Religion as Distraction: Economic Shocks and Media Reporting in India*

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Abstract

We examine whether pro-government media redirect public attention toward social divisions in response to unfavourable economic news. Using a large language model, we classify millions of tweets posted by twelve major Indian news organizations between 2018 and 2023, analyzing both news content and audience responses. Exploiting scheduled releases of inflation, unemployment, and GDP figures, we find that more pro-government outlets systematically increase their religious coverage following unfavourable economic announcements, with no comparable response to favourable releases. This increase is driven almost entirely by divisive religious content emphasizing intergroup conflict and grievances, which generates particularly high audience engagement and negative reactions. At the individual level, users who previously engaged more heavily with pro-government outlets devote a smaller share of their attention to economic news and exhibit smaller increases in government blame following unfavourable announcements, providing suggestive evidence of attention reallocation. Our findings reveal a distinctive form of political distraction: rather than suppressing unfavourable economic information or countering it with positive narratives, politically aligned media amplify alternative sources of grievance. This mechanism may weaken economic accountability while reinforcing social divisions.

JEL Codes: L82, D72, D82, Z12, O53

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1 Introduction

> *"Everything is driven by TRP. They sensationalise things, serve an agenda."*
> — Justice K.M. Joseph, Supreme Court of India, in January 2023 on television news channels[1]

In January 2020, as India's economy slowed and protests spread against the Citizenship Amendment Act (CAA), a controversial law introducing religion-based eligibility criteria for a pathway to Indian citizenship, 43 percent of respondents to a national opinion poll believed that the government had introduced the legislation to divert attention from rising prices and slowing economic growth (India Today, 2020). This perception raises a broader question about political incentives: when economic performance deteriorates, might governments seek to redirect public attention toward issues on which they command greater political support? In societies characterized by salient ethnic, religious, or cultural divisions, emphasizing these divisions may be particularly effective.

In this paper, we investigate whether pro-government media contribute to such shifts in attention by amplifying divisive identity-based content following unfavourable economic news. We examine this question in India, where religious identity and communal divisions have long played a prominent role in political and public life.

We assemble a dataset of 3.6 million tweets and nearly 21 million associated replies from twelve major Indian news organizations between January 2018 and March 2023. These organizations span a broad political spectrum and collectively had approximately 65 million Twitter followers at the end of our sample period. Using a large language model, we classify news content into different subject areas and distinguish between divisive religious content, which emphasizes conflict, threats, or grievances between religious communities, and non-divisive religious content. We find that religious coverage, particularly divisive content, attracts substantially greater audience engagement than other types of news and elicits disproportionately negative reactions. To measure political alignment, we construct a continuous measure of each news organization's stance toward the incumbent government based on its coverage of three highly contested national policies.

Our empirical strategy exploits scheduled releases of three major indicators of economic performance: inflation, GDP growth, and unemployment. We compare changes in news coverage between the twenty-four hours preceding and following these announcements across media organizations with different political orientations, distinguishing between favourable and unfavourable releases. Our specification includes announcement fixed effects, which absorb contemporaneous events and shifts in newsworthiness common to all organizations, and news organization-by-month fixed effects, which account for differences in coverage patterns across organizations and their evolution over time. We benchmark changes in coverage around economic announcements against those observed over equivalent intervals on ordinary days. This approach allows us to assess whether more

[1] TRP: television rating points, the industry's measure of audience size.

pro-government organizations respond differentially to unfavourable economic news, both relative to other organizations covering the same announcement and relative to their own coverage patterns on ordinary days.

We assess the robustness of our findings to alternative sample definitions, the exclusion of each outlet in turn, and alternative classifications of economic announcements as favourable or unfavourable. We also conduct placebo exercises using fictitious release dates assigned to ordinary days. Given the small number of news organizations, we complement conventional statistical inference with permutation tests that randomly reassign political stance across outlets.

We find that more pro-government media systematically increase their religious coverage following unfavourable economic announcements. A one-standard-deviation increase in an organization's pro-government stance is associated with an additional 0.66 percentage point increase in the share of religious content, equivalent to approximately 6 percent of the average share of religious coverage. The magnitude of this response is substantial: the estimated difference in the increase in religious coverage between the most and least pro-government organizations exceeds the average increase in economic coverage following an unfavourable announcement. No comparable differential response occurs following favourable economic releases.

Importantly, virtually the entire increase is driven by content emphasizing divisions between religious communities. We find no corresponding increase in non-divisive religious coverage, entertainment, sports, or non-religious political news. Nor do more pro-government organizations systematically reduce their economic coverage following unfavourable relative to favourable announcements. Rather than suppressing unfavourable economic information or countering it with positive narratives, they disproportionately amplify alternative sources of grievance. This suggests a distinctive form of political distraction in which divisive content competes for public attention precisely when economic news may be politically damaging.

Additional findings support a strategic interpretation of this behaviour. The increase in religious coverage is concentrated in the days immediately following unfavourable economic announcements and subsequently dissipates. To examine whether this response is anticipatory, we use Reuters surveys that collect economists' forecasts of inflation and GDP figures ahead of their official release. We find that more pro-government outlets begin increasing their religious coverage *before* the publication of figures expected to signal unfavourable economic conditions. By contrast, economic coverage increases only after the official announcements. This difference in timing is consistent with forward-looking editorial decisions, suggesting that the shift toward religious content is not simply a reaction to newly released economic information.

We further uncover that the additional religious content attracts increased audience engagement, consistent with a reallocation of attention toward these issues. At the aggregate level, however, unfavourable economic announcements generate a sharp increase in replies blaming the government across all news organizations, regardless of their political alignment. A different pattern emerges

when we track individual users over time. Those who previously engaged more heavily with pro-government outlets devote a smaller share of their replies to economic news and exhibit a smaller increase in government blame following unfavourable announcements, relative to users who engaged with less pro-government outlets. These differences are concentrated around the announcement day and are substantially smaller following favourable releases. Although the individual-level results do not establish a causal effect of media coverage, they provide suggestive evidence that the amplification of divisive religious content may redirect the attention of regular audiences away from unfavourable economic news, potentially weakening political accountability.

This paper contributes to several strands of literature in political economy and media economics.[2] First, we contribute to research on the strategic manipulation of public attention. A growing literature documents how political actors exploit competing news events to reduce scrutiny of politically costly decisions. Eisensee and Strömberg (2007) show that competition for media attention affects the allocation of US disaster relief, while Durante and Zhuravskaya (2018) find that Israeli military attacks are strategically timed to coincide with major US news events. Similarly, Djourelova and Durante (2022) show that US presidents time controversial executive orders to coincide with periods of heightened news coverage. Closest to our study, King et al. (2017) document how the Chinese government produces social media content emphasizing positive and patriotic themes to divert attention from politically contentious issues. We extend this literature by showing that political distraction need not involve countering negative information with positive or unrelated content. Instead, politically aligned media may amplify alternative sources of grievance, redirecting attention toward divisive issues rather than attempting to reduce public dissatisfaction.

This mechanism also connects our paper to the literature on negativity bias and the role of emotions in shaping attention to news. Research documents that individuals respond more strongly to negative than to positive information (Soroka, 2006; Soroka et al., 2019; Robertson et al., 2023). Relatedly, expressions of out-group hostility generate particularly high engagement on social media (Rathje et al., 2021). These findings suggest that negative and divisive content may be especially effective at attracting public attention. We contribute to this literature by examining how political incentives shape the supply of such content. Our findings suggest that the same forces that make negative information particularly salient may also create opportunities for strategic distraction, as media organizations amplify alternative grievances when economic news is unfavourable.

Second, our findings contribute to the extensive literature on media bias, information manipulation, and political accountability.[3] Particularly relevant is Rozenas and Stukal (2019), who show that Russian state-controlled television responds asymmetrically to economic news, attributing favourable outcomes to domestic political leadership while blaming unfavourable outcomes on external factors. We document a different response to adverse economic information. Rather than systematically

[2] See Zhuravskaya et al. (2020) for a review of these intersecting literatures.

[3] See, for example, Besley and Prat (2006), Enikolopov et al. (2011), Qin et al. (2018), Guriev and Treisman (2019), Gentzkow and Shapiro (2010), Gentzkow and Shapiro (2008), and Durante and Knight (2012), among many others.

suppressing negative economic news or reframing responsibility for poor economic performance, more pro-government media increase the prominence of an unrelated but politically salient issue: religious grievances. Our findings thus highlight a form of media bias operating through the allocation of attention across competing issues, rather than solely through the selection or framing of information within a particular issue.

Third, our analysis relates to research on the political supply of intergroup hostility and the role of media in shaping social divisions. Glaeser (2005) develops a framework in which political actors have incentives to promote hostility toward particular groups when doing so serves their political interests. Related research documents the potentially severe consequences of inflammatory media content for intergroup relations, ranging from hate crimes to mass violence (Yanagizawa-Drott, 2014; Adena et al., 2015; Müller and Schwarz, 2021). While much of this literature examines the consequences of exposure to hostile content, we investigate the circumstances under which such content is supplied. Our findings suggest that unfavourable economic performance may create additional incentives for politically aligned media to amplify existing social divisions. More broadly, they point to a potential connection between efforts to limit economic accountability and the intensification of identity-based conflict.

Our paper also relates to research on Hindu-Muslim relations and the political economy of religious conflict in India. Existing studies show that religious conflict responds to economic conditions (Mitra and Ray, 2014) and electoral incentives (Wilkinson, 2004; Iyer and Shrivastava, 2018; Nellis et al., 2016).[4] Electoral outcomes, in turn, also shape partisan views of the economy among Hindus and Muslims (Ghosh et al., 2026b). We contribute to this literature by identifying an additional potential political incentive for emphasizing religious divisions: diverting public attention from unfavourable economic performance.

Finally, our findings contribute to research on the role of Indian media in shaping religious identities and political discourse. Political science scholarship has linked the media to the rise of Hindu nationalism, from the televised *Ramayan* (Rajagopal, 2001)[5] to the expansion of the Hindi-language press (Jeffrey, 2000; Neyazi, 2018), as well as to the attribution of blame following communal riots (Brass, 2003).[6] More recently, prime-time debates on Times Now and Republic have been found to promote religious majoritarianism and defend government policies (Bhat and Chadha, 2023), while news audiences exhibit partisan reasoning (Badrinathan, 2021). Although commentators frequently suggest that communal debates in Indian media divert attention from other pressing issues, systematic empirical evidence for this claim remains limited. Our analysis provides quantitative evidence consistent with this interpretation, documenting how the prominence of divisive religious coverage changes in response to unfavourable economic news.

[4]Religious divisions can also generate frictions in everyday economic interactions. Recent studies show that organized contact between groups can help reduce these frictions (Ghosh, 2025; Ghosh et al., 2026a).

[5]See Yang et al. (2025) for a systematic analysis of its impact on Hindu identity.

[6]The media can also strengthen government accountability. Besley and Burgess (2002) show that Indian state governments respond more strongly to droughts and floods in areas with greater newspaper circulation.

The remainder of the paper is organized as follows. The next section describes the Twitter data, our classification methods, and the economic announcements. Section 3 presents descriptive patterns in news coverage, audience engagement, and sentiment. Section 4 presents our core empirical analysis, and Section 5 concludes.

2 Data

Our study focuses on the Twitter accounts of twelve major national news organizations in India: the television channels Republic, Times Now, Zee News English, CNN-News18, NewsX, India Today, Mirror Now, and NDTV; the news agencies ANI and PTI; the newspaper Indian Express; and the digital outlet The Wire. Collectively, these accounts had approximately 65 million followers as of March 2023. Since these organizations often post similar content across social media platforms, including Facebook and Instagram, their Twitter audiences likely understate the broader reach of the content and coverage patterns we study.

Our sample includes several of India's largest media groups, including the Times Group (Times Now and Mirror Now), the India Today Group, the Indian Express Group, Network18, Zee Media, and NDTV.[7] The selected organizations span a broad political spectrum, from Republic to The Wire, and are particularly well suited to our analysis. As national outlets, they are exposed to the same economic announcements at the same time. Their Twitter content is also predominantly in English (97% of tweets), allowing us to apply a consistent classification procedure across organizations. Moreover, all twelve regularly cover both economic and religious issues: economic news accounts for between 5% and 13% of each organization's tweets, while religious news accounts for between 7% and 17% (Table A3). Finally, the organizations differ substantially in their political alignment (Section 2.2), providing the variation central to our empirical strategy. Because our sample is restricted to English-language accounts, our findings may not generalize to Hindi-language or regional media, although several of the organizations operate parallel Hindi-language accounts that publish similar content.

We collected all tweets posted by these accounts between January 1, 2018, and March 14, 2023, using Twitter's full-archive search interface, which was then freely available to researchers. The resulting dataset contains 3.6 million tweets and nearly 21 million associated replies, each linked to the original news organization tweet. Our main analytical sample comprises approximately 2.2 million tweets that received at least one reply. Restricting the sample in this way ensures consistency between our analyses of news coverage and audience responses, since measures of reply sentiment and government blame require at least one reply. We verify that our main findings on news coverage remain robust when using the full sample of 3.6 million tweets (Section 4.1.1).

[7] One notable omission is The Hindu Group. Our data were collected through Twitter's free research access, which ended in 2023. Obtaining comparable data for an additional account, including its tweets and associated replies, would now cost tens of thousands of dollars at reported prices (X Corp., 2026; Stokel-Walker, 2023).

Our sample ends in March 2023 because changes to Twitter following its acquisition in October 2022 substantially restricted researchers' access to historical data. The discontinuation of free research access made collecting additional data considerably more costly and difficult (Ledford, 2023; Davidson et al., 2023).

2.1 Tweets Classification

We use the large language model Claude Haiku 5.5 to classify tweets and replies. More advanced models, such as Claude Opus 5.5, are substantially more expensive but yield broadly similar classifications, as we demonstrate using a random subsample of tweets (Appendix A). We classify each tweet posted by a news organization into one of five categories: religion, economy, entertainment and sports, non-religious politics, and other. Tweets are classified as religious when religion or religious activity is central to the story, including legislation and protests with a religious dimension, such as those concerning the Citizenship Amendment Act (CAA). Under this definition, religious content accounts for approximately 11% of all tweets in our sample, while economic content accounts for roughly 8%. We further classify religious tweets as divisive if they portray religious communities in opposition to one another, emphasizing intergroup conflict, threats, or grievances, or depicting a religious group as an adversary. By this measure, 66% of religious tweets are classified as divisive.

To characterize audience responses, we construct two measures. The first captures the tone of replies, measured as the share of a tweet's English-language replies with a negative VADER sentiment score.[8] The second measures whether replies to economic news attribute responsibility to the central government. Using Claude Haiku 5.5, we classify each reply, together with the original tweet, in English, Hindi, or "Hinglish," into one of four categories: blaming the central government for economic conditions, defending the government, discussing the economy without assigning blame or offering a defence, or not discussing the economy. Among these replies, 23% blame the government, while 8% defend it. Table A2 provides illustrative examples of these classifications.

2.2 Outlet Classification

To measure each news organization's political alignment, we examine its coverage of three highly contested national policies: the Citizenship Amendment Act (CAA) and National Register of Citizens (NRC), the farm laws, and the abrogation of Article 370. Using Claude Haiku 5.5, we classify nearly 53,000 tweets concerning these policies as supportive, critical, or neutral toward the government's position. For each organization, we construct a stance score equal to the share of supportive tweets minus the share of critical tweets. This yields a single, time-invariant measure of political alignment for each organization, which we use as a continuous variable throughout the analysis. The scores range from -0.45 for The Wire to $+0.34$ for Republic (Table A3), with a standard deviation of 0.20 across organizations.

[8] VADER (Valence Aware Dictionary and Sentiment Reasoner) is an open-source, lexicon- and rule-based sentiment analysis tool designed to capture the emotional tone of text, particularly in social media and other short, informal communications. Its compound sentiment score ranges from -1 (most negative) to $+1$ (most positive).

2.3 Economic Releases

We focus on three major scheduled economic releases: consumer price inflation (CPI), GDP growth, and urban unemployment from the Periodic Labour Force Survey. We classify a release as unfavourable if CPI inflation exceeds 6%, the upper bound of the Reserve Bank of India's tolerance band; GDP growth falls below 6%, slightly below estimates of India's potential growth during this period, which range from 6% to 7% (Bhoi and Behera, 2016; International Monetary Fund, 2025); or urban unemployment exceeds 9%, its average over the seven quarters preceding the pandemic. Applying these thresholds yields 41 unfavourable and 53 favourable release days between January 2018 and February 2023. We compare changes in news coverage around these announcements with those observed on 1,489 ordinary days, defined as days with no major economic release on that day or either adjacent day.

To examine the timing of media responses in Section 4.2, we additionally use Reuters surveys of economists conducted ahead of CPI and GDP announcements, for which we obtain forecasts for 65 releases. We classify a release as anticipated to be unfavourable if the median forecast crosses the corresponding threshold defined above. These forecasts are highly predictive of the subsequent announcements: the anticipated and realized classifications coincide in 58 of the 65 cases.

3 Descriptive Patterns

Before examining how news organizations respond to economic announcements, we document several patterns in their coverage and audience engagement. We first compare the attention and reactions generated by different types of news, with particular emphasis on divisive religious content. We then examine how religious coverage varies across organizations and over time.

3.1 Audience Engagement and Sentiment

To measure engagement with each tweet, we construct an index based on its likes, retweets, and replies. We apply the inverse hyperbolic sine transformation to each measure, standardize it within each outlet-month, and take the average of the three standardized measures. This allows us to compare engagement across types of news while accounting for differences in audience size and engagement patterns across organizations and over time.

Figure 1 (Panel A) shows that religious tweets receive, on average, 0.22 standard deviations more engagement than the average tweet posted by the same outlet in the same month. The corresponding figures are 0.08 for non-religious politics, -0.05 for entertainment and sports, and -0.14 for economic news. Within religious coverage, divisive content attracts substantially more engagement than non-divisive content, with average engagement scores of 0.27 and 0.13, respectively. Economic news, by contrast, generates the lowest engagement among the four main categories.

Religious content also elicits disproportionately negative audience reactions. Figure 1 (Panel B)

reports the share of English-language replies classified as negative, adjusting for outlet-month differences. Approximately 37% of replies to religious tweets are negative, compared with 35% for non-religious politics, 31% for economic news, and 27.5% for entertainment and sports. Once again, the difference is driven primarily by divisive religious content: nearly 40% of replies to divisive religious tweets are negative, compared with approximately 31% for non-divisive religious tweets.

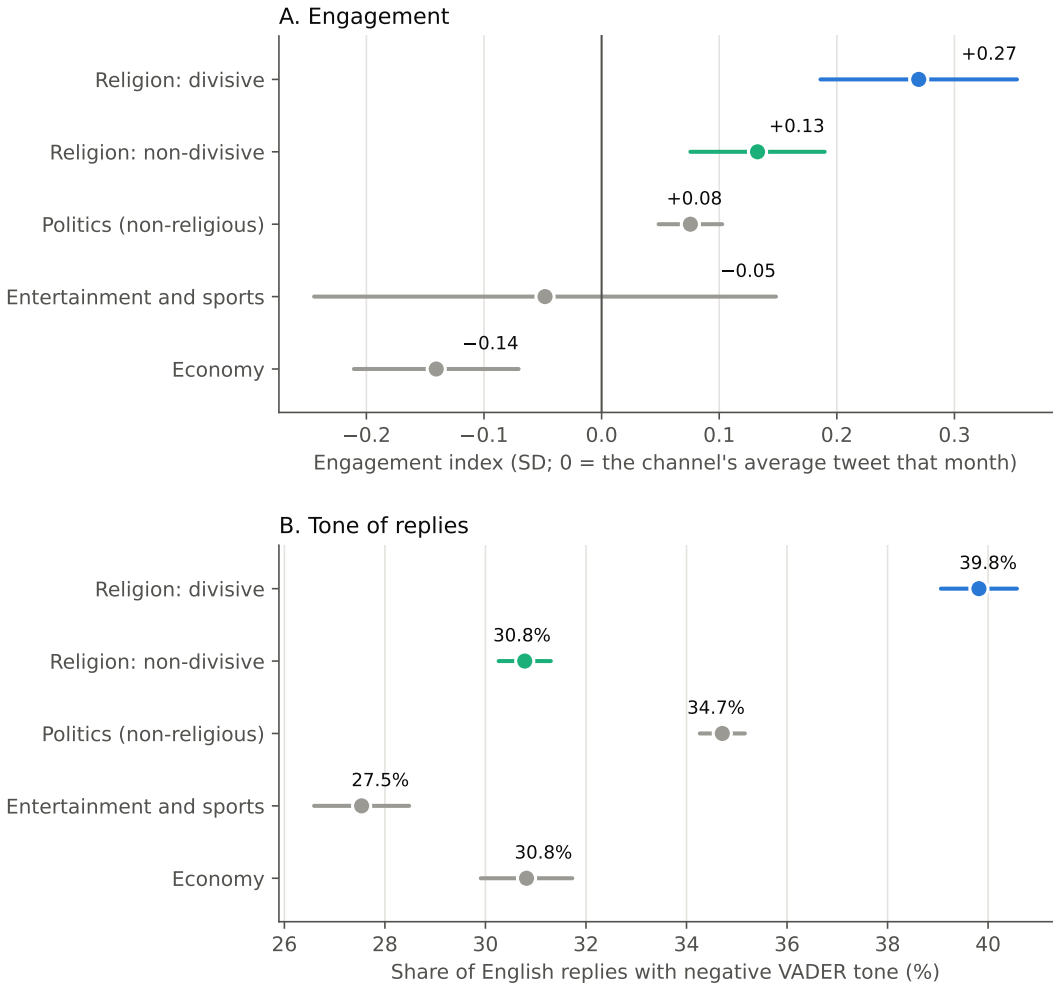


Figure 1: Engagement (panel A) and share of negative replies (panel B) by type of tweet.

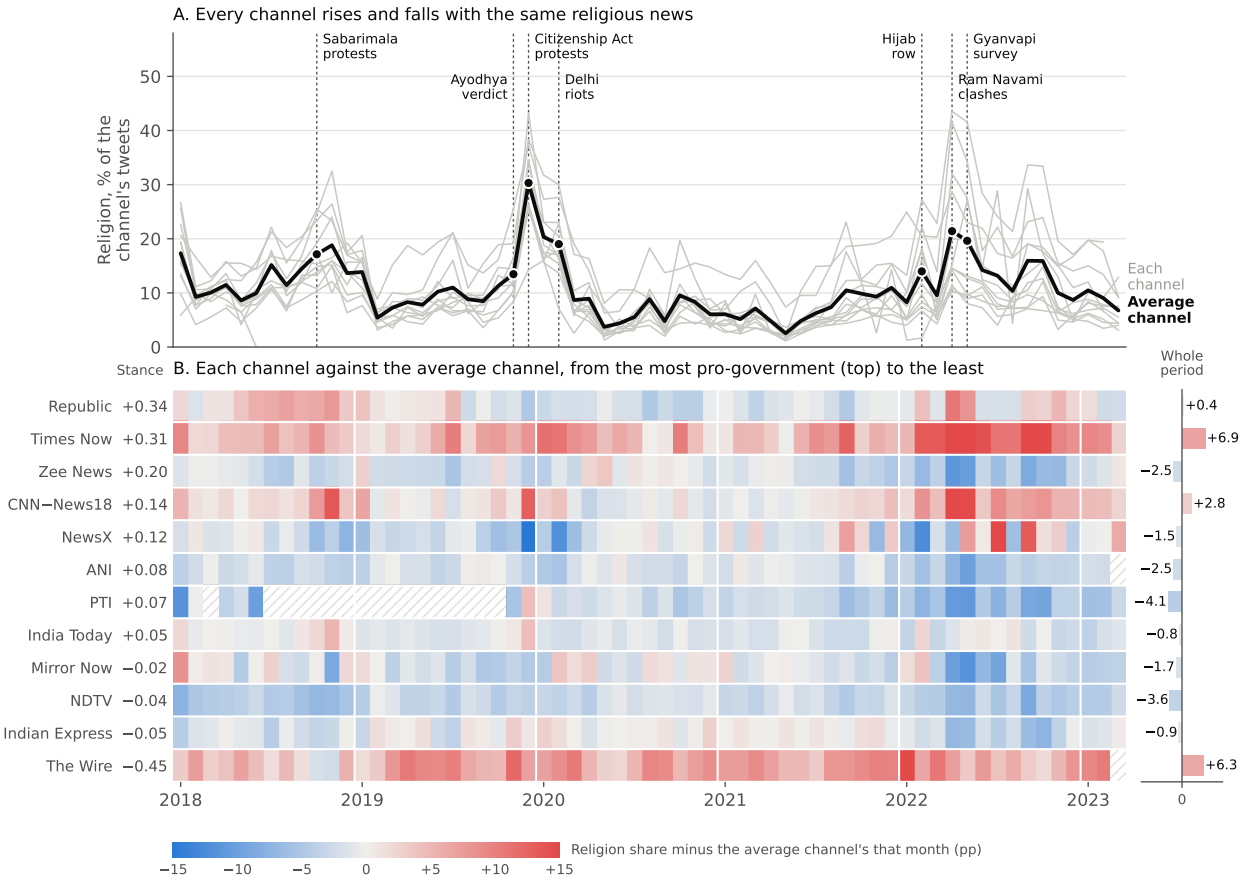
Note: Panel A: engagement index, the mean of the z-scores of asinh(likes), asinh(retweets) and asinh(replies), each standardized within outlet × month; 0 is the outlet's average tweet that month. Panel B: share of a tweet's English replies with negative VADER tone (compound score ≤ -0.05), adjusted for outlet × month; tweets with at least one English reply. Tweets with at least one reply, 12 outlets, January 2018 to March 2023. Religion is split into divisive and non-divisive by the divisive label. 95% confidence intervals clustered by outlet.

These patterns indicate that divisive religious content generates both the highest audience engagement and the most negative reactions. This combination suggests that such content may be particularly effective in redirecting public attention toward alternative sources of grievance.

3.2 Religious Coverage across News Organizations

Table A3 summarizes the characteristics and coverage patterns of the twelve news organizations. Posting frequency varies considerably, with Times Now and Republic each publishing more than 170 tweets per day on average. Non-religious political news accounts for between 36% and 53% of tweets across organizations, while religious coverage ranges from 7% to 17% and economic coverage from 5% to 13%. Interestingly, Times Now and The Wire, which lie near opposite ends of our political stance measure, devote the largest shares of their coverage to religion, approximately 17% each.

Figure 2: Religious Coverage Over Time by News Organization



Notes: The figure reports the monthly share of each news organization's tweets classified as religious. The average outlet is the unweighted mean of the twelve organizations' monthly shares. In Panel B, organizations are ordered by their political stance scores, displayed alongside their names. Hatched cells indicate months in which an organization posted fewer than 30 tweets. PTI posted few or no tweets between March 2018 and October 2019; archived versions of its Twitter profile indicate that its cumulative tweet count remained unchanged between October 2018 and September 2019. Whole-period differences are calculated as the mean of each organization's monthly deviations from the average outlet.

Religious coverage also fluctuates substantially over time, often in response to major religious or political events. Figure 2, Panel A, shows that these fluctuations are broadly synchronized across news organizations. In the median month, religious content accounts for approximately 10% of the average outlet's tweets. However, this share rises sharply during several prominent episodes, reaching

19% in November 2018 amid protests against a Supreme Court ruling allowing women of all ages to enter the Sabarimala Hindu temple; 30.3% in December 2019 during nationwide protests against the Citizenship Amendment Act, which introduced religion-based eligibility criteria for certain migrants seeking Indian citizenship; and 22% in April 2022 amid Hindu-Muslim clashes during processions celebrating the Hindu festival of Ram Navami. Coverage remained elevated in May 2022 following a court-ordered survey of the Gyanvapi mosque in Varanasi, which intensified a longstanding dispute over religious claims to the site.

Despite these common fluctuations, organizations differ substantially in their average levels of religious coverage. Relative to the average outlet, Times Now and The Wire devote the largest additional shares of their coverage to religion, at 6.9 and 6.3 percentage points, respectively. PTI and NDTV devote the smallest shares, at 4.1 and 3.6 percentage points below the average, while Republic is only slightly above the average, by 0.4 percentage points. As illustrated in Figure 2, Panel B, these differences do not follow a simple pattern of political alignment.

Although geographic information is available for only a small fraction of audience replies, the geocoded responses suggest that engagement with these news organizations extends across India. Replies to religious tweets outnumber those to economic tweets in every state, however their relative prevalence does vary geographically (Appendix Figure B7).

4 Empirical Analysis

Our main empirical analysis examines whether news organizations that are more supportive of the government disproportionately increase their coverage of religious issues following unfavourable economic announcements. We exploit variation in political alignment across organizations and compare changes in their coverage around scheduled economic releases with those observed on ordinary days. For news organization c and event e, where an event is either one of the 94 scheduled economic releases or one of the 1,489 ordinary days, we estimate

$$\Delta y_{ce} = \beta^{\text{bad}}(S_c \times \text{Bad}_e) + \beta^{\text{good}}(S_c \times \text{Good}_e) + \alpha_e + \gamma_{c,m(e)} + \varepsilon_{ce}, \tag{1}$$

where Δy_{ce} is the share of outlet c's tweets devoted to a particular news category between the 24 hours preceding and following event e. For ordinary days, we define the corresponding windows around 17:30 IST. The variable S_c denotes the outlet's political stance score, standardized to have unit standard deviation, while Bad_e and Good_e indicate unfavourable and favourable economic releases, respectively. Both indicators equal zero on ordinary days.

Event fixed effects, α_e, absorb all factors common to news organizations on a given day, including the economic announcement and the average response to it, other contemporaneous news, day-of-week effects, and broader fluctuations in religious coverage (Figure 2). Identification therefore comes from

differences in how organizations with different political alignments adjust their coverage around the same announcement. In particular, β^{bad} measures the differential change in coverage following an unfavourable release associated with a one-standard-deviation increase in pro-government alignment.

We additionally include organization-by-month fixed effects, $\gamma_{c,m(e)}$, which account for differences in coverage patterns across media outlets that may evolve over time. They matter because our sample includes television channels promoting their programming, news agencies publishing continuously, a newspaper, and a digital-only outlet. These organizations differ in their posting frequency, editorial focus, and day-to-day coverage patterns (Table A3). Organization-by-month fixed effects absorb persistent differences in these characteristics, including changes associated with programming or editorial priorities, within each month. Together with event fixed effects, they allow us to assess whether political alignment predicts differential responses to economic announcements, rather than simply reflecting differences in the composition or timing of coverage across organizations.

Standard errors are clustered at the media organization level, corresponding to the level at which political stance varies. Given the small number of media organization, we also report randomization inference based on permutations of the stance scores (Appendix Table B5). The estimation sample contains 18,271 organization-event observations.[9]

4.1 Baseline Results

Figure 3 presents the estimates from equation (1). Following an unfavourable economic release, a one-standard-deviation increase in pro-government alignment is associated with an additional 0.66 percentage point increase in the share of religious tweets, equivalent to 6.2% of the average religious news share ($p < 0.01$). In contrast, the estimated response following favourable releases is small and statistically insignificant. The difference between the responses to unfavourable and favourable releases is approximately one percentage point ($p < 0.01$).

[9] Appendix Figure B1 presents a dynamic specification that interacts outlet stance with indicators for days -5 through $+5$ around economic releases, grouped into two-day windows, and includes date fixed effects in place of event fixed effects.

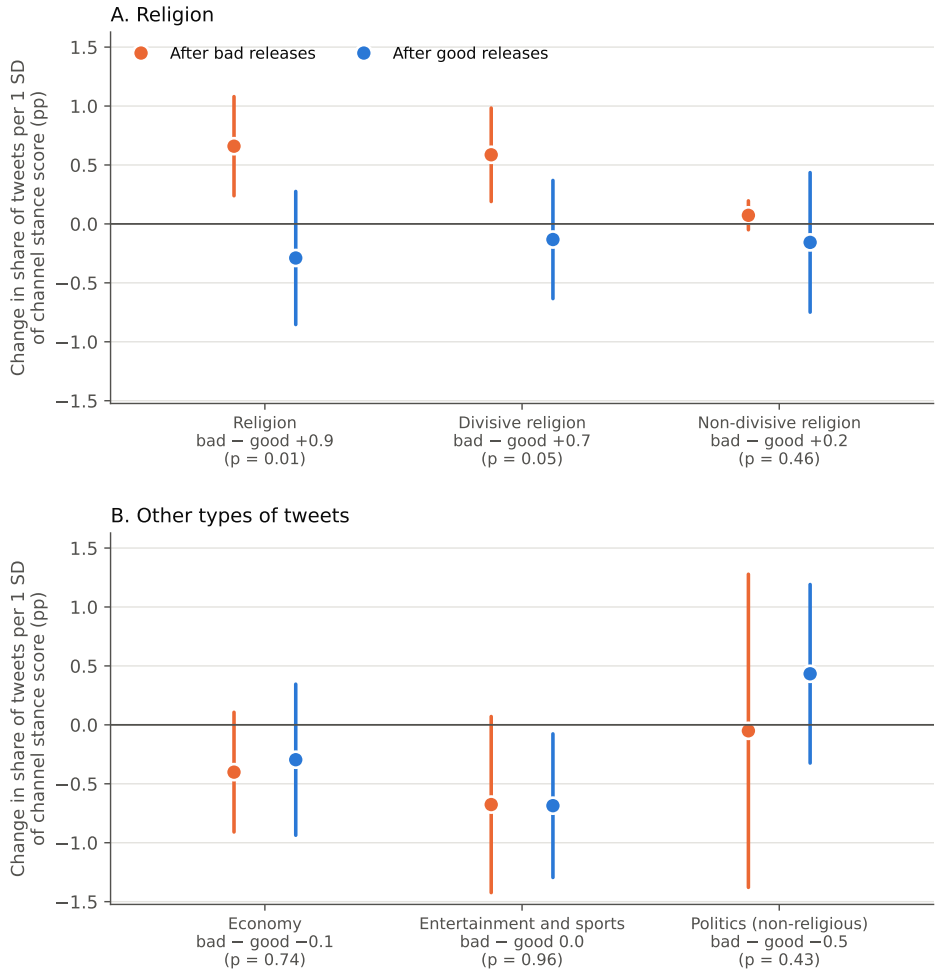


Figure 3: Change in share of tweets after releases, against ordinary days, by outlet stance: religion (panel A) and economy, entertainment and sports, and non-religious politics (panel B).

Note: Change in each outlet's share of tweets in the 24 hours after a release minus the 24 hours before, against the same change on ordinary days (no release within a day; windows around 17:30 IST). Coefficients on the outlet's stance score, per SD across the 12 outlets, with event and outlet × month fixed effects. 41 bad and 53 good releases (CPI > 6%, GDP growth < 6%, urban unemployment > 9%) and 1,489 ordinary days. Tweets with at least one reply. Below each type: the difference between bad and good releases and its p-value. 95% confidence intervals clustered by outlet.

These effects are economically meaningful. An unfavourable release increases the share of economic tweets by approximately 2.0 percentage points for the average outlet. The differential increase in religious coverage associated with a one-standard-deviation increase in pro-government alignment is therefore approximately one-third as large. Across the full range of political alignment, from The Wire to Republic, the implied difference in the religious news response is 2.6 percentage points, exceeding the average increase in economic coverage and amounting to roughly one-quarter of the average religious news share.

The increase in religious coverage is driven almost entirely by divisive content. Following an un-

favourable economic release, a one-standard-deviation increase in pro-government alignment is associated with an additional 0.59 percentage point increase in the share of divisive religious tweets, equivalent to 8.7% of its average share ($p < 0.01$). In contrast, non-divisive religious coverage shows no significant response. We find no comparable differential response in other news categories, including non-religious politics, entertainment and sports, or economic news (Figure 3, Panel B). Notably, more pro-government organizations do not systematically reduce their economic coverage following unfavourable releases relative to favourable ones. Instead, their distinctive response is to increase the share of divisive religious content.

4.1.1 Robustness

We conduct several robustness checks to assess the sensitivity of our core findings to sample selection, the inclusion of individual news organizations, and the classification of economic announcements. We also examine whether the increase in divisive religious coverage reflects a broader shift toward negatively toned news, investigate the dynamics of the response, and assess the robustness of our statistical inference through randomization inference and placebo tests.

Tweet sample. Our main sample is restricted to tweets receiving at least one reply, ensuring consistency between our analyses of news coverage and audience responses. The proportion of tweets without replies varies considerably across outlets, from 18% for PTI to 79% for NewsX. Including these tweets would alter the relative weight of posting activity across outlets and reduce comparability between our coverage and audience analyses. However, because receiving a reply depends on audience engagement, this sample restriction could affect our estimates. Figure B3 therefore replicates the analysis using the full sample of 3.6 million tweets. The results are very similar: following unfavourable releases, more pro-government outlets increase their religious coverage in both samples, with an estimated coefficient of 0.57 percentage points per standard deviation of political alignment in the full sample, compared with 0.66 in the main sample. Neither sample shows a comparable response following favourable releases.

Leaving out one organization. Given that our sample includes only twelve media outlets, we examine whether the results are driven by any particular organization. Figure B10 re-estimates equation (1), excluding one organization at a time while retaining the original standardization of the stance scores. The estimates barely move. After bad releases, the coefficient on stance ranges from 0.56 to 0.88 across the twelve samples, against 0.66 with all outlets, and it is statistically significant at conventional levels in every sample. After good releases, it stays close to 0 or below in every sample. The estimates for divisive religion are similarly stable, confirming that the overall effects are driven by divisive content.

Alternative definitions of favourable and unfavourable releases. Table B4 examines the sensitivity of our findings to alternative classifications of economic announcements. We consider

thresholds that are 0.5 percentage points stricter or more lenient than our baseline definitions, classify releases relative to the average of the preceding four announcements, and restrict the sample to CPI and GDP releases. Across all specifications, more pro-government outlets increase their religious coverage following unfavourable announcements, with estimated coefficients ranging from 0.42 to 1.11 percentage points per standard deviation of political alignment. Divisive religious content accounts for most of this response. The difference between unfavourable and favourable releases remains statistically significant under all but one classification. When announcements are classified relative to the preceding four releases, the estimated difference is smaller and imprecise for religious coverage overall, but remains statistically significant for divisive religious coverage.

Tone of Tweets. Appendix Figure B4 presents estimates of equation (1) using the tone of each outlet's tweets as an alternative outcome. The purpose of this exercise is to examine whether the increase in divisive religious coverage reflects a shift specifically toward religious grievances or a more general shift toward negatively toned news. We consider two measures of tone: the average VADER sentiment score of tweets (Panel A) and the share of tweets classified as having a negative VADER tone (Panel B). For both measures, we estimate the specification using all tweets and restricting the sample to non-religious tweets. Across both samples and measures, we find no statistically significant differences in the responses of more pro-government outlets to unfavourable relative to favourable economic announcements. These results suggest that the disproportionate increase in divisive religious coverage is not simply a manifestation of a broader shift toward negatively toned content.

Dynamics of the response. Appendix Figure B1 examines changes in religious coverage over the five days preceding and following economic announcements, using two-day windows. Religious coverage on more pro-government outlets shows no systematic increase in the days preceding an unfavourable release, but rises afterward, peaking on days 2 and 3 at 1.1 percentage points per standard deviation of political alignment ($p < 0.01$), before gradually declining. No comparable response follows favourable releases. This relatively short-lived increase is consistent with a response concentrated in the period when economic announcements remain salient and the potential for diverting public attention is greatest.

Randomization inference. With only twelve media outlets, conventional cluster-robust standard errors may understate statistical uncertainty. We therefore supplement our main inference with a permutation exercise in which the twelve political stance scores are randomly reassigned across organizations 500 times, and the regressions are re-estimated for each assignment. Table B5 reports the resulting randomization-inference p-values. The increase in religious coverage following unfavourable releases remains statistically significant ($p = 0.036$), as does the difference between unfavourable and favourable releases ($p = 0.022$). Randomization inference also supports the timing results and the increase in divisive religious coverage following unfavourable releases.

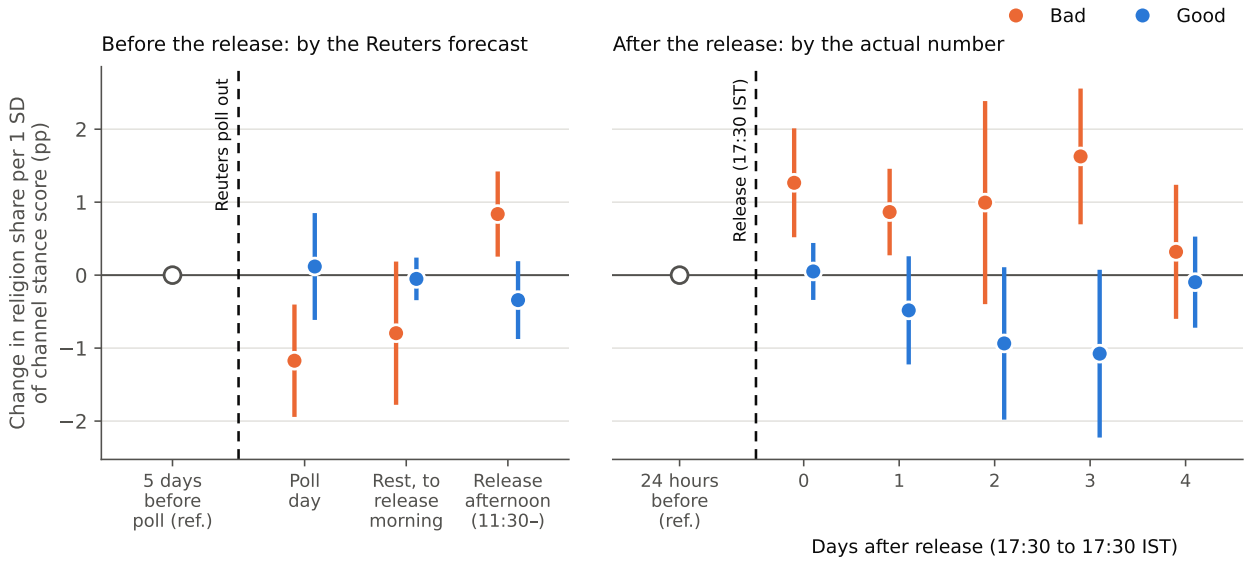
Placebo release dates. Finally, we conduct a placebo exercise in which each economic announcement, retaining its classification as favourable or unfavourable, is reassigned to a randomly selected ordinary day falling on the same day of the week. We repeat this procedure 200 times, re-estimating the dynamic specification in Figure B1 for each assignment. As shown in Figure B5, the average estimated responses across placebo assignments are close to zero and statistically insignificant in all event-time windows, both before and after favourable and unfavourable placebo releases.

4.2 Strategic Behaviour

The preceding results show that more pro-government news organizations disproportionately increase their coverage of divisive religious issues following unfavourable economic announcements. We now examine the timing of this response to assess whether it reflects a reaction to the economic news itself or an anticipatory adjustment in coverage. If organizations strategically seek to redirect attention away from unfavourable economic information, they may begin shifting their coverage before the official announcement, particularly when its likely outcome is already known.

Economic announcements are often anticipated. In the days preceding CPI and GDP releases, Reuters surveys economists and publishes their median forecasts. These forecasts are highly informative: of the 25 releases predicted to fall on the unfavourable side of our thresholds, 24 were subsequently classified as unfavourable. News organizations therefore have considerable information about the likely outcome before the official figures are published.

Figure 4: Religious Coverage Around Reuters Forecasts and Economic Releases, by Political Alignment



Notes: Each point represents the differential change in an outlet's share of religious tweets relative to the reference window, compared with the corresponding change on ordinary days (1,489 days, with windows defined around 17:30 IST and a placebo poll date five days earlier). Coefficients are expressed per standard deviation of the outlet's political stance score. The sample includes 65 CPI and GDP releases with an identifiable Reuters poll date, using the publication date for 35 polls and the end of survey fieldwork for the remaining 30. In the left panel, forecasts are classified as unfavourable if median predicted CPI inflation exceeds 6% or predicted GDP growth falls below 6% (25 unfavourable and 40 favourable forecasts); windows follow IST calendar days. In the right panel, releases are classified using the realized figures, as in Figure 3 (30 unfavourable and 35 favourable releases); days are measured in 24-hour intervals from the official release time. The panels use different reference periods. All specifications include event and outlet-by-month fixed effects. Error bars represent 95% confidence intervals based on standard errors clustered by outlet.

Figure 4 examines how religious coverage evolves around these announcements. Following an unfavourable forecast, more pro-government outlets initially reduce their religious coverage between the Reuters poll and the morning of the official release. However, their religious coverage begins to increase during the afternoon of the release day, before the official figures are published, and remains elevated for several days afterward. No comparable pattern emerges around favourable announcements.

The increase in religious coverage before the official announcement is particularly informative. If outlets were responding solely to newly released economic information, we would expect their coverage to change only after its publication. Instead, the anticipatory increase suggests that more pro-government organizations adjust their religious coverage in response to the expected economic news, consistent with a deliberate shift in editorial attention around unfavourable announcements.

The timing of economic coverage provides a useful contrast. Figure B2 shows changes in the share of economic tweets in the hours surrounding an announcement, relative to the corresponding hours on ordinary days. Economic coverage remains largely unchanged before the official release, then

increases sharply in the hours immediately afterward. For the average outlet, the increase reaches approximately 2.7 percentage points before dissipating within six hours. This response is driven primarily by less pro-government organizations and news agencies.

Thus, while economic coverage responds to the publication of official figures, the increase in religious coverage among more pro-government organizations begins before the announcement. This difference in timing is difficult to reconcile with an explanation based solely on reactions to newly released information. Instead, it is consistent with news organizations anticipating unfavourable economic announcements and adjusting their coverage accordingly, potentially to redirect audience attention toward religious issues.

4.3 Attention Reallocation

We next investigate whether the increase in religious coverage following unfavourable economic announcements is indeed associated with changes in audience engagement and political accountability. If the shift toward religious content serves to divert attention from poor economic performance, we would expect audiences to engage with this additional content and potentially devote less attention to economic news or express less blame toward the government.

Figure B6 compares changes in daily posting and engagement over the five days following an economic release with the five preceding days, allowing the aggregate response to vary with the political stance of the media outlet. Following an unfavourable release, a one-standard-deviation increase in pro-government alignment is associated with a 6.4% increase in the total number of religious tweets ($p = 0.02$). Replies to these tweets increase by a similar 6.1% ($p = 0.06$), while combined engagement through likes, retweets, and replies rises by 5.2% ($p = 0.12$). No comparable changes occur following favourable releases. Notably, more pro-government media outlets do not reduce their economic posting following unfavourable releases (-1.1%, $p = 0.50$), nor do they experience a significant change in the overall number of replies to their economic tweets.

Engagement alone, however, does not establish whether audiences become less likely to hold the government responsible for poor economic conditions. We measure government blame using the inverse hyperbolic sine of the daily number of replies blaming the government for economic conditions on each media outlet's economic tweets. We regress this outcome on indicators for days -5 through $+5$ around favourable and unfavourable releases, including organization-by-month fixed effects. We initially omit date fixed effects to capture the overall response common to news organizations. We then include date fixed effects and interact the event-time indicators with outlet stance to examine whether this response differs systematically with political alignment.

Table 1 (Panel A) shows that unfavourable economic announcements generate a substantial increase in government blame. On the day of an unfavourable release, the number of replies blaming the government rises by approximately 43 log points on the average outlet, relative to the preceding five days ($p < 0.01$). Following favourable releases, the corresponding increase is considerably smaller,

at 14 log points ($p = 0.047$).[10] The difference of 29 log points ($p < 0.01$) suggests that the increase reflects the unfavourable nature of the economic information rather than simply the additional attention generated by scheduled announcements.

This response is short-lived. Averaged over days 0–5, government-blaming replies increase by 10 log points following unfavourable releases and 8 log points following favourable releases, with no statistically significant difference between them. Moreover, Columns 2 and 4 show that the response does not vary significantly with outlet stance. Government blame rises following unfavourable economic announcements even in replies to pro-government organizations, despite their disproportionate increase in religious coverage.

These aggregate patterns may, however, conceal important differences in audience composition. To investigate instead individual-level behaviour, we track users' replies over time to examine whether individuals who previously engaged more heavily with pro-government news organizations respond differently to economic announcements. To this end, we estimate:

$$y_{irs} = \theta^{\text{bad}}(E_{ir} \times \text{Post}_s \times \text{Bad}_r) + \theta^{\text{good}}(E_{ir} \times \text{Post}_s \times \text{Good}_r) + \alpha_{ir} + \lambda_{rs} + \varepsilon_{irs}, \tag{2}$$

for individual i, release r, and period s, indicating whether the observation falls before or after the release. The variable y_{irs} is the share of individual i's replies that blame the government for economic conditions. The variable E_{ir} measures prior engagement with pro-government media, defined as the average political stance of the organization to which the individual replied during the three months preceding release r. Individual-by-release fixed effects, α_{ir}, absorb differences in each user's propensity to blame the government within a given release window, while release-by-period fixed effects, λ_{rs}, absorb changes common to all users around each announcement. The coefficient θ^{bad} therefore measures whether individuals with greater prior engagement with pro-government outlets exhibit a different change in government blame following an unfavourable release. Standard errors are clustered by the media outlet to which each individual replied most frequently during the pre-release period.

[10] Whether an economic announcement is perceived as favourable or unfavourable may vary across individuals, so some increase in government blame following favourable releases is not unexpected. Nevertheless, the response to unfavourable releases is approximately three times as large.

Table 1: Blame of the government after releases: replies to each outlet and individual repliers.

	Day 0		Days 0 to 5	
Panel A. Replies to each outlet				
	(1) All	(2) By stance	(3) All	(4) By stance
Bad release	42.80***		9.55**	
	(7.91)		(3.63)	
Good release	14.14**		7.86**	
	(6.33)		(3.53)	
Bad release × stance (per SD)		−0.88		1.55
		(7.95)		(2.70)
Good release × stance (per SD)		−7.30		1.53
		(6.84)		(3.77)
Bad − good	28.66	6.42	1.69	0.01
p-value	[0.002]	[0.201]	[0.725]	[0.996]
Date fixed effects	No	Yes	No	Yes
Outlet × month fixed effects	Yes	Yes	Yes	Yes
Mean blaming replies per outlet-day		13.07		
Outlet-days		22,063		
Panel B. Individual repliers, by exposure to pro-government outlets				
	(5) Blaming the government	(6) Replies to economy tweets	(7) Blaming the government	(8) Replies to economy tweets
Exposure (per SD) × bad release	−0.63***	−1.14***	−0.13**	−0.42**
	(0.10)	(0.22)	(0.06)	(0.17)
Exposure (per SD) × good release	−0.11	−0.36*	−0.16*	−0.19
	(0.09)	(0.19)	(0.08)	(0.16)
Bad − good	−0.52	−0.79	0.03	−0.23
p-value	[<0.001]	[0.011]	[0.718]	[0.059]
Mean (% of replies)	1.58	6.26	1.49	6.04
Person × release fixed effects	Yes	Yes	Yes	Yes
Release × side fixed effects	Yes	Yes	Yes	Yes
People	80,405		137,867	
Person × release pairs	273,232		698,389	
Observations	546,464		1,396,778	

Note: Panel A: replies labelled as blaming the government on the outlet's economy tweets, by the day the tweet was posted; asinh × 100, approximately percent changes. Coefficients: the change from the mean of days −5 to −1 to day 0 (columns 1–2) or to the mean of days 0 to 5 (columns 3–4). The sample is every outlet-day; days outside the release windows are the omitted category. Columns 1 and 3: all outlets, without date fixed effects. Columns 2 and 4: per SD of outlet stance, with date fixed effects. Standard errors clustered by outlet. Panel B: the percentage of a person's replies to the 12 outlets that are labelled as blaming the government (columns 5 and 7) or that reply to economy tweets (columns 6 and 8). Coefficients: change from days −5 to −1 to day 0 (columns 5–6) or to days 0 to 5 (columns 7–8), per SD of exposure, in percentage points. Exposure: the mean stance of the outlets the person replied to in days −95 to −6, each outlet counted once. People with at least three replies in days −95 to −6 and with replies on both sides of the release. Standard errors clustered by the outlet the person replied to most in days −95 to −6. Both panels: 41 bad and 53 good releases; standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

We also estimate the same specification using the share of an individual's replies directed toward

economic tweets as an alternative outcome. This allows us to examine whether differences in government blame are accompanied by changes in engagement with economic news itself.

Table 1 (Panel B) reveals a different pattern at the individual level. On the day of an unfavourable release, individuals with greater prior engagement with pro-government outlets exhibit a smaller increase in government blame. A one-standard-deviation increase in prior engagement is associated with a 0.63 percentage point reduction in the share of replies blaming the government ($p < 0.001$), relative to a sample mean of 1.58%. For context, one standard deviation in the engagement measure approximately corresponds to the difference between individuals at the 10th and 90th percentiles of prior engagement with pro-government outlets. The estimated reduction therefore amounts to roughly 40% of the mean.

These individuals also devote a smaller share of their replies to economic news. Following an unfavourable release, a one-standard-deviation increase in prior engagement with pro-government outlets is associated with a 1.14 percentage point reduction in the share of replies to economic tweets ($p < 0.001$), relative to a mean of 6.26%. Both responses are considerably smaller following favourable releases, with estimated coefficients of -0.11 percentage points for government blame and -0.36 percentage points for economic replies. The differences between unfavourable and favourable releases are -0.52 percentage points for government blame ($p < 0.001$) and -0.79 percentage points for economic replies ($p = 0.011$).

These differences diminish over time. Averaged over days 0–5, the estimated reduction in government blame is 0.13 percentage points following unfavourable releases and 0.16 percentage points following favourable releases, yielding a negligible difference of 0.03 percentage points ($p = 0.72$). The reduction in engagement with economic news is somewhat more persistent: the corresponding estimates are -0.42 and -0.19 percentage points, a difference of -0.23 percentage points ($p = 0.059$).

An important caveat concerns statistical inference. Unlike the increase in religious coverage, the individual-level results are less robust to randomization inference (Appendix Table B5). The randomization-inference p-value for the difference in government blame between unfavourable and favourable releases is 0.07, while that for engagement with economic tweets is 0.28. We therefore interpret these findings as suggestive rather than conclusive evidence of differential audience responses.

4.4 Stock-Market Declines

As a final consideration, we also explore whether news organizations respond similarly to other forms of unfavourable economic news, focusing on large stock-market declines.

We identify the 5% of trading days with the largest declines in the Sensex between January 1, 2018, and March 14, 2023, corresponding to daily returns of -1.65% or lower, and the 5% with the largest increases. Excluding days within one day of a scheduled economic release leaves 48 large declines

and 53 large increases. We classify tweets as stock-market related if they mention the Sensex, Nifty, stock market, share market, Dalal Street, BSE, or NSE.

Stock-market news attracts substantially less audience attention than broader economic news. Stock-market tweets account for only 0.3% of all tweets and receive an average of 3.0 replies, compared with 7.8 replies to economic tweets. Figure B8 compares the additional coverage and audience engagement generated by large stock-market declines and unfavourable economic releases, using the relevant news category for each event.

On days with large stock-market declines, media outletw post an additional 0.47 stock-market tweets on average, more than doubling the usual 0.21 tweets per day ($p = 0.001$). These additional tweets generate 1.8 more replies ($p = 0.099$), of which 0.28 blame the government ($p = 0.066$). In contrast, unfavourable economic releases generate an additional 2.9 economic tweets per outlet, attracting 23 more replies ($p = 0.019$), including 5.8 blaming the government ($p = 0.030$). Thus, unfavourable economic releases generate approximately thirteen times as many additional replies and twenty times as many additional expressions of government blame as large stock-market declines.

Consistent with these differences in audience attention, we find no comparable increase in religious coverage following large stock-market declines. Figure B9 replicates our baseline specification in Figure 3, replacing unfavourable and favourable economic releases with large stock-market declines and increases, respectively. We measure changes in coverage over a 24-hour window beginning at the market opening.

Following a large decline, a one-standard-deviation increase in pro-government alignment is associated with a 0.23 percentage point increase in religious coverage ($p = 0.66$). The corresponding estimate following a large increase is 0.18 percentage points ($p = 0.70$), yielding a negligible difference of 0.05 percentage points ($p = 0.87$). Although the confidence interval following declines is relatively wide (-0.92 to 1.38 percentage points), the point estimate is approximately one-third of that following unfavourable economic releases, and the responses to market declines and increases are nearly identical.

Overall, large stock-market declines generate considerably less audience engagement and government blame than scheduled economic announcements, and more pro-government organizations do not systematically increase their religious coverage in response. This contrast could be consistent with a distraction mechanism in which the incentive to redirect attention is greater when unfavourable economic news attracts substantial public scrutiny.

5 Conclusion

On February 13, 2023, the statistics office reported that retail inflation was 6.52 percent, above the RBI's 6 percent tolerance ceiling. In the 24 hours after the release, the share of religious tweets of the four most pro-government outlets in our sample rose from 9 to 16 percent, while those of

the four least pro-government outlets remained at around 5 percent.[11] Most of the increase in religious tweets from the pro-government outlets was not about that day's news but a return to earlier stories, such as a Muslim cleric's remark at an interfaith meeting in Delhi the day before, and the nomination, announced a few days earlier, of a man accused of murdering a BJP youth worker seven months ago, as a candidate of the Social Democratic Party of India (SDPI).

We document that this is not an isolated case but a systematic relationship between political alignment and news organizations' responses to scheduled economic announcements. Following unfavourable economic releases, more pro-government media outlets disproportionately increase their coverage of divisive religious issues. This pattern is consistent with a form of political distraction that operates through the amplification of alternative sources of grievance rather than the suppression of unfavourable economic information. The timing of the response, which begins before some announcements are officially released, further suggests that these shifts in coverage reflect forward-looking editorial decisions.

Our findings contribute to the literature on media bias and political distraction by identifying a potential mechanism through which politically aligned media can redirect public attention without suppressing unfavourable news or promoting positive government narratives. Amplifying socially divisive issues that attract attention and generate competing grievances has potentially important consequences for both political accountability and social cohesion. By shifting attention away from economic performance, politically aligned media may weaken the ability of citizens to evaluate and hold governments accountable for economic outcomes. At the same time, the amplification of divisive religious issues may reinforce social and political polarization.

[11] Both groups increased their share of economy related tweets: from 8 to 12 percent by the pro-government outlets, and from 7 to 17 percent by the less pro-government ones.

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Appendix
For Online Publication

A Data Summary

Replies. Replies are linked to the earliest outlet tweet in their conversation, so replies to other replies in the thread are included. We drop duplicate replies, replies posted by the outlet itself, and replies time-stamped more than a minute before the tweet they are linked to. Tweets in the sample have about 10 linked replies on average.

Types of tweet. Of the tweets in the sample, 11 percent are about religion, 8 percent the economy, 9 percent entertainment and sports, 49 percent non-religious politics, and 24 percent other subjects. A tweet is about religion if religion, religious groups or religious identity is central to the story, even if the story is also political. Laws, policies and protests with a religious dimension, including the CAA and the National Register of Citizens, the uniform civil code, anti-conversion laws and triple talaq, are classified as religion.

Divisive religion. A religion tweet is divisive if it emphasizes conflict, tension, threat or grievance between religious communities, or casts a religious group, its members or those defending it as a threat, aggressor or adversary. A neutral factual report of a communal clash counts as divisive, because it centers conflict between religious groups. Festivals, worship, religious leaders' activities, interfaith greetings and neutral reporting of religious law do not. In the validation sample, Claude Opus 5.5 labels a smaller share of tweets as divisive than Claude Haiku 5.5 (52 percent against 66 percent).

Reply tone. A reply is negative if its VADER compound score is at or below -0.05. We use English replies only because VADER, a sentiment dictionary built for English and for social media, does not handle Hindi. The measure is available for 1.86 million tweets, 87 percent of the sample.

Blame. We label all 1.28 million linked replies to economy tweets in the sample. A reply is labeled *blame* if it criticizes the central government, the prime minister, the Bharatiya Janata Party or a minister over the economy, including by sarcasm; *defend* if it defends the government on the economy or shifts responsibility elsewhere, such as to global conditions, Covid, the opposition, or earlier or state governments; *other economy* if it is about the economic issue but does neither; and *not economy* otherwise. The shares are 23, 8, 28 and 41 percent.

Stance. We use keywords to identify 54,853 tweets on the three issues among all tweets by the 12 outlets. The model labels each as supportive, critical, neutral or irrelevant to the issue; 53,280 are relevant, and the scores are computed on these. A tweet that only reports what someone said

is neutral unless the outlet's own wording takes a side. In the regressions we divide the score by its standard deviation across outlets.

Table A1: Agreement between the labels of Claude Haiku 5.5 and Claude Opus 5.5.

Classification	Random sample	Agreement	Precision / recall
Type of tweet	500 tweets	0.90	Religion: 0.90 / 0.93
Divisive religion	300 religion tweets	0.85	
Outlet stance	300 issue tweets	0.80	
Blame of the government	300 replies	0.78	Blame: 0.76 / 0.81

Releases. There are 98 releases on 94 days: 60 of CPI, 21 of GDP and 17 of unemployment, the last from the quarterly bulletins of the Periodic Labour Force Survey. A day with two releases is bad if either is bad. The bulletin of May 31, 2019, which covers three quarters, is one release, judged on its newest quarter. Ordinary days have no CPI, GDP, unemployment or wholesale price release on that day, the day before or the day after.

Reuters polls. We have the poll median for 80 CPI and GDP releases and can date the poll for 65 of them, either by its publication date (35) or by the last day of fieldwork (30). Polls precede the release by 3.4 days on average, and by between 1 and 7 days. Of the 30 bad releases among the 65, 24 were forecast to be bad. These 65 releases come out between 17:20 and 17:45 Indian Standard Time.

Table A2: Examples of each classification.

Label	Source	Text
A. Types of tweet		
Religion, divisive	Republic May 2018	#ChurchTargetsModi: Want a secular government in India: Delhi Archbishop to Republic TV
Religion, divisive	Indian Express Mar 2020	Paswan called the Delhi riots a national disgrace and demanded the strictest action against the rioters and those who delivered hate speeches
Religion, not divisive	The Wire Apr 2021	Islamic scholar Maulana Wahiduddin Khan passed away on Wednesday at the age of 96. He had recently tested positive for Covid-19
Economy	India Today Sep 2020	RBI has announced new measures to maintain stability in the financial system amid the coronavirus pandemic #Business #RBI #coronavirus
Entertainment and sports	Republic Oct 2021	#T20WorldCup points table 2021: How do groups look after Australia's win over Sri Lanka
Politics	ANI Nov 2019	Mumbai: Devendra Fadnavis takes oath as Maharashtra Chief Minister again. Oath administered by Governor Bhagat Singh Koshyari at Raj Bhawan
Other	Indian Express Jan 2023	Odisha allows fresh registration for vintage vehicles of more than 50 years
B. Outlet's framing of the three contested policies		
Supportive	Times Now Dec 2020	Intelligence sources: Left-wing extremists have hijacked the farmers' protests. Watch explosive #EXCLUSIVE at 6 PM
Critical	The Wire Dec 2019	BJP chief [. . .] has set a 2024 deadline for implementing the hugely divisive NRC across the country, asserting each and every infiltrator will be identified and expelled before the next general election
Neutral	PTI Feb 2021	Former Haryana Chief Minister Bhupinder Singh Hooda says Centre should take initiative and restart dialogue with farmers protesting against farm laws to find solution to issue
C. Replies to economy tweets		
Blame	Indian Express Apr 2020	*Tweet:* Nobody has come to help us with ration or money. The grocer downstairs is giving us items on credit, but how long can this continue? *Reply:* PM should also address these concerns, not just claps and diyas
Defend	Zee News Feb 2019	*Tweet:* Modi hitting sixer in the form of Budget ahead of Lok Sabha election 2019 *Reply:* Relief for every walk of society, especially farmers and workers in unorganised sectors. Bravo once more Modi ji
Other economy	NDTV Apr 2021	*Tweet:* PM praises Tata Group's compassionate gesture to ease oxygen crisis *Reply:* Tata has bailed this country time and again
Not economy	Republic May 2021	*Tweet:* US looking at Johnson and Johnson vaccine production in India, in talks with Serum Institute *Reply:* India do not accept this proposal. This is having immense side effects and it's garbage

Notes: Our text data omit capitalization, punctuation, links and account handles. We restore capitalization, punctuation and hashtag symbols here for readability; [. . .] marks a removed handle. We do not show the names of repliers. Examples are drawn from the random samples on which Claude Haiku 5.5 and Claude Opus 5.5 gave the same label, and all are in the sample.

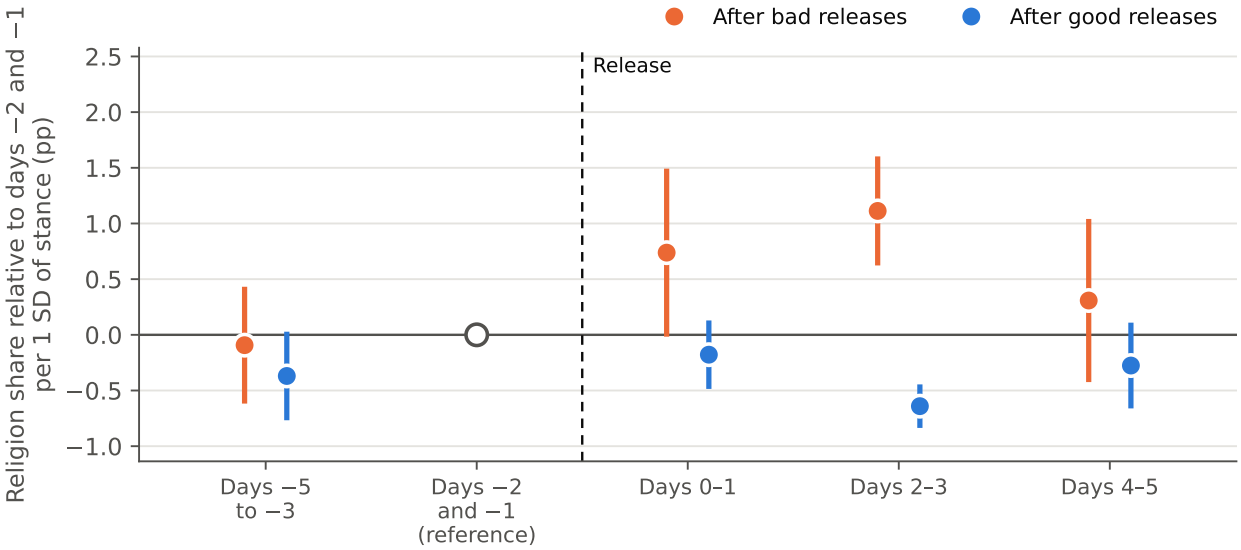
Table A3: Stance, tweets per day and types of tweet, by outlet.

Outlet	Stance	Tweets per day	Share of the channel's tweets (%)					
			Religion	Divisive	Economy	Entertain.	Politics	Other
Republic	+0.34	171.6	11.1	7.8	4.9	16.9	53.3	13.7
Times Now	+0.31	211.0	17.2	13.0	7.6	5.6	52.4	17.2
Zee News	+0.20	54.5	8.1	4.4	8.6	26.0	36.1	21.1
CNN-News18	+0.14	99.6	13.0	8.7	6.8	8.9	52.4	18.9
NewsX	+0.12	8.8	8.6	5.0	7.3	26.0	43.8	14.3
ANI	+0.08	126.1	8.0	3.6	7.2	4.7	46.1	34.0
PTI	+0.07	35.9	7.1	4.2	13.3	3.8	44.0	31.8
India Today	+0.05	151.6	9.4	5.8	7.1	7.9	49.5	26.2
Mirror Now	−0.02	26.1	8.9	5.4	11.0	7.5	41.5	31.1
NDTV	−0.04	148.7	7.1	3.9	8.0	5.7	44.7	34.5
Indian Express	−0.05	63.5	9.9	5.8	11.3	3.1	48.7	27.0
The Wire	−0.45	31.5	16.8	12.2	10.3	3.6	47.7	21.6

Note: Outlets are sorted by stance score; the horizontal rule separates the eight outlets with a positive score. Stance: the share of the outlet's tweets on CAA/NRC, the farm laws and Article 370 that support the government minus the share that criticise it (Section 2). Tweets per day: mean over each outlet's days from its first to its last active day between 1 January 2018 and 14 March 2023, with days without tweets counted as zero. Shares: percent of the outlet's tweets with at least one reply. Religion, economy, entertainment and sports, politics (non-religious) and other sum to 100; divisive religion is part of religion.

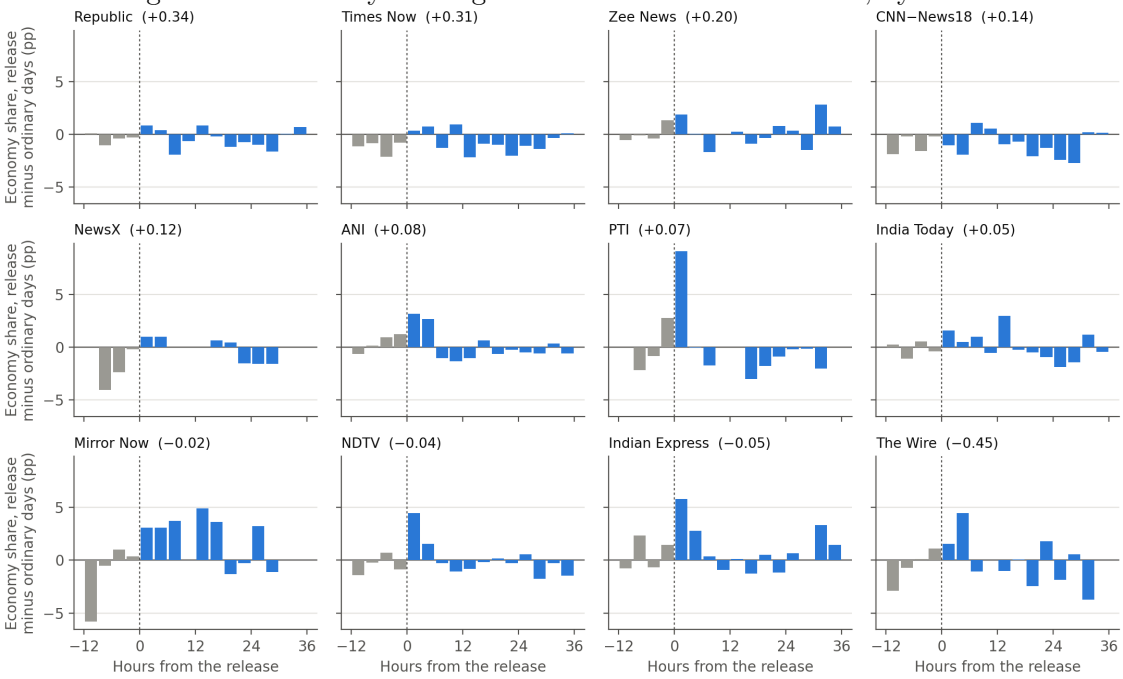
B Additional Figures and Tables

Figure B1: Religion share by day around releases, by outlet stance.



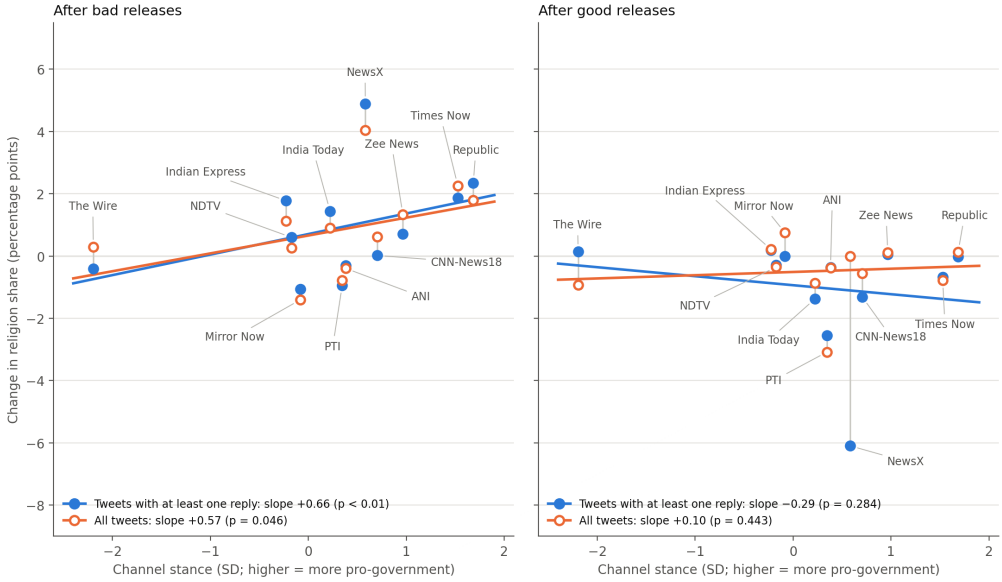
Note: Each point is the outlet's religion share in that window minus its share on days −2 and −1, per standard deviation of the outlet's stance score: the mean of the daily coefficients in the window minus their mean for days −2 and −1. Days run from 17:30 to 17:30 IST; day 0 starts at the release. Estimated on all outlet-days, 1 January 2018 – 14 March 2023, with date and outlet × month fixed effects; days outside every ±5-day window are the comparison. 41 bad and 53 good releases.

Figure B2: Economy coverage in the hours around releases, by outlet.



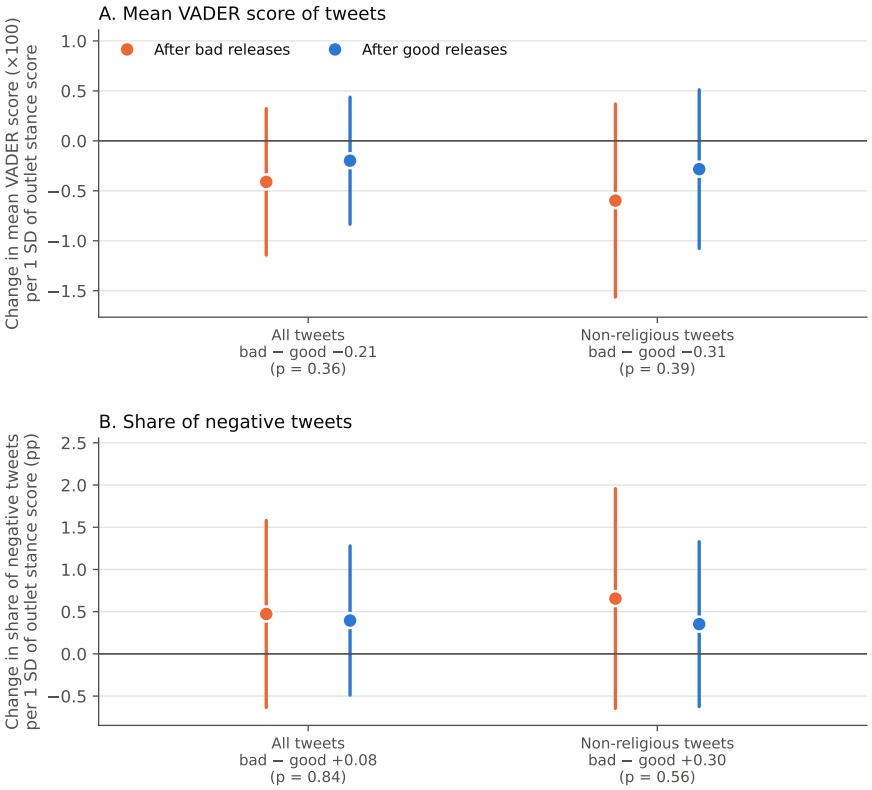
Note: Each bar is the outlet's share of tweets labelled economy in a three-hour bin around the 94 CPI, GDP and unemployment releases (pooled), minus its share in the same hours around 17:30 IST on the 1,489 ordinary days. Tweets with at least one reply. Blank: fewer than 30 release-day tweets from the outlet in the bin. Outlets are ordered by stance score (in brackets). Descriptive; no regression.

Figure B3: Religious content after releases by outlet, tweets with at least one reply and all tweets.



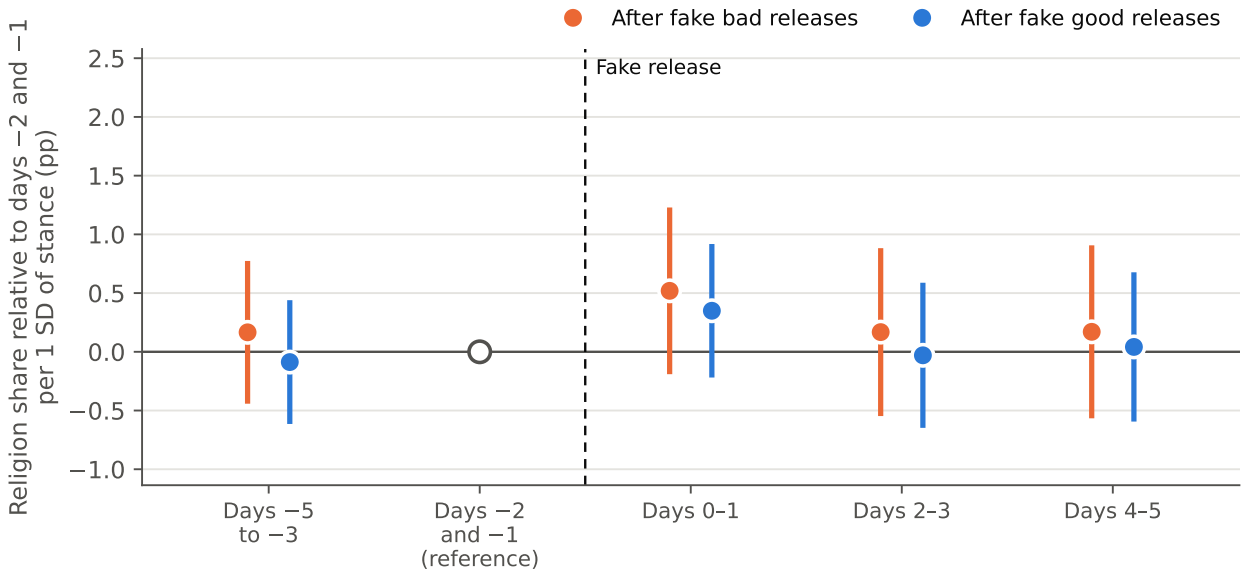
Note: Each dot is an outlet's change in the share of religious tweets in the 24 hours after a release relative to the 24 hours before, after bad (left) and good (right) releases, against the same change on its ordinary days in the same month. Filled: tweets with at least one reply; hollow: all 3.6 million tweets. Lines and slopes: the regression of Figure 3 (event and outlet × month fixed effects) for each set of tweets; p-values from standard errors clustered by outlet.

Figure B4: Change in the tone of tweets after releases by outlet stance.



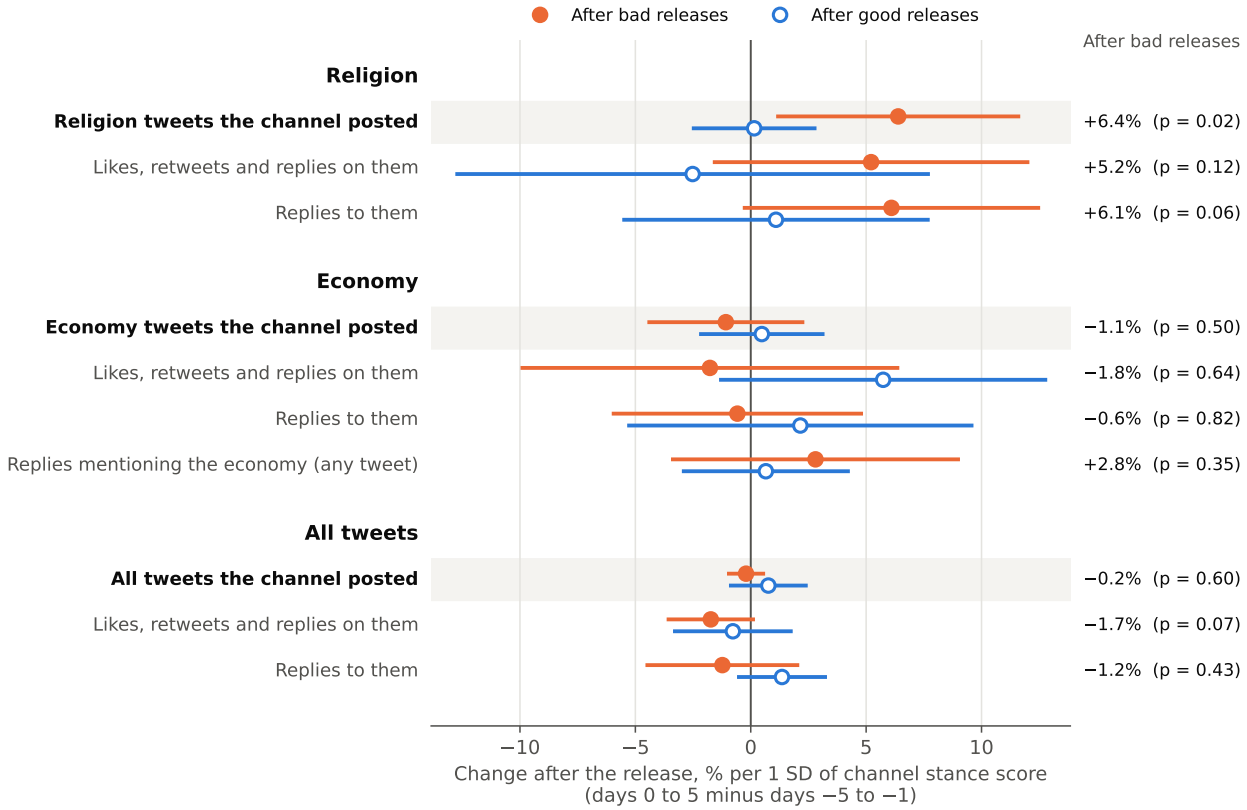
Note: Estimates of equation (1) with the tone of each outlet's tweets as the outcome: the change in the 24 hours after a release relative to the 24 hours before, against the same change on ordinary days. Tone is the VADER compound score of the tweet's own text. Panel A: mean score (×100); panel B: share of tweets with a score of −0.05 or below, in percentage points. Non-religious tweets: tweets not classified as religion. Coefficients on stance × bad release (orange) and stance × good release (blue), per SD of stance across the 12 outlets, with event and outlet × month fixed effects. The difference between the bad and good coefficients and its p-value are under each pair. 95% confidence intervals clustered by outlet.

Figure B5: The event study on fake releases on the same weekday.



Note: Each of the 94 releases, with its bad or good label, is given to a random ordinary day on the same weekday; 200 draws. Each draw adds the fake days −5 to +5 to the regression of Figure B1, with the real release windows kept as controls; fake windows are relative to fake days −2 and −1, per standard deviation of the outlet's stance score. Points and bars: average estimate and average 95% interval across draws. Otherwise as in Figure B1, on the same vertical scale.

Figure B6: Tweets posted and audience engagement after releases, by outlet stance.



Note: Each row is the regression of Figure B1 with asinh of the outlet-day count as the outcome (×100, approximately a percent change): stance (per SD) × day indicators for bad and good releases, date and outlet × month fixed effects. The estimate is the mean of the coefficients for days 0 to 5 minus the mean for days −5 to −1. Shaded rows: tweets the outlet posted. Other rows: likes, retweets and replies on those tweets as counted by Twitter at collection; the replies to them that we collected; and collected replies whose text mentions the economy. All are assigned to the day the tweet was posted. 22,063 outlet-days. 95% intervals clustered by outlet.

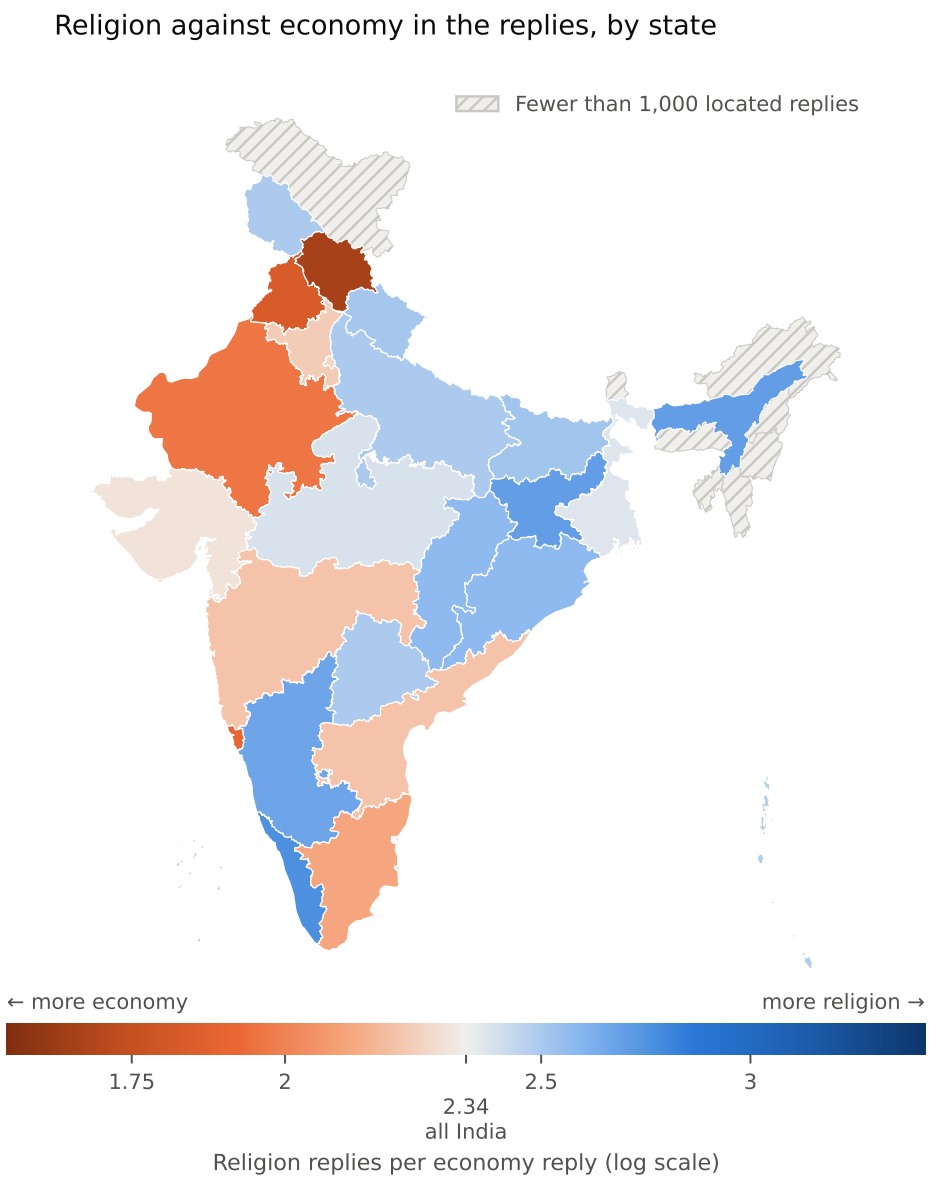
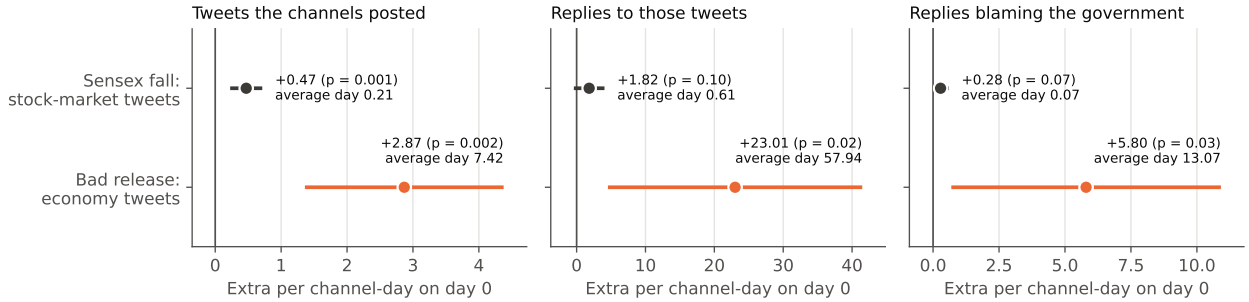


Figure B7: Location of repliers.

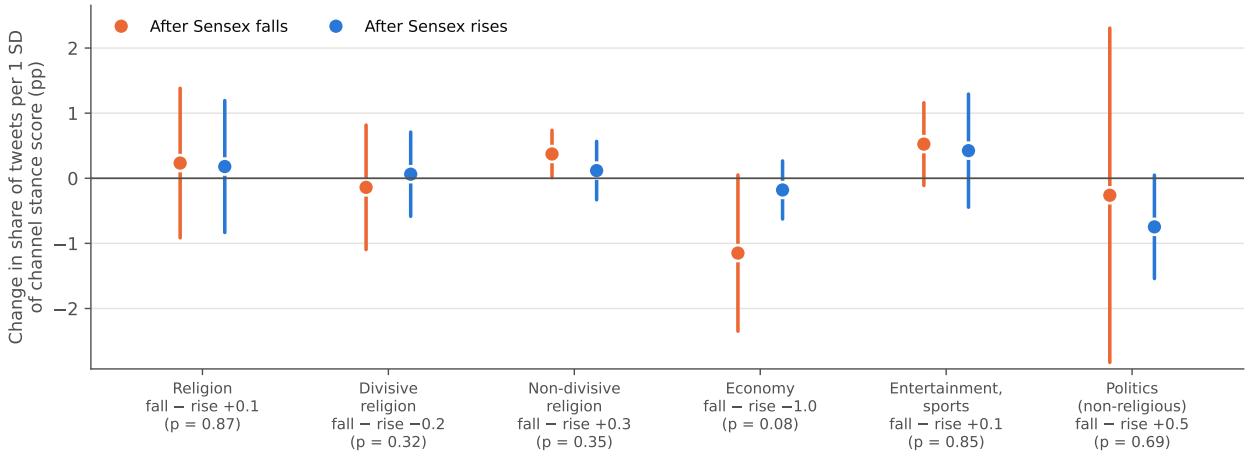
Note: For each state or union territory, its located replies to the outlets' religion tweets divided by its located replies to their economy tweets, against the same ratio for all located replies (2.34); log scale. Located replies: the 552,121 replies geotagged by Twitter to a place in India below the country level, assigned to the state that contains the place's centroid. 12 outlets, January 2018 – March 2023. State boundaries: DataMeet India community (CC BY 4.0).

Figure B8: Attention to Sensex falls and a bad indicator release.



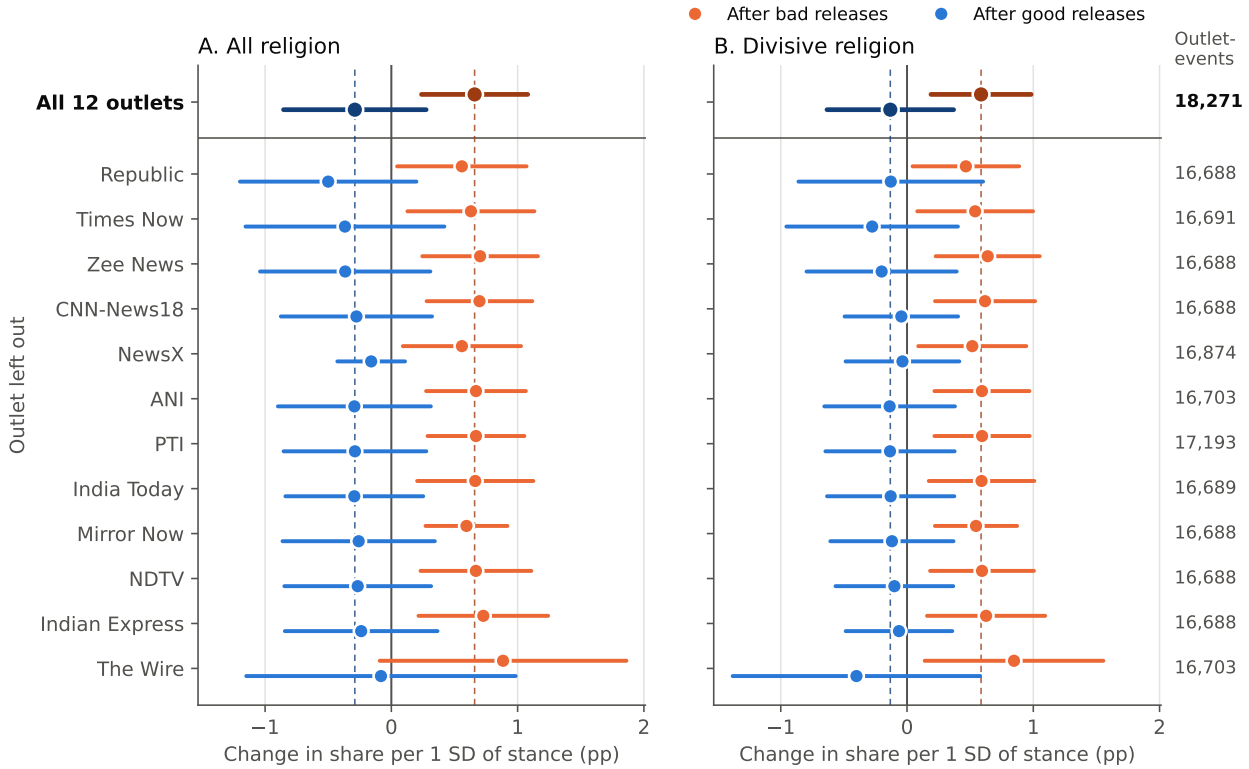
Note: Each point is the count per outlet-day on day 0 minus the mean of days −5 to −1, from one regression of the count on day indicators −5 to +5 around bad and good releases and Sensex falls and rises, with outlet × month fixed effects and no stance term (as in Table 1, column 1, in counts). Sensex fall: the outlets' stock-market tweets, the replies to them, and those labelled as blaming the government. Bad release: the outlets' economy tweets, the replies to them, and blame replies. Average day: mean per outlet-day. Tweets with at least one reply; replies are assigned to the day the tweet was posted. 95% intervals clustered by outlet.

Figure B9: Types of tweets after Sensex falls and rises, by channel stance.



Note: Change in each outlet's share of tweets in the 24 hours after the Sensex opens (09:15 IST) minus the 24 hours before, against the same change on ordinary days (no release, fall or rise within a day; windows around 17:30 IST). Falls and rises: the 5% of trading days with the largest fall and the largest rise, excluding days within a day of a release. Slope on the outlet's stance score, per standard deviation across the 12 outlets. Event and outlet × month fixed effects, as in Figure 3. 95% intervals clustered by outlet.

Figure B10: Change in religion share after releases by outlet stance, leaving out one outlet at a time.



Note: Each row re-estimates equation (1) without the outlet named; the top row uses all 12 outlets. Outlets are listed in order of stance, from the most pro-government. Panel A: all religious tweets; panel B: divisive religious tweets. Coefficients on stance × bad release (orange) and stance × good release (blue), in percentage points per SD of stance across the 12 outlets, with event and outlet × month fixed effects. Dashed lines: the estimates for all 12 outlets. 95% confidence intervals clustered by outlet, using a t distribution with degrees of freedom equal to the number of outlets minus one. Right: the number of outlet-events in each sample.

Table B4: Other definitions of bad and good releases.

	Religion			Divisive religion		
Definition of a bad release	Bad	Good	Bad − good	Bad	Good	Bad − good
Main definition	0.66^{***}	-0.29	0.95^{***}	0.59^{***}	-0.13	0.72^{**}
41 bad, 53 good	(0.19)	(0.26)	(0.29)	(0.18)	(0.23)	(0.32)
Thresholds half a point stricter	0.78^{***}	-0.24	1.02^{***}	0.69^{***}	-0.10	0.79^{**}
34 bad, 60 good	(0.24)	(0.23)	(0.32)	(0.21)	(0.20)	(0.32)
Thresholds half a point looser	0.59^{***}	-0.43	1.01^{**}	0.67^{***}	-0.40	1.08^{***}
51 bad, 43 good	(0.16)	(0.32)	(0.34)	(0.13)	(0.27)	(0.32)
Worse than the previous four releases	0.42^{**}	-0.29	0.71	0.46^{***}	-0.38	0.84^{**}
45 bad, 39 good	(0.15)	(0.47)	(0.54)	(0.09)	(0.32)	(0.35)
CPI and GDP releases only	1.11^{***}	-0.37	1.48^{***}	0.80^{***}	-0.01	0.82^{**}
32 bad, 45 good	(0.23)	(0.25)	(0.37)	(0.20)	(0.27)	(0.32)

Notes: Estimates of equation (1) with the 94 release days labelled bad or good as in each row; a day is bad when at least half of the indicators released that day are. The main definition counts a release as bad when CPI inflation is above 6 percent, GDP growth below 6 percent or urban unemployment above 9 percent. The stricter thresholds are 6.5, 5.5 and 9.5 percent, and the looser ones 5.5, 6.5 and 8.5 percent. "Worse than the previous four releases" compares each indicator with the mean of its four previous values (10 days without four previous values are left out). "CPI and GDP releases only" leaves out the 17 days with an unemployment release. Coefficients in percentage points per standard deviation of stance. Standard errors clustered by outlet in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B5: Estimates by outlet stance: clustered and randomization-inference p-values.

	Bad releases			Good releases			Bad − good		
	Est.	p	p_{RI}	Est.	p	p_{RI}	Est.	p	p_{RI}
A. Change in share, 24 hours after the release against 24 hours before (points per SD of stance)									
Religion	0.66	0.005	0.036	−0.29	0.284	0.365	0.95	0.008	0.022
Divisive religion	0.59	0.008	0.054	−0.13	0.573	0.663	0.72	0.049	0.140
Non-divisive religion	0.07	0.218	0.347	−0.16	0.572	0.685	0.23	0.458	0.591
B. Religion share around the Reuters poll and after the release (points per SD of stance)									
By forecast: poll day	−1.17	0.006	0.062	0.12	0.729	0.796	−1.29	0.007	0.046
next day to 11:30 IST on release day	−0.80	0.102	0.242	−0.05	0.705	0.814	−0.74	0.159	0.347
11:30 IST to the release	0.84	0.009	0.058	−0.34	0.186	0.275	1.18	0.004	0.054
By release: day 0	1.27	0.003	0.038	0.05	0.781	0.856	1.21	<0.001	0.016
day 1	0.86	0.008	0.060	−0.48	0.180	0.345	1.35	0.024	0.076
day 2	0.99	0.144	0.301	−0.94	0.074	0.184	1.93	0.043	0.134
day 3	1.63	0.003	0.030	−1.08	0.064	0.134	2.70	0.011	0.038
day 4	0.32	0.460	0.559	−0.10	0.741	0.794	0.42	0.529	0.635
C. Replies blaming the government, by outlet stance (asinh × 100 per SD of stance)									
Day 0	−0.88	0.914	0.922	−7.30	0.308	0.427	6.42	0.201	0.329
Days 0–5	1.55	0.578	0.643	1.53	0.693	0.752	0.01	0.996	0.996
D. Individual repliers, by exposure (points per SD of outlet stance)									
Blaming the government, day 0	−0.63	<0.001	0.124	−0.11	0.241	0.523	−0.52	<0.001	0.068
days 0–5	−0.13	0.040	0.503	−0.16	0.077	0.303	0.03	0.718	0.838
Replies to economy tweets, day 0	−1.14	<0.001	0.265	−0.36	0.091	0.401	−0.79	0.011	0.279
days 0–5	−0.42	0.027	0.503	−0.19	0.264	0.561	−0.23	0.059	0.361

Est.: the estimate in the corresponding figure or table. p: standard errors clustered by outlet (individual repliers: by the person's main outlet), t with 11 degrees of freedom. p_{RI}: stance scores reassigned to the outlets at random, 500 times. Panel A: Figure 3. Panel B: Figure 4. Panel C: Table 1, columns 2 and 4. Panel D: Table 1, Panel B; exposure is the mean stance of the outlets the person replied to in days −95 to −6, each outlet counted once. The all-outlet blame estimates have no stance term and are not included.