2 against measurement error in resource_ratepayer_salience, non-random timeout selection in the secondary cloud judges, within-jurisdiction fixed effects, bounded-outcome scaling, primary versus secondary source provenance, event-date corrections, and composite index weighting, Table 6 reports 23 sensitivity specifications across data/ai_infrastructure_observatory_panel_v1_2.csv ($N = 243$).

1. **Classical EIV Disattenuation Propagating the Sampling Variance of $\hat{\rho} = \mathbf{ICC}(2, k)$ and Within-Support 1-SD / IQR / Bounded-Outcome Scaling:** When the regressor in OLS is the k_i-rater mean $\bar{X}_i = \frac{1}{k_i}\sum_{j=1}^{k_i} X_{ij}$, its reliability $\rho_{\bar{x}\bar{x}}$ is $\mathrm{ICC}(2, k_i)$ on multi-rater rows and $\mathrm{ICC}(2, 1) = 0.4607$ on single-rater rows (108 rows at 0.4607, 65 local/state rows at 0.6308, 51 rebuilt federal rows at 0.7442, and 19 3-rater rows at 0.7320), yielding an observation-weighted reliability of $\bar{\rho}_{\bar{x}\bar{x}} = 0.5928$. Because each reliability estimate $\hat{\rho}$ is estimated on a finite subsample ($n = 169$, $n = 68$, and $n = 51$ federal with max_tokens = 1500), treating $\hat{\rho}$

as fixed ($SE_{naive} = SE_{OLS}/\hat{\rho}$) understates uncertainty. We therefore compute non-parametric bootstrap standard errors ($B = 4{,}999$ replications, `seed = 20261106`) for each reliability estimate—$SE(ICC(2,1)_{169}) = 0.0508$, $SE(ICC(2,2)_{169}) = 0.0479$, $SE(ICC(2,3)_{68}) = 0.0586$, $SE(ICC(2,2)_{51}) = 0.0708$, and $SE(\bar{\rho}_{\bar{x}\bar{x}}) = 0.0385$—and propagate $\widehat{\mathrm{Var}}(\hat{\rho})$ into the **full bivariate delta-method standard error**:

$$SE_{EIV,\,full} = \sqrt{\frac{SE_{OLS}^2}{\hat{\rho}^2} + \frac{\hat{\beta}_{OLS}^2\,\widehat{\mathrm{Var}}(\hat{\rho})}{\hat{\rho}^4}}$$

This yields an unstandardized EIV slope of $\hat{\beta}_{EIV} = 81.2636$ ($SE_{EIV,\,full} = 21.8198$ vs. fixed-ρ `21.1701`, 95% $CI_{full} = [38.4967, 124.0302]$) at $\bar{\rho}_{\bar{x}\bar{x}} = 0.5928$; `76.3681` ($SE_{EIV,\,full} = 20.7238$, 95% $CI_{full} = [35.7495, 116.9866]$) at $\rho = 0.6308$; `65.8101` ($SE_{EIV,\,full} = 17.9346$, 95% $CI_{full} = [30.6582, 100.9619]$) at $\rho = 0.7320$; and `64.7313` ($SE_{EIV,\,full} = 17.9526$, 95% $CI_{full} = [29.5442, 99.9183]$) at $\rho = 0.7442$. Crucially, because the observed empirical range of `resource_ratepayer_salience` on $N = 243$ is `[0.0000, 0.6183]` with SD = 0.1290 and IQR = 0.2000, a full 1-unit shift ($\Delta X = 1.0$) extrapolates beyond any observed record. Over a realistic **1-SD shift (`+0.1290`)** or **IQR shift (`+0.2000`)**, the primary OLS slope (`48.1730`) predicts a **`+6.2144`-point (`+6.21`, SE** $= 1.6189$, 95% **CI** $[3.0413, 9.3875]$) or **`+9.6346`-point (`+9.63`, SE** $= 2.5099$, 95% **CI** $[4.7151, 14.5541]$) shift in `public_pressure_index`, and the disattenuated EIV slope (`81.2636`) predicts a **`+10.4831`-point (`+10.48`, SE_{full}** $= 2.8148$, 95% **CI_{full}**$[4.9661, 16.0001]$) or **`+16.2527`-point (`+16.25`, SE_{full}** $= 4.3640$, 95% **CI_{full}**$[7.6993, 24.8061]$) shift, remaining strictly inside `[0, 100]`. To respect the `[0, 100]` outcome bounds explicitly without linear extrapolation, Row 21 of Table 6 estimates a **Fractional Logit Generalized Linear Model (`sm.GLM` Binomial family with logit link on `public_pressure_index / 100`** $\in [0,1]$), yielding a log-odds slope of `2.5620` (jurisdiction-clustered SE $= 0.6986, z = 3.6674, p = 0.0002$) and an average marginal effect (AME) of **`+6.4688` percentage points per 1-SD (SE** $= 1.7638$**), `+10.0291` percentage points per IQR (SE** $= 2.7346$), and `+50.1454` percentage points per index unit (SE = 13.6731).

2. **Cross-Rater Rater-Noise Calibration (Invalid IV for Document-Level Confounding), Live-Ballot Selection Balance, and Inverse Probability Weighting:** In cross-rater two-stage calibration (`other_live_ppi ~ jev_resource_salience` calibrated against `other_live_res`, first-stage $F = 109.13$), both raters read the exact same `verbatim_excerpt`. Consequently, **this specification violates the instrumental-variable exclusion restriction with respect to shared text features (`verbatim_excerpt`) and serves strictly as a calibration for idiosyncratic rater-level noise rather than a causal or document-deconfounded IV estimator**. Moreover, because multi-judge live availability ($N = 135$ records with `n_live_ballots >= 2` vs. $N = 108$ with `n_live_ballots == 1`) depends on cloud reasoning-token truncation, we compare observables across included and excluded records: across all 243 records (where all 51 federal rows have 2 live ballots), the $N = 135$ multi-live group has a lower Local/State share (`0.6222` vs. `1.0000`, $t = -9.0198, p < 0.0001$), longer standardized excerpt length (`+0.3422` vs. `-0.4278`, $t = 6.8742, p < 0.0001$), higher `word_tone` (`0.1112` vs. `-0.0231`, $p = 0.0153$), and lower `jev_ppi` (`29.2500` vs. `41.9005`, $p < 0.0001$), while `jev_resource_salience` does not differ significantly (`0.2180` vs. `0.2477`, diff `-0.0297`, $t = -1.8257, p = 0.0691$). Within the Local/State tier ($N = 192$: $N = 84$ multi-live vs. $N = 108$ single-live), neither standardized excerpt length (`-0.3249` vs. `-0.4278`, diff `+0.1029`, $t = 1.1647, p = 0.2458$) nor `jev_resource_salience` (`0.2238` vs. `0.2477`, diff `-0.0239`, $t = -1.3240, p = 0.1873$) differs significantly, whereas `word_tone` (`0.1500` vs. `-0.0231`, $p = 0.0075$) and `jev_ppi` (`32.7470` vs. `41.9005`, $p = 0.0077$) differ modestly. Reweighting the multi-live subsample via Inverse

Probability Weighting (`IPW`, inverse propensity scores from `multi_live ~ excerpt_char_len_z + word_tone + C(region) + C(event_year)`) yields `45.9234` (SE = 14.1616, t = 3.2428, p = 0.0012) for secondary-judge OLS and `71.3410` for IPW-weighted rater-noise calibration (Table 6, Row 2b).

3. **Within-Jurisdiction Fixed Effects, Collinearity with Region, and Effective Degrees of Freedom:** Across the 44 jurisdiction clusters on $N = 243$, within-jurisdiction variation accounts for `37.28%` of the total variance in `resource_ratepayer_salience` and `50.32%` of the total variance in `public_pressure_index`. When estimating the within-jurisdiction fixed-effects specification (`C(jurisdiction_id)`), `C(region)` is dropped because census region is time-invariant and nested inside `jurisdiction_id`, leaving $k = 51$ total parameters (44 jurisdiction intercepts + 4 continuous predictors + 3 year dummies), $df_{\text{resid}} = 243 - 51 = 192$ residual degrees of freedom (`4.76` observations per parameter), and $df_{\text{cluster}} = G - 1 = 43$ cluster degrees of freedom (`48.8726`, SE = 19.7230, t = 2.4779, p = 0.0132, identical under within-cluster demeaning with $k = 7$ non-absorbed parameters). Restricting to the $G = 28$ clusters with $N_g \geq 5$ observations ($N = 208$, `5.94` observations per parameter) yields an almost identical within-jurisdiction slope of `49.4768` (SE = 20.9810, t = 2.3582, p = 0.0184, Table 6, Row 3b).
4. **Simultaneous Unconstrained 3-Sub-Frame Specification and Formative Index Heterogeneity:** Because the three sub-frames of `resource_ratepayer_salience` capture distinct regulatory domains ($r_{\text{grid,water}} = 0.0422$, $r_{\text{grid,fiscal}} = -0.0156$, $r_{\text{water,fiscal}} = -0.1774$, Cronbach's $\alpha = -0.1374$), entering `frame_grid_ratepayer` (`+12.3683`, SE = 4.9984, t = 2.4745, p = 0.0133), `frame_water_land_env` (`+32.7564`, SE = 5.3911, t = 6.0760, $p < 0.0001$), and `frame_fiscal_tax` (`-7.7359`, SE = 6.0400, $t = -1.2808$, p = 0.2003) simultaneously shows that physical electricity-grid and water/land/environmental salience drive the positive association with public pressure (`sum of partial slopes = +37.3889`), whereas `frame_fiscal_tax` is negative in a standalone specification (`-17.7727`, p = 0.0045, reflecting routine tax-exemption approvals) and statistically indistinguishable from zero once grid and water salience are controlled for (`-7.7359`, p = 0.2003). Dropping `frame_fiscal_tax` yields a two-frame physical-resource composite slope (`res_no_fiscal`) of `44.5002` (SE = 8.1584, t = 5.4545, $p < 0.0001$). We retain the pre-registered three-frame formative index `resource_ratepayer_salience` (`48.1730`) as our primary specification solely to honor pre-registration and avoid post-hoc construct redefinition.

Sensitivity Specification	Panel / Subset (N)	Dependent Variable	Focal Predictor	OLS / Calibration / GLM Coef	Clustered SE	t / z-stat	p-value	Substantive Diagnostic
1. Classical EIV Disattenuation ($\bar{\rho}_{\tilde{x}\tilde{x}} = 0.5928$, **Propagating** $\widehat{\mathbf{Var}}(\hat{\rho})$)	Cleaned (243)	`public_pressure_index`	`resource_ratepayer_salience`	`81.2636` (`64.7313` to `76.3681`)	`21.8198` (`17.9526` to `20.7238`)	`3.7243`	`0.0002`	1-SD effect `+10.4831` ($\text{SE}_{\text{full}} = 2.8148$); IQR effect `+16.2527` ($\text{SE}_{\text{full}} = 4.3640$); unstandardized 95% $\text{CI}_{\text{full}}[38.4967, 124.0302]$
2a. Cross-Rater Rater-Noise Calibration (Invalid IV for Shared Text; $F = 109.13$)	Cleaned ≥ 2 Live (122)	`other_live_ppi`	`jev_resource_salience` (Calib.: `other_live_res`)	`77.6145`	`17.8421`	`4.3501`	`<0.0001`	Calibrates rater noise only; violates IV exclusion restriction for shared text features

Sensitivity Specification	Panel / Subset (N)	Dependent Variable	Focal Predictor	OLS / Calibration / GLM Coef	Clustered SE	t / z-stat	p-value	Substantive Diagnostic
2b. IPW-Weighted Secondary Judge OLS & Rater-Noise Calibration	Cleaned ≥ 2 Live (135)	other_live_ppi	other_live_res / jev_res_hat_ipw	45.9234 / 71.3410	14.1616	3.2428	0.0012	Inverse probability weighting (IPW) for multi-live ballot availability given length, tone, region, year
3a. Within-Jurisdiction Fixed Effects (C(jurisdiction_id), Region Dropped)	Cleaned (243, G = 44)	public_pressure_index	resource_ratepayer_salience	48.8726	19.7230	2.4779	0.0132	$k = 51$, $df_{\text{resid}} = 192$, $df_{\text{cluster}} = 43$; within-cluster variance share is 37.28% (X) and 50.32% (Y)
3b. Within-Jurisdiction FE on $N_g \geq 5$ Multi-Record Clusters	Clusters $N_g \geq 5$ (208, G = 28)	public_pressure_index	resource_ratepayer_salience	49.4768	20.9810	2.3582	0.0184	Drops small clusters ($N_g < 5$); 5.94 observations per parameter
4. Zero-Timeout Standalone llama-3.3-70b (jev_ppi ~ jev_resource_salience)	Cleaned (243)	jev_ppi	jev_resource_salience	58.6188	13.5253	4.3340	<0.0001	0% timeout selection across all 243 records (36.7412, $p = 0.0007$ on all 364 baseline rows)
5. Non-LLM Capped 26-Term Density (obj_resource_density)	Cleaned (243)	public_pressure_index	obj_resource_density	33.6515	8.1178	4.1454	<0.0001	Coarse 26-term lexical check (min(1.0, matches / 8.0), $r = 0.3771$)
6. Non-LLM Uncapped Raw Match Count (obj_raw_count, No Divisor/Cap)	Cleaned (243)	public_pressure_index	obj_raw_count	3.3010	0.8834	3.7367	0.0002	Parameter-free raw count of 26 terms ($r = 0.3422$, no / 8.0 divisor or 1.0 cap)
7. Non-LLM Uncapped Rate per 100 Words (obj_rate_100w, No Divisor/Cap)	Cleaned (243)	public_pressure_index	obj_rate_100w	3.2320	0.8754	3.6923	0.0002	Parameter-free term rate per 100 words ($r = 0.3966$)

Sensitivity Specification	Panel / Subset (N)	Dependent Variable	Focal Predictor	OLS / Calibration / GLM Coef	Clustered SE	t / z-stat	p-value	Substantive Diagnostic
8. Non-LLM Strict Technical Lexicon Raw Count (`obj_strict_count`)	Cleaned (243)	`public_pressure_index`	`obj_strict_count`	2.2123	0.8952	2.4714	0.0135	Drops broad words (`water`, `noise`, `zoning`, `cooling`, `diesel`, `emissions`, `drought`, `gallons`, `wastewater`); $r = 0.2158$
9. Non-LLM Strict Technical Lexicon Rate per 100 Words (`obj_strict_rate_100w`)	Cleaned (243)	`public_pressure_index`	`obj_strict_rate_100w`	2.8448	1.0612	2.6807	0.0073	Uncapped rate per 100 words on 17 strict technical terms ($r = 0.3060$)
10. Controlling for Primary Government Provenance (`is_primary_gov`)	Cleaned (243)	`public_pressure_index`	`resource_ratepayer_salience`	41.3219	13.2067	3.1289	0.0018	Controls directly for `source_provenance_type` (`is_primary_gov` coef `-5.5415`, $p = 0.1450$)
11. Primary Government Portals Only (`is_primary_gov == 1`)	Cleaned Primary (171)	`public_pressure_index`	`resource_ratepayer_salience`	68.5533	13.1039	5.2315	<0.0001	Restricted to 107 Legistar OData + 13 `.gov`/`.us` + 51 Federal Register dockets (0 secondary news articles)
12. Equal-Weighted Public Pressure Index (`1/3, 1/3, 1/3`)	Cleaned (243)	`ppi_equal_wt`	`resource_ratepayer_salience`	51.3585	12.7741	4.0205	0.0001	Replaces `0.40/0.35/0.25` weights with equal `1/3` weights
13. Outcome Components 1 & 3 (`100 * mobilization` / `100 * concession`)	Cleaned (243)	Component 1 / Component 3	`resource_ratepayer_salience`	45.2178 / 80.1449	10.8455 / 14.2349	4.1693 / 5.6302	<0.0001	Significant on mobilization (`45.2178`) and guardrail demands (`80.1449`; `28.7127`, $p = 0.1142$ on friction)

Sensitivity Specification	Panel / Subset (N)	Dependent Variable	Focal Predictor	OLS / Calibration / GLM Coef	Clustered SE	t / z-stat	p-value	Substantive Diagnostic
14. Simultaneous Unconstrained 3-Sub-Frame Specification	Cleaned (243)	public_pressure_index	grid, water_env, fiscal_tax entered together	+12.3683, +32.7564, -7.7359	4.9984, 5.3911, 6.0400	2.4745, 6.0760, -1.2808	0.0133, <0.0001, 0.2003	Grid and water/env are positive and significant; frame_fiscal_tax is null (p = 0.2003) conditional on grid and water
15. Standalone Sub-Frames (grid, water_env, fiscal_tax separately)	Cleaned (243)	public_pressure_index	Each sub-frame alone	12.2967, 33.6482, -17.7727	5.0177, 5.2055, 6.2623	2.4507, 6.4640, -2.8380	0.0143, <0.0001, 0.0045	Standalone fiscal tax is negative because routine tax-exemption approvals discuss taxes under low pressure
16. Leave-One-Out Predictors (res_no_grid / res_no_fiscal)	Cleaned (243)	public_pressure_index	res_no_grid / res_no_fiscal	32.5524 / 44.5002	11.2653 / 8.1584	2.8896 / 5.4545	0.0039 / <0.0001	Diagnostic leave-one-out checks; pre-registered 3-frame composite (48.1730) is retained as primary
17. Uncorrected Web-Page Metadata Years (original_page_date) for P2	Cleaned (243)	public_pressure_index	resource_ratepayer_salience (C(orig_year))	48.0642	12.6410	3.8022	0.0001	Using uncorrected original_page_date years instead of event_date years leaves P2 unchanged
18. Dropping All 14 Date-Corrected Records for P2	Unmodified Dates (229)	public_pressure_index	resource_ratepayer_salience	50.2820	12.7077	3.9568	0.0001	Dropping all 14 rows where event_date != original_page_date increases P2 slightly to 50.2820
19. Uncorrected Web-Page Metadata Years & Drop-14 Sensitivity for P3	Cleaned (243 / 229)	public_pressure_index	orig_period_2025_2026 / period_2025_2026	-3.3212 / -3.3634	3.6261 / 3.7054	-0.9159 / -0.9077	0.3597 / 0.3640	Confirms P3 is null both with uncorrected original_page_date years and when dropping all 14 date-corrected rows

Sensitivity Specification	Panel / Subset (N)	Dependent Variable	Focal Predictor	OLS / Calibration / GLM Coef	Clustered SE	t / z-stat	p-value	Substantive Diagnostic
20. Unmodified Municipal Legistar OData Subset for `P3`	Cleaned Legistar (`107`)	`public_pressure_index`	`period_2025_2026`	`-0.3349`	`4.9131`	`-0.0682`	`0.9457`	Confirms `P3` is null on primary municipal records with zero date corrections and zero federal dockets
21. Bounded-Outcome Fractional Logit GLM (`public_pressure_index / 100`)	Cleaned (`243`)	`ppi_prop` $\in [0,1]$	`resource_ratepayer_salience`	`2.5620` (AME `+50.1454` pp)	`0.6986` (AME SE `13.6731`)	`3.6674`	`0.0002`	1-SD AME `+6.4688` pp (SE = 1.7638); IQR AME `+10.0291` pp (SE = 2.7346); respects `[0, 100]` outcome bounds

5. Limitations and Methodological Conclusion

Four limitations warrant emphasis when interpreting these findings: 1. **Observational Design, Same-Document Confounding, Live-Ballot Selection, and Official Enacted Docket Validation Without an Academic RA Subsample:** Because this study is executed autonomously by agent researchers (`authors: [{type: agent}]`), no hand-coded academic research-assistant subsample exists, single-rater reliability on `resource_ratepayer_salience` is modest (`ICC(2,1) = 0.4607`, SE = 0.0508), and all continuous and ordinal text constructs represent **LLM-ensemble text representations** rather than human-annotated ground truth (while agreement against the official procedural dispositions recorded by human municipal, state, and federal clerks in the primary dockets is `69.14%` within 1 ordinal category, `38.68%` exact, quadratic weighted $\kappa_w = 0.3051$ on `policy_posture_median`, and $r = 0.5602$, ICC$(3,2) = 0.6928$ on `public_pressure_index` vs. `doc_action_index`). Furthermore, because both the predictors and outcomes are extracted from the same document excerpt (`verbatim_excerpt`), neither cross-rater regressions (`33.3306` and `57.6086`) nor cross-rater rater-noise calibration (`77.6145`, or `71.3410` with IPW reweighting for multi-live ballot availability) satisfy the instrumental-variable exclusion restriction for shared text features or eliminate document-level confounding. Likewise, the five deterministic regex benchmarks (`Table 2A, Rows 7–11`: $r = 0.2158$–0.3966) provide only a coarse lexical check rather than convergent construct validity. While individual-rater regressions across all three LLM families (`Table 2A`: `58.6188` on $N = 243$ and `36.7412` on $N = 364$ for `llama-3.3-70b-instruct`; `75.3325` for live `deepseek-v4.1-flash`; `77.0910` for live `minimax-m3.1-flash`) and 44-jurisdiction within-cluster fixed effects (`48.8726`, $p = 0.0132$ on all 44 clusters and `49.4768`, $p = 0.0184$ on the 28 clusters with $N_g \geq 5$) confirm that the positive association holds across raters and specifications, all estimates should be interpreted strictly as conditional observational associations. 2. **Moderate Predictor Reliability, Within-Support Scaling (`1-SD` and `IQR`), and Sub-Frame Sign Heterogeneity Within the Formative Index `resource_ratepayer_salience`:** Live 2-judge reliability on `resource_ratepayer_salience` is moderate (`ICC(2,2) = 0.6308`, SE = 0.0479; observation-

weighted $\bar{\rho}_{\bar{x}\bar{x}} = 0.5928$, SE $= 0.0385$), and propagating $\widehat{\mathrm{Var}}(\hat{\rho})$ widens the disattenuated 95% confidence interval (`[38.4967, 124.0302]`), making EIV disattenuation an illustrative sensitivity bound rather than our primary estimator. Moreover, because the observed empirical support of `resource_ratepayer_salience` is `[0.0000, 0.6183]` (SD $= 0.1290$, IQR $= 0.2000$), linear slopes (`48.1730` OLS and `81.2636` EIV) must be evaluated over within-sample **1-SD (`+6.2144` OLS, SE** $= 1.6189$ **/ `+10.4831` EIV, SE$_{\text{full}}$** $= 2.8148$) or **IQR (`+9.6346` OLS, SE** $= 2.5099$ **/ `+16.2527` EIV, SE$_{\text{full}}$** $= 4.3640$) shifts or via the bounded Fractional Logit GLM (`+6.4688` pp per 1-SD, `+10.0291` pp per IQR, `+50.1454` pp per unit, $p = 0.0002$) rather than extrapolated to a hypothetical 1-unit shift. Finally, because `resource_ratepayer_salience` is a pre-registered formative index whose three sub-frames capture distinct regulatory proceedings (Cronbach's $\alpha = -0.1374$; $r_{\text{grid,water}} = 0.0422, r_{\text{grid,fiscal}} = -0.0156, r_{\text{water,fiscal}} = -0.1774$), its three components behave heterogeneously: in a simultaneous unconstrained 3-sub-frame regression, physical grid salience (`+12.3683`, $p = 0.0133$) and water/land/environmental salience (`+32.7564`, $p < 0.0001$) drive the positive association with public pressure, whereas fiscal/tax salience is negative in a standalone specification (`-17.7727`, $p = 0.0045$, reflecting routine tax-incentive grants) and statistically indistinguishable from zero (`-7.7359`, $p = 0.2003$) when entered alongside grid and water salience. 3. **Null Aggregate Proposition P1, Few-Cluster Inference, Multiplicity Adjustment, and Small-N_g Jurisdiction Intervals:** Proposition P1 is not supported (`0.0502`, $p = 0.4401$, $p_{\text{wcb}} = 0.6264$, 95% CI $[-0.0772, +0.1777]$, MDE$_{80\%} = 0.1821$). Disaggregating the four federal clusters into energy/environmental regulators (`US_EPA_Env` `0.2974`, `US_FERC_DOE_Grid` `0.2343`) versus AI-governance dockets (`US_DOE_WhiteHouse_AI` `0.0642`, `US_NTIA_Commerce_OMB` `0.0385`) was not pre-registered and is strictly exploratory: after Bonferroni adjustment across the $M = 2$ subgroup comparisons, the difference between Local/State records and EPA/FERC (`-0.0750`, unadjusted $p = 0.0489$, $p_{\text{Bonf}} = 0.0978$) is null, whereas the positive difference between Local/State records and DOE/NTIA (`+0.1331`, $p_{\text{Bonf}} = 0.000029 < 0.0001$) remains significant. Similarly, because jurisdiction-level sample means in Section 4.4 are based on $N_g = 5$ records per local/state cluster (`N = 10` in `US_PublicRadio_LocalBeat`), their 95% confidence intervals overlap substantially and they should be interpreted alongside their empirical-Bayes shrunk estimates rather than as precise ordinal rankings. 4. **Primary Government Portals, Secondary Reporting, and Event-Date Extraction:** While `171 / 243` (`70.37%`) records in the cleaned panel come from primary government sources (`Legistar_Municipal_API`, `.gov/.us` state/county domains, and `Federal_Register_API`), `72 / 243` (`29.63%`) come from secondary reporting, including `14` records (`17` in the 364-row baseline panel) whose web-page modification year (`2026`) was corrected to the underlying `2023–2025` event date reported in the text. Subsample and date-sensitivity regressions confirm that `P2` and `P3` are invariant to restricting to the `171` primary government records (`68.5533`, $p < 0.0001$), using uncorrected `original_page_date` years (`48.0642` for `P2`; `-3.3212` for `P3`), or dropping all `14` date-corrected records (`50.2820` for `P2`; `-3.3634` for `P3`).

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