Between a Rock and a Polarized Place: How Lawmakers Absorb Pressure Without Taking Positions*

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Abstract

How do lawmakers navigate politically perilous moments post-crises? We argue that when focusing events make ignoring polarized policy domains untenable, legislators face a tension between demands for visible responsiveness and the electoral risks associated with position-taking. To resolve this tension, they engage in *salience absorption*—using expressive communication to signal attentiveness without policy commitment. We analyze how legislators' discourse changes after 25 mass shootings using large language models to classify over 2.7 million tweets from 961 state legislators (2013–2022). We find that the odds of tweeting about gun violence increase by 572% following an in-state shooting. However, the composition of communication shifts: legislators turn to expressive rhetoric rather than substantive policy debate. The shift is most pronounced among Republicans and legislators representing competitive districts. Our findings demonstrate how elites leverage symbolic communication to absorb pressure during periods of heightened issue salience, intensifying representational activity while thinning its substantive content.

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1 Introduction

Theories of democratic responsiveness rest on a foundational assumption that elite communication is the medium through which constituents observe what their representatives think (Fenno, 1978; Mayhew, 1974; Grimmer, 2013), demand accountability for those positions (Arnold, 1990; Mansbridge, 2003), and ultimately translate public preferences into policy (Dahl, 1971; Stimson, MacKuen and Erikson, 1995; Wlezien, 1995). This assumption is especially consequential when responsiveness is most demanded: when sudden, salient crises focus public attention on a policy domain and voters look to elected officials for answers (Birkland, 1997; Kingdon, 1995). In those moments, the informational preconditions of accountability are met, as the public is attentive, opinionated, and primed to take in positional cues from elites that could later be used to evaluate them (Fiorina, 1981; Key, 1966).

These expectations coexist uneasily with polarized political environments. Crisis events such as natural disasters affect voters' turnout, attribution of blame, and ability to hold government accountable (Hazlett and Mildenberger, 2020; Malhotra and Kuo, 2008; Healy and Malhotra, 2009), suggesting that elites would benefit from direct engagement with the issues at hand. Yet polarization appears to incentivize the avoidance of policy areas that may increase a representative's electoral exposure (Binder, 1999; Lee, 2009; Luca, Malhotra and Poliquin, 2020; Wittman, 1995). When a crisis activates a domain whose policy options are sorted along partisan lines, communication becomes fraught. Issue avoidance predicts that legislators reduce attention to politically costly domains, deflecting toward friendlier terrain (Sulkin, 2005; Egan, 2013). Position-blurring predicts that legislators who do engage adopt deliberately ambiguous stances to maximize appeal across diverse constituencies (Tomz and Van Houweling, 2009). But disengagement and ambiguity are harder to sustain in public-facing venues like social media, where silence itself is politically costly and visible engagement is expected (Dickson and Hobolt, 2025; Barberá et al., 2019; Russell, 2018; Schöll, Gallego and Le Mens, 2024). Legislators must say *something* but cannot freely commit to a position. What, then, do they say?

We argue that legislators resolve this tension through *salience absorption*: the systematic conversion of crisis-driven pressure into expressive communication. Expressive content performs attentiveness through condolences, expressions of grief, calls for unity, and informational updates, satisfying the demand for visible engagement at minimal positional cost. Salience absorption is not avoidance, because topic engagement rises sharply. It is not ambiguity, because the substantive dimension is not blurred but displaced—replaced by expressive content that runs orthogonal to the policy debate. Where avoidance withdraws and blurring obscures, absorption performs care. It is a distinct and strategic response to salience shocks in pre-sorted domains, and its intensity depends on two things: whether a legislator's party owns the salient issue, and how electorally exposed they are. The result is representation that dilutes substance rather than supplements it. Legislators meet the demand to be seen responding while supplying little of the positional content that would let constituents judge where they stand.

Mass shootings provide a clear test. They generate emotional engagement, activate latent policy preferences, and briefly place gun policy—a highly polarized issue owned by the Democratic party in the United States—at the top of the political agenda (Rossin-Slater et al., 2020; Yousaf, 2021; Newman and Hartman, 2019; Markarian and Newman, 2025;

Shoub and Morris, 2025). By conventional accounts of focusing events, this should push firearm policy onto the legislative docket. Yet policy rarely changes following such tragedies (Chen and Kappelman, 2026; Markarian, Napolio and Newman, 2026; Goel and Nelson, 2024; Luca, Malhotra and Poliquin, 2020; Reich and Barth, 2017), even as legislators are hardly silent. They post, issue statements, and engage publicly in ways that imply attentiveness (Zhang et al., 2025; Markarian, 2024; Bukhanevych, Succar and Porfiri, 2025; Schildkraut and Carr, 2019). What this activity consists of, and what kind of information environment it constructs, is what this paper characterizes.

We test these claims using a corpus of 2.78 million tweets posted by 961 state legislators in California, Texas, Florida, and Washington between January 2013 and December 2022. We use large language models (LLMs) to classify tweet content at scale and estimate the causal effect of mass shootings on the composition of legislative discourse using a regression discontinuity in time design across twenty-five events.

Three findings organize the paper. First, mass shootings produce dramatic increases in gun violence discourse: the odds of a tweet addressing gun violence rise by roughly 572 percent in the days following an in-state shooting. Second, the composition of that surge is overwhelmingly expressive; substantive content declines as a share of gun violence discourse, while expressive content accounts for the bulk of the increase. Third, absorption is structured by partisanship and electoral exposure: legislators pushed to communicate on issues they do not own and those in competitive districts absorb the most, avoiding policy discussion in favor of expressive discourse.

The information environment salience absorption constructs differs from the one accountability theory presupposes. Standard models assume voters can use periods of heightened attention to extract positional information from elites and evaluate them on its basis (Dahl, 1971; Arnold, 1990; Fiorina, 1981; Key, 1966; Stimson, MacKuen and Erikson, 1995; Wlezien, 1995). We show that in pre-sorted domains, elites have both the motive and the rhetorical means to make positional content scarce precisely when accountability theory predicts it should be abundant.[1] Legislators provide more information simply by communicating more, but that communication carries less of the positional content voters need to infer where an official stands. If legislators can routinely absorb crisis-driven pressure through expressive communication, the public's ability to convert salient events into policy change is conditioned less by legislative inaction than by legislative activity itself—activity that thins the informational basis on which accountability is conventionally thought to operate.

2 Elite Communication as Representation or Advertisement?

Representational theories of elite rhetoric hold that what legislators say is not merely a byproduct of representation but a constitutive activity: communication is how representatives stand for constituents, how constituents form impressions of representatives, and how

[1] We do not mean to claim that expressive communication is inherently undemocratic, as condolences can serve real representational functions. The concern is narrower: when expressive content systematically displaces substantive engagement at moments of peak salience, the informational preconditions for the kind of accountability that conventional models presume may not be met, even as representational activity intensifies.

the dyadic relationship that representative democracy presumes is sustained between elections (Fenno, 1978; Mayhew, 1974; Grimmer, 2013; Dahl, 1971; Stimson, MacKuen and Erikson, 1995; Wlezien, 1995). The descriptive scholarship has documented this activity across home styles (Fenno, 1978), the communicative strategies[2] employed by politicians (Mayhew, 1974), and the representational claims legislators make in public statements (Grimmer, 2013).

Yet lawmakers are not open books, expressing their every idea, whim, and desire. Legislators are, first and foremost, single-minded seekers of reelection (Mayhew, 1974). They cultivate carefully constructed presentations of self, deciding what to emphasize, what to downplay, and what to leave unsaid (Fenno, 1978). Communication, in this view, is not a transparent window onto positions but a strategic activity through which legislators manage their public profiles and the accountability exposure those profiles create.

2.1 Polarization and the Foreclosure of Substantive Engagement

The strategic stakes of communication are heightened in periods of intense partisan competition, when control of legislative chambers is closely contested and every issue becomes a potential vehicle for party messaging or party damage (Lee, 2016). The cost of clear positional commitment rises, particularly on issues where coalitions are sorted along partisan lines and well-organized constituencies stand ready to mobilize against deviation. Position avoidance, in this framework, is not a failure of representation but a strategic response to the structure of accountability itself.

When legislating under these conditions, legislators evaluate whether voters can trace policy outcomes back to specific actions, and they adjust their behavior to obscure that trace when the underlying position is electorally costly (Arnold, 1990). Scholarship on communication in these environments highlights two strategies. Egan (2013) and Sulkin (2005) show that legislators reduce attention to issues their party does not own, deflecting toward terrain where party reputation provides cover; Tomz and Van Houweling (2009) show that legislators who do engage contested issues adopt deliberately ambiguous positions to maximize appeal across heterogeneous constituencies. Salience absorption is neither. The legislators we study do not avoid gun violence and do not blur their positions on it; they sharply increase their engagement with the domain while channeling that engagement into expressive registers orthogonal to the policy dimension entirely.

2.2 Focusing Events and Demands for Visible Representation

The strategic logic of avoidance can clash with the political reality of representational demands. This tension is most visible when sudden, unexpected events causing harm push event-relevant issues to the top of the political agenda (Kingdon, 1995; Birkland, 1997).

[2]Mayhew (1974) distinguishes three core communicative behaviors: (1) position-taking, where legislators stake out a substantive stance on a policy question; (2) credit-claiming, where legislators assert personal responsibility for desirable outcomes; and (3) advertising, where legislators generate favorable visibility and signal engagement with a salient issue without staking out an ideological position or committing to a policy solution. Expressive content, in a Mayhewsian sense, is closest to advertising.

Natural disasters, oil spills, mass shootings, and terrorist attacks—"focusing events"—concentrate public attention, activate latent policy preferences, and create windows of opportunity in which policy entrepreneurs can advance proposals that would otherwise face indifferent or hostile audiences (Birkland, 1998).

These events have meaningful effects on mass behavior. Focusing events, particularly geographically proximal ones, can shift mass opinion, activate latent preferences, and concentrate public attention on event-relevant policy domains (Hazlett and Mildenberger, 2020; Malhotra and Kuo, 2008; Healy and Malhotra, 2009; Newman and Hartman, 2019; Markarian and Newman, 2025; Shoub and Morris, 2025; Reny et al., 2023). Models of dynamic representation extend this expectation to elite behavior, suggesting legislators not only attend to public opinion but visibly shift their positions in response to it (Stimson, MacKuen and Erikson, 1995; Wlezien, 1995, 2004; Soroka and Wlezien, 2010). Together, these literatures generate a coherent baseline expectation: following sudden, salient events, elites should elevate the relevant policy domain on the agenda, engage substantively with the policy questions the event raises, and translate heightened salience into legislative activity.

Yet little research suggests this expectation plays out in legislative arenas when the relevant domain is highly polarized (Chen and Kappelman, 2026; Markarian, Napolio and Newman, 2026; Goel and Nelson, 2024; Luca, Malhotra and Poliquin, 2020; Reich and Barth, 2017). The gravitational pull of polarization appears to overwhelm the disruptive force of focusing events. But the avoidance and ambiguity that polarization fosters depend on venues that provide institutional cover for selective engagement. Roll-call abstentions, committee assignments, and cosponsorship choices let legislators manage their issue portfolios without facing direct demands for public engagement. In public-facing venues, silence itself becomes legible as a position, and ambiguity is harder to sustain when audiences are explicitly looking for an answer (Dickson and Hobolt, 2025; Barberá et al., 2019; Russell, 2018; Schöll, Gallego and Le Mens, 2024). The strategic problem for legislators in polarized domains is therefore most acute when audiences expect them to speak.

3 Towards a Theory of Salience Absorption

We argue that legislators resolve this tension through *salience absorption*: the systematic conversion of crisis-driven pressure into expressive rather than substantive communication. In a pre-sorted policy domain, position-taking is informationally redundant for co-partisan constituents and politically costly with everyone else, so the marginal return to substantive commitment is small relative to the marginal risk, while expressive content satisfies the demand for visible engagement at minimal cost. Legislators flood the communicative zone with expressive content: volume rises, satisfying the demand for engagement, while positional content thins, evading the demand for commitment. Under salience absorption, expressive representation displaces rather than supplements substantive representation.

3.1 Asymmetric Responses

The intensity of absorption varies systematically with the structural conditions each legislator faces. Issue ownership theory holds that parties cultivate distinct reputational advantages across policy domains, and that legislators are most credible communicating on issues their party owns (Petrocik, 1996; Egan, 2013). When the post-event opinion environment aligns with a legislator's party position, the substantive dimension remains open, and position-taking reinforces a credible, popular stance. When it runs against the party position, the substantive dimension becomes foreclosed in both directions: the party's owned position is conspicuously unpopular, while moving toward the opposing position invites backlash from core constituencies and the party base. Legislators in this latter position should concentrate in the purest forms of expressive rhetoric, not because they reflexively avoid the issue, but because the opinion environment makes non-avoidance specifically costly for them in a way it is not for legislators whose party position aligns with activated opinion.

Within parties, absorption should also vary with the electoral cost of positional commitment. Legislators in competitive districts, where margins are thin and the cost of alienating constituents is highest, have the strongest incentives to absorb (Canes-Wrone, Brady and Cogan, 2002; Fenno, 1978). Expressive content is most valuable to legislators for whom the electoral stakes of positional exposure are highest (Mayhew, 1974). Where the substantive dimension remains open for a party, electoral exposure should compress the available repertoire, with cross-pressured legislators in competitive districts retreating from substantive engagement most sharply, while legislators in safe districts can afford the fuller engagement that core constituency preferences invite. Where the substantive dimension is foreclosed in both directions regardless of district context, absorption should operate as a near-universal response. If absorption is a strategic adaptation to the accountability environment, it should intensify where electoral stakes are highest and where the substantive dimension is most foreclosed; if it is instead a reflexive response to tragedy, it should be uniform across legislators regardless of electoral exposure or partisan position.

3.2 Gun Politics and Mass Shootings as a Case Study

To test our theory, we analyze lawmakers' gun violence discourse, leveraging mass shootings as focusing events that heighten salience within a polarized policy domain. The two parties have staked out increasingly stark positions on gun policy over recent decades, with Democrats claiming ownership over gun control and Republicans defending gun rights (Petrocik, 1996; Conley, 2019; Bukhanevych, Succar and Porfiri, 2025). This polarization extends to the mass level, with Democratic and Republican voters exhibiting large and growing gaps in their attitudes toward gun regulation (Parker et al., 2017). While mass opinion favors stricter gun laws on aggregate (Brenan, 2022), gun rights organizations are well-resourced and influential, viable policy alternatives are ideologically divisive, and high-salience shootings generate counter-mobilization among gun rights groups, who increase campaign donations (Roemer, 2023; Spitzer, 2020; Goss, 2010; Baldwin, Iwasaki and Donohue, 2025). Gun policy also challenges theories of legislative responsiveness: state firearm laws align with majority preferences far less than laws in other domains, with congruence rates below 25% (Lax and Phillips, 2012), and legislators systematically misperceive their constituents as more conservative on guns than they are (Broockman and Skovron, 2018).

Mass shootings fit the classic definition of a focusing event: sudden, relatively uncommon, clearly harmful, geographically concentrated, and simultaneously visible to policymakers and the public (Birkland, 1998). They are also highly covered and symbol-rich—the exact events that under Kingdon's (1995) model *should* reframe entrenched narratives, open policy windows, elevate gun policy on the agenda, and create opportunities for change. They represent a particularly powerful case for examining salience absorption: the focusing event activates a domain where the substantive dimension is foreclosed in the way described above, and the public-facing demand for response is acute.

While only a small share of respondents ordinarily rank gun policy as the nation's most important problem, after highly salient shootings like Las Vegas in 2017 or Parkland in 2018, support for gun control spiked briefly before regressing to prior levels (Jones, 2018). These effects are pronounced locally but temporally bounded, and effects on two-party vote share appear largely muted (Newman and Hartman, 2019; Hassell and Holbein, 2025; Markarian and Newman, 2025). Heightened short-term salience, in turn, creates pressure for agenda change, potentially elevating gun policy as a legislative priority.

Even so, policy-making on firearms remains largely stagnant (Chen and Kappelman, 2026; Markarian, Napolio and Newman, 2026; Goel and Nelson, 2024; Luca, Malhotra and Poliquin, 2020; Reich and Barth, 2017), though legislators are not necessarily silent (Zhang et al., 2025; Markarian, 2024; Bukhanevych, Succar and Porfiri, 2025; Schildkraut and Carr, 2019). The empirical question is what this activity consists of, and whether its composition reflects the substantive engagement conventional accountability models presume. We predict that it will not.

The asymmetry of post-shooting public opinion sharpens the strategic problem differently for the two parties. Democrats can engage substantively at relatively low cost when post-shooting opinion aligns with their position. Republicans face a sharper bind: gun rights advocacy is conspicuously unpopular in the post-shooting moment, while any move toward control puts them at odds with their base.[3] We therefore expect Republican absorption to be near-universal, since neither substantive direction is viable, and Democratic absorption to be selective, concentrated among cross-pressured legislators in competitive districts (Canes-Wrone, Brady and Cogan, 2002; Fenno, 1978).

3.3 Social Media as the Arena of Salience Absorption

Testing salience absorption requires a venue where the mechanism can operate freely. Social media is uniquely suited because, unlike floor speeches, committee testimony, or roll-call votes, it imposes fewer institutional constraints on what legislators say or how they frame an issue (Straus and Glassman, 2016; Barberá et al., 2019; Grimmer, 2013). If legislators engage in genuine position-taking after mass shootings, this is where we should see it; if they retreat to expressive content even here, the evidence for absorption is especially compelling.

Social media is also well-suited on practical grounds. Most US lawmakers use it actively, making our sample broadly representative (Lassen and Brown, 2011; Straus and Glassman, 2016), and because legislators address multiple audiences at once rather than a single room of donors, the messages we analyze are unlikely to be micro-targeted. The policy issues lawmakers raise in tweets track their agenda in other media, including websites and newsletters, suggesting tweets reflect broader patterns of constituent communication (Casas and Morar,

[3]The reputational risk is not merely theoretical. See "Texas governor's campaign website drops shotgun voucher giveaway after school shooting," WRAL News.

2015).

Taken together, the framework developed here generates a coherent set of predictions. Mass shootings create salience pressure that produces volume surges in gun violence discourse. That pressure is absorbed through expressive communication that satisfies the appearance of responsiveness without positional commitment. The parties deploy distinct expressive repertoires, reflecting the asymmetric constraints their coalitions impose. And the intensity of absorption is amplified among legislators facing the greatest electoral exposure. The sections that follow test each prediction.

4 Data & Methods

4.1 Data

4.1.1 Twitter Activity of State Legislators

Our primary data source is Quorum,[4] a commercial platform that systematically tracks the social media activity of elected officials across the United States. From Quorum's full repository of tweets, we retain all tweets posted by accounts linked to individuals who served as state legislators in California, Texas, Florida, or Washington at any point between January 2013 and December 2022.[5] Information on legislators' party affiliation, chamber, district, and tenure is drawn from LegiScan,[6] a comprehensive state legislative tracking database, which we use to match Quorum accounts to individual lawmakers. Our final analytic sample, restricted to legislators for whom we observe at least one tweet during the study period, consists of 961 legislators and over 2.78 million tweets.[7]

4.1.2 State and Shooting Selection

Our analysis examines legislators in California, Texas, Florida, and Washington. We chose these states because each experienced three or more mass shootings in our study window, yielding incident-level variation, and they span the ideological spectrum of American gun politics (Chen and Kappelman, 2026; Markarian, Napolio and Newman, 2026): California and Washington maintained Democratic legislative majorities for the majority of the study period, while Texas and Florida were Republican-dominated, enabling meaningful partisan comparisons that are not an artifact of chamber composition. Additionally, their large, geographically and demographically diverse chambers represent a range of urban and rural constituencies, and the cost of coding tweets through LLMs limited our sample. These states are not a random sample, and we address external validity in the conclusion.

Our definition, following the Congressional Research Service (e.g., Peterson and Densley, 2022; Luca, Malhotra and Poliquin, 2020), requires four or more gunfire fatalities, excluding

[4] `https://www.quorum.us`

[5] A large body of accounts tracked by Quorum includes staff associated with governmental offices, which we filter out to retain a sample of accounts linked directly to elected state legislators.

[6] `https://legiscan.com/`

[7] Supplemental analyses in Appendix A.7.1 restrict the sample to legislators who were in office at the time of the relevant shooting, which modestly reduces sample size but leaves results substantively unchanged.

the shooter. This restrictive standard aligns with our theory: salience absorption depends on crisis-driven pressure, which unambiguously lethal and widely covered mass shootings produce by sustaining attention and creating constituent demands. Events below four fatalities rarely achieve the acute, concentrated attention necessary for focusing events. A more permissive definition would admit events with uncertain salience pressure, attenuating estimates and muddying null results.

4.2 Methods

4.2.1 Classification of Tweets

We classify tweets in two sequential stages using GPT-4.1 mini, an instruction-tuned LLM accessed via the OpenAI API. GPT-class models classify short political texts with accuracy comparable to expert coders and crowdworkers at a fraction of the cost (Gilardi, Alizadeh and Kubli, 2023; Törnberg, 2025), and political scientists have begun to integrate such models into measurement workflows (Ornstein, Blasingame and Truscott, 2025). Each tweet is classified independently with a prompt combining task instructions, a small number of worked examples (in-context few-shot learning), and the tweet content; we set the temperature to zero and constrain output to structured JSON. Full prompts, API parameters, and classifier validation appear in Appendices A.1 and A.2; Table 1 provides example tweets for each category.

In the first stage, every tweet is submitted to a topic-and-tone prompt that returns one or more policy labels and a single tone label (positive, negative, sarcastic, or neutral). The two policy categories are *gun violence* and *sports*, with the latter serving as a placebo outcome. The prompt instructs the model to assign a label only when the tweet directly engages the subject, not when it merely mentions a keyword. Of our 2.78 million tweets, 89,723 (3.22%) advance to Stage 2 as gun-violence tweets and 198,208 (7.12%) are classified as sports. Whereas Demszky et al. (2019) hand-labeled a smaller mass-shooting corpus to train a supervised classifier, the few-shot prompt extends to our full corpus without category-specific labeled data.

In the second stage, gun-violence-related tweets are submitted to a targeted prompt that extracts four variables: a binary indicator for pro-gun-rights content, a binary indicator for pro-gun-control content, the primary policy domain emphasized (e.g., "background checks," "red flag laws") if any, and the actor or entity blamed for gun violence if any. The two ideological indicators are not mutually exclusive by design; a tweet may, for instance, call for expanded background checks while opposing broader restrictions on firearm ownership. Open-ended fields are reduced to binary indicators equal to one when the model returns a non-empty value. Tweets classified as gun-violence-related but carrying no substantive flag form the residual we analyze as expressive in Section 5.3.

4.2.2 Measuring Tweeting Intensity

We measure legislative topic attention using log-odds of topic-specific tweeting rather than raw proportions, and formal definitions for these measures are provided in Appendix A.3. In brief, raw proportions are poorly suited to this setting because they are bounded between

Table 1: Example Tweets by Classification Type

Sports (Stage 1)	
Anna Eskamani (D-FL), Sep 19, 2019 Always proud to be @UCF Knight!	Drew MacEwen (R-WA), Sep 21, 2019 Welcome back @GardnerMinshew5![1]
Gun Violence (Stage 1)	
Beth Gaines (R-CA), Oct 24, 2014 Our prayers go out to the officers affected by these terrible shootings in Sacramento and Auburn, we wish them safety and protection.	Cindy Polo (D-FL), May 29, 2020 As the daughter of Colombian immigrants, I am proud to be endorsed by @latinovictoryus, an org that has worked to build Latino political power across the country... moved to run in 2018 after the Parkland shooting...
Pro-Gun Control (Stage 2)	
Vikki Goodwin (D-TX), Jun 17, 2021 RT @tweet_elva: "Thirty-five law enforcement officers killed in the line of duty by civilians with guns under @GovAbbott's watch... Instead of passing laws to make them safer, he's signing #HB1927 over objections from police chiefs, sheriffs & LEO unions..."	Anna Eskamani (D-FL), Apr 13, 2019 We plan to re-file because we're tired of seeing stories like this, because it's not the 1st time someone w/a history of DV has murdered others & then taken their own life...
Pro-Gun Rights (Stage 2)	
Matt Schaefer (R-TX), Sep 29, 2021 Cawthorne says he voted FOR a red flag law so that the Senate could vote against it. Brilliant... I DO NOT support red flag laws...	Devon Mathis (R-CA), Sep 01, 2016 RT @gunpolicy: Thank you @ShannonGrove @AD26Mathis and @J_GallagherAD3 for FIGHTING for #2A rights this year!
Policy (Stage 2)	
Gina Calanni (D-TX), Sep 01, 2019 I feel trapped in a cycle of thoughts and prayers and no action. I'm asking for action from everyone. Let's talk about background checks and proper gun storage...	Richard Pan (D-CA), Mar 25, 2021 RT @LAMedicalAssn: "As we grieve the events of the past week, many thoughts and emotions come back to the surface..." Read the full statement from our LACMA leaders...[2]
Blame (Stage 2)	
Anna Eskamani (D-FL), Sep 26, 2018 RT @FLHouseVictory: .@StocktonReeves earned an "A" grade from the NRA. Now he wants to shame @AnnaForFlorida for standing up to the gun lobby. The choice in this race could not ...	Bobby DuBose (D-FL), Apr 19, 2021 bad for Florida. It's a heavy-handed solution in search of a problem that does NOT exist here. Riots and violence are already illegal. The people don't want it and law enforceme...

Note: Two sample tweets are shown per classification type. Tweet content truncated where necessary. "RT" denotes a retweet. Legislator party and state shown in parentheses.
[1]Gardner Flint Minshew II is an American football player.
[2]Tweet links to "LACMA Health Equity Council Statement on the GA Killings and Ongoing Violence Against the AAPI Community," Los Angeles County Medical Association.

zero and one, which creates statistical problems for legislators whose topic shares cluster near the extremes. Even more importantly, proportions may conflate changes in a legislator's topical focus with changes in their overall tweeting volume. The log-odds transformation resolves both issues, yielding a measure that captures how legislators allocate their messaging attention across topics rather than how much they tweet in absolute terms.

We report exponentiated log-odds coefficients throughout, which are interpretable as odds ratios. An odds ratio greater than one indicates that a topic becomes relatively more prevalent in a legislator's tweets following a shooting. An estimate of 6.717, for instance, means the odds of a given tweet addressing gun violence are 6.717 times higher immediately after a shooting than before—a 572% increase. An odds ratio less than one indicates that the topic becomes a smaller share of legislative discourse after the shooting. An estimate of 0.388, for example, means the odds of a gun violence tweet being pro-gun control fall to roughly 39% of their pre-shooting level, or a 61% decrease in relative prevalence. RDD estimates can therefore be interpreted as proportional shifts in the relative allocation of messaging attention.

4.2.3 Regression Discontinuity in Time Design

We employ a sharp regression discontinuity in time (RDDiT) design to estimate the causal effect of mass shootings on state legislators' social media discourse (Hausman and Rapson, 2018). The treatment is the occurrence of a mass shooting in a legislator's home state, and the running variable is time in days relative to the shooting event, normalized to zero on the event date. Our identification strategy exploits the temporal discontinuity created by the shooting: if shootings causally affect legislative discourse, we expect a sharp change in tweeting behavior immediately following the event, relative to the counterfactual trend absent the shooting.

For each of the 25 mass shootings in our sample, we estimate a separate local linear regression discontinuity model. The estimating equation for shooting s is:

$$Y_{its} = \alpha_s + \tau_s \cdot \mathbb{I}(t \geq 0) + \beta_s t + \gamma_s \cdot \mathbb{I}(t \geq 0) \cdot t + \varepsilon_{its}, \tag{1}$$

where Y_{its} is the log-odds outcome for legislator i on day t relative to shooting s, $\mathbb{I}(t \geq 0)$ is an indicator for the post-treatment period, and t is the running variable (days from shooting). β_s is the pre-treatment trend and γ_s captures the difference in slopes across the cutoff. The parameter of interest is τ_s, which captures the discontinuous shift in the outcome at the shooting date for shooting s.

We estimate Equation (1) using the `rdrobust` package in R (Calonico et al., 2017), which fits the model locally within the MSE-optimal bandwidth using triangular kernel weights and applies bias correction (Calonico, Cattaneo and Farrell, 2020). Within each shooting-specific regression, standard errors are clustered at the legislator level to account for serial correlation in individual legislators' tweeting patterns. We apply a mass-points adjustment to account for the discreteness of the daily running variable (Cattaneo et al., 2021).

The MSE-optimal bandwidth varies across shootings and outcomes, ranging from 2.56 to 15.88 days, with a mean bandwidth of 8.35 days on either side of the shooting. This data-driven approach allows the bandwidth to adapt to the local variability in tweeting patterns around each shooting. Details on sample sizes, bandwidths, and other diagnostics are reported along with the full tabular results in Appendix A.5.1.

Individual shooting-specific estimates exhibit substantial heterogeneity, reflecting variation in shooting characteristics, state contexts, and legislative responses. Because we are running as many as 25 RDDs for each outcome measure, we employ a random-effects meta-analysis to obtain a summary estimate of the average treatment effect across shootings. For each outcome, we pool the shooting-specific point estimates $\{\hat{\tau}_s\}_{s=1}^{25}$ and their standard errors $\{\mathrm{SE}(\hat{\tau}_s)\}_{s=1}^{25}$ using restricted maximum likelihood (REML) estimation with the

Knapp-Hartung adjustment for small sample inference (Knapp and Hartung, 2003).

5 Results

5.1 Descriptive Results

Table 2: Percentage of tweets by topic

	State				
Metric	CA	FL	TX	WA	All States
Total Tweets	814,148	670,283	1,081,085	218,051	2,783,567
Sports	**45,005 (5.53%)**	**51,410 (7.67%)**	**85,742 (7.93%)**	**16,051 (7.36%)**	**198,208 (7.12%)**
Gun Violence	**25,459 (3.13%)**	**23,758 (3.54%)**	**33,311 (3.08%)**	**7,195 (3.30%)**	**89,723 (3.22%)**
Pro-Gun Rights	1,044 (0.13%)	2,856 (0.43%)	6,033 (0.56%)	774 (0.35%)	10,707 (0.38%)
Pro-Gun Control	10,228 (1.26%)	6,739 (1.01%)	7,170 (0.66%)	2,427 (1.11%)	26,564 (0.95%)
Policy	19,205 (2.36%)	16,214 (2.42%)	23,010 (2.13%)	5,476 (2.51%)	63,905 (2.30%)
Blame	12,163 (1.49%)	10,901 (1.63%)	15,827 (1.46%)	3,685 (1.69%)	42,576 (1.53%)
N Legislators	236	282	274	169	961
N Democrats	167	103	105	102	477
N Republicans	66	177	168	67	478
N Party Switchers	2	2	1	0	5
N Shootings	9	6	7	3	25

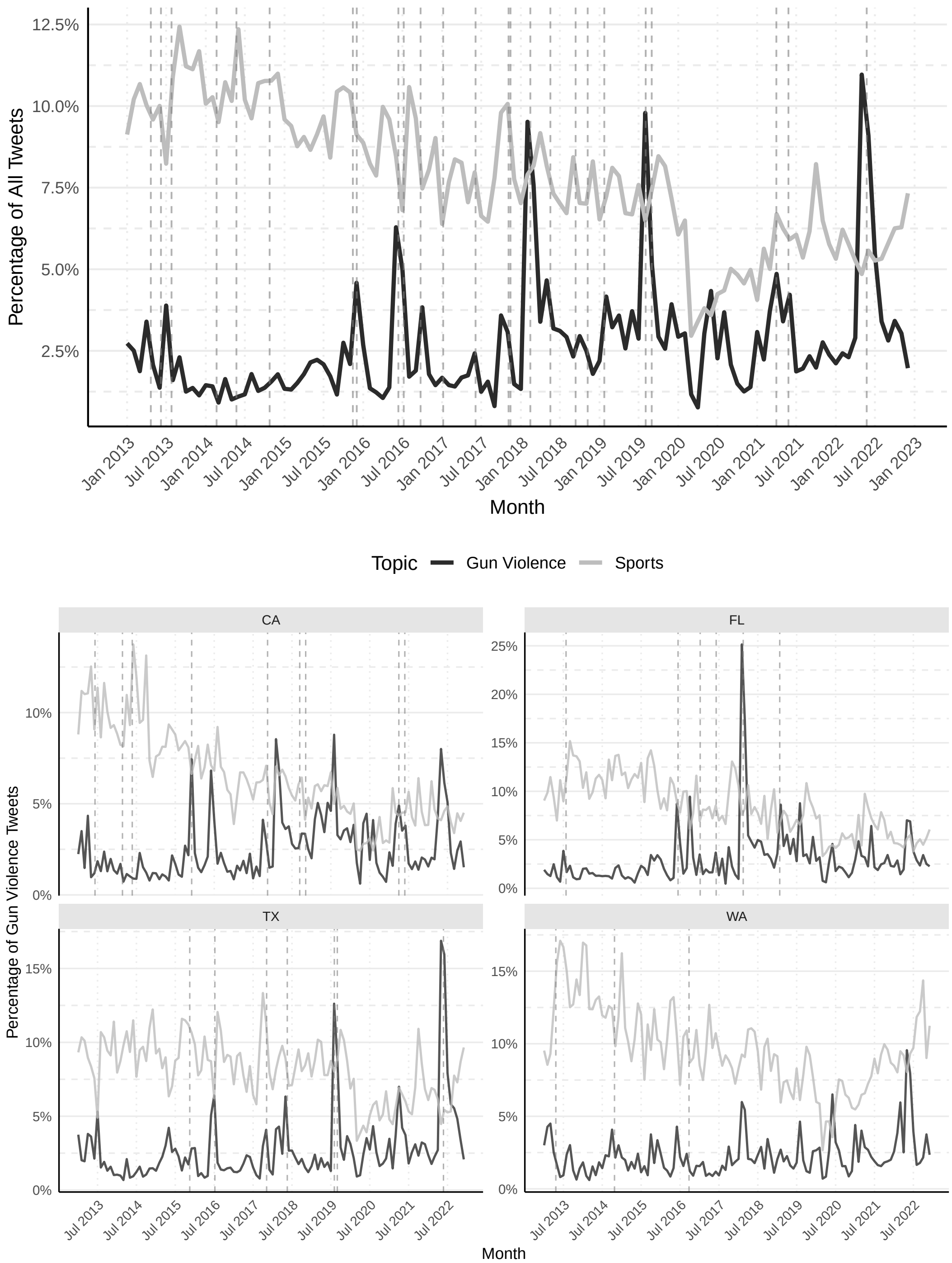
Note: Counts and percentages are shown as N (% of Column Total Tweets).

As seen in Table 2, across the four states in our sample, legislators in California, Texas, Florida, and Washington generated over 2.78 million tweets between January 2013 and December 2022,[8] of which 3.22% explicitly discuss gun violence and 7.12% relate to sports. Substantive discussions of gun policy (2.30%) and blame attribution (1.53%) occur with moderate frequency, but explicitly ideological tweets are rare: pro-gun rights tweets account for only 0.38% of all tweets, and pro-gun control tweets for 0.95%. These categories are not mutually exclusive, so a single gun-violence tweet may register on more than one. The sample includes 961 unique legislators, with Democrats and Republicans nearly equally represented (477 and 478, respectively), 5 legislators who switched parties during the study period, and 1 legislator who could not be matched to LegiScan party records.

Figure 1 plots the monthly percentage of tweets classified as relating to gun violence and sports over the study period, with dashed vertical lines marking the mass shootings in our sample. Gun violence discourse is sparse in most months but spikes sharply in the immediate aftermath of major shooting events; the highest monthly peaks follow the May 2022 Uvalde school shooting, the August 2019 Dayton and El Paso shootings, and the February 2018 Parkland school shooting. The most dramatic single-day concentration occurred on May 25th, 2022, the day after Uvalde, when gun violence accounted for 693 of 1,430 total tweets, with an additional 571 of 1,627 tweets on the shooting day itself. In percentage terms, the daily peak came on August 4th, 2019, the day after the Dayton shooting, when gun violence was present in roughly half of all tweets posted that day (419 of 824). The sports series exhibits a seasonal rhythm tied to the sporting calendar rather than to crises: the highest

[8]In Appendix A.4, we describe patterns of tweet activity among individual lawmakers in our data.

Figure 1: **Discussion of gun violence (and sports) varies over time**



Note: This figure presents monthly time series of the percentage of tweets classified into gun-related topics. The top panel aggregates tweets across all states in the study and displays the share of tweets referencing gun violence and sports (the latter serving as a placebo reference category). The bottom panel reports time series with separate panels for each state. Dashed vertical lines indicate the timing of mass shooting events occurring in the study states. Percentages are calculated relative to all tweets in a given month.

daily count of sports tweets coincided with Super Bowl LV (267 of 871 tweets on February 7th, 2021), while the highest single-day share coincided with the United States winning the FIFA Women's World Cup Final on July 7th, 2019 (222 of 595 tweets, or 37%). Gun violence tweets appear episodic and crisis-driven, while sports tweets are more calendrical and predictable, which reinforces their validity as a placebo outcome in our design.

5.2 Mass Shootings Cause Large Increases in Discussion of Gun Policy, Asymmetry in Partisan Responses, and Dilution of Substantive Framing

5.2.1 RDDiT Results

Figure 2 presents the core volume result. The occurrence of a mass shooting is associated with a dramatic increase in the odds of a legislator's tweet being about gun violence. The pooled meta-analysis (found in Appendix A.5, Table A.5.1) estimates approximately 572% higher odds that a tweet addresses gun violence in the days immediately following an in-state shooting. The effect is largest among Democrats (662% higher odds) and still substantial among Republicans (392%). As Figure 2 shows, this effect appears to be short-lived, as the odds ratio reaches pre-shooting levels by approximately 25 days after a shooting, on average. The sports placebo shows no discontinuity, confirming that shootings increase gun violence discourse rather than just increase tweeting volume.

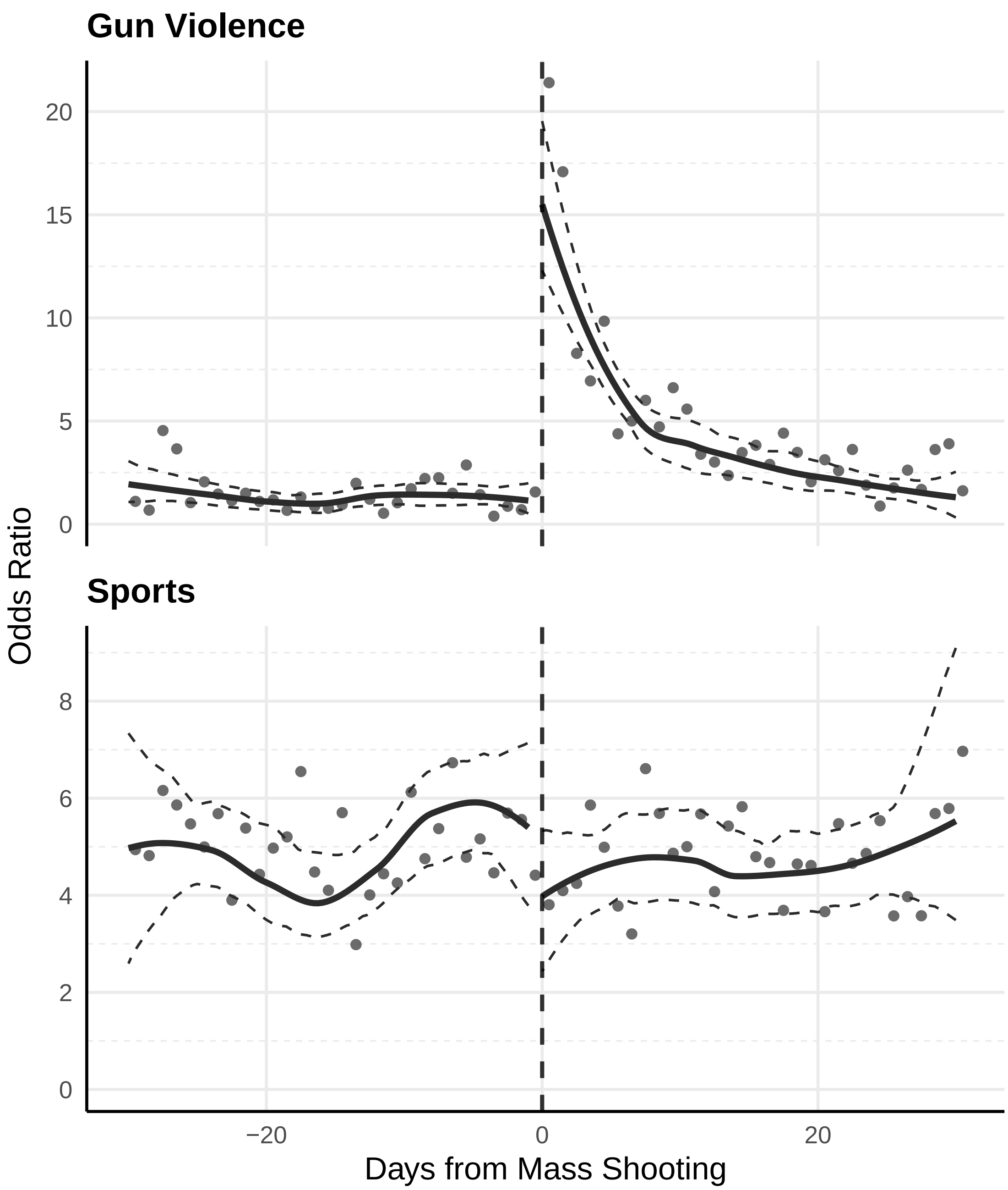
Mass shootings also reshape how legislators discuss gun violence substantively, though here the pattern is more nuanced (second section of Table A.5.1). When conditioning substantive categories against all other tweets (top panel of Figure 3), Democrats increase their pro-gun control rhetoric significantly while Republicans show no such change. Neither party significantly changes its rhetoric supporting gun rights. Both parties increase discussion of policy and blame attribution, with Democrats showing stronger effects in both dimensions (167% v. 19.5% and 61.2% v. 13.7%, respectively).

5.2.2 The Composition of the Surge

The aggregate increase in gun violence discourse is clear. But as a share of tweets explicitly about gun violence (the third section of Table A.5.1 and bottom panel of Figure 3), every substantive discourse category we measure *decreases* as a share of gun violence rhetoric following a shooting. This pattern holds for both Democrats and Republicans.

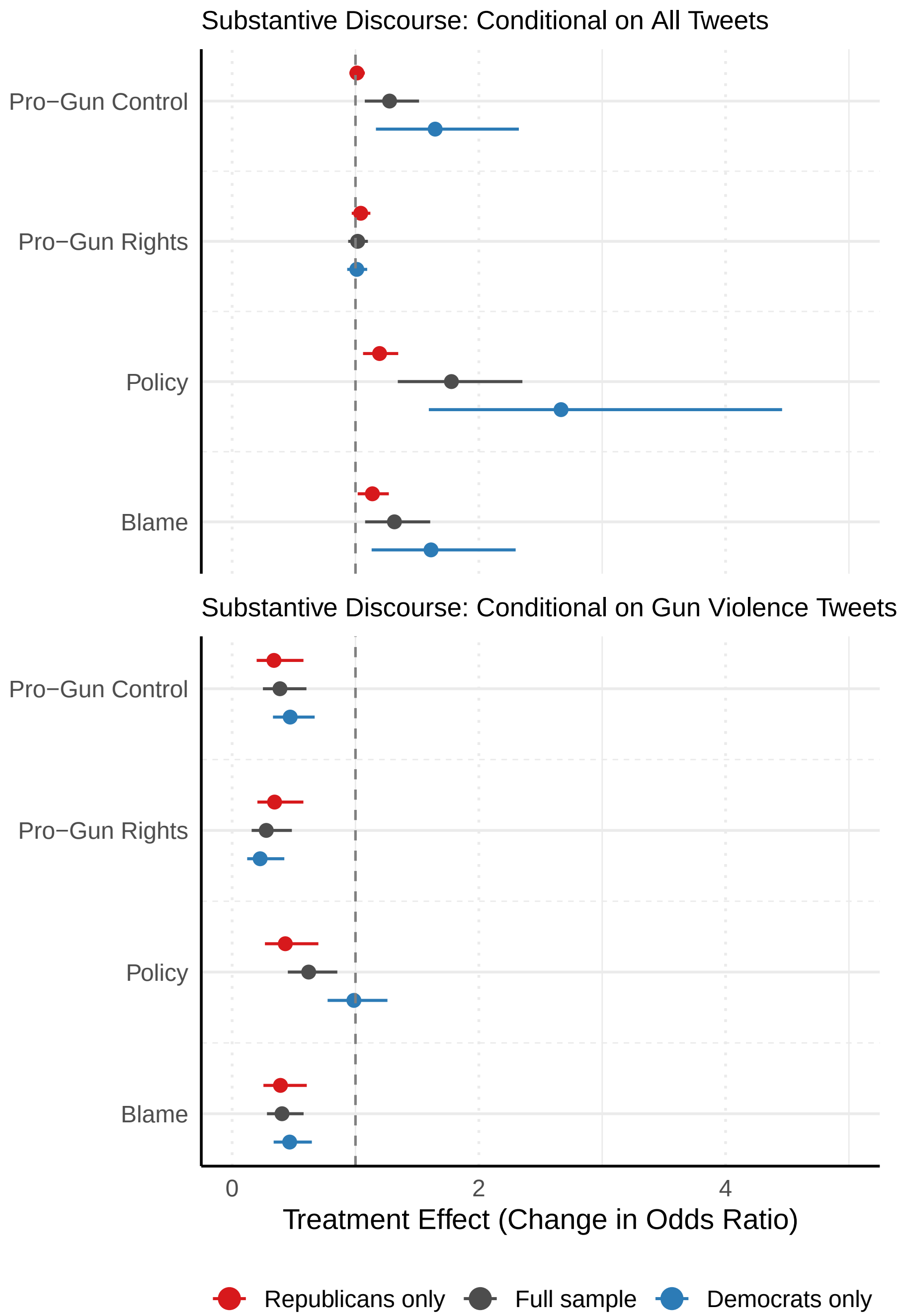
This distinction is critical to interpreting the results in the top panel of Figure 3. The absolute increases in pro-control framing, policy discussion, and blame attribution observed relative to all tweets reflect a mechanical consequence of the large overall expansion in gun violence discourse, not a proportional shift toward substantive engagement. Among Democrats, the increase in pro-control tweets relative to all tweets is driven by more gun violence tweets overall, not by disproportionate movement toward policy stances *within* gun violence discourse. Among Republicans, the share of gun violence discourse devoted to policy, blame, or ideological positioning falls significantly even as the volume of gun violence tweets rises.

Figure 2: **Legislators tweet more about gun violence after mass shootings; no change in discussion of sports**



Note: The figure plots pooled changes in the odds of posting about gun violence (versus not) and sports (versus not) in the days surrounding mass shooting events. The horizontal axis shows days relative to the shooting date (day 0, dashed vertical line), and the vertical axis reports odds ratios derived from log-odds outcomes. Points represent daily means of the odds ratio, pooling observations across all shootings. Solid lines show locally weighted (LOESS) fits estimated separately on the pre-shooting and post-shooting periods using the underlying, unbinned data; dashed bands denote 95% confidence intervals obtained via bootstrap resampling. Odds ratios above one indicate increased attention to the topic relative to all other Tweets.

Figure 3: **Legislators tweet more about ideology, policy, and blame relative to all tweets after mass shootings, but substantive topics are LESS prevalent in gun violence tweets**



Note: Treatment effect distributions by topic for shooting events in study. Top panel: Odds ratio of topic versus all other non-topic Tweets. Bottom panel: Odds ratio of topic versus non-topic *gun violence* Tweets. Points and confidence intervals represent pooled meta-analysis estimates, for models run on the full sample of legislators, only Democrats, and only Republicans. For a full reporting of the results, please see Table A.5.1.

Taken together, these initial results confirm that mass shootings function as focusing events in the minimal sense: they clearly and substantially elevate gun violence on the agenda of legislative discourse. Whether that elevated discourse constitutes genuine responsiveness or something closer to salience absorption is the question we turn to next.

5.3 What Fills the Gap? Expressive Content Dominates Post-Shooting Rhetoric

The preceding results establish what legislators do *not* do after mass shootings: they do not shift their gun violence discourse toward substantive content (Table A.5.1 and Figure 3). We find that volume surges while positional content thins. Our theory predicts that the volume surge would be driven by expressive content that generates visible engagement without incurring the electoral risk of position-taking—for example, condolences, prayers for victims, acknowledgments of tragedy, and calls for unity. We expect legislators to *perform* responsiveness without committing to a policy response.

We isolate this content through what we call "Black Box" tweets: gun violence tweets carrying no ideological, policy, or blame signal in our second-stage classification. These are the residual of our coding scheme, and through training the LLM to flag substantive content, we intentionally leave everything non-substantive unflagged. That residual should, in theory, be expressive. In the analyses that follow, we verify that assumption.

We classify these remaining tweets into thematic categories using BERTopic (Grootendorst, 2022), a modular topic modeling framework.[9] The model partitions tweets into three distinct thematic categories reported in the top panel of Figure 4: Thoughts and Prayers (37.7%), Information (32.5%), and Healing and Solidarity (29.8%). The bottom panel reports example tweets from each category. We fix $K = 3$ based on a stability sweep across $K \in \{3, \ldots, 8\}$ in which the same three substantive topics recur at every value of K, with additional clusters small or noise-like. Full technical details on the model's embeddings, clustering parameters, and topic representation are provided in Appendix A.6, and the keywords associated with each category are shown in Figure A.6.1.

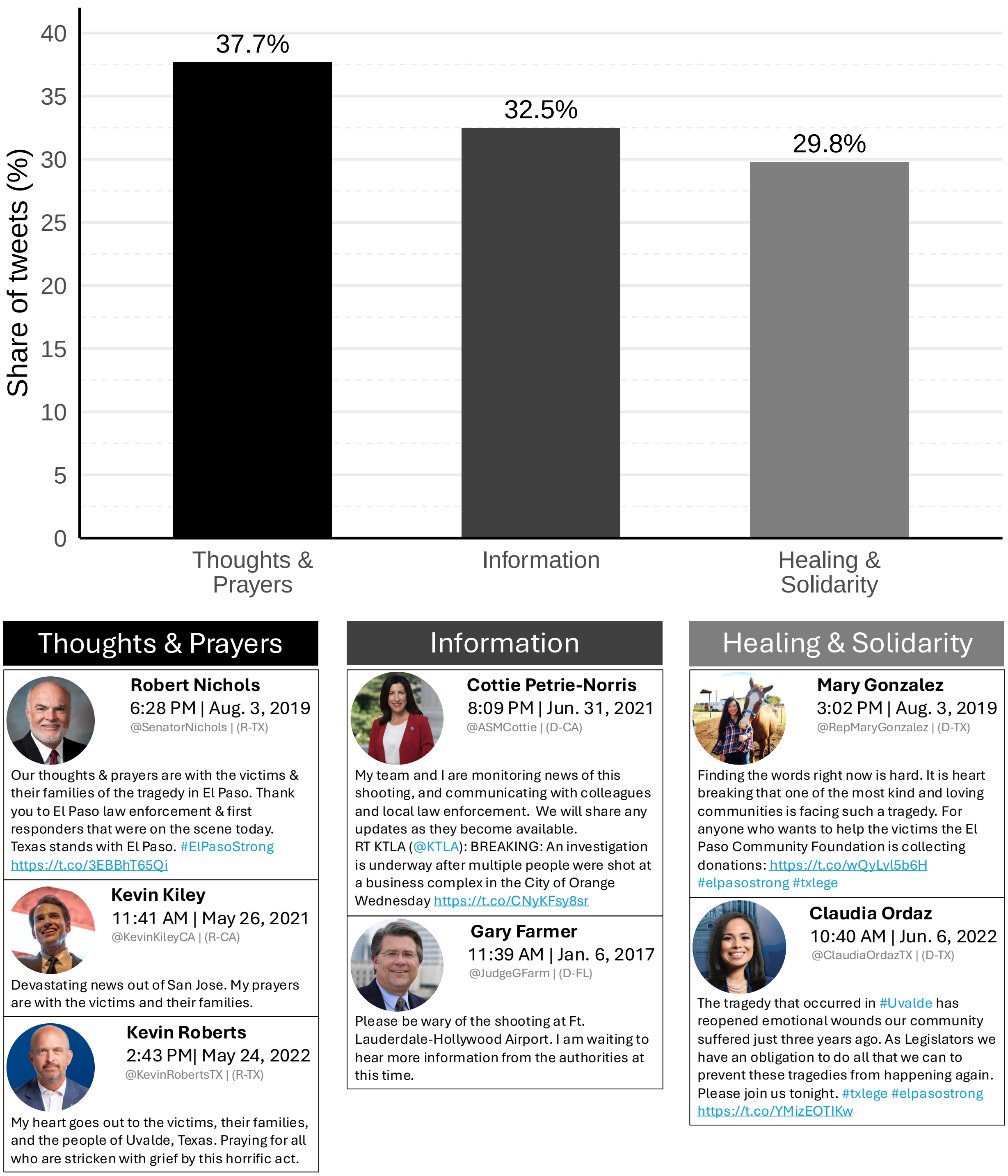
To quantify the shift from substantive to expressive rhetoric, we estimate the change in the odds of Black Box tweeting using two specifications: first, relative to the legislator's entire corpus, and second, conditional on the subset of tweets already discussing gun violence. We also disaggregate the Black Box into the three BERTopic categories, constructing log-odds outcomes for Information, Healing and Solidarity, and Thoughts and Prayers conditional on Black Box tweets. Figure 5 reports the main results, with full results reported in Appendix Table A.5.2.

5.3.1 The Expressive Surge

The magnitude of the expressive surge is striking. Across the full sample, the odds of a legislator posting a Black Box tweet increase by approximately 246% (OR = 3.458). This effect is large for both parties (Democrats: OR = 2.836; Republicans: OR = 3.881). The

[9]Starting from 4,955 tweets posted by state legislators within 30 days of mass shooting events, we apply standard pre-processing (removing URLs, mentions, retweet prefixes, and HTML entities) and filter to English-language tweets using the `langdetect` library, yielding a final corpus of 4,827 tweets.

Figure 4: **Unclassified gun violence tweets are all expressive registers**



Note: Distribution of non-LLM-classified gun violence tweets across three thematic categories identified via BERTopic. Each category represents the share of gun violence tweets classified into that topic among all tweets not coded as pro-gun control, pro-gun rights, policy discussion, or blame attribution. Tweet examples are drawn from the study sample and are representative of each category's modal content.

volume surge documented in Table A.5.1 is predominantly expressive messaging rather than substantive policy engagement.

Conditioning on tweets about gun violence allows us to examine the frequency of expressive rhetoric among legislators *already* talking about guns. Here, we observe a significant compositional shift toward expressive discourse (OR = 1.542) among all legislators, but this shift is not symmetric across parties. Democrats' gun violence tweets show no change in their pre-shooting compositional character (OR = 0.986). Republican discourse, by contrast, becomes significantly more expressive (OR = 2.204).

Disaggregating to the subtopics reveals a further pattern. The share of discourse classified as Information or Healing & Solidarity actually decreases as a proportion of expressive content for both parties, suggesting a displacement of the more representational functions of expressive communication (such as providing resource information or fostering community solidarity). Among Republicans, Thoughts & Prayers fills the gap: Republican legislators see a significant increase in the odds of using this specific rhetorical register (OR = 1.684). The post-shooting period triggers a condolence ritual that allows high-volume engagement with the public while systematically avoiding position-taking costs.

If the surge in expressive tweets were simply a natural human response to loss, we would expect to see a symmetric increase across both parties as legislators react to the same exogenous shock. Instead, the results reveal partisan divergence: while both parties increase their volume of discourse, Republicans specifically concentrate their surge in the Thoughts & Prayers register. For these legislators, expressive discourse serves a protective function, creating the appearance of responsiveness while foreclosing substantive positional commitment. Thoughts & Prayers operates not merely as an expression of grief but as a rhetorical sink that occupies the salience of a mass shooting without engaging with its political causes.

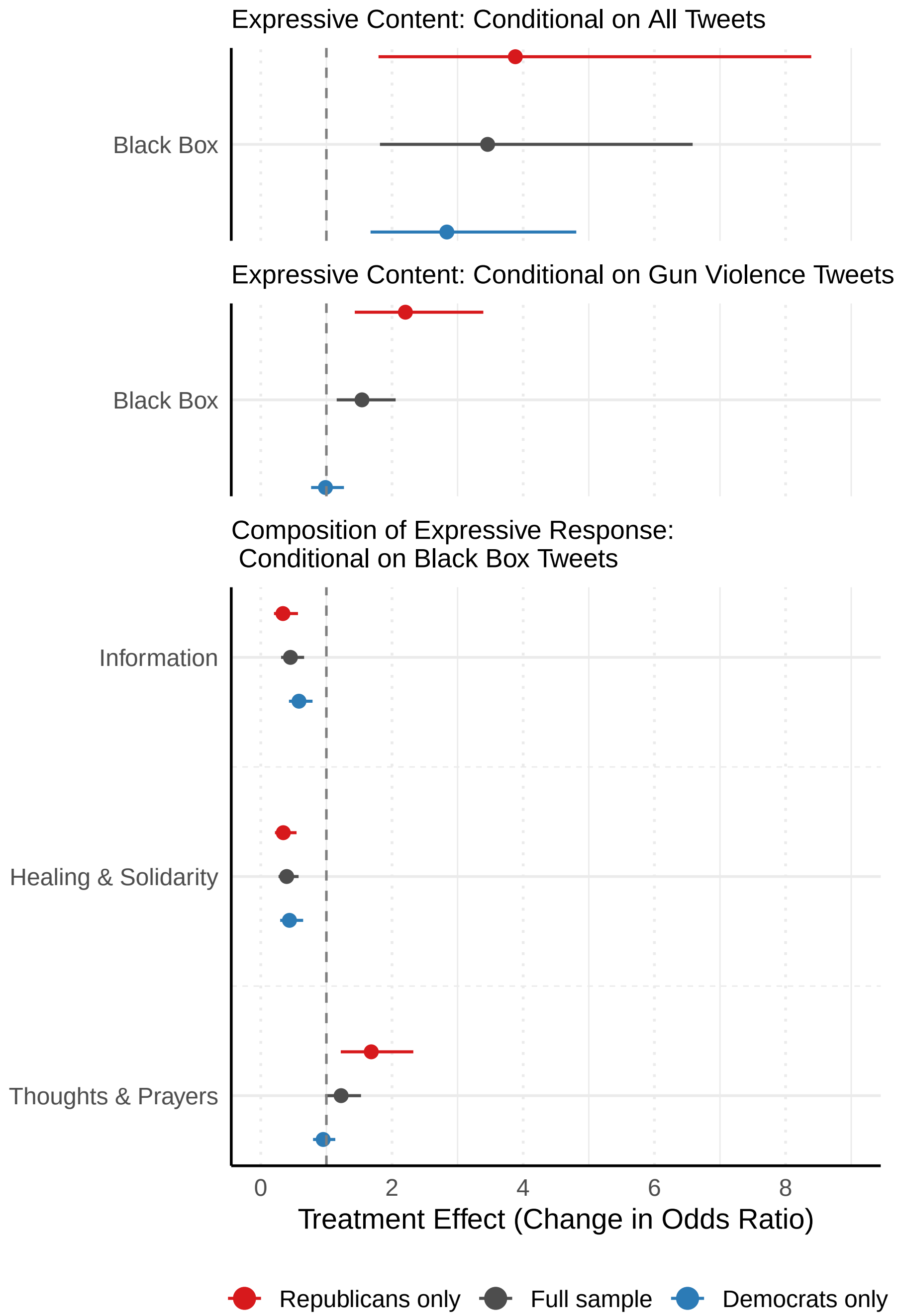
6 Strategic, Not Reflexive: Electoral Exposure Amplifies Salience Absorption

Salience absorption suggests that legislators in more competitive districts, where thin margins raise the cost of alienating voters, should intensify expressive communication to avoid positional risk. Competitiveness is an observable signal: a marginal-district legislator recognizes that expressive, noncommittal language is safer without calculating specific gun-policy costs. We treat competitiveness as a proxy for the broader electoral calculus that intensifies expressive behavior, not a direct measure of position-taking costs. If the shift reflects strategic calculation, it should be greatest in the most competitive environments. We test this directly.

We measure district competitiveness using the average Democratic two-party vote share ($D/(D+R)$) across all contested general elections from 2010–2022 from Klarner (2025). Competitive districts are those with average lean within 10 percentage points of 50-50 ($|\text{lean} - 0.5| \leq 0.10$), yielding 361 competitive and 439 safe legislators (800 of 961; remaining cases lack contested D–R elections or service in session-years). Uncontested and same-party general elections are excluded. The median district lean is 0.48.

Table A.5.4 reports full results. The core pattern replicates in both subsamples: surges

Figure 5: **Expressive content dominates post-shooting rhetoric**



Note: Treatment effect distributions for the expressive content topics. Top panel: effect on "Black Box" tweets versus all other non-topic tweets. Middle panel: effect on "Black Box" tweets versus gun-violence-related tweets only. Bottom panel: composition of the expressive response—effects on "Information", "Healing & Solidarity", and "Thoughts & Prayers" versus all other non-topic tweets, conditional on the tweet being inside the "Black Box" category. Points and confidence intervals represent pooled meta-analysis estimates for the full sample of legislators, Democrats only, and Republicans only. For complete reporting, see Table A.5.2.

in gun violence discourse, declines in substantive frames, and increases in expressive tweets occur in competitive and safe districts. Salience absorption is a general feature, not an artifact of vulnerability, and competitiveness amplifies it.

Among competitive-district legislators, the odds of producing expressive content conditional on a gun violence tweet increase by 76% (OR = 1.763), compared to a 44% increase among safe-district legislators (OR = 1.443). This difference is statistically significant in a paired meta-regression that estimates within-shooting differences in treatment effects between competitive and safe districts, isolating the competitiveness contrast from shooting-level confounds (Figure 6).[10] The suppression of policy content among legislators already discussing gun violence is also more pronounced in competitive districts (OR = 0.531) than in safe ones (OR = 0.656), and this difference is also significant in the paired test. Legislators with the most to lose electorally are the most aggressive in displacing substantive content from their gun violence communication.

Taken together, the results provide the strongest evidence that salience absorption is a strategic response to focusing events rather than a reflexive one. The post-shooting shift towards expressive discourse is concentrated where the electoral costs of positional commitment are highest.

6.1 Electoral Competitiveness by Party

We further decompose the competitiveness result by party in Appendix A.5.2. This reveals a ceiling effect among Republicans: both safe-seat and competitive-seat Republicans shift sharply toward expressive content after shootings (OR = 1.92 and 2.09, respectively), with no significant difference between them. On the other hand, both competitive- and safe-district Democrats show no significant change in expressive content, but the difference between these groups *is* statistically significant. This suggests that competitive-district Democrats are more likely to engage in expressive tweeting than safe-district co-partisans, and competitive-district Democrats suppress policy discussion significantly more than safe-seat counterparts (paired OR ratio = 0.80). This is consistent with our theory: Republican absorption is near-universal because the post-shooting opinion environment constrains discursive options regardless of electoral safety, leaving no variance for competitiveness to explain. Among Democrats, where the baseline permits substantive engagement, electoral risk compresses the available repertoire toward expressive content.

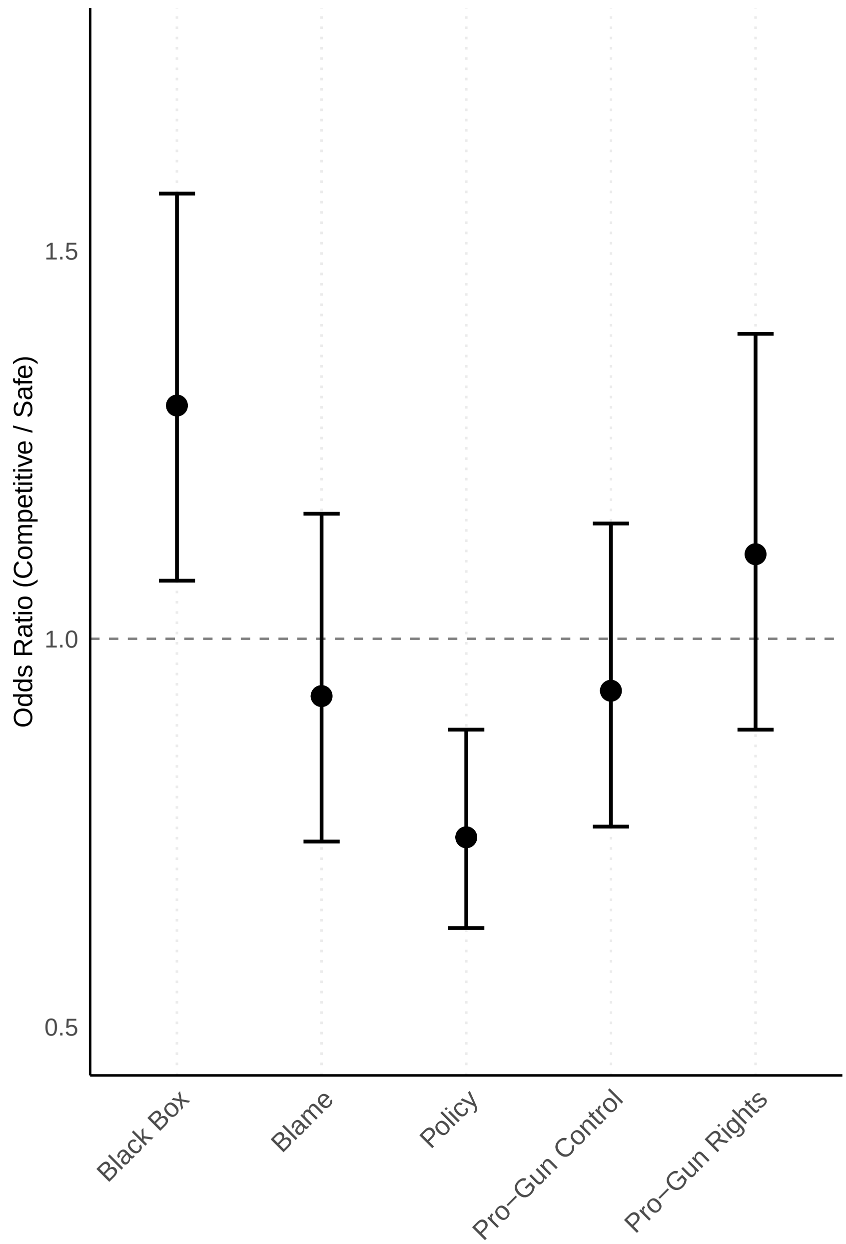
7 Robustness

7.1 Legislators In Office

In Appendix A.7.1, we restrict our sample of twitter accounts to only those of legislators known to be currently serving in office during the session-year of a shooting. We find no

[10] We compute the within-shooting difference in the estimated treatment effect (log-odds scale) between competitive- and safe-district legislators, and then fit a random-effects meta-analysis on these differences to test whether the average difference differs from zero. This paired approach accounts for the fact that estimates from the same shooting may be correlated and isolates the effect of competitiveness.

Figure 6: **Legislators in competitive districts retreat to expressive content and avoid policy discussion more than those in safe districts**



Note: Paired meta-regression comparing competitive and safe districts within each shooting event; black points and confidence intervals represent pooled estimates.

evidence that our main findings are driven by out-of-office accounts, or those of former or future legislators who may tweet differently from active officeholders.

7.2 School Shootings

In Appendix A.7.2, we examine whether our results differ across school and non-school shootings. Prior research has found that school shootings produce differential responses among PACs (Baldwin, Iwasaki and Donohue, 2025), suggesting they may operate as distinct windows of opportunity, though there is little evidence of differential effects among the mass public (Hassell, Holbein and Baldwin, 2020). The broad pattern of our main results holds, as seen in Table A.7.2: legislators increase their gun violence tweeting following a shooting, particularly for school shootings, and shift away from ideological and policy content conditional on tweeting about gun violence. The consistency in direction across all outcomes suggests that the main findings are not driven by any particular type of shooting.

7.3 Retweets

Retweets amplify others' content rather than originate it, raising the question of whether the absorption pattern reflects legislators' own communicative choices or merely their curation of others' expressive output. If salience absorption is strategic, we would expect it to be at least as pronounced in legislators' original posts. In Appendix A.7.3, we drop the 39.3% of tweets in our data that are retweets[11] and re-estimate our models on original posts only. The main findings are substantively unchanged. One divergence is that the Thoughts & Prayers share rises from a null effect in the full sample to a significant increase among original posts only, suggesting that legislators across parties post this expressive content at higher rates than they amplify it by retweeting—reinforcing our theory.

8 Conclusion

Salience absorption is the conversion of crisis-driven pressure into expressive communication. Mass shootings, as we show, function as focusing events in the minimal sense: they elevate gun violence on the agenda of legislative discourse, sharply and consistently. But the content of that discourse does not meet the standard of substantive responsiveness that representation theories anticipate. The volume of engagement rises by an order of magnitude while its positional content thins. Legislators flood the communicative channel with condolences, expressions of grief, and calls for unity, performing representation and attentiveness at the moment constituents demand it without committing to any policy response. The energy of the focusing event is redirected into advertising rather than position-taking.

Salience absorption is not the strategy that the existing literature would predict for a polarized domain. Tomz and Van Houweling argue that in partisan settings, voters "optimistically perceive the locations of ambiguous candidates from their own party without

[11] 1,094,309 tweets are dropped; five legislators are excluded whose feeds leave no original tweet-days. These are Devon Mathis (CA), Monique Limon (CA), Avelino Valencia (CA), Larry Metz (FL), and J.M. Lozano (TX).

pessimistically perceiving the locations of vague candidates from the opposition," (2009, p. 83). A blurred position is still a position, as the candidate has taken a stance and simply stated it imprecisely. Copartisan voters simply perceive the candidate as nearer to themselves than the evidence warrants. Salience absorption removes even the imprecision. The legislator offering thoughts and prayers has not taken a vague position on background checks; she has taken no position on the policy dimension at all, leaving voters nothing to evaluate. Where blurring muddies a stance that *is* taken, absorption supplies no stance to muddy at all.

Nor is salience absorption issue avoidance (Egan, 2013; Sulkin, 2005), since topic engagement surges rather than falls. Sigelman and Buell complicate the avoidance account, and show that candidates converge on the same issues more than avoidance would suggest, but they concede that such convergence "may well have taken the form of superficiality, vagueness, or ambiguity rather than close reasoning and clear, precise articulation" (2004, p. 660), and that this makes "the nature and quality of what [elites] say when they address these issues" the "crucial" question. Salience absorption answers that question for a polarized domain under acute pressure. Avoidance withdraws attention, blurring obscures a position taken, and absorption does neither, converting salience pressure into volume without valence. Naming this response is our paper's central theoretical contribution.

Absorption may also offer a distinct upside the other strategies lack. Avoidance signals indifference and blurring signals evasion, but expressive content can credibly display attentiveness, empathy, and fitness for representational office. Whether voters in fact read it this way, and whether they distinguish it from substantive engagement, are empirical questions our data cannot adjudicate, but the asymmetric availability of this signal helps explain why absorption is the preferred strategy in the moment when visible care matters most.

Polarization is the condition that makes absorption available and attractive to legislators. The pressure to engage a salient issue is not in dispute: the logic of "riding the wave" holds that candidates gain some advantage by addressing whatever issue ranks highest on the public agenda and lose by ignoring it, needing "to be seen as concerned, responsive, and informed" about the major issues of the day (Ansolabehere and Iyengar, 1994, p. 337). That account presumes engagement and substance travel together. Polarization severs them. In a pre-sorted domain, position-taking is informationally redundant for co-partisans, who already know where their representative stands, and politically costly with everyone else, who will punish deviation, so the marginal return to substantive commitment falls while the marginal risk rises. The wave still arrives and legislators still ride it, but they ride it expressively: they supply the visible engagement the salience demands while withholding the position the domain makes dangerous. This is why the pattern tracks the structure of the issue. Republicans absorb near-universally, as their owned position is less popular after a shooting and their base would punish movement toward gun control. Democrats absorb selectively, with absorption concentrated among the competitive-district legislators for whom the electoral stakes of any positional commitment are highest, while safe-seat Democrats retain the room to engage substantively. Absorption is not a reflex of grief common to all legislators but a strategic adaptation to the accountability environment that a sorted domain creates—its intensity rises exactly where that environment is most constraining.

The information environment salience absorption constructs differs from the one accountability theory presupposes. Standard models treat heightened salience as the condition under which voters extract positional information from elites and evaluate them on its basis. We find that in pre-sorted domains, the salience itself becomes a resource elites use to perform responsiveness without supplying the positional content the model requires. The channel remains open and, by sheer volume, more active than usual, but what flows through it is informationally thinner. Salience absorption also reveals how legislators perceive the electoral landscape of gun policy independent of what they say in surveys or how they vote on the floor, both of which face limitations our measure does not: surveys capture stated belief, and roll-call votes are contaminated by party discipline, agenda control, and strategic timing. That legislators systematically convert salience into expressive rather than substantive communication shows they treat gun policy as a domain where positional commitment is costly. Whether that perception is accurate or whether, following Broockman and Skovron (2018), it rests on misperception, we cannot adjudicate, and the distinction matters: in one case absorption is an equilibrium response to real constraints, in the other a deviation sustained by misperception that itself contributes to stasis.

This latter possibility raises the prospect that salience absorption is self-reinforcing. If legislators avoid substantive engagement because they perceive it as risky, and their avoidance prevents the public from observing elite disagreement on specific policies, then the public never receives the cue structure that would update preferences or signal that policy change is possible. The absence of substantive elite discourse after shootings may itself sustain the perception that gun policy is a political third rail, which in turn sustains the absorption that produced the lack of substance.

However, our analysis is limited in ways that bear on generalizability. We study four states that span the ideological spectrum of American gun politics, but partisan dynamics elsewhere may differ in ways that would alter our findings. Gun policy is also an extreme case of sorting, and while the logic of salience absorption should extend to other polarized domains where focusing events create visibility pressure—immigration after border crises, abortion after court decisions, policing after high-profile use-of-force incidents—the intensity of absorption likely varies with the degree of sorting in the domain. Whether the patterns we document among state legislators, who face less media scrutiny than members of Congress, replicate at the federal level is an open question. They may attenuate if national media accountability disciplines legislators toward substantive engagement, or intensify if the national spotlight makes positional commitment even riskier.

The standard account of focusing events holds that elevated salience produces substantive elite engagement, which in turn opens policy windows. Salience absorption breaks this chain at the critical link: salience rises, but elite engagement is channeled into expressive registers that perform responsiveness without generating policy action. If the public reads expressive communication as functionally equivalent to substantive responsiveness, the demand the focusing event produces is satisfied without action being taken. The system is not gridlocked in the conventional sense. Legislators are not silent and they are not inactive. They are, by every visible measure, responding—albeit in a register designed to absorb the very pressure that might otherwise produce change, and in doing so foreclosing the conditions under which the next response might be any different.

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Supplemental Materials

Intended for online publication only.

Contents

A.1 LLM Classification Prompts

All tweet classification was performed using OpenAI's GPT-4.1 mini. For every API call we set the sampling temperature to 0, top-p to 1, the maximum response length to 200 tokens, and the response format to JSON (`response_format = {"type": "json_object"}`). Tweets were processed one at a time in independent API calls, with the tweet text passed as the user message; the system prompt for each stage is reproduced verbatim below.

Stage 1: Topic and Sentiment Classification

The following system prompt was applied to every tweet in the corpus.

```
Classify tweets into two sets of categories: policy labels and a single
sentiment/tone label.

Policy Labels: gun_violence, sports.
Sentiment/Tone Labels: positive, negative, sarcastic, neutral.

Steps

  1. Read the Tweet: Carefully examine the tweet content.
  2. Identify Policy Keywords or Themes: Look for words or themes falling
     under the policy labels.
  3. Identify Sentiment/Tone Keywords or Expressions: Determine the tweet's
     primary sentiment or tone.
  4. Label Assignment: Assign all applicable policy categories and the most
     appropriate sentiment/tone category.

Output Format

Output should follow this JSON structure:

{"policy_labels": ["applicable policy labels"], "sentiment_label": "applicable
sentiment/tone label"}

Examples

Example 1.
Input: ‘‘As lawmakers, we support initiatives to reduce gun violence and
pass commonsense reforms.’’
Output: {"policy_labels": ["gun_violence"], "sentiment_label": "positive"}

Example 2.
Input: ‘‘It is vital that we address the impact of sports regulations as
legislators.’’
Output: {"policy_labels": ["sports"], "sentiment_label": "neutral"}
```

Example 3.
Input: ‘‘We’re committed to addressing every instance of gun violence with thorough legislation. The situation is grave.’’
Output: {"policy_labels": ["gun_violence"], "sentiment_label": "negative"}

Notes

- Ensure that the content relates genuinely to the subject, not just mentioning the terms.
- For sentiment/tone, choose the label that most accurately represents the tweet’s overall tone.

Stage 2: Gun Policy Position Classification

The following system prompt was applied only to tweets classified as gun-violence-related in Stage 1.

Classify each tweet by answering these four variables, then output only the final result as a JSON object---never include any intermediate steps, reasoning, or commentary.

1. Is the tweet pro-gun rights? (1 = yes, 0 = no)
2. Is the tweet pro-gun control? (1 = yes, 0 = no)
3. Primary policy domain emphasized (max 2 words), or NA if not about policy.
4. Actor blamed (max 2 words), or NA if none.

Internally reason step-by-step for each variable, but output only the JSON; never include your reasoning. For policy_domain and blamed_actor, use NA (no quotes) if the tweet lacks clear information or is ambiguous. Never force a category. Field order and data types must match exactly.

Output Format

Output a JSON object with these fields and values:

- "pro_gun_rights": 0 or 1
- "pro_gun_control": 0 or 1
- "policy_domain": string (max 2 words, or NA)
- "blamed_actor": string (max 2 words, or NA)

Do not quote NA; use the bare identifier. Output only the JSON.

Examples

Example 1.
Input: ‘‘We need to focus on enforcement to reduce gun violence. Stronger

enforcement matters more than banning guns.''
Output: {"pro_gun_rights": 1, "pro_gun_control": 0, "policy_domain": "enforcement", "blamed_actor": NA}

Example 2.
Input: ''Blaming video games for shootings is just scapegoating. Focus on real solutions.''
Output: {"pro_gun_rights": 0, "pro_gun_control": 0, "policy_domain": "gun policy", "blamed_actor": "video games"}

Notes

- Always use NA for policy_domain or blamed_actor if information is missing or unclear---never speculate.
- Output nothing but the JSON.
- Maintain exact field order and types.

Reminder. Carefully analyze and reason internally for each field, but always output only the required JSON structure. If information is lacking, use NA (unquoted) for open-ended fields.

Because Stage 2 poses two independent yes/no questions, `pro_gun_rights` and `pro_gun_control` are not constrained to be mutually exclusive: a tweet expressing positions consistent with both registers as 1 on both indicators.

A.2 Classifier Validation

To validate the Stage 2 classifier, two authors independently coded 100 gun-violence tweets each. 25 of these tweets, stratified across observed combinations of the four Stage 2 outcomes, are shared across both coders to assess inter-coder reliability; the remaining 75 per coder are drawn at random from the pool of valid gun-violence tweets. Coders worked from a codebook that reproduced the operational definitions supplied to the LLM in the Stage 2 prompt, and completed a calibration round on a separate set of practice tweets before coding the validation set. Coders were blind to the LLM's predictions throughout.

On the shared tweets, Cohen's κ across the two coders is 0.702 for pro-gun-rights, 0.603 for pro-gun-control, 0.679 for policy domain, and 0.688 for blamed actor. For policy domain and blamed actor, κ is computed on binary indicators (any non-NA value coded 1, NA coded 0) rather than on the underlying free-text labels.

By these benchmarks, agreement is substantial for all variables. Per-variable agreement rates and Cohen's κ between each coder and the LLM are reported for all four Stage 2 variables in Table A.2.1.

Table A.2.1: Human–LLM agreement by coder and Stage 2 variable

Variable	Coder	% Agree	Cohen's κ	N
Pro-gun-rights	Coder 1	95	0.787	100
	Coder 2	95	0.772	100
Pro-gun-control	Coder 1	84	0.612	100
	Coder 2	89	0.770	100
Policy domain	Coder 1	80	0.608	100
	Coder 2	82	0.610	100
Blamed actor	Coder 1	79	0.547	100
	Coder 2	84	0.648	100

Notes: Per-coder agreement and Cohen's κ against LLM labels on 100 gun-violence tweets each. Policy domain and blamed actor computed on binary non-NA indicators.

A.3 Measuring Tweeting Intensity

Our primary outcomes are smoothed log-odds of topic-specific tweeting. For a given topic k, we define:

$$Y_{its}^{k} = \log\left(\frac{C_{its}^{k} + \epsilon}{C_{its}^{\neg k} + \epsilon}\right), \tag{2}$$

where C_{its}^{k} denotes the number of tweets posted by legislator i on day t (relative to shooting s) that are classified as topic k, and $C_{its}^{\neg k}$ denotes the number of tweets not classified as topic k (i.e., the complementary count). The parameter ϵ is a small constant (set to 0.01 in estimation) added to avoid undefined values when counts are zero. For our broad topical categories (e.g., gun violence or sports), each tweet is coded as a binary indicator (1 if the topic is present, 0 otherwise), making this formulation equivalent to the log-odds that a tweet on a given legislator-day addresses that topic. For gun violence tweets, the denominator is the total number of all other tweets not classified as being about gun violence.

For framing analyses conditional on gun violence tweets, the denominator is restricted to the complementary framing category within gun violence tweets. For example, the pro-gun control framing outcome is defined as:

$$Y_{its}^{\text{control}|\text{GV}} = \log\left(\frac{C_{its}^{\text{pro-control}} + \epsilon}{C_{its}^{\neg\text{pro-control}|\text{GV}} + \epsilon}\right). \tag{3}$$

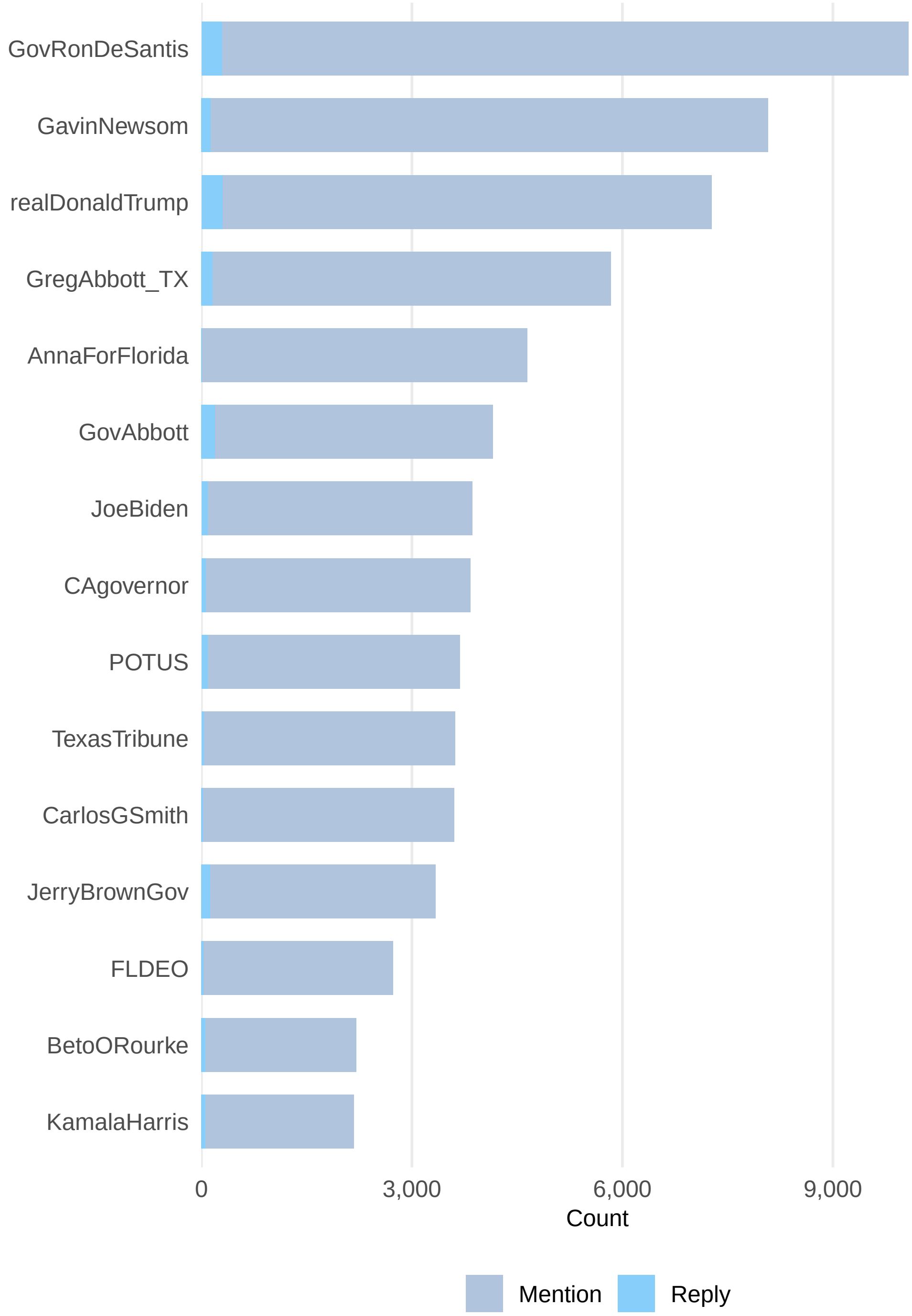
Finally, ideological positioning between pro-gun rights and pro-gun control is measured as:

$$Y_{its}^{\text{rights/control}} = \log\left(\frac{C_{its}^{\text{pro-rights}} + \epsilon}{C_{its}^{\text{pro-control}} + \epsilon}\right). \tag{4}$$

All RDD estimates therefore capture the discontinuous change at the shooting date in the log-odds of topic-specific tweeting.

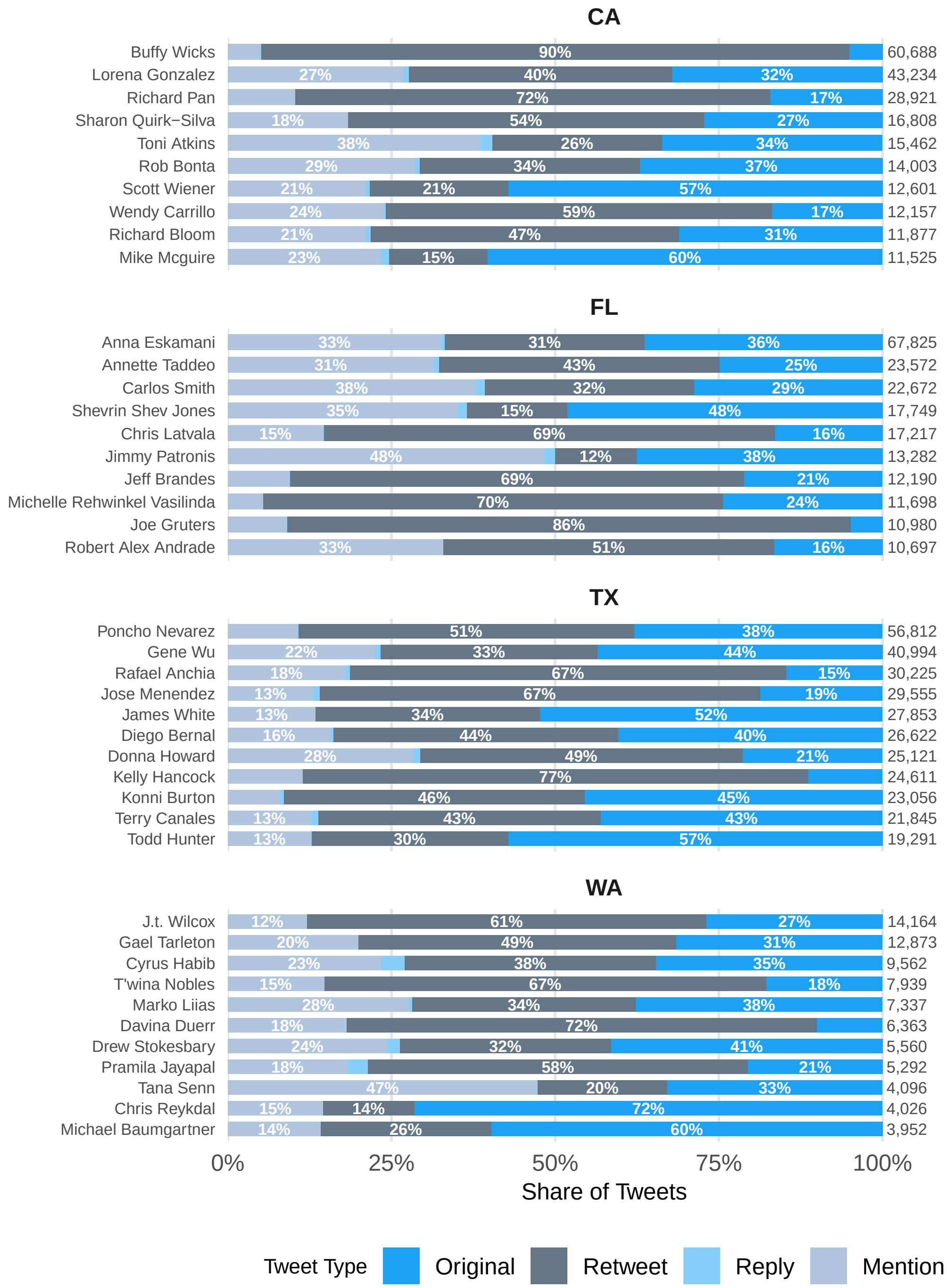
A.4 Twitter Descriptives

Figure A.4.1: **Top 15 Accounts Mentioned or Replied To by State Legislators**



Note: This figure displays the 15 accounts most frequently mentioned or replied to by state legislators across all four study states over the full study period. Bars are stacked by interaction type: mentions (any @username appearing in the body of an original tweet) and replies (tweets directed at a specific account). Accounts are ranked by total interactions across both types.

Figure A.4.2: **Top 10 Tweeters by State and Tweet Type Composition**



Note: This figure displays the ten most active Twitter users among state legislators in each of the four study states, ranked by total tweet volume (shown at the right end of each bar). Stacked bars show the share of each legislator's tweets falling into four mutually exclusive categories: original tweets, retweets, replies, and mentions. Categories are assigned by priority (retweet > reply > mention > original), such that each tweet is counted once. Total tweet counts reflect activity over the full study period, January 2013–December 2022.

A.5 Main RDDiT Results

The ideological framing measure in the final section of Table A.5.1, and not discussed in the main text, captures the odds of a tweet being pro-gun rights relative to pro-gun control. The ratio falls significantly for Democrats (OR = 0.579), indicating a shift toward pro-control framing; Republicans show no significant change. Democratic legislators drive the aggregate pro-control effects almost entirely.

Table A.5.1: Effect of Mass Shootings on Legislator Twitter Activity

	All Legislators	Democrats Only	Republicans Only
Main Topics			
Gun Violence	6.717***	7.662***	4.919***
	(2.854, 15.811)	(3.126, 18.779)	(2.139, 11.314)
Sports (Placebo)	0.987	0.925	1.127
	(0.720, 1.353)	(0.667, 1.282)	(0.716, 1.773)
Substantive Discourse: Conditional on All Tweets			
Pro-Gun Control	1.276**	1.646**	1.012
	(1.075, 1.515)	(1.166, 2.324)	(0.952, 1.076)
Pro-Gun Rights	0.987	1.011	1.042
	(0.941, 1.101)	(0.933, 1.095)	(0.970, 1.121)
Policy Discussion	1.778***	2.666***	1.195**
	(1.343, 2.353)	(1.595, 4.458)	(1.061, 1.346)
Blame Attribution	1.316**	1.612*	1.137*
	(1.078, 1.606)	(1.131, 2.298)	(1.018, 1.270)
Substantive Discourse: Conditional on Gun Violence Tweets			
Pro-Gun Control	0.388***	0.471***	0.339***
	(0.250, 0.602)	(0.331, 0.669)	(0.199, 0.578)
Pro-Gun Rights	0.277***	0.227***	0.344***
	(0.158, 0.484)	(0.122, 0.423)	(0.205, 0.578)
Policy Discussion	0.621**	0.987	0.431**
	(0.452, 0.853)	(0.774, 1.259)	(0.266, 0.699)
Blame Attribution	0.404***	0.466***	0.392***
	(0.282, 0.579)	(0.337, 0.646)	(0.254, 0.605)
Ideological Framing			
Rights/Control Ratio	0.739**	0.579**	1.029
	(0.604, 0.903)	(0.405, 0.826)	(0.948, 1.116)

Significance: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

Notes: This table reports pooled treatment effects from random-effects meta-analyses of shooting-specific regression discontinuity (RD) estimates, estimated separately for all legislators, Democrats only, and Republicans only (excluding party switchers). For each mass shooting and topic, we estimate a sharp RD using the `rdrobust` package (Calonico et al., 2017), with day relative to shooting as the running variable, cutoff at day 0. We employ a triangular kernel and the MSE-optimal bandwidth selector ('mserd'). Standard errors are clustered at the legislator level. The pooled effect (odds ratio) and its 95% Confidence Interval are exponentiated from the log-odds scale. All outcomes are log-odds of tweeting about a given topic (or ratio of topics), with a constant offset ($\epsilon = 0.01$) to accommodate zero counts.

Table A.5.2: Expressive Content Dominates Post-Shooting Rhetoric

	All Legislators	Democrats Only	Republicans Only
Expressive Content: Conditional on All Tweets			
Black Box	3.458***	2.836***	3.881**
	(1.816, 6.583)	(1.673, 4.809)	(1.795, 8.391)
Expressive Content: Conditional on Gun Violence Tweets			
Black Box	1.542**	0.986	2.204***
	(1.157, 2.056)	(0.767, 1.268)	(1.433, 3.392)
Composition of Expressive Response: Conditional on Black Box Tweets			
Information	0.452***	0.582**	0.338***
	(0.310, 0.661)	(0.429, 0.789)	(0.201, 0.567)
Healing & Solidarity	0.395***	0.437***	0.343***
	(0.270, 0.576)	(0.296, 0.646)	(0.216, 0.545)
Thoughts & Prayers	1.224	0.951	1.684**
	(0.981, 1.528)	(0.797, 1.136)	(1.219, 2.325)

Significance: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

Notes: This table reports pooled treatment effects from random-effects meta-analyses of shooting-specific regression discontinuity (RD) estimates, estimated separately for all legislators, Democrats only, and Republicans only (excluding party switchers). For each mass shooting and topic, we estimate a sharp RD using the `rdrobust` package (Calonico et al., 2017), with day relative to shooting as the running variable, cutoff at day 0. We employ a triangular kernel and the MSE-optimal bandwidth selector ('mserd'). Standard errors are clustered at the legislator level. The pooled effect (odds ratio) and its 95% confidence interval are exponentiated from the log-odds scale. All outcomes are log-odds of tweeting about a given topic (or ratio of topics), with a constant offset ($\epsilon = 0.01$) to accommodate zero counts.

A.5.1 Main RDDiT Diagnostics

Table A.5.3 reports the diagnostic underpinnings of the main meta-analytic estimates from Tables A.5.1 and A.5.2. For the 16 outcomes in our analysis, each pooled estimate aggregates shooting-specific RDDiTs estimated separately for each of the 25 mass shootings in our window. Topics that condition on the presence of gun-violence content (Panel B) or non-ideological "black box" content (Panel C) lose a small number of shootings that produced none of the relevant tweets, which is why the count drops to 18 for the rights/control ideology ratio, to 19–21 for Panel C, and stays at 25 for every other outcome.

Effective sample sizes within the MSE-optimal bandwidth are large and roughly balanced across the cutoff: most outcomes use on the order of 42,000–44,000 legislator-days on each side, with bandwidths averaging between 7 and 10 days. Bandwidths are consistent across panels and outcomes, so the meta-analytic pooling is not comparing fundamentally different local windows for different topics. Pre-treatment outcome means line up with what one would expect mechanically from the construction of the log-odds: in Panel A, where the denominator is all tweets, the average pre-shooting share of any individual topic is small and the corresponding log-odds is therefore strongly negative (roughly -5.3 across topics, or about a 0.5% share); in Panels B and C the denominator narrows to gun-violence or black-box content, and pre-treatment log-odds approach zero, indicating that even before a shooting these subsets are non-trivial fractions of the within-category content.

Table A.5.3: Effective Sample Sizes, Bandwidths, and Pre-Treatment Outcome Means for the Main RDDiT Estimates

Topic	N Shootings	N Leg.-Days Left	N Leg.-Days Right	Mean Bandwidth	Pre-Treatment Mean
Panel A: Conditional on All Tweets					
Gun Violence	25	42,792	44,267	7.2	-5.029
Sports	25	42,792	44,267	7.7	-4.270
Pro-Gun Control	25	42,792	44,267	9.0	-5.325
Pro-Gun Rights	25	42,792	44,267	9.7	-5.379
Policy	25	42,792	44,267	8.4	-5.168
Blame	25	42,792	44,267	9.0	-5.256
Ideology (Rights/Control)	18	32,990	33,577	8.7	-0.046
Black Box	25	42,792	44,267	7.2	-5.316
Panel B: Conditional on Gun Violence Tweets					
Pro-Gun Control	25	42,792	44,267	7.2	-0.182
Pro-Gun Rights	25	42,792	44,267	7.0	-0.243
Policy	25	42,792	44,267	7.3	0.114
Blame	25	42,792	44,267	7.2	-0.024
Black Box	25	42,792	44,267	7.6	-0.132
Panel C: Conditional on Black Box Tweets					
Information	19	36,511	37,549	7.1	-0.041
Healing & Solidarity	20	36,782	37,823	6.0	-0.078
Thoughts & Prayers	21	37,411	38,597	7.7	-0.041

Notes: This table reports diagnostics for the shooting-specific regression discontinuity (RD) estimates pooled in the main meta-analyses. "N Shootings" is the number of mass shootings for which a topic-specific RD could be estimated; topics that condition on the presence of gun-violence (Panel B) or black-box (Panel C) tweets drop shootings that produced none of the relevant content. "N Leg.-Days Left" and "N Leg.-Days Right" are the effective legislator-day sample sizes within the MSE-optimal bandwidth on each side of the cutoff (day 0), summed across shootings (`fit$N` from `rdrobust`; Calonico et al., 2017). "Mean Bandwidth" is the unweighted average of the shooting-specific MSE-optimal bandwidths (`bwselect = "mserd"`, triangular kernel). "Pre-Treatment Mean" is the average of the winsorized log-odds outcome on days within the bandwidth and strictly before the shooting, weighted by each shooting's left-side effective sample size. Pre-treatment means in Panel A are computed against all tweets in the legislator-day denominator and so are large and negative (rare events); in Panels B and C the denominator restricts to gun-violence or black-box content, producing means closer to zero. The full set of shooting-specific estimates underlying these summaries is available from the authors.

A.5.2 Results for Electoral Competitiveness by Party

We cross-classify legislators by party and district competitiveness, yielding four cells: safe Democrats ($N = 235$), competitive Democrats ($N = 153$), safe Republicans ($N = 203$), and competitive Republicans ($N = 205$); 4 legislators who switched parties during the study period are excluded from this cross-classification. We estimate the full set of shooting-specific RDDiTs within each cell and pool via random-effects meta-analysis. Table A.5.5 reports the four-cell results for outcomes conditional on gun violence tweets. To formally test whether the competitive–safe gap differs across parties, we compute within-shooting paired differences (competitive minus safe) separately for each party. Table A.5.6 reports these results.

Table A.5.4: Competitive v. Safe Districts

	All Legislators	Competitive Districts	Safe Districts
Substantive Discourse: Conditional on All Tweets			
Pro-Gun Control	1.276**	1.185	1.327**
	(1.075, 1.515)	(0.986, 1.424)	(1.080, 1.631)
Pro-Gun Rights	1.018	0.986	1.012
	(0.941, 1.101)	(0.899, 1.081)	(0.929, 1.103)
Policy	1.778***	1.580**	1.771***
	(1.343, 2.353)	(1.186, 2.105)	(1.305, 2.404)
Blame	1.316**	1.263	1.321**
	(1.078, 1.606)	(0.988, 1.614)	(1.084, 1.610)
Black Box	3.458***	3.915***	3.378***
	(1.816, 6.583)	(1.905, 8.045)	(1.802, 6.332)
Substantive Discourse: Conditional on Gun Violence Tweets			
Pro-Gun Control	0.388***	0.359***	0.405***
	(0.250, 0.602)	(0.217, 0.594)	(0.272, 0.602)
Pro-Gun Rights	0.277***	0.281***	0.266***
	(0.158, 0.484)	(0.154, 0.512)	(0.152, 0.466)
Policy	0.621**	0.531***	0.656*
	(0.452, 0.853)	(0.375, 0.752)	(0.469, 0.918)
Blame	0.404***	0.406***	0.428***
	(0.282, 0.579)	(0.273, 0.604)	(0.293, 0.624)
Black Box	1.542**	1.763**	1.443*
	(1.157, 2.056)	(1.233, 2.522)	(1.055, 1.974)
Expressive Discourse: Conditional on Black Box Tweets			
Information	0.452***	0.557**	0.450***
	(0.310, 0.661)	(0.388, 0.801)	(0.303, 0.667)
Healing & Solidarity	0.395***	0.361***	0.422***
	(0.270, 0.576)	(0.237, 0.550)	(0.294, 0.607)
Thoughts & Prayers	1.224	1.163	1.286
	(0.981, 1.528)	(0.934, 1.448)	(0.931, 1.775)

Significance: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.
Notes: This table reports pooled odds ratios from random-effects meta-analyses of legislator-day RD estimates, separately for all legislators, those from competitive districts, and those from safe districts. Competitiveness is defined at the district level using the average Democratic two-party vote share across all contested general elections in the 2010–2022 period (*partisan lean*). Competitive districts are those whose partisan lean falls within 10 percentage points of 50% ($|\text{lean} - 0.5| \leq 0.10$); safe districts are those outside this band. For each shooting and topic, we estimate a sharp RD using `rdrobust` (Calonico et al., 2017), with day relative to the shooting as the running variable (cutoff at day 0). We employ a triangular kernel and the MSE-optimal bandwidth selector ('mserd'). Standard errors are clustered at the legislator level. Odds ratios and standard errors are exponentiated from the log-odds scale. Outcomes are the log-odds of tweeting about a given topic (or ratio of topics), with a constant offset ($\epsilon = 0.01$) to accommodate zero counts. The bottom row shows the number of unique legislators in each analysis.

Table A.5.5: Party $\times$ Competitiveness Interaction

	Safe Democrats	Comp. Democrats	Safe Republicans	Comp. Republicans
Conditional on Gun Violence Tweets				
Pro-Gun Control	0.514***	0.535**	0.334***	0.324***
	(0.360, 0.732)	(0.355, 0.808)	(0.208, 0.539)	(0.175, 0.602)
Pro-Gun Rights	0.227***	0.224***	0.321***	0.344**
	(0.111, 0.467)	(0.118, 0.422)	(0.197, 0.524)	(0.190, 0.624)
Policy	1.143	0.857	0.470**	0.433**
	(0.943, 1.384)	(0.700, 1.049)	(0.292, 0.758)	(0.263, 0.713)
Blame	0.488***	0.476***	0.488**	0.398**
	(0.330, 0.720)	(0.326, 0.695)	(0.324, 0.735)	(0.239, 0.663)
Black Box	0.868	1.222	1.924**	2.092**
	(0.717, 1.052)	(0.866, 1.724)	(1.280, 2.892)	(1.317, 3.324)
Conditional on Black Box Tweets				
Information	0.541**	0.750*	0.413***	0.337***
	(0.365, 0.804)	(0.583, 0.964)	(0.262, 0.651)	(0.196, 0.579)
Healing & Solidarity	0.582**	0.450**	0.452***	0.324***
	(0.418, 0.812)	(0.281, 0.720)	(0.315, 0.650)	(0.191, 0.549)
Thoughts & Prayers	0.920	0.900	1.605*	1.634**
	(0.833, 1.015)	(0.742, 1.092)	(1.071, 2.405)	(1.177, 2.268)
N Legislators	235	153	203	205

Significance: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.
Notes: This table reports pooled odds ratios from random-effects meta-analyses of shooting-specific regression discontinuity (RD) estimates, cross-classified by legislator party and district competitiveness. Competitiveness is defined using the average Democratic two-party vote share across all contested general elections in the 2010–2022 period; competitive districts are those within 10 percentage points of 50% ($|\text{lean} - 0.5| \leq 0.10$).

Table A.5.6: Within-Party Competitiveness Gaps

	Democrats: Comp. − Safe		Republicans: Comp. − Safe	
Topic	OR Ratio	95% CI	OR Ratio	95% CI
Pro-Gun Control	0.996	(0.751, 1.322)	0.949	(0.726, 1.240)
Pro-Gun Rights	1.191	(0.851, 1.668)	0.986	(0.725, 1.342)
Policy	0.801*	(0.650, 0.987)	0.902	(0.660, 1.232)
Blame	0.961	(0.654, 1.413)	0.852	(0.645, 1.127)
Black Box	1.254*	(1.008, 1.561)	1.045	(0.776, 1.409)

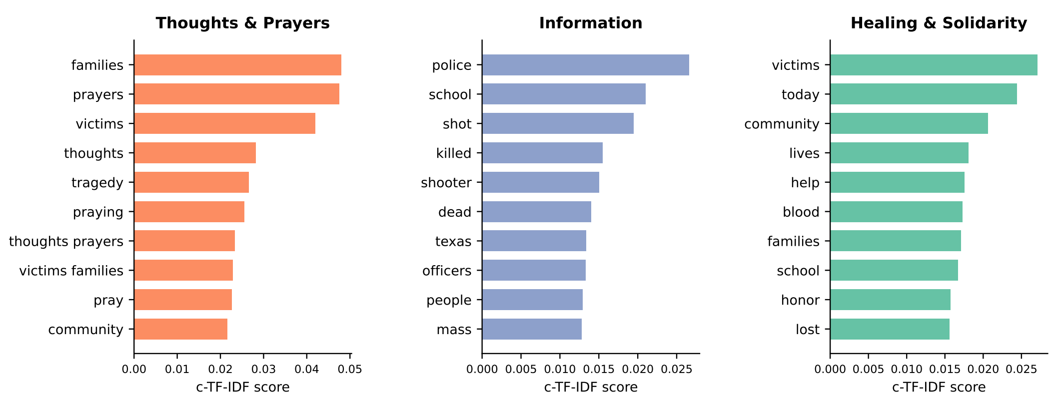
Significance: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.
Notes: OR Ratio reports the ratio of competitive-district to safe-district odds ratios within each party, estimated via paired random-effects meta-analysis on within-shooting differences. Values above 1 indicate that the treatment effect is larger in competitive districts. All outcomes are conditional on gun violence tweets. Standard errors for differences assume independence of competitive and safe subsamples within each shooting.

A.6 BERTopic Results

To ensure that the model clusters on thematic content rather than event-specific proper nouns, we construct two parallel text representations: one for embedding and one for topic representation. For the embedding input, we use spaCy's `en_core_web_sm` named entity recognizer to strip entities of types PERSON, GPE, LOC, FAC, EVENT, and ORG, and additionally remove a curated list of 29 event-specific terms (e.g., "uvalde," "parkland," "sandy hook") and all hashtags. These NER-stripped texts are encoded into 384-dimensional dense vectors using the `all-MiniLM-L6-v2` sentence transformer.

The encoded documents are projected into a five-dimensional space via UMAP (`n_neighbors` = 15, `n_components` = 5, `min_dist` = 0.0, cosine metric) and partitioned into $K = 3$ clusters using K-means (`n_init` = 10). We select $K = 3$ based on a systematic sweep from $K = 3$ to $K = 8$: the same three substantive topics emerge at every value of K, with balanced proportions (29 to 38 percent each), while any additional clusters beyond $K = 3$ contain no more than 6 percent of tweets or represent noise. For the c-TF-IDF topic representation, BERTopic operates on the original (non-stripped) tweet text with a CountVectorizer that includes unigrams and bigrams and excludes both standard English stopwords and event-specific terms. This two-track design allows event names to appear in human-readable topic descriptions while preventing them from driving the clustering. The resulting three topics are labeled Thoughts and Prayers (37.7%), Information (32.5%), and Healing and Solidarity (29.8%). All random seeds are fixed for reproducibility (UMAP `random_state` = 42, KMeans `random_state` = 42, `langdetect` seed = 0).

Figure A.6.1: **BERTopic Keywords**

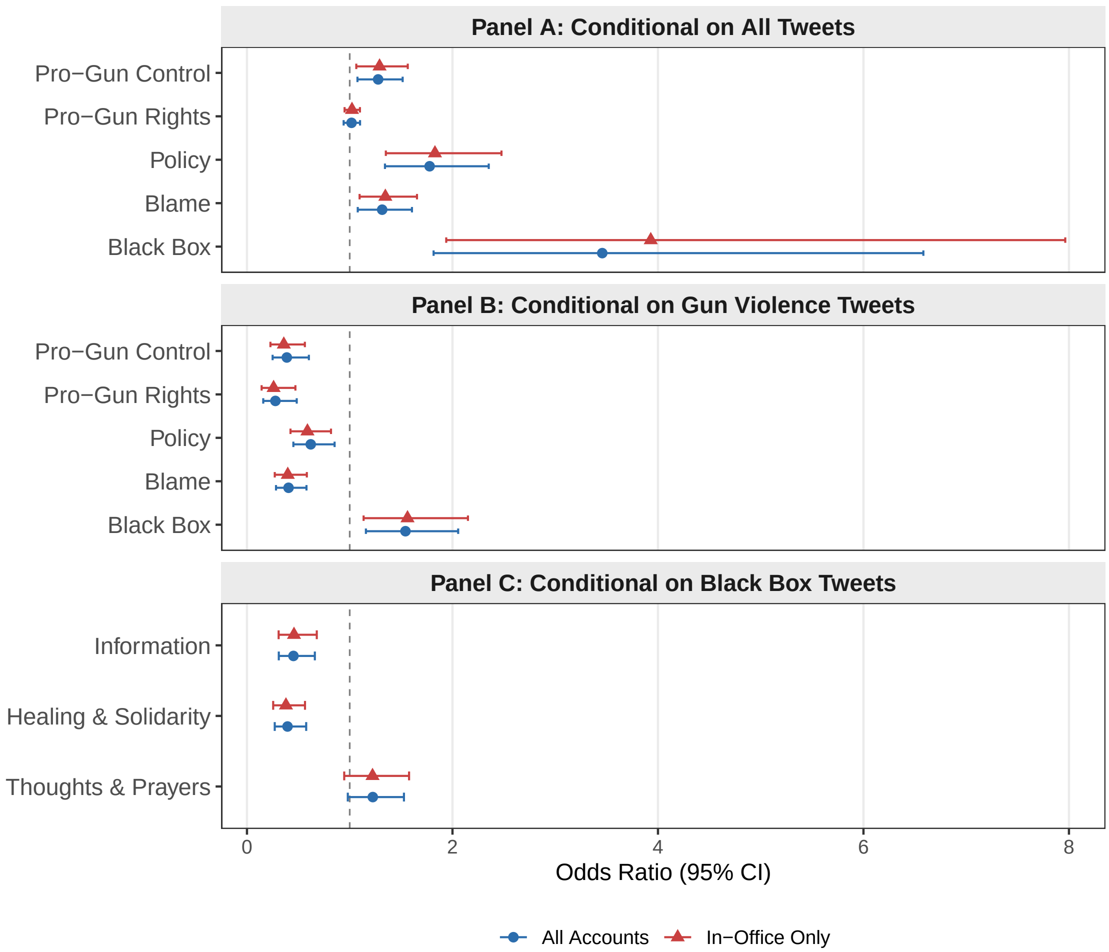


Note: Top 10 keywords for each of the three BERTopic topics, ranked by c-TF-IDF score. Higher scores indicate terms more distinctive of the topic relative to the rest of the corpus. Panels from left to right: Thoughts and Prayers, Information, Healing and Solidarity.

A.7 Robustness Checks

A.7.1 Results for In-Office Legislators Only

Figure A.7.1: **All Accounts vs. In-Office Only**



Note: Figure presents RDDiT meta-analysis results for models run on full sample (all twitter accounts of individuals known to be state legislators between 2013 and 2022) and accounts of legislators known to be in office at the time of the shooting (and ±30 day window).

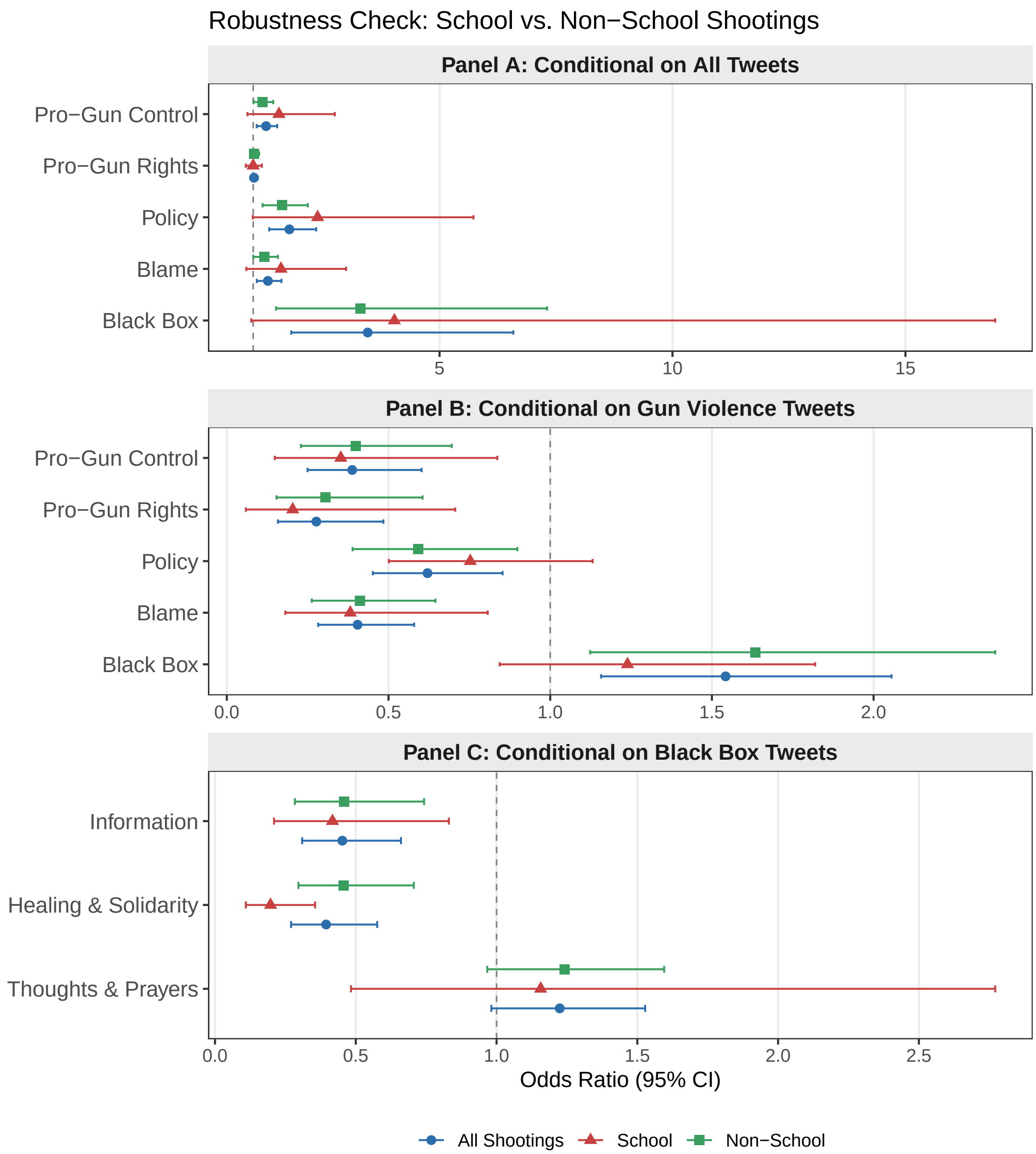
Table A.7.1: All Accounts vs. In-Office Only

	All Legislators	In-Office
Panel A: Conditional on All Tweets		
Gun Violence	6.717***	7.353***
	(2.854, 15.811)	(2.998, 18.033)
Sports	0.987	0.932
	(0.720, 1.353)	(0.663, 1.311)
Pro-Gun Control	1.276**	1.290*
	(1.075, 1.515)	(1.064, 1.565)
Pro-Gun Rights	1.018	1.022
	(0.941, 1.101)	(0.950, 1.099)
Policy	1.778***	1.830***
	(1.343, 2.353)	(1.351, 2.477)
Blame	1.316**	1.347**
	(1.078, 1.606)	(1.096, 1.655)
Black Box	3.458***	3.930***
	(1.816, 6.583)	(1.939, 7.964)
Panel B: Conditional on Gun Violence Tweets		
Pro-Gun Control	0.388***	0.359***
	(0.250, 0.602)	(0.228, 0.563)
Pro-Gun Rights	0.277***	0.259***
	(0.158, 0.484)	(0.142, 0.471)
Policy	0.621**	0.589**
	(0.452, 0.853)	(0.424, 0.818)
Blame	0.404***	0.397***
	(0.282, 0.579)	(0.270, 0.583)
Black Box	1.542**	1.562**
	(1.157, 2.056)	(1.135, 2.151)
Panel C: Conditional on Black Box Tweets		
Information	0.452***	0.458***
	(0.310, 0.661)	(0.308, 0.679)
Healing & Solidarity	0.395***	0.379***
	(0.270, 0.576)	(0.255, 0.565)
Thoughts & Prayers	1.224	1.222
	(0.981, 1.528)	(0.946, 1.578)
N Accounts	961	836

Significance: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.
Notes: This table reports pooled treatment effects from random-effects meta-analyses of shooting-specific regression discontinuity (RD) estimates.

A.7.2 Results for School Shootings

Figure A.7.2: **School vs. Non-School Shootings**



Note: Figure presents RDDiT meta-analysis results for models run on full sample, school shootings, and non-school shootings.

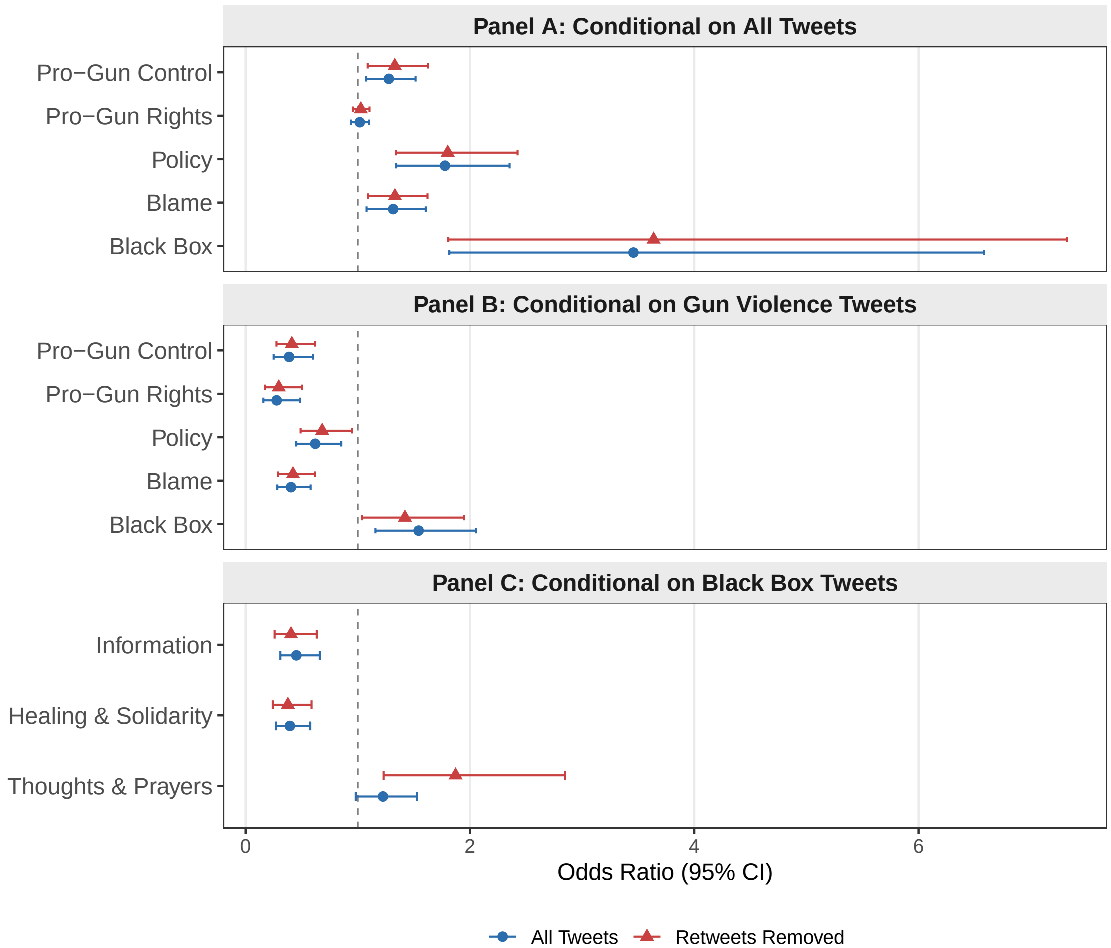
Table A.7.2: School Shootings

	All Shootings	School Shootings	Non-School Shootings
Panel A: Conditional on All Tweets			
Gun Violence	6.717***	10.415*	5.854**
	(2.854, 15.811)	(1.355, 80.054)	(2.081, 16.469)
Sports	0.987	0.660	1.088
	(0.720, 1.353)	(0.347, 1.258)	(0.746, 1.588)
Pro-Gun Control	1.276**	1.552	1.201*
	(1.075, 1.515)	(0.876, 2.752)	(1.009, 1.430)
Pro-Gun Rights	1.018	0.999	1.024
	(0.941, 1.101)	(0.842, 1.187)	(0.929, 1.129)
Policy	1.778***	2.383	1.615**
	(1.343, 2.353)	(0.991, 5.728)	(1.201, 2.173)
Blame	1.316**	1.597	1.238*
	(1.078, 1.606)	(0.852, 2.995)	(1.002, 1.530)
Black Box	3.458***	4.030	3.300**
	(1.816, 6.583)	(0.960, 16.927)	(1.490, 7.308)
Panel B: Conditional on Gun Violence Tweets			
Pro-Gun Control	0.388***	0.352*	0.399**
	(0.250, 0.602)	(0.149, 0.836)	(0.229, 0.696)
Pro-Gun Rights	0.277***	0.204*	0.305**
	(0.158, 0.484)	(0.059, 0.706)	(0.154, 0.605)
Policy	0.621**	0.753	0.591*
	(0.452, 0.853)	(0.501, 1.131)	(0.389, 0.898)
Blame	0.404***	0.382*	0.412***
	(0.282, 0.579)	(0.181, 0.807)	(0.263, 0.645)
Black Box	1.542**	1.239	1.634*
	(1.157, 2.056)	(0.844, 1.819)	(1.123, 2.376)
Panel C: Conditional on Black Box Tweets			
Information	0.452***	0.417*	0.459**
	(0.310, 0.661)	(0.210, 0.831)	(0.284, 0.743)
Healing & Solidarity	0.395***	0.197**	0.457**
	(0.270, 0.576)	(0.109, 0.355)	(0.296, 0.706)
Thoughts & Prayers	1.224	1.157	1.242
	(0.981, 1.528)	(0.483, 2.771)	(0.967, 1.595)
N Shootings	25	6	19

Significance: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.
Notes: This table reports pooled treatment effects from random-effects meta-analyses of shooting-specific regression discontinuity (RD) estimates.

A.7.3 Results for Retweets

Figure A.7.3: **Main Model v. Retweets Excluded**



Note: Figure presents RDDiT meta-analysis results for models run on full sample and a model excluding all retweets.

Table A.7.3: All Tweets vs. Retweets Excluded

	All Tweets	Retweets Excluded
Panel A: Conditional on All Tweets		
Gun Violence	6.717***	7.259***
	(2.854, 15.811)	(3.058, 17.232)
Sports	0.987	1.038
	(0.720, 1.353)	(0.791, 1.362)
Pro-Gun Control	1.276**	1.330**
	(1.075, 1.515)	(1.088, 1.626)
Pro-Gun Rights	1.018	1.027
	(0.941, 1.101)	(0.955, 1.104)
Policy	1.778***	1.802***
	(1.343, 2.353)	(1.339, 2.424)
Blame	1.316**	1.331**
	(1.078, 1.606)	(1.093, 1.622)
Black Box	3.458***	3.638***
	(1.816, 6.583)	(1.807, 7.323)
Panel B: Conditional on Gun Violence Tweets		
Pro-Gun Control	0.388***	0.412***
	(0.250, 0.602)	(0.275, 0.617)
Pro-Gun Rights	0.277***	0.296***
	(0.158, 0.484)	(0.174, 0.501)
Policy	0.621**	0.682*
	(0.452, 0.853)	(0.490, 0.950)
Blame	0.404***	0.422***
	(0.282, 0.579)	(0.288, 0.619)
Black Box	1.542**	1.421*
	(1.157, 2.056)	(1.037, 1.946)
Panel C: Conditional on Black Box Tweets		
Information	0.452***	0.405***
	(0.310, 0.661)	(0.258, 0.634)
Healing & Solidarity	0.395***	0.377***
	(0.270, 0.576)	(0.242, 0.588)
Thoughts & Prayers	1.224	1.872**
	(0.981, 1.528)	(1.230, 2.848)
N Accounts	961	836

Significance: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.
Notes: This table reports pooled treatment effects from random-effects meta-analyses of shooting-specific regression discontinuity (RD) estimates.