Fear as a Campaign Tool: Evidence from the 2014 U.S. Ebola Scare*

Filipe Campante† Emilio Depetris-Chauvin‡ Ruben Durante§

November 2026

Abstract

We study the supply of fear-based political communication using the 2014 Ebola scare, an unanticipated threat shock that hit weeks before the midterm elections. Analyzing the content of Twitter posts and congressional newsletters of House and Senate candidates, we find that Republicans sharply increased Ebola-related communication, emphasizing negative sentiment and pairing the disease with immigration and with President Obama. This response was strongest among Republicans in safe seats, consistent with a model in which strategic communication about a threat mobilizes core supporters to increase both the probability of winning and the vote margin. The supply side was active rather than reactive: the disproportionate Republican response did not vary with proximity to the diagnosed cases despite voter anxiety being concentrated there, and politician tweets predicted public Ebola activity but not vice versa.

Keywords: political communication, electoral strategy, fear appeals, epidemics, mobilization, Ebola

*We thank David Schwartsman and Mateo Servent for excellent research assistance. Emilio Depetris-Chauvin acknowledges financial support from ANID, FONDECYT Regular 1240631. All errors are our own.

†Johns Hopkins University & NBER. Email: fcampante@jhu.edu

‡Instituto de Economía, Pontificia Universidad Católica de Chile. Email: edepetris@uc.cl

§National University of Singapore, ICREA-UPF, CESifo, IZA & CEPR. Email: rubendurante@gmail.com

"Ladies and gentlemen, we've got an Ebola outbreak,
we have bad actors that can come across the border.
We need to seal the border and secure it."

Thom Tillis, Republican Senate candidate [1]
in North Carolina, during the 2014 campaign

1 Introduction

Fear and anxiety are widely seen as a potent force in political life (Marcus, Neuman and MacKuen, 2000; Brader, 2005; Huddy, Feldman and Cassese, 2007). Candidates stand to gain from framing a salient threat in ways that align with their platform, and thereby activating voters' emotions. This paper investigates the strategic choice by politicians to exploit fear-based appeals in an election campaign, in the presence of an unanticipated shock raising the perception of threat among the electorate.

In the fall of 2014, four cases of Ebola were diagnosed on U.S. soil in the weeks immediately before the midterm elections. The episode triggered intense public anxiety out of all proportion to the actual epidemiological risk: polls indicated that nearly 40 percent of Americans were worried that they or a family member might be exposed (SteelFisher, Blendon and Lasala-Blanco, 2015), while Ebola attracted more sustained news interest than any previous public health crisis in the country (Motel, 2014). Taking advantage of the plausible exogeneity of the timing and location of cases (Campante, Depetris-Chauvin and Durante, 2024), we study how politicians responded to the shock in their campaign communications, how they framed that response in ways that were strategically advantageous, and how that response was not merely driven by their constituents' anxiety.

To guide our empirical analysis, we first lay out a simple model of a candidate choosing how intensively to promote a threat frame, trading off the gains from mobilizing their core supporters against the risk of alienating other voters. The candidate cares about the

[1] The quote comes from a televised debate on October 7, 2014. A clip containing it is available on `https://www.c-span.org/video/?c4510790/user-clip-tillis-ebola&start=1567`.

probability of winning, but also about their winning margin, capturing the idea that the latter can strengthen their position in the party and future career prospects. The model yields a number of predictions: (i) candidates from the party that owns the issue triggered by the threat choose to promote it; (ii) communication increases with the strength of the candidate's electoral position; and (iii) this effect is stronger when the audience is disproportionately composed of core supporters. Of note, the nature of the response to the candidate's electoral position hinges on the combination of winning and vote margin motives: if only winning mattered, communication would be concentrated in relatively competitive races, and candidates far ahead and far behind would respond alike.

We take these predictions to the data, using a panel on the complete Twitter output of every Republican and Democratic candidate for House and Senate seats who was active on the platform, as well as the congressional newsletter record of incumbent members of Congress competing in the 2014 election cycle. Combining candidate-level panel data with text coded by a large language model (GPT-4o-mini), we construct week-by-week measures of Ebola-related communication that capture both the extensive margin (any mention) and the intensive margin (number of mentions), as well as the tone (negative sentiment) and framing (Ebola mentioned together with immigration). We implement a differences-in-differences (DiD) strategy that compares the change in communication by Republican and Democratic candidates before and after the onset of the first U.S. Ebola case in late September 2014, absorbing candidate and week fixed effects.

Our main findings are as follows. First, Republican candidates increased their Ebola-related communication after the first U.S. case far more than Democratic candidates did. On Twitter, Republicans were about 6 percentage points more likely to mention Ebola in any given post-onset week, and sent roughly 0.32 more Ebola-related tweets per week, quadrupling the pre-onset Republican mean. The Republican response was specifically targeted: it featured elevated negative sentiment and a disproportionate tendency to pair Ebola with immigration, the issue where Republicans had a clear competitive advantage and where Ebola

anxiety actually moved voter attitudes (Campante, Depetris-Chauvin and Durante, 2024). Republicans also tied Ebola to President Obama: about one in ten of their post-onset Ebola tweets, and three in ten of their Ebola newsletters, dealt with the President, while their messages about him unrelated to Ebola became less frequent.

We then turn to the role of electoral incentives in shaping politicians' response. We find that, among Republicans, the intensity of the response is strongest for candidates in the safest seats rather than those in competitive races, a gradient that is statistically clear on Twitter and points the same way, though more weakly and without conventional significance, in newsletters. Through the lens of the model, this suggests that the response is substantially driven by the value of a larger margin, and not only by the probability of winning: if only winning mattered, Republicans in safe and in hopeless races would respond alike. Additional evidence helps interpret this pattern: comparing within individual members of Congress, the gradient shows up on Twitter but not in their newsletters, which reach a broader audience of constituents, as distinct from self-selected social media followers, consistent with the frame being targeted at the more partisan audience.

We next disentangle supply from demand drivers in politicians' response to the Ebola shock. First, we find that the Republican response does not vary with the geographic proximity of candidates' districts to the Ebola cases. While voter anxiety (and electoral effects) are concentrated in proximate areas (Campante, Depetris-Chauvin and Durante, 2024), the disproportionate Republican response did not vary with how close or far their constituents were from the cases (though communication by Democrats rose modestly more near a just-diagnosed case). This asymmetry between supply and demand suggests that the decision to exploit Ebola was not driven by politicians reading local constituent anxiety, but was instead a broadly adopted partisan communication strategy aimed at fueling concerns. Consistent with that, we exploit the high-frequency variation in the timing of communications to find that politicians' Ebola tweets predict tweets and searches from the public, and not vice versa.

Our paper contributes to several strands of literature. A rich experimental literature

has documented that fear, anxiety and disgust shift political preferences in predictable ways (Brader, 2005; Jost et al., 2003; Thórisdóttir and Jost, 2011), and correlational research has shown that such emotions are associated with more conservative political orientations (Inbar, Pizarro and Bloom, 2008; Inbar et al., 2012). Consistent with that, Campante, Depetris-Chauvin and Durante (2024) show in the context of the 2014 Ebola shock that Republicans benefited electorally, with demand-side effects being geographically concentrated around the places closest to where Ebola cases were diagnosed. We build on this work by examining the strategic supply of fear-based political content in response to an exogenous anxiety shock. In the same context, Cormack (2014) and Adida, Dionne and Platas (2018) provide, respectively, correlational and experimental evidence of the relationship between Republican messaging and public attitudes during the Ebola episode. We improve on correlational evidence using a within-candidate DiD identification strategy, and on experimental evidence by measuring behavior in actual campaign communications rather than survey responses.[2] These allow us to further unpack the role of electoral incentives and of supply versus demand considerations.

To the extent that the communication strategies we document are making use of negative sentiments, we also relate to the negative campaigning literature (Ansolabehere and Iyengar, 1995; Skaperdas and Grofman, 1995; Druckman, Jacobs and Ostermeier, 2004).[3] This literature has theorized about when candidates go negative and who does so strategically; we contribute evidence on the role of electoral safety that is inconsistent with the "front-runner stays positive, underdog attacks" prediction of Skaperdas and Grofman (1995), suggesting instead that safe seats create mobilization incentives. This is consistent with work showing that politicians take positions to signal to partisans, and especially so when they are mostly concerned with primary rather than general electorates (Mayhew, 1974; Fenno,

[2]Importantly, our evidence does not establish that the electoral impact found in Campante, Depetris-Chauvin and Durante (2024) was necessarily caused by the strategic actions of politicians that we document here.

[3]To be clear, our results do not speak to whether candidates where directly attacking opponents in the context of their Ebola communication, so they are not about negative campaigning strictly defined in that sense.

1978; Brady, Han and Pope, 2007; Hall, 2015; Anderson, Butler and Harbridge-Yong, 2020). Finally, our finding that the Republican supply-side response does not vary with proximity while demand-side responses are geographically concentrated contributes to a broader understanding of how political communication interacts with local context to produce heterogeneous electoral effects (Zaller, 1992; Huckfeldt and Sprague, 1995).

The remainder of this paper is organized as follows. Section 2 provides background on the Ebola episode and the 2014 elections, Section 3 presents the model, and Section 4 describes the data and empirical strategy. Section 5 reports the main results, and Section 6 examines alternative explanations and presents additional evidence. Section 7 concludes.

2 Background: The 2014 Ebola Episode and the U.S. Midterm Elections

The 2014–15 Ebola outbreak originated in Guinea in late 2013 and grew into the largest recorded Ebola epidemic, with the vast majority of cases and deaths concentrated in Guinea, Liberia, and Sierra Leone. Although the virus spread to several other countries, no significant outbreak ever materialized outside sub-Saharan Africa. Nonetheless, when the CDC confirmed the first U.S. case on September 30, 2014 (Thomas Eric Duncan, a Liberian national visiting Dallas, Texas), the episode generated extraordinary public attention. Two nurses who had treated Duncan were subsequently diagnosed (October 11 and 14), and a physician returning from Guinea was diagnosed in New York City on October 23. In total, four individuals were diagnosed with Ebola on U.S. soil; all but Duncan survived.

The media response was massive: over 3,000 Ebola-related news segments aired on the top cable networks in the five weeks following the first case, and survey data indicate that 85 percent of Americans incorrectly believed Ebola could be transmitted through sneezing or coughing (SteelFisher, Blendon and Lasala-Blanco, 2015). Crucially, the episode unfolded during a politically charged moment: all 435 House seats and 36 Senate seats were on the

ballot in elections held November 4, 2014.

The contrast between the objective health risk, which was negligible, and the intense popular reaction makes the episode particularly well suited to our analysis. Given that public anxiety so plainly exceeded any epidemiological basis, a candidate's decision to amplify the episode may not reflect a genuine public-health concern but rather a strategic calculation.

The intersection of a public health scare and an upcoming election created obvious strategic incentives. Republicans had long been competitive on immigration-related issues and had opposed the Obama administration's policy of maintaining commercial flights from affected West African countries. The Liberian origin of the first case, combined with the proximity of the elections, made Ebola a potentially attractive issue for Republican candidates seeking to link the disease to immigration, border security, and the competence of the incumbent administration (Cormack, 2014).

Figure 1 provides a first look at the evidence. It plots the weekly share of candidates who tweeted about Ebola, who used negative sentiment when doing so, and who mentioned Ebola together with immigration, separately for Republicans and Democrats, from August through three weeks after the election. The figure is striking in several respects. Until the first U.S. diagnosis (Dallas, September 30, which falls in week 39), Ebola appeared only sporadically in candidate communication: in any given week, at most 4 percent of candidates of either party tweeted about it. Starting with the Dallas diagnosis, Republican communication about Ebola shoots up sharply and remains elevated over the following weeks, in contrast to a much more muted Democratic response. The Republican differential peaks in mid-October and fades over the last weeks of the campaign, as public attention to Ebola declined, even though the epidemic in West Africa kept growing: cumulative reported cases in Guinea, Liberia and Sierra Leone rose from about 8,000 at the first U.S. diagnosis to about 14,000 by election day, and to about 20,000 by the end of December, according to WHO situation reports and national ministries of health (Rivers, 2014); it does not reappear after the election (Section 6).

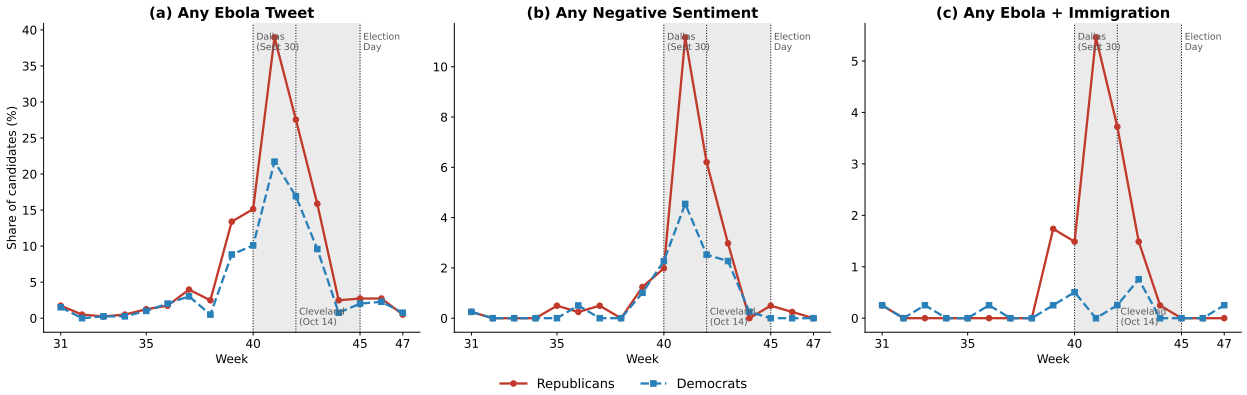


Figure 1: Weekly Ebola Communication by Party, August to November 2014

Notes: Each panel plots the weekly share of candidates (as a percentage) who published at least one tweet in the relevant category, separately for Republicans (solid, red) and Democrats (dashed, blue). Weeks run Monday to Sunday. The shaded region covers the post-onset period of the baseline specification (weeks 40–45). Vertical dotted lines mark the first full week after the Dallas diagnosis of September 30 (week 40) and the first full week after the November 4 election (week 45).

3 A Model of Strategic Threat Exploitation

Motivated by our context, we start by laying out a simple model of a candidate in a general election, choosing how intensively to promote a threat frame.[4] The model is deliberately stylized: its purpose is to guide the empirical analysis, by making explicit which features of the electoral environment should shape the response, rather than to provide a full account of campaign behavior.

3.1 Setup

Consider a race in district (or state, for Senate) d. A share ρ_d of the district's voters leans toward the Republican candidate, and the remaining $1-\rho_d$ toward the Democrat. Leaning reflects partisanship, but also attachment to the candidates themselves, for instance through incumbency, so we write $\rho_d = p_d + h_d$, where p_d is the Republican partisan share and h_d is the net personal following of the Republican candidate. For candidate i of party $P \in \{R, D\}$, let s_i be the share of voters who lean toward them ($s_i = \rho_d$ for the Republican and $1-\rho_d$ for the Democrat), so that their expected margin is $x_i = 2s_i - 1$. The realized margin is

[4]Recall that all four U.S. cases were diagnosed after the parties' nominees had been chosen.

subject to a shock ε_i (e.g. turnout or late deciders), symmetric and unimodal around zero, with CDF G and density g. The candidate wins with probability $G(x_i)$, and $g(x_i)$, which peaks at $x = 0$, is the marginal effect of their expected margin on that probability.

We assume there is a threat perceived by voters, with (national) salience S. The alignment of that threat perception with party P's agenda, which we refer to as the party's fit, is parameterized by $\lambda_P \geq 0$: a higher value of the parameter indicates that the party "owns" the issue made salient by the threat (Petrocik, 1996; Aragonès, Castanheira and Giani, 2015) (e.g. immigration in the case of an epidemic risk coming from abroad), or is in the opposition (resp. in power) when the threat perception works against (resp. in favor of) the incumbent. Each candidate chooses the intensity $e_i \geq 0$ with which they communicate about the threat. Their vote margin is then:

$$v_i = x_i + S\,\Gamma_{Pd}(s_i)\,e_i + \varepsilon_i, \qquad \Gamma_{Pd}(s) = \lambda_P\big[\,b\,s + \gamma A_d\,\big] - m\,(1-s). \tag{1}$$

The effect of communication is more positive when the salience is high and the party benefits from the issue, but it also depends on who is being reached.

This embeds two key assumptions. First, the communication frame mobilizes the candidate's own supporters, at a rate $\lambda_P b$ that rises with the party's fit, but alienates voters who lean toward the opponent, at a rate m. In other words, a frame that fits the party's agenda energizes its supporters, while it antagonizes the other side.[5] Second, the frame can also persuade anxious voters, to an extent that depends on the average anxiety of the district's voters, $A_d = p_d A_d^R + (1-p_d)A_d^D$, where A_d^R and A_d^D are the anxiety of Republican and Democratic partisans, respectively.[6] Note that the net return to communication thus rises with the candidate's share of supporters, at rate $\theta_P \equiv \lambda_P b + m$; setting anxiety aside, that is positive when that share exceeds a break-even level defined as $\bar{s}_P \equiv m/(\lambda_P b + m)$, which

[5] Note that we could impose symmetry as a special case: $m = \lambda_P b$.

[6] We can also assume that the opponent's messages and the direct effect of anxiety on votes also shift the margin, but if we impose that they do so additively, they do not affect the candidate's choice, and we can omit them.

is lower the higher the party's fit.

We then turn to the candidate's optimization. They value winning, with weight W, but also the vote margin, with weight μ. The latter captures the idea that a larger margin helps their future prospects: it may deter future challengers (including in primaries), strengthen standing within the party and in Congress, and can be presented as a mandate (Jacobson and Kernell, 1981). We also assume that communication may happen in response to the anxieties of the candidate's partisan supporters, $\sigma\, p_d^P A_d^P\, e_i$, where p_d^P is the partisan share of party P in the district.[7] Finally, we impose that messages are costly, at $\frac{k}{2}e_i^2$. Taking the first-order condition, the optimal intensity is then

$$e_i^* = \max\left\{0,\ \frac{\big(W g(x_i) + \mu\big)\, S\, \Gamma_{Pd}(s_i) + \sigma\, p_d^P\, A_d^P}{k}\right\}. \tag{2}$$

Note that the corner solution is meaningful: a candidate for whom the frame lowers their margin ($\Gamma_{Pd} < 0$), and who has little reason to reassure their supporters, will stay silent.

3.2 Predictions

The model yields four predictions, which we state formally and prove in Appendix A. These predictions will guide our empirical implementation.

Prediction 1 (party and frame) At any electoral position, the response should be larger for the party with the higher fit λ_P (Proposition 1). The intuition is simple: the fit both raises the return to the frame and widens the range of races in which it pays off. In our context, during the Ebola crisis in 2014, that was the Republican Party, which owned the immigration issue and was out of the executive, and we would expect communication by Republican candidates to pair the threat with immigration and attacks on the executive (President Obama). This is the central prediction from our framework.

[7] We take anxiety to be a partisan trait, so the anxious constituents the candidate responds to are the party's supporters, and not their personal support beyond that.

Prediction 2 (electoral position) Our model also allows us to investigate the role of a candidate's electoral position in shaping their communication efforts around the perceived threat. If candidates cared only about winning ($\mu = 0$), communication would be concentrated in relatively competitive races in which the frame pays off, and would fall to the baseline level of responsiveness to anxious partisans in non-competitive seats, whether the candidate happens to be far ahead and far behind. If, instead, the return to the frame did not depend on the partisan composition of the electorate (Γ_d constant in s, say, because $b = m = 0$ and communication merely persuades all anxious voters equally), then communication effort would be symmetric in the candidate's own advantage. With both a margin motive and composition effects, communication increases with the candidate's own advantage (Proposition 2).

To understand the intuition, consider three discrete cases, which we can label "far-behind" (FB), "competitive" (C), and "far-ahead" (FA), according with the candidate's relative position in the race. A comparison between the cases reveals the role of each motive. Let the candidate's share of supporters in the three cells be s_L, $\frac{1}{2}$, and s_H, with $s_L = 1 - s_H$; in safe seats $g \approx 0$, so that only the margin motive is at play. We can thus compare the levels of effort chosen by different candidates as follows:

$$\underbrace{e_{\text{FA}} - e_{\text{FB}}}_{\text{margin gradient}} \approx \frac{\mu S \theta_P \left(s_H - s_L\right)}{k}, \qquad \underbrace{e_{\text{C}} - \tfrac{1}{2}\left(e_{\text{FA}} + e_{\text{FB}}\right)}_{\text{midpoint gap}} \approx \frac{W g(0)\, S\, \Gamma_{Pd}(\tfrac{1}{2})}{k}. \tag{3}$$

In words, the gap between the far-ahead and far-behind cells reflects the margin motive: if candidates cared only about winning, they would both be at the level given by responsiveness to the demand from anxious partisan constituents. A positive margin gradient therefore rejects this benchmark. The midpoint gap, in turn, reflects the value of winning, scaled by the return to the frame in a balanced district: it is zero if winning carries no weight or if the frame neither helps nor hurts there. It can also be negative, for a party whose fit is so low that the frame loses votes in balanced districts: in that case, competitive candidates may

stay silent, at the corner solution.[8]

Prediction 3 (partisan composition of the audience) We can also consider differences in the communication response according to the different channels on which it takes place. If the frame pays off disproportionately among the candidate's supporters, its return should depend on the composition of the audience exposed to the frame. In particular, we draw a distinction between communications that reach all constituents (e.g. congressional newsletters) and those where the audience self-selects and would hence be more partisan (e.g. social media). If the share of supporters in a candidate's social media audience rises more steeply with their electoral position than that of their constituency, the same member's response should be more sensitive to their electoral position on social media than in newsletters (Proposition 3). (Note that the model still predicts a positive gradient in newsletters, only flatter.)

Prediction 4 (distance) Finally, we can also exploit the spatial patterns in voter anxiety in the data, by imposing additional assumptions on those patterns. Specifically, in our context (in line with the findings of Campante, Depetris-Chauvin and Durante (2024)), we can assume that A_d^D decreases with distance to the Ebola cases, while A_d^R is spatially flat, so that the district average A_d also falls with distance. This implies that responsiveness should not generate a distance gradient in the Republican communication effort around the threat. Such a gradient would only arise if the frame's return rose with local anxiety ($\gamma > 0$). In contrast, responsiveness should by itself generate a Democratic proximity gradient, in every type of race (Proposition 4).

[8]The winning motive also shows up in the slope of the response around competitive races, $(Wg(0) + \mu)S\theta_P/k$, which exceeds the average slope across safe seats, $\mu S\theta_P/k$, by a factor of $1 + Wg(0)/\mu$.

4 Data and Empirical Strategy

4.1 Data

4.1.1 Candidate Twitter Data and GPT Coding

Our primary dataset consists of all tweets published by Republican and Democratic candidates for House and Senate seats in the 2014 election cycle, covering the period from August 1 through December 31, 2014. The underlying tweet corpus was initially compiled by Evans et al. (2017); we extended it to include pre-campaign and post-election periods. For the difference-in-differences analysis we use a balanced twelve-week window around the onset of the first U.S. case (diagnosed September 30, 2014; the post-onset period starts in week 40, the first full week after the diagnosis): the six weeks before the onset (weeks 34–39) and the six-week post-onset campaign period (weeks 40–45, running through the first full week after the election). This covers 799 Republican and Democratic candidates with active Twitter accounts, each observed over all twelve weeks (9,588 candidate-weeks). Coverage of the platform is high: 90.7 percent of the Democratic and Republican general-election candidates for the House had a Twitter account, with no difference between the parties, and coverage is lower only among candidates running in seats that are safe for the opposing party (Appendix Table A1). The descriptive time series in Figure 1 and the event-study figures use a wider window (weeks 31–47) to display the full pre-period and the post-election reversal.

While standard keyword search methods can identify whether a tweet mentions "Ebola," they are poorly suited to capturing tone or the co-occurrence of multiple topics in natural language (Grimmer and Stewart, 2013). We use GPT-4o-mini to code each Ebola-related tweet along two dimensions: (1) whether the tweet expresses negative sentiment about the disease or its management; and (2) whether the tweet also deals with immigration or border-related themes, so that Ebola and immigration are mentioned together (we refer to this as Ebola-immigration co-mention). We also use the classifier's code for messages that deal with President Obama, to measure Ebola-Obama co-mentions; the code records that a message

deals with the President, not whether it criticizes him. (Appendix E describes the coding procedure in greater detail.)

This yields six outcome measures for the Twitter analysis. At the extensive margin, we construct indicators for any Ebola tweet in a given week, any Ebola tweet with negative sentiment, and any Ebola tweet mentioning immigration. At the intensive margin, we use the corresponding weekly counts. We construct the same indicator and count for the Ebola-Obama co-mention. Together, these measures allow us to examine not just whether politicians mentioned Ebola but how they chose to frame it. To make the textual content underlying these measures concrete, Appendix I reproduces a set of representative tweets that the GPT-4o-mini procedure flags as mentioning Ebola together with immigration and border security, illustrating the recurring rhetorical move (treating border security as the remedy for an incoming epidemic) that the immigration indicator is designed to capture.[9]

4.1.2 Congressional Newsletter Data

To assess whether the Twitter results generalize to a complementary communication channel, we use comprehensive data on all e-newsletters sent by members of Congress to their constituents, available from the DCinbox dataset (Cormack, 2017). DCinbox provides the complete text of every official newsletter sent by every sitting representative and senator between August and November 2014, for approximately 4,900 newsletter-week observations. We apply the same GPT-4o-mini coding procedure to newsletter text to identify Ebola mentions, negative sentiment, and immigration co-mentions. Because newsletters are sent to constituents at the discretion of incumbents, the newsletter sample is restricted to sitting members of Congress. The two datasets provide complementary perspectives: Twitter captures candidates (including non-incumbents) communicating publicly; newsletters capture incumbents communicating directly with their districts. As with the Twitter data, Appendix H provides illustrative excerpts from the newsletter corpus, reproducing verbatim

[9]These excerpts are purely illustrative of the coded content and are not a representative sample.

passages in which members frame the Ebola outbreak alongside immigration or border-security themes; these examples put concrete language to the GPT-4o-mini-coded measures and parallel the tweet examples in Appendix I.

4.1.3 Electoral Competitiveness and Candidate Characteristics

We use data from the Cook Political Report (CPR), as of September 19, 2014 (that is, before the first Ebola case), to classify each race by its competitiveness. The CPR Race Ratings assigns each race to one of seven categories: Solid Democrat, Likely Democrat, Lean Democrat, Toss Up, Lean Republican, Likely Republican, and Solid Republican. We use this in two ways. First, we construct a binary indicator for competitive races (Toss Up, Lean Democrat, or Lean Republican). Second, we use the underlying seven-point numeric score (ranging from -3 for Solid Democrat to $+3$ for Solid Republican) as a finer measure of Republican electoral advantage.

4.1.4 Distance to Ebola Cases

Following Campante, Depetris-Chauvin and Durante (2024), we compute the minimum great-circle distance from the centroid of each candidate's congressional district to the three locations associated with U.S. Ebola diagnoses (Dallas, TX; Cleveland/Akron, OH; and New York City, NY). Campante, Depetris-Chauvin and Durante (2024) show that this variable strongly predicts voter anxiety on the demand side and use it as an instrumental variable to identify the electoral effects of Ebola concerns. Here, we examine whether the same geographic variation is reflected in politician behavior on the supply side. Because the three diagnoses arrived sequentially, for the supply-side analysis we measure distance to the nearest case known as of each week (Dallas from week 40, with Cleveland/Akron added in week 42 and New York in week 43), so that the measure never incorporates case locations that had not yet been diagnosed.

4.2 Empirical Strategy

We estimate the following differences-in-differences model:

$$Y_{p,t} = \alpha + \beta\,(\text{Post}_t \times \text{Republican}_p) + \eta_p + \tau_t + \boldsymbol{\pi}' X_{p,t} + u_{p,t}, \tag{4}$$

where $Y_{p,t}$ is one of the six Ebola communication measures for candidate (or member) p in week t. Post_t is an indicator equal to one for weeks 40–45. Weeks run Monday to Sunday, and we date each event from the first full week after it: the Dallas diagnosis (Tuesday, September 30) falls in week 39, so Post starts in week 40 (October 6), and the sample ends in week 45, the first full week after the November 4 election. Treating the diagnosis week itself as post-onset leaves the results unchanged (Appendix Table A2). Republican_p is an indicator for the candidate's party affiliation. η_p and τ_t denote candidate and week fixed effects, respectively, which absorb all time-invariant candidate characteristics and common weekly shocks. $X_{p,t}$ includes the weekly word count and cumulative word count of a candidate's communications, to control for overall communication intensity.[10] Standard errors are clustered at the race level.

The coefficient of interest, β, measures the differential change in Ebola-related communication by Republican candidates relative to Democrats upon the onset of the first U.S. Ebola case. The candidate fixed effect removes any persistent partisan differences in communication style; identification comes from within-candidate changes over time. The identification assumption is that, absent the Ebola episode, Republican and Democratic candidates would have followed parallel trends in their Ebola-related communication. Ebola mentions were rare before the first U.S. diagnosis (at most 4 percent of candidates of either party in any week from August to late September), although Republicans were somewhat more likely to

[10] Because these controls are themselves measures of communication, they could in principle be affected by the Ebola response. Appendix F re-estimates all of the main specifications without them; the coefficients of interest are essentially unchanged (Twitter estimates move by at most a few percent, and newsletter estimates are, if anything, slightly larger), so the results are not driven by conditioning on communication volume.

mention it in September, when the West African outbreak and the deployment of U.S. troops were in the news. The assumption can be checked directly in the pre-period, which we do with event studies.

To examine the role of geographic proximity, we augment equation (4) with the interaction:

$$\begin{aligned} Y_{p,t} = \alpha + \beta\,(\text{Post}_t \times \text{Republican}_p) + \phi_1\,\text{Dist}_{p,t} + \phi_2\,(\text{Post}_t \times \text{Dist}_{p,t}) \\ + \phi_3\,(\text{Post}_t \times \text{Republican}_p \times \text{Dist}_{p,t}) + \eta_p + \tau_t + \boldsymbol{\pi}' X_{p,t} + u_{p,t}, \end{aligned} \tag{5}$$

where $\text{Dist}_{p,t}$ is the (log, demeaned) minimum distance from candidate p's district to the nearest Ebola case known as of week t. The variable carries a time subscript because the set of diagnosed locations expands over the campaign: with the Cleveland/Akron and New York diagnoses in weeks 42 and 43, distance can fall within candidate over time. This within-candidate variation also identifies the main effect ϕ_1, which we include even though the time-invariant component of distance is absorbed by the candidate fixed effects. Since every candidate is either a Republican or a Democrat, the coefficient ϕ_2 captures whether Democratic candidates (the omitted category) respond more in proximate districts after the onset; ϕ_3 captures the differential response by Republicans, so that the within-Republican distance gradient is $\phi_2 + \phi_3$. This specification mirrors directly the demand-side identification in Campante, Depetris-Chauvin and Durante (2024), allowing us to ask whether the geographic gradient that shapes voter anxiety on the demand side is present in politician behavior on the supply side.

To examine electoral incentives, we further augment equation (4) with a continuous interaction between the post-onset Republican indicator and the Cook electoral advantage score, and compute predicted effects for six cells defined by party and the Cook race rating (Solid Democrat, Competitive, Solid Republican). This design allows us to formally test the prediction of the standard persuasion account, namely that competitive races drive strategic communication more than safe seats, by comparing the cell estimates directly and testing

whether the Solid Republican and Competitive cells are statistically distinguishable.

The validity of our design rests on three features. First, Ebola played only a marginal role in candidate communication before the first U.S. diagnosis on September 30, 2014, and pre-onset differences between the parties are small. Second, the onset of the first U.S. Ebola case was driven by an individual traveler's infection in West Africa and is plausibly exogenous to domestic electoral competition. Third, the response is specific to Ebola: Republican messaging on immigration without any reference to Ebola did not change differentially after the onset (Section 6). Event-study estimates presented in Appendix Figures A2-A9 validate these claims.

5 Results

5.1 The Republican Strategic Response

5.1.1 Main Results

We start by testing our central prediction (Prediction 1): in the context of the Ebola shock in 2014, Republicans should respond by increasing their communication effort, and framing it around the issue they owned (immigration) and the incumbent President Obama.

Table 1 presents the baseline DiD estimates for the Twitter sample. Republican candidates significantly increased Ebola-related communication across every outcome measure upon the onset of the first U.S. case. Relative to Democratic candidates, Republicans became about 6 percentage points more likely to mention Ebola in any given week (column 1), against pre-onset means of 2.6 percent for Democratic and 3.9 percent for Republican candidates. On the intensive margin, Republicans sent 0.32 additional Ebola-related tweets per week (column 2), about four times the pre-onset Republican mean of 0.08 tweets per week.

The framing results are equally striking. Republicans were 1.8 percentage points more

likely to tweet about Ebola with negative sentiment (column 3) and 1.7 percentage points more likely to mention Ebola together with immigration in the same tweet (column 5). Both margins represent large proportional increases given how rarely Ebola appeared in candidate communications before the onset, and the immigration linkage in particular connects directly to the finding in Campante, Depetris-Chauvin and Durante (2024) that voter anti-immigration sentiment shifted in the areas most exposed to Ebola anxiety.

Table 1: The Republican Strategic Response: Twitter and Newsletters

	(1) Any Ebola	(2) # Ebola	(3) Any Neg. Sent.	(4) # Neg. Sent.	(5) Any Ebola+Immig.	(6) # Ebola+Immig.
Panel A: Twitter						
Post × Republican	0.060***	0.321***	0.018***	0.032***	0.017***	0.023***
	(0.012)	(0.060)	(0.005)	(0.011)	(0.003)	(0.005)
Candidate FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	9,588	9,588	9,588	9,588	9,588	9,588
Panel B: Newsletters						
Post × Republican	0.076***	0.082***	0.072***	0.076***	0.014***	0.015***
	(0.013)	(0.014)	(0.011)	(0.011)	(0.005)	(0.005)
Member FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	4,908	4,908	4,908	4,908	4,908	4,908

Notes: The unit of observation is a candidate-week (Panel A) or a member of Congress-week (Panel B). Panel A covers all Republican and Democratic House and Senate candidates with active Twitter accounts, weeks 34–45 of 2014; Panel B covers members who sent at least one newsletter between August and November 2014. Post equals 1 in weeks 40–45 (from October 6, 2014, the first full week after the September 30 diagnosis; Appendix Table A2 codes the diagnosis week as post-onset). Outcomes in columns 1–2 measure any Ebola communication and the count; columns 3–4 the same for content classified by GPT-4o-mini as expressing negative sentiment; columns 5–6 for content that mentions both Ebola and immigration. Controls include weekly and cumulative word count. Standard errors clustered at the race level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Panel B replicates the analysis for the newsletter sample. The results are qualitatively identical and, if anything, quantitatively larger. Republican members of Congress were 7.6 percentage points more likely to send an Ebola-related newsletter in any given post-onset week. The negative-sentiment result is especially pronounced (7.2 percentage points), and the immigration linkage is again positive and significant (1.4 percentage points). The cross-platform consistency substantially strengthens the inference that the Republican response

reflects a genuine strategic decision rather than an idiosyncratic feature of any one medium. Importantly, our measure of Ebola-related communication does not hinge on the use of a language model. In the working-paper version of our companion study (Campante, Depetris-Chauvin and Durante, 2020), we measured Ebola content in congressional newsletters with a simple keyword rule, defined by us in advance: a newsletter counts as Ebola-related if the word "Ebola" appears in its subject or body. Applying that same rule to both tweets and newsletters yields an indicator that coincides with the LLM-based one in more than 99 percent of candidate-weeks, in both channels, and reproduces columns 1–2 of both panels almost exactly (Appendix Table A3). In other words, the language model matters only for the tone and framing outcomes in columns 3–6.

Republicans also paired Ebola with President Obama. Appendix Table A4 (Panel A) shows that, after the onset, Republicans became 3.0 percentage points more likely than Democrats to tweet about Ebola and the President in a given week (3.2 points in newsletters), almost twice the corresponding effect for the Ebola-immigration co-mention. Over the post-onset weeks, 9.3 percent of Republican Ebola tweets and 29.1 percent of Republican Ebola newsletters dealt with the President, against 2.2 and 11.8 percent for Democrats (the shares for immigration were 4.8 and 14.8 percent for Republicans). At the same time, Republicans became less likely to mention the President in messages unrelated to Ebola (columns 4 and 5), which suggests that the epidemic became a vehicle for their messaging about the administration rather than an addition to it.

5.1.2 Electoral Incentives: Safe Seats vs. Swing Districts vs. Underdogs

We now examine whether the intensity of the Republican response to the Ebola shock varied with the electoral landscape. The conventional wisdom in the campaign literature suggests that strategic communication intensifies in competitive races, where the marginal value of persuading an additional voter is highest (Skaperdas and Grofman, 1995; Druckman, Jacobs and Ostermeier, 2004). Our model nests this view as the special case where candidates only

care about winning. In contrast, if vote margins also matter and communication mobilizes supporters while alienating others, we predict that communication should rise with the candidate's own advantage (Prediction 2). Table 2 distinguishes between these accounts by interacting the post-onset Republican indicator with the continuous Cook electoral advantage score.

Since Prediction 2 concerns each candidate's own advantage, the relevant objects in Table 2 are the within-party slopes. For Republicans, this is the "Republican advantage gradient"; for Democrats, since the Cook score measures Republican advantage, it is minus the Post × Advantage coefficient. On Twitter, Republican communication rises by 1.8 percentage points per step of the Cook scale (0.083 tweets per week on the intensive margin), and Democratic communication rises with Democratic advantage by 1.0 points per step. Both parties thus communicate more where they are further ahead, as the model predicts when candidates value their margin and the return to the frame rises with their share of supporters. Also, the gradient is steeper for Republicans, the party with the higher fit. In newsletters, the Republican slope is small and insignificant (0.005); we return to this difference between channels in Section 5.1.3 (Prediction 3).[11]

Figure 2 further investigates the pattern by plotting the predicted post-onset effects for six cells defined by party and the Cook race rating (Solid Democrat, Competitive, Solid Republican), for the Twitter sample. Among Republicans, the estimated effect rises steeply from a statistically insignificant 3.3 percentage points in Solid Democrat races, to 9.1 points in Competitive races, to 14.6 points in Solid Republican races. The difference between the Solid Republican and Competitive Republican cells is 5.5 points and statistically significant ($p < 0.05$).

[11] Note that electoral safety may proxy for other district attributes, most obviously the district's partisan lean. Appendix Table A5 compares the Cook rating with the Cook Partisan Voting Index (PVI), which reflects the partisan lean of the district but not the candidate's personal following. When both are included, the Republican gradient on Twitter loads on the rating (0.040) rather than on PVI (0.010), as the model predicts if the frame pays off by mobilizing all of the candidate's supporters, rather than reflecting responsiveness to anxious partisans; the Democratic gradient, in contrast, loads on PVI. Since the two measures are highly correlated (0.85), we read this split as suggestive.

Table 2: Electoral Advantage and the Intensity of the Ebola Response

	Twitter		Newsletters	
	(1) Any Ebola	(2) # Ebola	(3) Any Ebola	(4) # Ebola
Post × Republican	0.056***	0.290***	0.109***	0.115***
	(0.011)	(0.053)	(0.026)	(0.029)
Post × Rep. × Advantage	0.028***	0.103***	0.020**	0.023**
	(0.004)	(0.020)	(0.010)	(0.011)
Post × Advantage	−0.010***	−0.020**	−0.014**	−0.016**
	(0.003)	(0.008)	(0.006)	(0.007)
Republican advantage gradient	0.018***	0.083***	0.005	0.007
	(0.003)	(0.018)	(0.008)	(0.008)
Candidate/Member FE	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Obs.	9,564	9,564	4,644	4,644

Notes: The Advantage variable is the Cook race ratings score as of September 19, 2014, ranging from −3 (Solid Democrat) to +3 (Solid Republican), demeaned. The "Republican advantage gradient" row reports the within-Republican slope in electoral advantage (the sum of the Post × Advantage and Post × Republican × Advantage coefficients), with its delta-method standard error; the triple interaction alone measures the Republican – Democratic difference in slopes. Columns 1–2 use the Twitter sample (candidate fixed effects); columns 3–4 use the newsletter sample (member fixed effects). Outcomes are the extensive margin (any Ebola message) and the intensive margin (number of Ebola messages). All other specifications as in Table 1 (Panels A and B). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

This monotone shape is precisely what our model predicts for the case when candidates value their margin and the return to the frame rises with the share of the candidate's supporters in the district (Prediction 2). A pure winning motive would instead concentrate the response in competitive races, leaving behind candidates both far ahead and far behind, while a return to the communication frame that did not depend on the composition of the electorate would make it symmetric. (We test these alternatives directly in Section 5.1.3.) Substantively, candidates comfortably ahead have little need to persuade swing voters, who are scarce in their districts. Instead, they may have a strong interest in signaling positions to their existing base, especially in a setting where they must worry more about the possibility of future primary challenges than about the need to appeal to the center in the general election (Brady, Han and Pope, 2007; Hall, 2015). Deploying a fear-based immigration frame is a natural way to do so.[12]

We also find that the Obama frame follows the same pattern: Republican messages pairing Ebola with the President also rise with electoral advantage, by 0.6 percentage points per step of the Cook scale on Twitter and 0.7 points in newsletters, while Republican messages about the President that do not mention Ebola fall with it (Appendix Table A4, Panel B).

5.1.3 Testing the Model's Mechanisms

We now turn to two more direct tests of the mechanisms highlighted by the model, reported in Table 3.

Margin versus winning (Prediction 2). Panel A uses the cells underlying Figure 2, now measuring electoral position from the perspective of each party. For Republicans, the margin gradient (the difference between the far-ahead and the far-behind cells) is 11.3 percentage points, and highly significant. This rejects two benchmarks at once: if candidates cared

[12]A natural question is whether the frame actually paid off. Appendix G shows that candidates who tweeted about Ebola obtained higher vote shares, but the association disappears once we control for incumbency, overall tweeting volume, or the district's partisan lean. This is what the model predicts even in the absence of any electoral return, since candidates further ahead both communicate more and win by more, so we do not read it as evidence on the return to the frame.

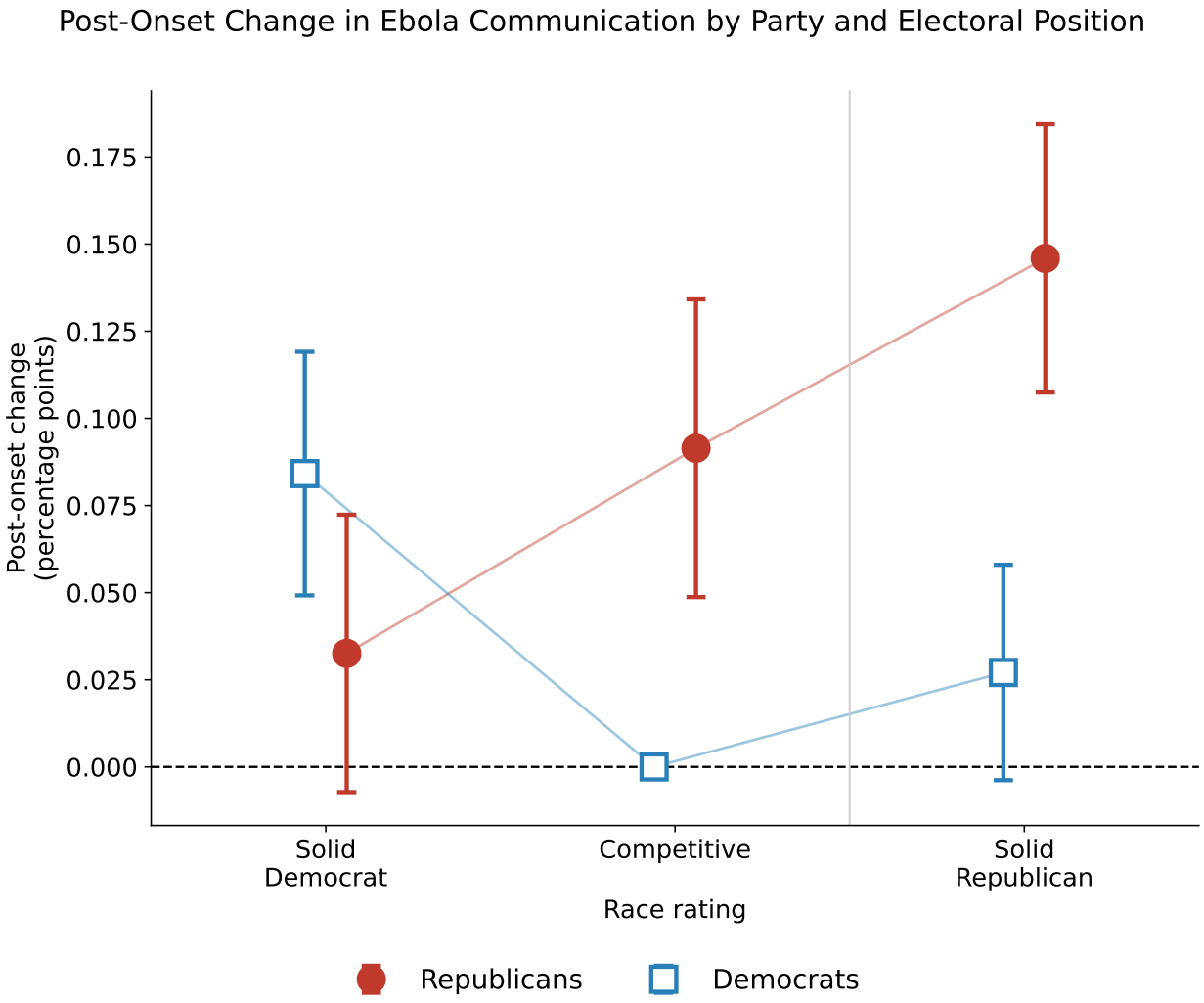


Figure 2: Post-Onset Change in Ebola Communication by Party and Electoral Position

Notes: Each dot shows the predicted post-onset change in the probability of an Ebola tweet for a given party-by-race-rating cell, relative to Democrats in Competitive races (the reference category). Error bars are 95% confidence intervals. The horizontal axis is the Cook race rating, defined from the Republican's perspective for both parties: "Solid Democrat" = Republican advantage score −3; "Solid Republican" = Republican advantage score +3; "Competitive" pools all intermediate ratings (Likely Democrat through Likely Republican, scores −2 to +2), and is therefore broader than the binary competitive-race indicator defined in Section 4; its mean advantage score in the estimation sample is 0.08, so the cell is centered on balanced races, as the decomposition in equation (3) assumes. The District of Columbia delegate race, which has no Cook rating, is excluded. Cell estimates are computed via the delta method from the Twitter specification with candidate and week fixed effects and controls as in Table 1.

only about winning, or if the return to the frame did not depend on the composition of the electorate, these two cells would be at the same level. The Republican response thus reflects a margin motive combined with a frame that plays better the more of the electorate leans toward the candidate. The competitive cell, in turn, sits almost exactly at the midpoint between the two extremes, with a midpoint gap of 0.2 percentage points. In terms of the model, this either means that winning carries little weight, or perhaps more plausibly, that the frame neither helps nor hurts Republicans in a balanced district.

Democrats display a margin gradient about half as large (5.7 percentage points), consistent with a lower fit λ_D, and a negative midpoint gap (-5.6 percentage points). This is what the model would predict: with a low fit, the frame's mobilizing effect on Democratic supporters is weaker than its alienating effect on Republican-leaning voters, so that in a competitive district, raising the salience of an issue owned by the other party lowers the Democrat's margin. As a result, competitive Democrats stay silent, choosing the corner solution. To the extent that the Democratic gap reflects the frame, it requires that winning carry some weight, again suggesting that the Republican zero gap reflects a frame that is neutral in balanced districts, rather than the absence of a winning motive.

The same members on two channels (Prediction 3). Panel B compares the 321 members of Congress who appear in both datasets (184 of them Republicans), in a stacked panel with member-by-channel and week-by-channel fixed effects. The average Republican response is virtually identical in the two channels (8.6 and 8.5 percentage points). What differs is its targeting: the Republican advantage gradient is 4.5 percentage points per step of the Cook scale on Twitter, but essentially zero in newsletters, and the difference between the two (5.9 percentage points) is statistically significant. Since these are the same people in the same weeks, the gap between the Twitter and newsletter gradients in Table 2 cannot be attributed to different samples of politicians. Instead, it is consistent with the frame being

tailored to the more partisan audience.[13]

Table 3: Testing the Model's Mechanisms

Panel A: Shape across electoral position (Twitter, any Ebola tweet)		
	Republicans	Democrats
Far behind (own party)	0.033	0.027*
	(0.020)	(0.016)
Competitive	0.091***	0 (ref.)
	(0.022)	
Far ahead (own party)	0.146***	0.084***
	(0.020)	(0.018)
Margin gradient: far ahead − far behind	0.113***	0.057***
	(0.021)	(0.017)
Midpoint gap: competitive − midpoint	0.002	−0.056***
	(0.022)	(0.015)

Panel B: The same members on both channels (any Ebola message)			
	Newsletters	Twitter	Twitter − Newsletters
Post × Republican	0.086***	0.085***	−0.001
	(0.015)	(0.021)	(0.023)
Republican advantage gradient	−0.014	0.045**	0.059***
	(0.019)	(0.020)	(0.018)
Members (Republicans)		321 (184)	

Notes: Panel A: cell estimates of the post-onset change in the probability of an Ebola tweet relative to Democrats in competitive races, from the specification behind Figure 2. Electoral position is measured from each party's own perspective: for Republicans "far ahead" is a Solid Republican seat; for Democrats it is a Solid Democrat seat. The margin gradient and the midpoint gap are the two differences in equation (3); delta-method standard errors. Panel B: members matched across the two panels by state, chamber, district, party and surname; stacked member-by-channel panel with member-by-channel and week-by-channel fixed effects and channel-specific word-count controls. The advantage gradient is the within-Republican slope in the demeaned Cook advantage score. All specifications: weeks 34–45; standard errors clustered at the race level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.2 Supply versus Demand

Our model allows the Republican response to come from two sources: the strategic use of the frame, on the supply side, and responsiveness to the anxiety of the candidate's own constituents (as captured by the parameter σ in equation (2)), on the demand side. We now

[13]It is worth noting that the model predicts a flatter gradient in newsletters, but still a positive one, since newsletters reach the candidate's constituency. A gradient close to zero thus suggests that official newsletters were also less suited to the frame for other reasons. For instance, official communications are also subject to House and Senate rules on mass mailings, which may limit campaign content in newsletters.

ask which of the two drove it, using two complementary approaches. First, we exploit how the response varied with distance to the Ebola cases, which Campante, Depetris-Chauvin and Durante (2024) show predicts public anxiety (Prediction 4): responsiveness to local anxiety should generate a proximity gradient, as it does among Democrats, whose voters became more anxious near the cases. Since the anxiety of Republican voters did not vary with proximity, this test speaks to whether Republicans responded to local anxiety in their districts, rather than to the anxiety of their own voters. Second, going beyond the model, we look at the timing of the response relative to that of the public, to see whether the former is plausibly driven by the latter or vice versa; this also speaks to responsiveness to the candidates' own voters.

5.2.1 Does Distance Matter for Politicians?

Campante, Depetris-Chauvin and Durante (2024) show that proximity to the Ebola cases is a powerful determinant of voter anxiety on the demand side: areas closer to Dallas, Akron, and New York City displayed greater public concern about Ebola, and it is in those areas that the electoral consequences of the scare are concentrated. A natural question is whether a parallel geographic gradient exists on the supply side: do politicians in Ebola-proximate districts respond more intensely than those far away?

Table 4 reports estimates of equation (5), with distance measured to the nearest case known as of each week (see above). Two patterns emerge. First, there is a modest proximity gradient for Democrats: the Post $\times$ Distance coefficient is negative in both samples, statistically significantly so on Twitter (columns 1–2), though not in newsletters (columns 3–4), indicating that Democratic communication rose somewhat more in districts closer to a just-diagnosed case. Second, and central to our interpretation, this is not the case for the Republican strategic response: the within-Republican distance slope (i.e., the sum of the Post $\times$ Distance and Post $\times$ Republican $\times$ Distance coefficients, reported as the "Republican distance gradient" at the foot of the table) is statistically indistinguishable from zero in

both samples. In other words, Democratic politicians displayed a mild response to local case salience, but the disproportionate Republican surge was essentially uniform across districts regardless of proximity. This is consistent with a partisan supply-side strategy, rather than a response to geographically concentrated demand. The Distance main effect, identified by the arrival of the later cases, is small and at most marginally significant, indicating little direct response to a case being newly diagnosed nearby over and above the post-onset gradients.

The same holds for the Obama frame. Since Ebola anxiety moved attitudes on immigration but not evaluations of the executive, a frame aimed at the administration cannot pay off by persuading anxious voters, only by mobilizing the candidate's supporters (in the model, it has no persuasion term), so it should follow electoral position, as we saw, and be unrelated to local anxiety. Indeed, the Republican Obama frame shows no distance gradient in either channel (Appendix Table A4, Panel C). Democratic messages pairing Ebola with the President, in contrast, are more frequent near the cases, which is what the reassurance motive would predict for the governing party, although our measure cannot tell apart defense from criticism.

This null result, which is in line with Prediction 4 of the model, implies a clear asymmetry between how the Ebola shock propagates on the demand and supply sides of the political market. On the demand side, Campante, Depetris-Chauvin and Durante (2024) show that geographic proximity is the key driver: voters are more anxious, and elections move more, where Ebola cases were diagnosed nearby. On the supply side, the disproportionate Republican response does not depend on proximity.

5.2.2 Does Politician Behavior Drive Public Anxiety, or Vice Versa?

The distance null result in Section 5.2.1 shows that Republican politicians did not respond more intensely in districts where constituents were more anxious. We can complement this evidence by looking at the high-frequency (daily) patterns in Ebola-related online behavior. If politicians were simply tracking pre-existing constituent anxiety, we would expect public

Table 4: Distance to Ebola Cases and the Strategic Response

	Twitter		Newsletters	
	(1) Any Ebola	(2) # Ebola	(3) Any Ebola	(4) # Ebola
Post × Republican	0.052***	0.300***	0.085***	0.091***
	(0.013)	(0.065)	(0.015)	(0.016)
Post × Rep. × Distance	0.011	0.071*	0.036**	0.040***
	(0.009)	(0.039)	(0.014)	(0.015)
Post × Distance	−0.030***	−0.157***	−0.023	−0.025
	(0.011)	(0.049)	(0.015)	(0.016)
Distance	0.017*	0.082*	0.002	0.003
	(0.010)	(0.044)	(0.014)	(0.014)
Republican distance gradient	−0.019	−0.086	0.012	0.015
	(0.012)	(0.065)	(0.016)	(0.016)
Candidate/Member FE	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Obs.	8,832	8,832	4,896	4,896

Notes: Distance is the log great-circle distance from the candidate's district centroid to the nearest Ebola case known as of that week (Dallas from week 40; Cleveland/Akron from week 42; New York from week 43), demeaned, so that the measure never uses not-yet-diagnosed locations. The Distance main effect is identified by the within-candidate changes in distance as the later cases are diagnosed; its time-invariant component is absorbed by the candidate fixed effects. Post × Distance captures the post-onset geographic gradient for Democratic candidates (the omitted category); Post × Republican × Distance the additional differential Republican response by proximity. The "Republican distance gradient" row reports the within-Republican slope (the sum of the Post × Distance and Post × Republican × Distance coefficients), with its delta-method standard error. Columns 1–2 use the Twitter sample (candidate fixed effects); columns 3–4 use the newsletter sample (member fixed effects). Outcomes are the extensive margin (any Ebola message) and the intensive margin (number of Ebola messages). All other specifications as in Table 1 (Panels A and B). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Ebola activity to predict subsequent politician behavior. If instead politicians are actively trying to amplify the issue, their behavior should predict subsequent public activity.

The results are in Table 5, with DMA-day as the unit of observation, covering the period from September 1 through election day. The dependent variable in columns 1, 2, 4, and 5 is public Ebola activity, specifically Ebola-related tweets per capita (columns 1–2) and Google search volume for "Ebola" (columns 4–5). The key independent variable is the Ebola activity of politicians (tweets) on the previous day, separately for Republican (columns 1 and 4) and Democratic (columns 2 and 5) candidates. In columns 3 and 6, the roles are reversed: the dependent variable is whether Republican politicians tweeted about Ebola, and the independent variable is the public's prior-day Ebola activity, allowing us to test for reverse causality directly. All specifications include DMA and day fixed effects as well as DMA-specific linear trends.

The results are unambiguous. Republican politician Ebola tweets on day t predict more public Ebola tweets on day $t + 1$, but only after the onset of the first U.S. case (column 1). The same relationship holds for Google searches, a fully private behavior unaffected by partisan retweeting (column 4). No analogous pattern exists for Democratic candidates: their Ebola tweets do not predict subsequent public concern on either measure (columns 2 and 5). Most importantly, there is no evidence of the reverse direction, that is, that prior-day public Ebola activity draws out Republican politician tweets. If anything the association runs the other way in the tweets column (column 3) and is statistically null for searches (column 6). In neither case does public activity positively predict subsequent politician messaging.[14] Finally, the triple interaction between politician activity, the post-onset indicator, and (log) distance to the nearest case is negative and significant (columns 1 and 4), indicating that Republican messaging predicts public anxiety more strongly in places already primed by

[14]The negative coefficient on the interaction Post-Onset × Distance may seem in tension with the result that distance does not predict behavior by Republican politicians, as in Table 4. Note however that, in the presence of the triple interaction term, the interpretation of this coefficient would pertain to what would happen under the counterfactual case of an absence of public activity. Given that the latter responds to distance, this is not a properly identified object of interest.

geographic proximity to the cases. While the timing patterns do not necessarily establish a causal impact of the messaging from politicians, this is nevertheless consistent with the supply and demand sides of the Ebola episode being mutually reinforcing in proximate areas.

Together with the distance null in Section 5.2.1, this pattern establishes that the supply side of political fear-mongering was active rather than reactive. Republican politicians did not merely respond to anxious constituents: at the very least, they jumped ahead of, and presumably tried to feed, their constituents' anxiety.

6 Alternative Explanations and Additional Evidence

The results so far point to a deliberate, campaign-driven strategy: Republicans adopted a frame that fit their party's agenda, used it most where their own supporters dominated the electorate, and did not tailor it to local anxiety. This section asks whether other explanations could account for the same patterns, and adds evidence on when and how the frame was used.

We first examine the timing of the response. We show that there were no differential pre-trends, that the response followed national attention rather than the course of the epidemic itself, and that it stopped once the election was over. We then show that it was the first U.S. case that triggered the response, while later cases, which shifted the geography of public anxiety, produced no further escalation. Finally, we show that the response was specific to Ebola, rather than part of a broader shift toward immigration messaging, and that it was neither tailored to the size of the district's immigrant population nor a reaction to the opponent's messaging, consistent with a frame adopted at the level of the party.

6.1 Timing and Pre-Trends

The most direct test of the parallel trends assumption is the event study, which plots week-by-week coefficients for the interaction of week indicators with the Republican indicator,

Table 5: Does Politician Behavior Predict Public Anxiety? (Daily DMA-Level Analysis)

	Public Ebola Tweets			Public Ebola Searches		
Dependent variable →	(1) Public Tweets	(2) Public Tweets	(3) Rep. Politician Tweets	(4) Public Searches	(5) Public Searches	(6) Rep. Politician Tweets
Politician Ebola activity$_{t-1}$	-0.065^{***}	0.010		-5.04^{**}	2.89	
	(0.022)	(0.014)		(2.33)	(3.17)	
Public Ebola activity$_{t-1}$			2.937^{**}			0.003
			(1.204)			(0.003)
Post-Onset × Politician activity$_{t-1}$	0.322^{***}	0.051		13.68^{***}	-5.22	
	(0.066)	(0.050)		(4.73)	(4.90)	
Post-Onset × Public activity$_{t-1}$			-2.807^{**}			0.001
			(1.250)			(0.004)
Activity$_{t-1}$ × Distance	0.010^{***}	-0.003	-0.425^{**}	0.68	-0.51	-0.000
	(0.004)	(0.002)	(0.176)	(0.43)	(0.58)	(0.000)
Post-Onset × Distance	-0.055^{***}	-0.066^{***}	-0.107^{***}	0.82	0.30	-0.091^{***}
	(0.013)	(0.016)	(0.017)	(1.48)	(1.57)	(0.019)
Triple Interaction	-0.052^{***}	-0.006	0.434^{**}	-1.97^{**}	1.27	-0.000
	(0.011)	(0.008)	(0.185)	(0.83)	(0.87)	(0.000)
Politicians	Rep.	Dem.	Rep.	Rep.	Dem.	Rep.
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
DMA FE	Yes	Yes	Yes	Yes	Yes	Yes
DMA trends	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.59	0.58	0.35	0.71	0.71	0.35
Obs.	12,978	12,978	12,978	12,915	12,915	12,915
Clusters (DMA)	206	206	206	205	205	205

Notes: The unit of observation is a DMA-day; sample covers September 1 through election day. In columns 1, 2, 4, and 5 the dependent variable is public Ebola activity (Ebola tweets per 10,000 inhabitants in columns 1–2; Google search volume in columns 4–5) and the key independent variable is lagged politician Ebola tweets, separately for Republican and Democratic candidates. In columns 3 and 6 the dependent variable is an indicator for whether at least one Republican candidate tweeted about Ebola, and the independent variable is lagged public Ebola activity, testing the reverse causal direction. Distance is the (natural) log distance to the nearest Ebola case; its level is absorbed by the DMA fixed effects, so the reported level ("activity$_{t-1}$") and Post-Onset coefficients are evaluated at the near-case reference and the geographic gradient is carried by the interaction rows. Each specification includes all lower-order constituent terms of the triple interaction: Post-Onset × Distance, Post-Onset × Activity, and Activity × Distance (the reported "Activity$_{t-1}$ × Distance" row). Triple Interaction = Post-Onset × Politician (or Public) activity$_{t-1}$ × Distance. Standard errors clustered at the DMA level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

re-centred on the pre-onset average (weeks 31–39). Figures A2–A9 in the Online Appendix display these estimates for the main Ebola outcomes in both the Twitter and newsletter samples. The pre-onset coefficients are close to zero: statistically indistinguishable from it on the extensive margin, and close to flat (with only a few marginally significant weeks) on the intensive margin. Note that, since weeks run from Monday to Sunday, the Dallas diagnosis (September 30) falls in week 39, which our baseline coding (and hence the reference period in the event studies) treats as pre-onset. The rise visible in week 39 is thus the response to the diagnosis itself, rather than a pre-trend: candidate tweets about Ebola jump on September 30, from zero the day before. The Republican differential peaks in week 41 (October 13–19, the week of Amber Vinson's diagnosis); it then fades over the following weeks, returning to the pre-onset baseline by around election day and remaining there through the post-election weeks.

Two features of this timing deserve further comment. First, the decline before election day tracks the evolution of media and public attention. National television coverage of Ebola, measured by the number of news clips mentioning the disease, peaked in week 41 and had fallen by 90 percent by week 44.[15] Public Ebola tweets in our DMA panel followed the same path, falling by 88 percent, as did Google searches (Appendix Figure A14, panel a). Relative to that attention, however, the Republican differential did not shrink before the election. Per 1,000 television clips, the gap between Republicans and Democrats in the share of candidates tweeting about Ebola roughly doubled, from 0.6 percentage points in weeks 39 and 40 to between 1.0 and 1.2 percentage points in each of weeks 41 to 44, and the newsletter gap behaves in a similar way (panel b).[16] In other words, the decline in Republican Ebola messaging before the election is more than accounted for by the decline

[15]We use the Television API of the GDELT Project (GDELT Project, 2026), which indexes the closed captions of the Internet Archive's Television News Archive. Our measure is the weekly number of 15-second clips mentioning "Ebola" across the national stations monitored in 2014 (Bloomberg, CNBC, CNN, C-SPAN, C-SPAN2, C-SPAN3, Fox Business, Fox News, and MSNBC). The weekly correlation between this series and public Ebola tweets is 0.94 over weeks 35 to 47.

[16]The same holds when we scale the gap by public Ebola tweets instead: per 10,000 public Ebola tweets, the Twitter gap rose from 1.1 percentage points in week 39 to 4.5 in week 43 (and 2.9 in week 44).

in coverage: Republican candidates kept up the frame relative to the news cycle, and even intensified it as election day approached.[17]

Second, once no race is at stake, $W = \mu = 0$ in equation (2), so that only responsiveness remains: the model implies that the frame should stop. Indeed, the Republican differential disappears once the election is over. To check that, Appendix Table A6 extends the sample through December: the Republican differential is 7.1 percentage points on Twitter and 10.8 in newsletters during the campaign weeks, but close to zero in the post-election weeks of November and in December, including among accounts active in a given week and among election winners.[18] The post-election drop does not reflect a general slowdown in communication: among active accounts, the share of Republican candidates tweeting about Ebola fell by 91 percent, while content favorable to either party fell by 30 to 60 percent, and tweets about immigration or the President that did not mention Ebola became more frequent (Appendix Table A7). That said, news coverage also fell after the election, so this comparison alone cannot disentangle the end of the electoral incentive from the end of the news cycle.[19]

6.2 Which Case Drove the Supply-Side Response?

If politicians were tracking public anxiety, each new U.S. case, and especially those that shifted where that anxiety was concentrated, should have triggered a further round of Ebola messaging; if instead they adopted the frame as a campaign strategy, the first case should have been enough. The U.S. episode offers a natural test, since it involved four distinct diagnoses of varying salience. Following Campante, Depetris-Chauvin and Durante (2024), we estimate the baseline DiD separately around each of the three case locations, using ±3-week windows around each onset: Dallas in week 40, Cleveland (Vinson's travel) in week 42,

[17] The decline in coverage was in spite of the epidemic accelerating in Africa, as discussed in Section 2.

[18] The post-election coefficients are statistically zero or slightly negative in all but one of the 16 estimates.

[19] Panel (b) of Appendix Figure A14 is suggestive in this respect: relative to television coverage, the Twitter gap falls by about two thirds in the two weeks after the election. When we scale the Republican differential by weekly attention in a regression, however, the post-election change is imprecisely estimated.

and New York (the October 23 diagnosis of Craig Spencer) in week 43. In each case the onset is the first full week after the event, so that the Cleveland and New York onsets fall in adjacent weeks rather than in the same week. The exercise also shows whether dating the onset from the Dallas case, as in our baseline, is appropriate.

Table 6 presents the results. The pattern is unambiguous: it is the first U.S. case (Dallas) that drives the Republican supply-side response. Republicans were about 9.5 percentage points more likely to tweet about Ebola in the three-week window following the Dallas onset relative to the pre-period, with corresponding increases in negative-sentiment and immigration-linked tweets. For the Cleveland and NYC windows, by contrast, the estimated coefficient is negative and statistically significant across all outcomes. These negative signs do not indicate a reduction in Ebola communication; rather, they reflect that the "pre-period" in each subsequent window already includes the elevated communication triggered by Dallas, so relative to that already-high baseline the later cases produced no further escalation. Importantly, this is not an artifact of the post-election decline in communication: because the Cleveland and NYC windows extend to weeks 45–46 (after election day), we re-estimate each window ending at week 44, the week of the election, and the pattern is essentially unchanged (for any Ebola tweet, Cleveland -0.051 and NYC -0.098, both still significant). Once Republicans adopted the Ebola frame after the first domestic case, subsequent cases generated no further escalation on the supply side.

This finding is informative in its own right. On the demand side, Campante, Depetris-Chauvin and Durante (2024) document that voter anxiety responded to all three cases, with the Cleveland case generating a particularly strong additional shock. On the supply side, by contrast, politicians responded to the initial signal and maintained a uniformly elevated level of Ebola communication through the election. This reinforces the strategic interpretation: the decision to exploit Ebola was made upon the first domestic case and sustained as a campaign-period communication strategy, without reacting to changes in the spatial distribution of Ebola concerns triggered by the new cases.

Table 6: Case-by-Case DiD: Twitter (Post × Republican, by event window)

	(1) Dallas Onset (Wk 40)	(2) Cleveland Onset (Wk 42)	(3) NYC Onset (Wk 43)
Panel A: Extensive margin (any tweet)			
Any Ebola tweet	0.095***	−0.063***	−0.106***
	(0.020)	(0.017)	(0.020)
Any neg. sentiment	0.038***	−0.020**	−0.035***
	(0.010)	(0.009)	(0.010)
Any Ebola + Immig.	0.028***	−0.024***	−0.033***
	(0.006)	(0.006)	(0.006)
Panel B: Intensive margin (count)			
No. Ebola tweets	0.581***	−0.444***	−0.638***
	(0.105)	(0.090)	(0.114)
No. neg. sentiment	0.064***	−0.059***	−0.067***
	(0.020)	(0.020)	(0.018)
No. Ebola + Immig.	0.035***	−0.033***	−0.044***
	(0.008)	(0.011)	(0.010)
Candidate FE	Yes	Yes	Yes
Week FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	4,794	4,794	4,794
Clusters	461	461	461

Notes: Each column reports the Post × Republican coefficient from a separate DiD regression estimated on the ±3-week window around each case onset (Dallas: week 40; Cleveland: week 42; NYC: week 43). Post equals 1 after each respective onset. Note that the Cleveland and NYC pre-periods include weeks already affected by the Dallas case, so negative coefficients reflect the absence of additional incremental escalation rather than a reduction in absolute Ebola communication; restricting each window to end at week 44 (before election day) leaves the pattern unchanged. Candidate and week fixed effects throughout; controls include weekly and cumulative word count; standard errors clustered at the race level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

6.3 Immigration as a Placebo

A natural concern is that the Republican-Democrat difference post-onset simply reflects a general increase in Republican communication about immigration, unrelated to Ebola. We therefore examine pure immigration communication, that is, content mentioning immigration but making no reference to Ebola (immigration net of the Ebola-linked immigration content). On the extensive margin we detect no significant change in pure immigration communication post-onset for Republican candidates (Figures A10–A13 in the Online Appendix): the week-41 differential is a statistically insignificant +0.6 percentage points on Twitter and is likewise flat for newsletters. The Twitter count of pure immigration tweets shows a small residual increase, so we read this as evidence that essentially all of the extensive-margin post-onset immigration response, and the bulk of the intensive-margin response, was tied to the Ebola frame rather than to a broad, Ebola-independent shift in immigration messaging. Because these event studies do not include a distance interaction, they speak to the timing of the immigration response and not to its geography; we accordingly do not draw conclusions about the distance gradient from them.

Two further checks are reported in Appendix D. First, the Republican response does not vary with the size of the district's immigrant population once we hold electoral position fixed, and the Ebola-immigration co-mention does not vary with it at all (Table A8). Second, candidates did not respond to their own opponent's Ebola messaging: with week fixed effects absorbing national salience, a candidate's Ebola tweets are unrelated to the opponent's in the same or the previous week (Table A9). Both results are consistent with a frame adopted at the national, party level rather than tailored to local conditions.

7 Conclusion

This paper studies the supply of fear-based political communication using the 2014 Ebola scare as an unanticipated threat shock. Using panel data on candidate Twitter output

and congressional newsletters coded by GPT-4o-mini, we show that Republican candidates sharply increased Ebola-related communication after the onset of the first U.S. case, emphasizing negative sentiment and pairing the disease with immigration and with the President. Democratic candidates responded much less, and among them the response was larger in safe Democratic seats than in competitive races.

A key finding concerns the distribution of the strategic response within the Republican party. Contrary to the standard prediction that competitive races drive strategic communication (Skaperdas and Grofman, 1995), the strongest response comes from Republicans in the safest seats. This is consistent with a base-mobilization motive: through the lens of the model, it is the combination of the value of a larger margin of victory and a frame whose return rises with the share of the candidate's supporters that creates the pattern we find in the data. In other words, safe-seat Republicans leveraged a nationally salient health scare to energize their existing coalition, unconstrained by the need to appeal to swing voters. It also points toward a longer-run career-concerns logic, in which signaling partisan alignment on a high-salience issue is particularly valuable for candidates who must worry more about future primary challenges than about the current general election (Fenno, 1978; Brady, Han and Pope, 2007; Anderson, Butler and Harbridge-Yong, 2020).

We then turn to the supply-versus-demand question: were politicians simply tracking constituent anxiety, or actively fueling it? Two pieces of evidence point toward the latter. First, the disproportionate Republican response shows no geographic gradient: unlike voter anxiety, which is concentrated near the diagnosed cases (Campante, Depetris-Chauvin and Durante, 2024), the Republican surge does not vary with how close or far a district is from Dallas, Akron, or New York City (though communication by Democrats rose modestly more near a just-diagnosed case). Second, the timing of the response runs from politicians to the public: Republican Ebola tweets predict subsequent public Ebola activity online, while prior public anxiety does not predict politician behavior.

Taken together, these results offer a more nuanced account of how political fear-mongering

works in practice than either a simple partisan-exploitation story or a simple constituent-response story. Politicians actively broadcast a fear-based frame because it fits their party's strategic position, not because their local voters are especially frightened. On the other hand, Campante, Depetris-Chauvin and Durante (2024) find that electoral results do respond to the variation in constituent fear, even if (as shown here) the supply response displays no such variation. Whether this generalizes to other health scares, security threats, or political crises is an important question for future research.

References

Adida, Claire L., Kim Yi Dionne and Melina R. Platas. 2018. "Ebola, Elections, and Immigration: How Politicizing an Epidemic Can Shape Public Attitudes." *Politics, Groups, and Identities* 7(4):1–27.

Anderson, Sarah E., Daniel M. Butler and Laurel Harbridge-Yong. 2020. *Rejecting Compromise: Legislators' Fear of Primary Voters*. Cambridge: Cambridge University Press.

Ansolabehere, Stephen and Shanto Iyengar. 1995. *Going Negative: How Political Advertisements Shrink and Polarize the Electorate*. New York: Free Press.

Aragonès, Enriqueta, Micael Castanheira and Marco Giani. 2015. "Electoral Competition through Issue Selection." *American Journal of Political Science* 59(1):71–90.

Brader, Ted. 2005. "Striking a Responsive Chord: How Political Ads Motivate and Persuade Voters by Appealing to Emotions." *American Journal of Political Science* 49(2):388–405.

Brady, David W., Hahrie Han and Jeremy C. Pope. 2007. "Primary Elections and Candidate Ideology: Out of Step with the Primary Electorate?" *Legislative Studies Quarterly* 32(1):79–105.

Campante, Filipe, Emilio Depetris-Chauvin and Ruben Durante. 2020. The Virus of Fear:

The Political Impact of Ebola in the U.S. NBER Working Paper 26897 National Bureau of Economic Research.

Campante, Filipe, Emilio Depetris-Chauvin and Ruben Durante. 2024. "The Virus of Fear: The Political Impact of Ebola in the U.S." *American Economic Journal: Applied Economics* 16(1):480–509.

Cormack, Lindsey. 2014. "The Ebola Outbreak Generated Greater Response from Republican Lawmakers." *Washington Post (Monkey Cage)* .

Cormack, Lindsey. 2017. "DCInbox: Capturing Every Congressional Constituent E-Newsletter from 2009 Onwards." *The Legislative Scholar* 2(1):27–34.

Druckman, James N., Lawrence R. Jacobs and Eric Ostermeier. 2004. "Candidate Strategies to Prime Issues and Image." *Journal of Politics* 66(4):1180–1202.

Evans, Heather K., Sean Smith, Alexis Gonzales and Kayla Strouse. 2017. "Mudslinging on Twitter During the 2014 Election." *Social Media + Society* 3(2):1–9.

Fenno, Richard F. 1978. *Home Style: House Members in Their Districts*. Boston: Little, Brown.

GDELT Project. 2026. "GDELT 2.0 Television API." `https://api.gdeltproject.org/api/v2/tv/tv`. Based on the Internet Archive Television News Archive. Accessed November 7, 2026.

Grimmer, Justin and Brandon M. Stewart. 2013. "Text as Data: The Promise and Pitfalls of Automatic Content Analysis Methods for Political Texts." *Political Analysis* 21(3):267–297.

Hall, Andrew B. 2015. "What Happens When Extremists Win Primaries?" *American Political Science Review* 109(1):18–42.

Huckfeldt, Robert and John Sprague. 1995. *Citizens, Politics, and Social Communication: Information and Influence in an Election Campaign*. Cambridge: Cambridge University Press.

Huddy, Leonie, Stanley Feldman and Erin Cassese. 2007. On the Distinct Political Effects of Anxiety and Anger. In *The Affect Effect: Dynamics of Emotion in Political Thinking and Behavior*, ed. W. Russell Neuman, George E. Marcus, Ann N. Crigler and Michael MacKuen. Chicago: University of Chicago Press pp. 202–230.

Inbar, Yoel, David A. Pizarro and Paul Bloom. 2008. "Conservatives Are More Easily Disgusted Than Liberals." *Cognition and Emotion* 23(4):714–725.

Inbar, Yoel, David A. Pizarro, Paul Bloom and Jonathan Haidt. 2012. "Disgust Sensitivity, Political Conservatism, and Voting." *Social Psychological and Personality Science* 3(5):537–544.

Jacobson, Gary C. and Samuel Kernell. 1981. *Strategy and Choice in Congressional Elections*. New Haven: Yale University Press.

Jost, John T., Jack Glaser, Arie W. Kruglanski and Frank J. Sulloway. 2003. "Political Conservatism as Motivated Social Cognition." *Psychological Bulletin* 129(3):339–375.

Marcus, George E., W. Russell Neuman and Michael MacKuen. 2000. *Affective Intelligence and Political Judgment*. Chicago: University of Chicago Press.

Mayhew, David R. 1974. *Congress: The Electoral Connection*. New Haven: Yale University Press.

Motel, Seth. 2014. "Interest in Ebola News Among Highest in Top Stories Since 2010.". Pew Research Center, October.

Petrocik, John R. 1996. "Issue Ownership in Presidential Elections, with a 1980 Case Study." *American Journal of Political Science* 40(3):825–850.

Rivers, Caitlin. 2014. "Data for the 2014 Ebola Outbreak in West Africa." `https://github.com/cmrivers/ebola`. Compiled from WHO situation reports and national ministries of health. Accessed November 8, 2026.

Skaperdas, Stergios and Bernard Grofman. 1995. "Modeling Negative Campaigning." *American Political Science Review* 89(1):49–61.

SteelFisher, Gillian K., Robert J. Blendon and Narayani Lasala-Blanco. 2015. "Ebola in the United States: Public Reactions and Implications." *New England Journal of Medicine* 373(9):789–791.

Thórisdóttir, Hulda and John T. Jost. 2011. "Motivated Closed-Mindedness Mediates the Effect of Threat on Political Conservatism." *Political Psychology* 32(5):785–811.

Zaller, John R. 1992. *The Nature and Origins of Mass Opinion*. Cambridge: Cambridge University Press.

Online Appendix

A The Model: Formal Statements and Proofs

This appendix states formally the four predictions of Section 3 and proves them. Throughout, we consider candidate i of party P and drop subscripts when no confusion arises. The return to the frame in equation (1) is linear in the candidate's share of supporters,

$$\Gamma_P(s) = \Gamma_P^0 + \theta_P\, s, \qquad \Gamma_P^0 \equiv \lambda_P \gamma A_d - m, \qquad \theta_P \equiv \lambda_P b + m > 0.$$

We write $c \equiv \sigma p_d^P A_d^P$ for responsiveness, and $e(s) = \big[\big(W g(x) + \mu\big) S\, \Gamma_P(s) + c\big]/k$, with $x = 2s - 1$, for the unconstrained solution, so that $e^* = \max\{0, e\}$. Unless otherwise noted, statements refer to an interior solution, $e^* > 0$. By the symmetry of ε, $g(x) = g(-x)$, so that g takes the same value at s and $1 - s$.

A.1 Prediction 1: party and frame

Proposition 1 (Party and frame)**.** *(i)* $\partial e^*/\partial \lambda_P = \big(W g(x) + \mu\big) S\, (bs + \gamma A_d)/k > 0$*: at any electoral position, the party with the higher fit communicates more. (ii) A higher fit lowers the break-even share,* $\bar{s}_P = (m - \lambda_P \gamma A_d)/\theta_P$*, widening the range of races in which the frame pays off. (iii) If the threat can be framed in terms of several issues, the candidate chooses the issue with the highest fit.*

Proof. (i) Differentiate e, using $\partial \Gamma_P/\partial \lambda_P = bs + \gamma A_d$. (ii) $\bar{s}_P$ solves $\Gamma_P(s) = 0$, and $\partial \bar{s}_P/\partial \lambda_P = -m(b + \gamma A_d)/\theta_P^2 < 0$. (iii) At the optimum, the candidate's payoff equals $\frac{k}{2}(e^*)^2$ plus terms that do not depend on the frame, and e^* increases in Γ_P, and hence in the fit. □

A.2 Prediction 2: electoral position

Proposition 2 (Shape across electoral position)**.** *Fix c and A_d.*

(i) Winning only *($\mu = 0$): $e^* \to c/k$ in safe seats, on both sides; the frame is concentrated in relatively competitive races in which it pays off.*

(ii) No composition effects *($b = m = 0$): $e^*(s) = e^*(1-s)$, so that communication is symmetric in the candidate's own advantage.*

(iii) Margin and composition *($\mu > 0$, $\theta_P > 0$): for $s > \frac{1}{2}$, $e^*(s) \geq e^*(1-s)$, with strict inequality whenever $e^*(s) > 0$. If, in addition, $\mu\,\theta_P > 2W\,\overline{|g'|}\,\overline{|\Gamma_P|}$, where the bars denote maxima over the relevant range, e^* increases with s.*

Proof. (i) With $\mu = 0$, $e - c/k = Wg(x)S\,\Gamma_P(s)/k$, which tends to zero in safe seats because $g \to 0$ and Γ_P is bounded, and is positive only where the frame pays off. (ii) With $b = m = 0$, $\Gamma_P = \lambda_P \gamma A_d$ does not depend on s, and $e(s) = e(1-s)$ inherits the symmetry of g. (iii) Since $\Gamma_P(s) - \Gamma_P(1-s) = \theta_P(2s-1)$, $e(s) - e(1-s) = (Wg + \mu)S\theta_P(2s-1)/k > 0$ for $s > \frac{1}{2}$, and $\max\{0, \cdot\}$ preserves the inequality. Moreover, $k\,e'(s)/S = 2Wg'(x)\Gamma_P(s) + (Wg + \mu)\theta_P \geq \mu\theta_P - 2W\overline{|g'|}\,\overline{|\Gamma_P|} > 0$ under the stated condition. □

The comparisons across cells. Equation (3) follows from evaluating e at $s_L = 1 - s_H$, $\frac{1}{2}$ and s_H, with $g \approx 0$ in safe seats. The margin gradient is $e(s_H) - e(s_L) = \mu S\theta_P(s_H - s_L)/k$. Since Γ_P is linear and $\frac{1}{2}$ is the midpoint of s_L and s_H, the margin motive cancels from the midpoint gap, which equals $Wg(0)S\,\Gamma_P(\frac{1}{2})/k$. The slopes in footnote 8 follow from $e'(\frac{1}{2}) = (Wg(0) + \mu)S\theta_P/k$, since $g'(0) = 0$, and from $\big(e(s_H) - e(s_L)\big)/(s_H - s_L) = \mu S\theta_P/k$. These comparisons assume that local anxiety is unrelated to electoral position, and that the competitive cell is centered on a balanced race, with symmetric far-ahead and far-behind cells.

Two caveats. First, since the frame loses votes for candidates who are behind (and, for a party with a low fit, also in balanced districts), far-behind candidates may be at the corner, relying on responsiveness alone; if they stay silent, the margin gradient understates μ. Since the Twitter sample covers fewer candidates in seats that are safe for the opposing party (Table A1), those observed in the far-behind cells are also positively selected, which works in the same direction. Second, responsiveness, c, rises with the party's partisan share, which rises with s, and so adds $\sigma A^P(p_H^P - p_L^P)/k$ to the margin gradient. The two can be told apart because the frame depends on all of the candidate's supporters, $\rho_d = p_d + h_d$, which the Cook rating reflects, whereas responsiveness depends only on the partisan share, p_d, which the PVI reflects. Holding the rating fixed, communication thus varies with the PVI only through responsiveness. This is the comparison reported in footnote 11.

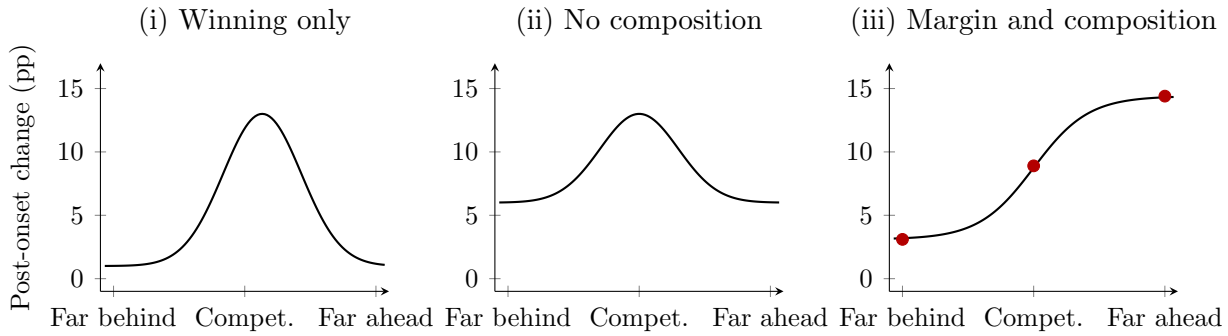


Figure A1: Predicted Shapes of the Post-Onset Response across Electoral Position

Notes: Illustrative functional forms; only the shapes matter. Panel (i) shows a party for which the frame pays off in a balanced district: communication is concentrated in relatively competitive races, and falls to the level of responsiveness at both ends. Panel (ii) shows the case $\lambda_P \gamma A_d > 0$; with $\lambda_P \gamma A_d < 0$ it is a U, still symmetric. Panel (iii) adds the Republican Twitter cells of Figure 2 (dots).

A.3 Prediction 3: audience

Let channel a reach an audience in which the share of the candidate's supporters is $s_a(s)$, let communication be chosen separately on each channel, with separable costs, and let responsiveness be the same on both channels. Newsletters reach constituents, so that $s_{\text{News}}(s) = s$, while Twitter reaches self-selected followers, with $s'_{\text{Tw}}(s) > 1$.

Proposition 3 (Audience)**.** *For the same member, with the margin motive dominant,*

$$\frac{\partial e^*_{Tw}}{\partial s} - \frac{\partial e^*_{News}}{\partial s} = \frac{\mu S \theta_P \left[s'_{Tw}(s) - 1 \right]}{k} > 0.$$

Proof. With Wg negligible relative to μ, $e^*_a(s) = \big(\mu S \, \Gamma_P(s_a(s)) + c\big)/k$ on channel a; differentiate in s. □

The proposition concerns the slope, not the level, which depends on s_{Tw} relative to s and is not pinned down by the model. It also implies that the newsletter gradient should be positive, if flatter.

A.4 Prediction 4: distance

Let D_d be log distance to the nearest known case. As documented by Campante, Depetris-Chauvin and Durante (2024), $\partial A^R_d / \partial D_d = 0$, while $\partial A^D_d / \partial D_d < 0$, and hence $\partial A_d / \partial D_d < 0$. For an interior solution,

$$\frac{\partial e^*_R}{\partial D_d} = \frac{(Wg + \mu) S \lambda_R \gamma}{k} \frac{\partial A_d}{\partial D_d}, \qquad \frac{\partial e^*_D}{\partial D_d} = \frac{(Wg + \mu) S \lambda_D \gamma}{k} \frac{\partial A_d}{\partial D_d} + \frac{\sigma(1 - p_d)}{k} \frac{\partial A^D_d}{\partial D_d}.$$

Proposition 4 (Local anxiety)**.** *(i) Since the anxiety of Republican partisans is spatially flat, responsiveness generates no Republican distance gradient, which can only arise if the return to the frame rises with local anxiety ($\gamma > 0$); a zero Republican gradient thus implies $\gamma \approx 0$. (ii) Since the anxiety of Democratic partisans depends on proximity, responsiveness generates a Democratic proximity gradient in all races, including safe ones.*

Proof. Direct differentiation of equation (2). □

The persuasion rate may differ across frames. Since anxiety moved attitudes on immigration but not evaluations of the executive (Campante, Depetris-Chauvin and Durante, 2024), a frame aimed at the administration has no persuasion term, so that its Republican distance gradient is zero, while it still rises with electoral position (Proposition 2).

B Event-Study Estimates

The figures in this appendix display event-study estimates of equation (4). Each plots a single series of week-by-week interaction coefficients between week indicators and the Republican indicator, re-centred on the pre-onset average (weeks 31–39), shown as point estimates with shaded 95% confidence bands. Pre-onset weeks (31–39) provide a test of the parallel trends assumption; post-onset weeks (40–45) show the dynamic of the Republican response through election day; and post-election weeks (46–47) show its reversal. Figures A2–A5 cover the Twitter sample; Figures A6–A9 cover the newsletter sample.

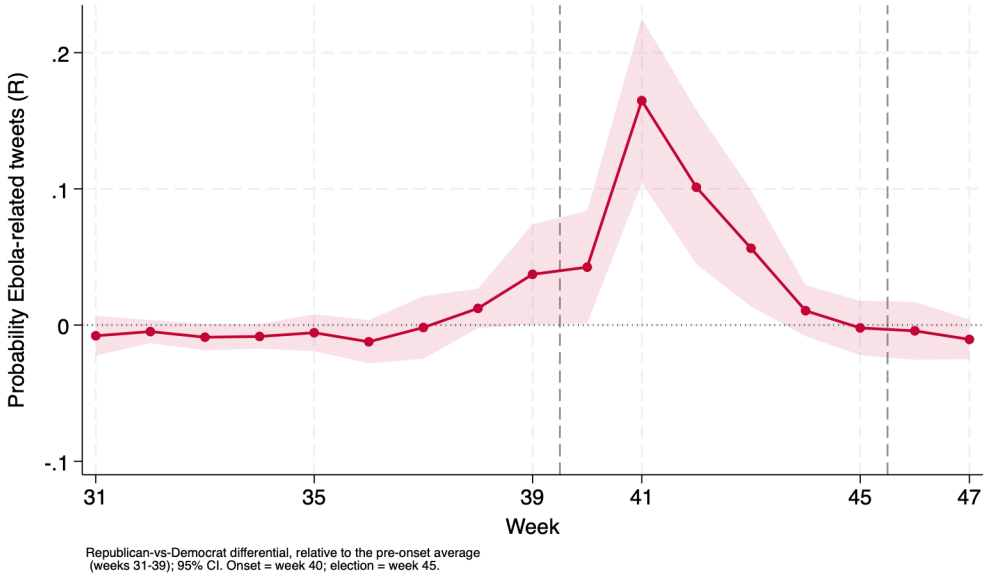


Figure A2: Event Study: Probability of Any Ebola Tweet (Twitter)

Notes: Week-by-week DiD coefficients (single series, with 95% confidence band) for the probability that a Republican candidate posted at least one Ebola-related tweet, relative to the pre-onset average (weeks 31–39). Sample: weeks 31–47. Candidate and week fixed effects; standard errors clustered at the race level. Onset = week 40; election = week 45.

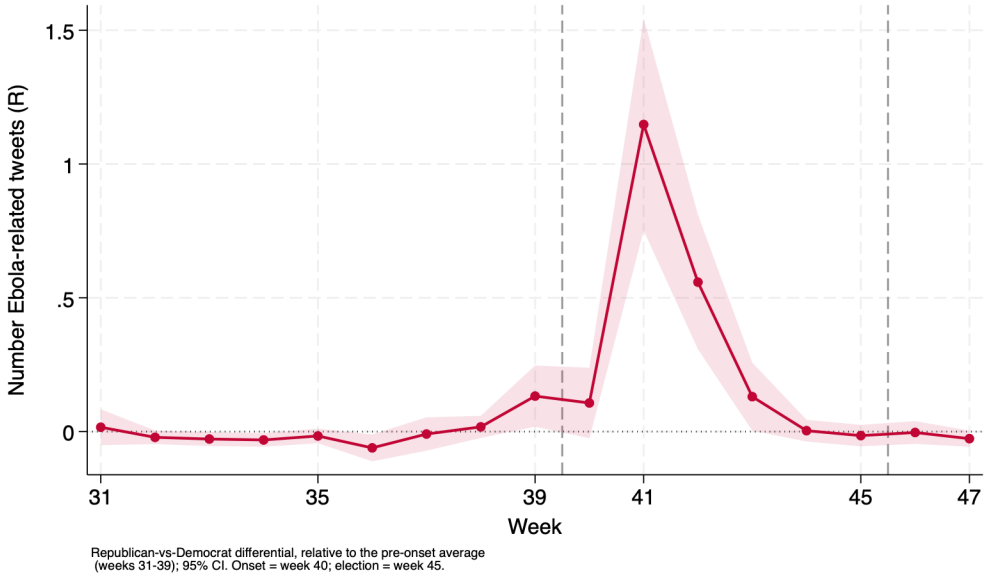


Figure A3: Event Study: Number of Ebola Tweets (Twitter)

Notes: Week-by-week DiD coefficients for the count of Ebola-related tweets by Republican candidates relative to Democrats, relative to the pre-onset average (weeks 31–39). Specification as in Figure A2.

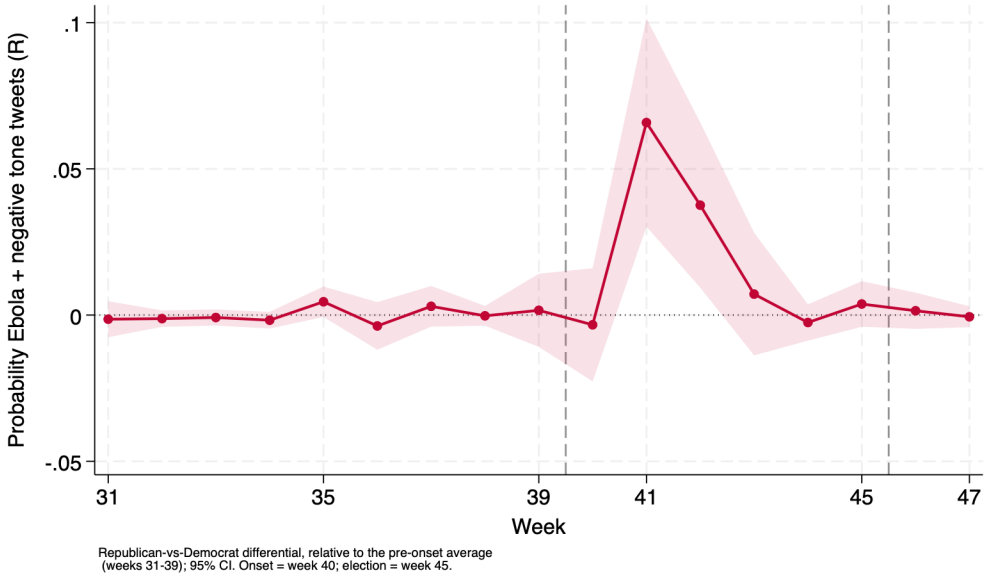


Figure A4: Event Study: Probability of Any Ebola Tweet with Negative Sentiment (Twitter)

Notes: Week-by-week DiD coefficients for the probability of an Ebola tweet classified by GPT-4o-mini as expressing negative sentiment. Specification as in Figure A2.

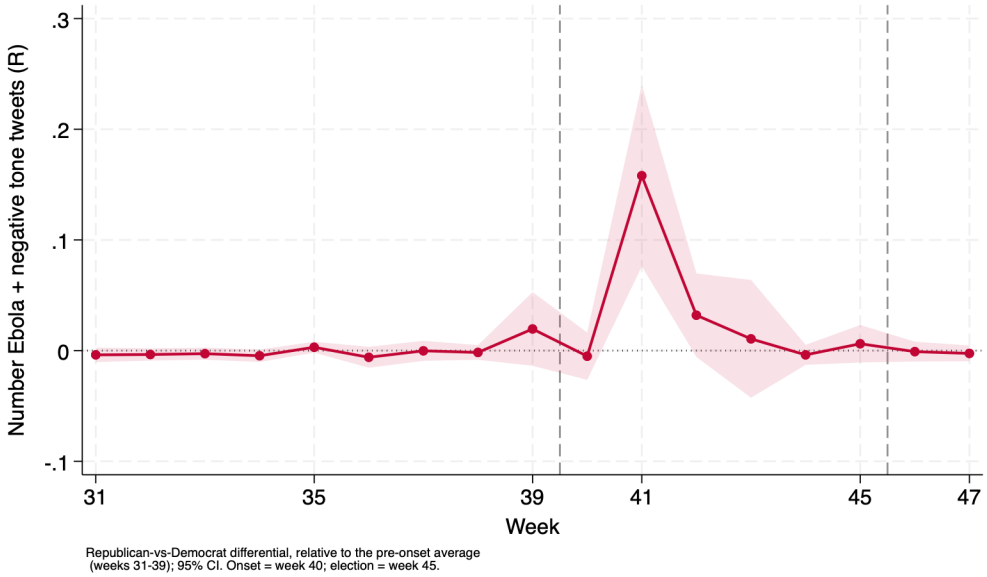


Figure A5: Event Study: Number of Ebola Tweets with Negative Sentiment (Twitter)

Notes: Week-by-week DiD coefficients for the count of Ebola tweets with negative sentiment. Specification as in Figure A2.

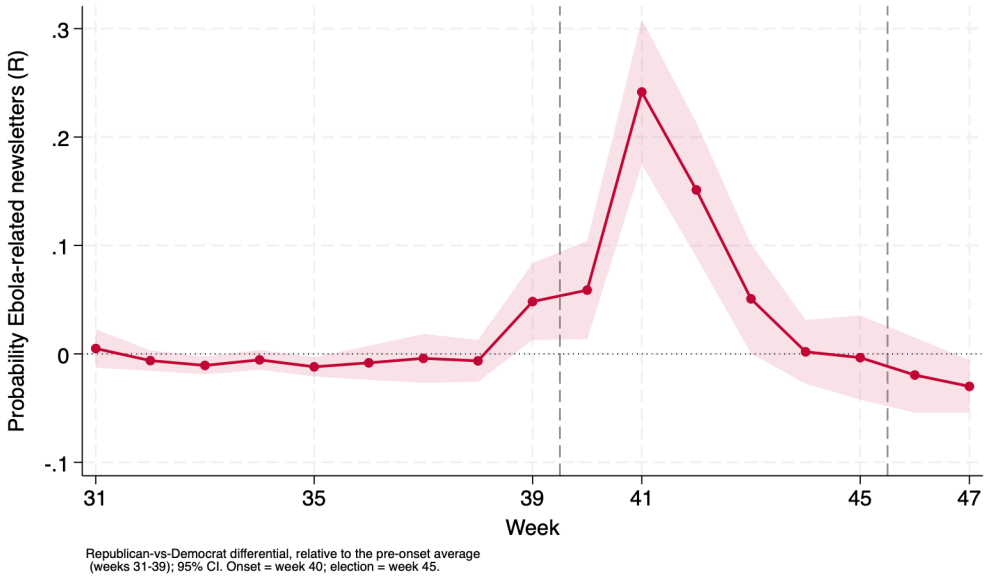


Figure A6: Event Study: Probability of Any Ebola Newsletter (Newsletters)

Notes: Week-by-week DiD coefficients (single series, with 95% confidence band) for the probability that a Republican member of Congress sent at least one Ebola-related newsletter, relative to the pre-onset average (weeks 31–39). Sample: weeks 31–47. Member and week fixed effects; standard errors clustered at the race level. Onset = week 40; election = week 45.

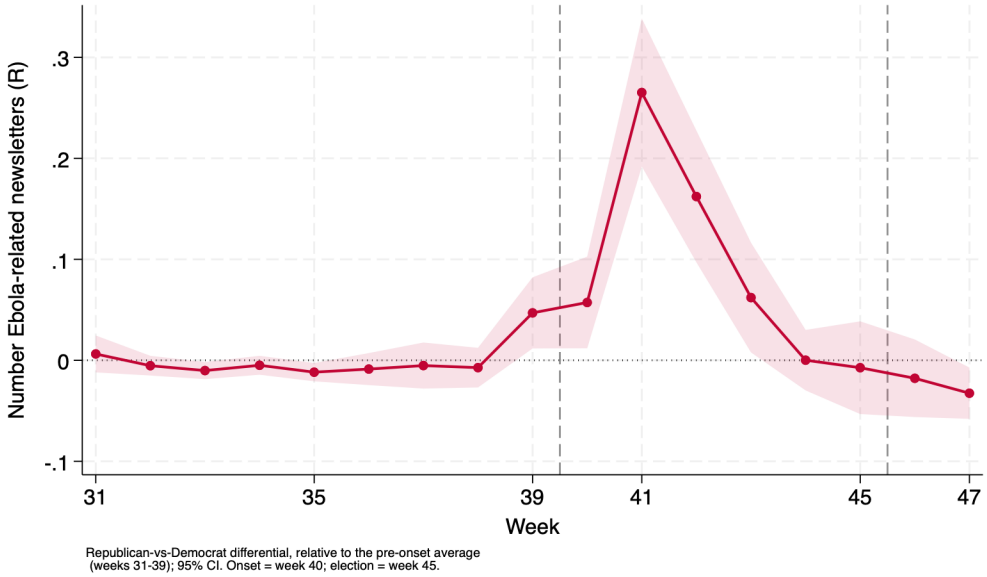


Figure A7: Event Study: Number of Ebola Newsletters (Newsletters)

Notes: Week-by-week DiD coefficients for the count of Ebola-related newsletters sent by Republican members relative to Democrats. Specification as in Figure A6.

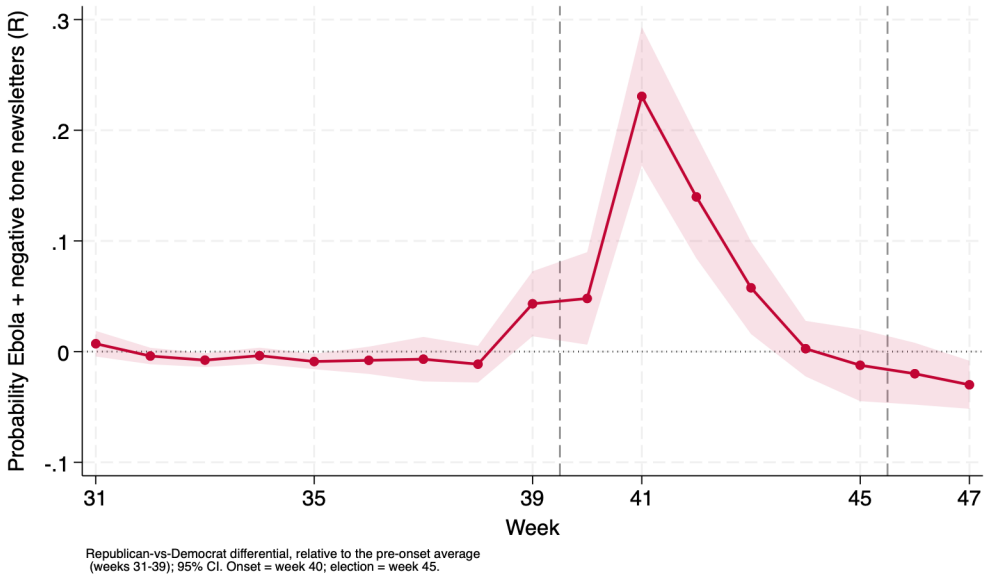


Figure A8: Event Study: Probability of Any Ebola Newsletter with Negative Sentiment (Newsletters)

Notes: Week-by-week DiD coefficients for the probability of an Ebola newsletter classified by GPT-4o-mini as expressing negative sentiment. Specification as in Figure A6.

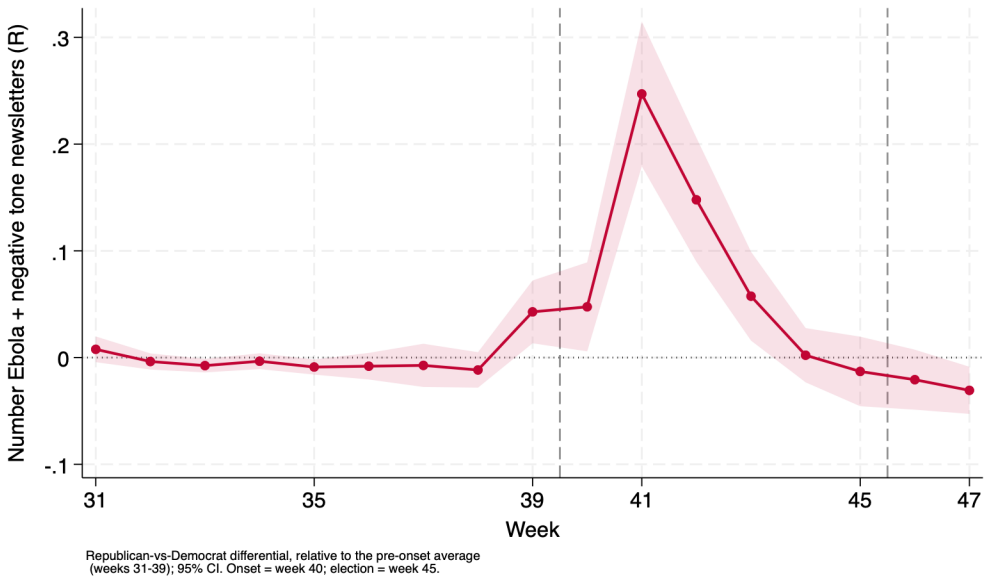


Figure A9: Event Study: Number of Ebola Newsletters with Negative Sentiment (Newsletters)

Notes: Week-by-week DiD coefficients for the count of Ebola newsletters with negative sentiment. Specification as in Figure A6.

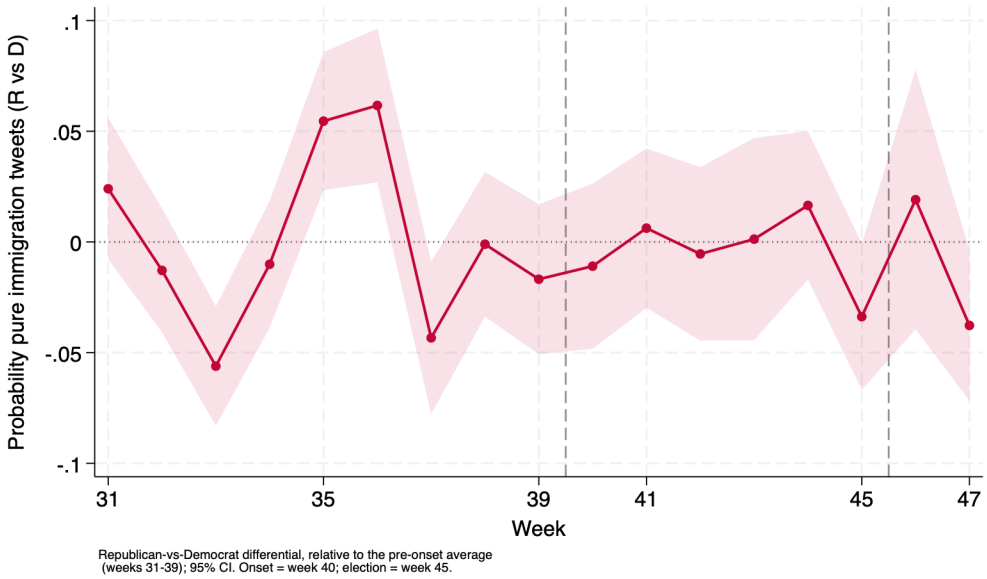


Figure A10: Event Study: Probability of Any Pure Immigration Tweet (Twitter)

Notes: Week-by-week DiD coefficients for the probability of a pure immigration tweet, that is, one mentioning immigration with no reference to Ebola (immigration net of Ebola-linked immigration). Relative to the pre-onset average (weeks 31–39). Specification as in Figure A2.

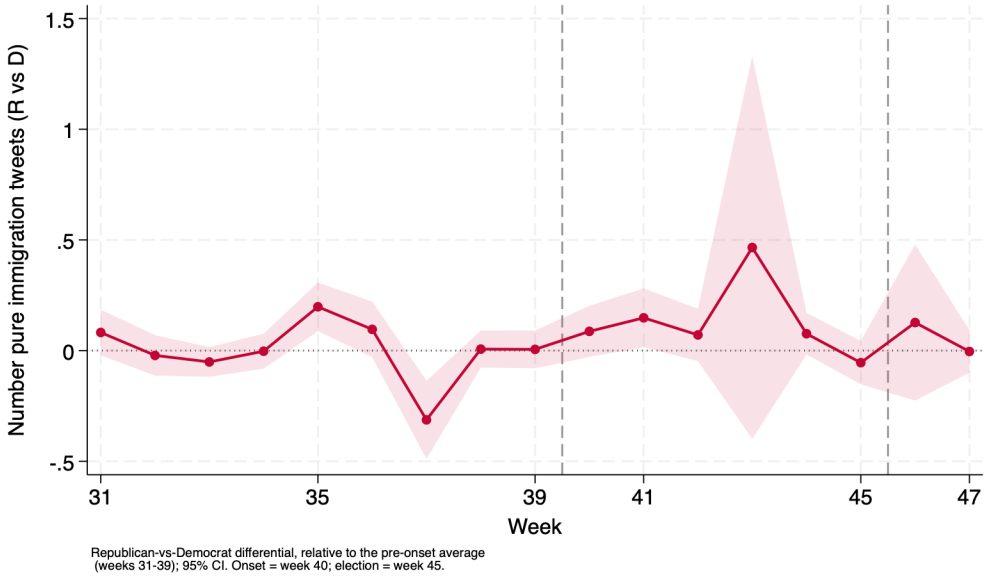


Figure A11: Event Study: Number of Pure Immigration Tweets (Twitter)

Notes: Week-by-week DiD coefficients for the count of pure immigration tweets (immigration net of Ebola-linked immigration). Relative to the pre-onset average (weeks 31–39). Specification as in Figure A2.

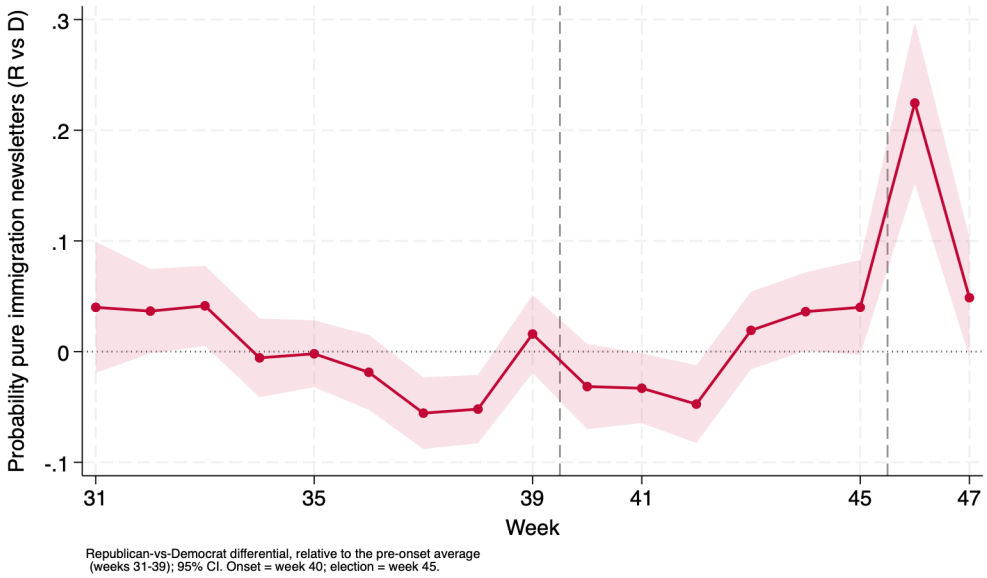


Figure A12: Event Study: Probability of Any Pure Immigration Newsletter (Newsletters)

Notes: Week-by-week DiD coefficients for the probability of a pure immigration newsletter, that is, one mentioning immigration with no reference to Ebola (immigration net of Ebola-linked immigration). Relative to the pre-onset average (weeks 31–39). Specification as in Figure A6.

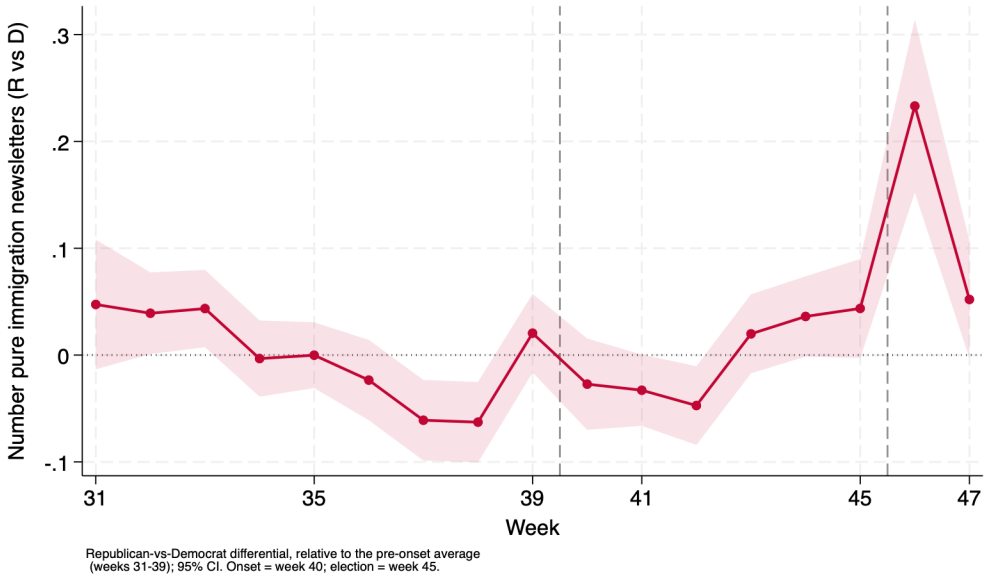


Figure A13: Event Study: Number of Pure Immigration Newsletters (Newsletters)

Notes: Week-by-week DiD coefficients for the count of pure immigration newsletters (immigration net of Ebola-linked immigration). Relative to the pre-onset average (weeks 31–39). Specification as in Figure A6.

C Measurement and Timing Checks

Coverage of the Twitter sample. Table A1 reports the share of the 794 Democratic and Republican general-election candidates for the House in 2014 who had a Twitter account. Coverage is 90.7 percent, and identical across parties. It is close to complete among incumbents and among candidates in competitive races or in seats that are safe for their own party, and lower (79 percent) only among candidates running in seats that are safe for the opposing party. Conditional on electoral position, coverage does not differ by party, so the missing candidates do not affect the party comparisons; if anything, the candidates we observe in the "far-behind" cells are positively selected on activity.

Table A1: Coverage of the Twitter Sample: House Candidates, 2014

Panel A: Share with a Twitter account			*Panel B: Linear probability model*	
	Share	Candidates		Has Twitter
All	0.907	794	Republican	−0.021
Democrats	0.907	399		(0.020)
Republicans	0.906	395	Incumbent	0.030*
Incumbents	0.984	316		(0.015)
Non-incumbents	0.856	478	Safe seat for opponent	−0.166***
Safe seat for own party	0.978	358		(0.031)
Not a safe seat	0.961	154	Safe seat for own party	0.006
Safe seat for opponent	0.787	282		(0.016)
			Candidates	794

Notes: Universe: Democratic and Republican candidates in the 2014 general elections for the U.S. House. Incumbents are candidates who sent at least one official e-newsletter in the DCinbox data. Safe seats are races rated Solid by the Cook Political Report on September 19, 2014. Panel B: linear probability model; the omitted category is a non-incumbent Democrat in a seat that is not safe; standard errors clustered at the race level. Adding interactions of the Republican indicator with incumbency and with each seat category yields coefficients below 0.02 in absolute value, none significant. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Dating the onset. Weeks in our panels run from Monday to Sunday, and the baseline specification dates each event from the first full week after it. The Dallas diagnosis (Tuesday, September 30) therefore falls in week 39 (September 29–October 5), which the baseline treats as pre-onset, even though candidate tweets about Ebola jump on September 30 itself, from zero on September 29. Table A2 codes week 39 as post-onset instead. Most coefficients

increase slightly (the estimate for any Ebola message rises by 0.003 on Twitter and by 0.004 in newsletters), and the largest decline is in the newsletter Ebola-immigration estimate, by 0.002. In sum, the results do not depend on how we code the week of the diagnosis.

Table A2: Coding the Diagnosis Week as Post-Onset

	(1) Any Ebola	(2) # Ebola	(3) Any Neg. Sent.	(4) # Neg. Sent.	(5) Any Ebola+Immig.	(6) # Ebola+Immig.
Panel A: Twitter						
$\text{Post}^{\text{wk 39}} \times$ Republican	0.063***	0.320***	0.016***	0.034***	0.019***	0.023***
	(0.013)	(0.061)	(0.005)	(0.010)	(0.003)	(0.005)
Obs.	9,588	9,588	9,588	9,588	9,588	9,588
Panel B: Newsletters						
$\text{Post}^{\text{wk 39}} \times$ Republican	0.080***	0.084***	0.075***	0.078***	0.012**	0.013**
	(0.012)	(0.013)	(0.010)	(0.011)	(0.005)	(0.005)
Obs.	4,908	4,908	4,908	4,908	4,908	4,908

Notes: As Table 1, but Post equals 1 from week 39 (September 29–October 5, the week of the Dallas diagnosis) rather than week 40. Weeks 34–45; candidate (member) and week fixed effects; weekly and cumulative word count; standard errors clustered at the race level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Keyword dictionary versus language model. Table A3 re-estimates Table 1, replacing the GPT-4o-mini Ebola indicators with the keyword approach we used in Campante, Depetris-Chauvin and Durante (2020), the NBER working-paper version of Campante, Depetris-Chauvin and Durante (2024). In that paper, we coded a congressional newsletter as Ebola-related if the word "Ebola" appeared in its subject or body, and measured Ebola framing by co-mentions of Ebola and immigration, terrorism, or Obama in the same newsletter. Here we apply the same rule to both tweets and newsletters. Since the dictionary is defined by the researchers in advance, rather than learned by a model, it involves no model judgment, and is fully transparent and exactly replicable. The two indicators coincide in 99.9 percent of candidate-weeks on Twitter, and in 99.5 percent of member-weeks in the newsletters, and the estimates are virtually identical (0.060 in both cases on Twitter; 0.076 and 0.077 in newsletters). The headline result thus does not depend on the language model, which matters only for the tone and framing outcomes. For the Ebola-immigration outcome, the keyword analogue is the co-mention measure of Campante, Depetris-Chauvin and Durante (2020), namely "ebola" and an immigration keyword appearing in the same

text. It is positive and significant in both channels, and in newsletters it amounts to 2.5 percentage points, the magnitude reported in that paper under a different specification.

Table A3: Keyword Dictionary versus LLM Classification

	(1)	(2)	(3)	(4)	(5)	(6)
	Any Ebola		# Ebola		Ebola + Immigration	
	LLM	Keyword	LLM	Keyword	LLM	Keyword co-mention
Panel A: Twitter						
Post × Republican	0.060***	0.060***	0.321***	0.322***	0.017***	0.009***
	(0.012)	(0.012)	(0.060)	(0.059)	(0.003)	(0.003)
Agreement with LLM indicator (%)		99.9		99.9		99.6
Obs.	9,588	9,588	9,588	9,588	9,588	9,588
Panel B: Newsletters						
Post × Republican	0.076***	0.077***	0.082***	0.081***	0.014***	0.025***
	(0.013)	(0.014)	(0.014)	(0.015)	(0.005)	(0.007)
Agreement with LLM indicator (%)		99.5		99.5		98.7
Obs.	4,908	4,908	4,908	4,908	4,908	4,908

Notes: Columns 1, 3 and 5 reproduce Table 1 (LLM classification). Columns 2 and 4 use the human-defined keyword indicator of Campante, Depetris-Chauvin and Durante (2020) (text contains "ebola"), which that paper applied to newsletters and we apply to both channels; column 6 uses the co-mention measure of the same paper, a co-mention of "ebola" and immigration keywords ("migration", "border", "ICE", "alien" on Twitter; "migration" in newsletters). Agreement is the share of candidate- (member-) weeks in which the keyword indicator and the LLM indicator coincide (for counts, whether the count is positive). Specification as in Table 1: weeks 34–45, candidate (member) and week fixed effects, weekly and cumulative word count; standard errors clustered at the race level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

D Additional Evidence

This appendix collects further evidence referred to in the main text. All regressions use the baseline specification (weeks 34–45, candidate or member and week fixed effects, weekly and cumulative word count, standard errors clustered at the race level) unless otherwise noted.

The administration frame. Table A4 reports the estimates for messages pairing Ebola with President Obama discussed in Section 5: the baseline response (Panel A), its gradient in electoral advantage (Panel B), and its gradient in distance to the known cases (Panel C). Columns 4 and 5 report the same estimates for messages about the President that do not mention Ebola.

District composition versus race rating. The logic of this test is discussed in Appendix A.2. Table A5 runs this comparison. Separately, each measure yields a positive Republican gradient on Twitter, of similar magnitude (columns 1–2). When both are included (column 3), the Republican gradient loads on the rating (0.040) rather than on PVI (0.010), which also suggests that Republican responsiveness was small. The Democratic gradient, in contrast, loads on PVI (-0.049): Democrats in more Democratic districts communicated more, which is consistent with responsiveness to anxious Democratic voters, as well as with the Solid-Democrat cell of Figure 2. In newsletters, neither measure is significant for Republicans, consistent with the flat newsletter gradient in Panel B of Table 3 (see Section 5.1.3 on why the model predicts a flatter, but still positive, newsletter gradient). Since the two measures have a correlation of 0.85, these splits are imprecise, and we read them as suggestive.

After the election. Table A6 extends the sample through December, and splits the post-onset period into the campaign (weeks 39–44, from the Dallas diagnosis through the week of the election), the three post-election weeks of November (45–47), and December (48–52), with weeks 34–38 as the reference period. In both channels and for every outcome, the

Table A4: The Administration Frame: Ebola Messages Mentioning President Obama

	Ebola + Obama			Obama, no Ebola	
	Twitter Any	Twitter #	Newsletters Any	Twitter Any	Newsletters Any
	(1)	(2)	(3)	(4)	(5)
Panel A: Baseline					
Post × Republican	0.030***	0.046***	0.032***	−0.034***	−0.029***
	(0.005)	(0.008)	(0.006)	(0.012)	(0.010)
Pre-onset Republican mean	0.004	0.004	0.006	0.233	0.091
Obs.	9,588	9,588	4,908	9,588	4,908
Panel B: Electoral position					
Post × Rep. × Advantage	0.006***	0.005*	0.011**	−0.010**	−0.016**
	(0.002)	(0.003)	(0.005)	(0.005)	(0.008)
Republican advantage gradient	0.006***	0.006**	0.007*	−0.010***	−0.013*
	(0.002)	(0.003)	(0.004)	(0.004)	(0.007)
Obs.	9,564	9,564	4,644	9,564	4,644
Panel C: Distance to the known cases					
Republican distance gradient	−0.001	0.001	0.009	0.033***	0.000
	(0.004)	(0.008)	(0.007)	(0.012)	(0.007)
Democratic distance gradient	−0.009***	−0.013***	−0.018***	0.014	0.005
	(0.003)	(0.005)	(0.006)	(0.012)	(0.008)
Obs.	8,832	8,832	4,896	8,832	4,896

Notes: Columns 1–3: outcomes are indicators (counts in column 2) for messages that GPT-4o-mini codes both as Ebola-related and as dealing with President Obama (code OB in the topic prompts; Appendix E, Section E.3.4). The code records that the message deals with the President, not whether it criticizes him. Columns 4–5: any message mentioning President Obama without being coded as Ebola-related. In our newsletter data no member sends more than one such newsletter in a week, so the count coincides with the indicator and is not reported. Panel A: specification of Table 1. Panel B: specification of Table 2; the Republican advantage gradient is the sum of Post × Rep. × Advantage and Post × Advantage. Panel C: specification of Table 4; the Republican gradient is the sum of Post × Rep. × Distance and Post × Distance, and the Democratic gradient is Post × Distance. Candidate (member) and week fixed effects, weekly and cumulative word count; standard errors clustered at the race level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A5: District Composition versus Race Rating

	Twitter			Newsletters		
	(1)	(2)	(3)	(4)	(5)	(6)
Republican slope in Cook rating	0.048***		0.040**	0.015		0.014
	(0.009)		(0.016)	(0.020)		(0.022)
Republican slope in PVI		0.046***	0.010		0.005	0.001
		(0.010)	(0.017)		(0.020)	(0.021)
Democratic slope in Cook rating	−0.028***		0.015	−0.038**		−0.029
	(0.007)		(0.014)	(0.016)		(0.019)
Democratic slope in PVI		−0.037***	−0.049***		−0.019**	−0.009
		(0.008)	(0.015)		(0.008)	(0.010)
Obs.	9,564	9,564	9,564	4,644	4,644	4,644

Notes: Outcome: any Ebola message in the week. The Cook advantage score and the Cook Partisan Voting Index (PVI, based on presidential vote) are standardized; their correlation is 0.85 in the Twitter sample. Each column interacts Post and Post × Republican with the measures listed; slopes are the post-onset slopes for each party (delta-method standard errors). Candidate (member) and week fixed effects, weekly and cumulative word count; weeks 34–45; standard errors clustered at the race level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Republican differential is large during the campaign and close to zero after the election. The only post-election coefficient that is positive and significant is the newsletter Ebola-immigration estimate for December (0.007), and only at the 10 percent level. The pattern holds among accounts active in a given week (column 2), as well as among election winners (column 3).

Table A6: The Fear Frame Before and After the Election

	Twitter					Newsletters		
	(1) Any Ebola	(2) Any Ebola Active weeks	(3) Any Ebola Winners	(4) Neg. Sent.	(5) Ebola+Immig.	(6) Any Ebola	(7) Neg. Sent.	(8) Ebola+Immig.
Republican × Campaign (wks 39–44)	0.071***	0.090***	0.063***	0.017***	0.021***	0.108***	0.103***	0.020***
	(0.015)	(0.016)	(0.020)	(0.006)	(0.004)	(0.015)	(0.013)	(0.005)
Republican × Post-election, Nov. (wks 45–47)	-0.005	0.011	-0.010	0.000	-0.001	0.003	0.000	-0.004
	(0.007)	(0.015)	(0.010)	(0.002)	(0.001)	(0.011)	(0.009)	(0.008)
Republican × December (wks 48–52)	-0.017***	-0.023	-0.023***	-0.003	0.000	0.004	0.005	0.007*
	(0.005)	(0.014)	(0.008)	(0.002)	(0.001)	(0.006)	(0.004)	(0.004)
p-value: Campaign = December	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.029
Obs.	15,181	9,662	8,740	15,181	15,181	7,771	7,771	7,771

Notes: Weeks 34–52 of 2014 (August 25–December 31); reference period weeks 34–38. Outcomes are indicators for at least one Ebola-related item (LLM classification) in the week. Column 2 restricts to weeks in which the candidate tweeted; column 3 to candidates with the highest vote share in their race. Candidate (member) and week fixed effects; weekly and cumulative word count; standard errors clustered at the race level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

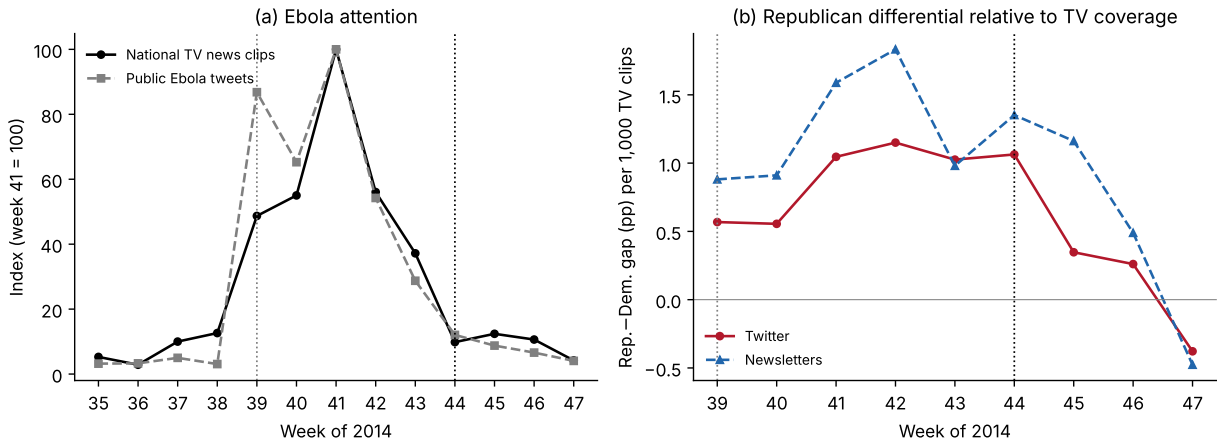


Figure A14: Media Attention and the Republican Ebola Differential

Notes: Panel (a) shows weekly national television news clips mentioning Ebola (GDELT Television API; Bloomberg, CNBC, CNN, C-SPAN 1 to 3, Fox Business, Fox News, and MSNBC) and weekly public Ebola tweets in our DMA panel, each indexed to its value in week 41 (October 13 to 19). Panel (b) shows, for weeks 39 to 47, the difference between Republicans and Democrats in the share of candidates (members) with at least one Ebola-related tweet (newsletter) in the week, in percentage points, divided by the number of television clips in thousands. The gray dotted line marks week 39 (Dallas diagnosis) and the black dotted line week 44 (election day, November 4). Weeks run Monday to Sunday.

Media coverage. Figure A14 compares the timing of candidate communication with national television coverage of Ebola. Coverage rose sharply in the week of the Dallas diagnosis, peaked in week 41, the week of Amber Vinson's diagnosis, and had fallen by 90 percent by the week of the election, closely tracking public Ebola tweets (panel a). Relative to that coverage, the Republican differential rose during the campaign and remained stable until election day, in both channels, before falling after the election (panel b).

Other topics after the election. If the end of Ebola messaging after election day simply reflected a general slowdown in candidate communication, other topics should fall by a similar proportion. Table A7 shows that they do not. Among candidates active in a given week, the share tweeting about Ebola falls by 91 percent for Republicans (and 78 percent for Democrats) between the campaign weeks and the post-election weeks. Content favorable to either party falls by 30 to 60 percent, health care and terrorism (outside Ebola) by at most 16 percent, and immigration and President Obama (outside Ebola) rise, the former in the run-up to the President's executive action on immigration of November 20. Within

candidate and topic, the post-election drop in Ebola is 24.8 percentage points (s.e. 2.3) larger than for the average other topic among Republicans, and 13.7 points (s.e. 2.0) larger among Democrats.

Table A7: Topics of Candidate Tweets during and after the Campaign

	Republicans			Democrats		
	Campaign	After	Ratio	Campaign	After	Ratio
Ebola	27.2	2.4	0.09	15.9	3.4	0.22
Immigration (no Ebola)	14.1	25.2	1.79	13.5	19.5	1.44
President Obama (no Ebola)	27.6	30.4	1.10	8.9	17.6	1.97
Health care (no Ebola)	31.0	25.8	0.84	33.3	31.9	0.96
Terrorism (no Ebola)	14.6	12.3	0.84	7.1	7.4	1.05
Republican-favorable topics	33.9	19.5	0.57	13.5	9.4	0.70
Democrat-favorable topics	8.5	4.7	0.56	35.3	14.7	0.42
Active candidate-weeks	1,644	1,223		1,670	1,223	

Notes: Percentage of candidates active on Twitter in a given week who posted at least one tweet coded by GPT-4o-mini in each category. Campaign: weeks 39–43 (September 29 to November 2); After: weeks 45–52 (November 10 to December 28). The election week (week 44) is excluded. "No Ebola" excludes tweets also coded as Ebola-related. Ratio: After divided by Campaign.

Immigrant population. Since the Republican frame linked Ebola with immigration, its use could depend on the size of the district's immigrant population. Table A8 interacts the baseline specification with the share of the district's population born abroad (standardized), for House candidates and members. On Twitter, the Republican response is weaker in districts with more immigrants, but this simply reflects that those districts are Democratic seats, where Republicans are far behind: once we control for the interaction with the Cook advantage score, the coefficient falls by more than two thirds and is insignificant. The Ebola-immigration co-mention does not vary with the immigrant share in either channel. Results are the same with the Hispanic share of the population.

Responses to the opponent. Did candidates respond to their own opponent's Ebola messaging? Table A9 regresses each candidate's weekly Ebola communication on that of the opponent in the same race, contemporaneously and with a one-week lag, for the 315 races in

Table A8: Heterogeneity by the District's Immigrant Population

	Twitter				Newsletters			
	Any Ebola		Any Ebola+Immig.		Any Ebola		Any Ebola+Immig.	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post × Rep. × Foreign-born share	−0.046***	−0.013	0.001	0.006	0.001	0.005	0.001	0.002
	(0.012)	(0.013)	(0.003)	(0.004)	(0.017)	(0.017)	(0.007)	(0.007)
Republican foreign-born gradient	−0.023***	0.002	0.001	0.005	0.006	0.006	0.005	0.005
	(0.009)	(0.009)	(0.003)	(0.004)	(0.014)	(0.014)	(0.006)	(0.006)
Democratic foreign-born gradient	0.023***	0.016	−0.001	−0.001	0.006	0.002	0.004	0.003
	(0.008)	(0.010)	(0.002)	(0.001)	(0.010)	(0.011)	(0.004)	(0.004)
Advantage interactions	No	Yes	No	Yes	No	Yes	No	Yes
Obs.	8,244	8,244	8,244	8,244	3,672	3,672	3,672	3,672

Notes: House candidates (Twitter) and House members (newsletters). Foreign-born share: share of the population born outside the United States, aggregated to districts from the county-level data used in Campante, Depetris-Chauvin and Durante (2024), standardized to mean zero and unit standard deviation in each sample. Each regression includes Post × Republican and Post × Foreign-born share; columns marked "Yes" add Post × Advantage and Post × Rep. × Advantage, as in Table 2. The Republican gradient is the sum of the triple and the Post × Foreign-born terms; the Democratic gradient is Post × Foreign-born share. Baseline specification otherwise. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

which we observe exactly one Democrat and one Republican on Twitter. With week fixed effects absorbing national salience, neither party responds to its opponent: the coefficients are small and insignificant, and for Democrats the confidence intervals rule out a response larger than about six percentage points, against a mean of 6.1 percent.

Table A9: Responses to the Opponent's Ebola Messaging (Twitter)

	Democrat			Republican
	Any Ebola	Any Ebola+Immig.	Any Ebola+Obama	Any Ebola
	(1)	(2)	(3)	(4)
Panel A: Opponent's any Ebola tweet, same week				
Opponent	0.017	−0.002	−0.003	0.028
	(0.020)	(0.004)	(0.005)	(0.031)
Panel B: Opponent's any Ebola tweet, previous week				
Opponent	−0.007	0.006	−0.001	−0.007
	(0.018)	(0.004)	(0.005)	(0.029)
Mean of outcome	0.061	0.002	0.004	0.110
Obs.	3,465	3,465	3,465	3,465

Notes: Races with exactly one Democratic and one Republican candidate in the Twitter panel (315 races), weeks 35–45. Each coefficient comes from a separate regression of the candidate's outcome on the opponent's indicator for any Ebola tweet, with candidate and week fixed effects and the candidate's and the opponent's weekly word count and the candidate's cumulative word count as controls. Standard errors clustered at the race level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

E Classification of Tweets and Newsletters

E.1 Summary

This appendix provides a brief report on the classification process applied to newsletters and tweets from U.S. politicians along five dimensions: *Immigration*, *Republican*, *Democrat*, *Negative_sentiment*, and *Ebola*, as well as a code for President Obama.

E.2 Data Description

Table A10 lists the data sources and the fields we analyze.

Table A10: Data sources and fields analyzed.

Source	**Data**	**Fields analyzed**
Politicians' Twitter accounts (U.S.)	229,464 tweets	Tweet text
Politicians' newsletters (U.S.)	68,997 emails	Subject line + email body

E.3 Classification Methodology

E.3.1 Prompt Design & Categories

We designed and applied four prompts as summarized in Table A11. Each prompt employed function-calling to enforce a structured JSON response compatible with downstream processing.

Table A11: Prompt design and categories evaluated.

Prompt	**Dataset**	**Categories evaluated**
Topics	Twitter	Immigration, Republican-favorable topics, Democrat-favorable topics (also coded: Obama, health care, terrorism)
Emotions & Ebola	Twitter	Negative sentiment, Ebola (also coded: fear, disgust)
Topics	Newsletters	Same as first row
Emotions & Ebola	Newsletters	Same as second row

E.3.2 API Calls & Storage

We used the following configuration for the classification calls:

- **Model:** `gpt-4o-mini-2024-07-18`
- **Key parameters:** `temperature = 0`, `max_tokens = 200`
- **Storage:** responses stored in separate columns.

Classification was carried out through the API using batch processing.

E.3.3 Output Variables

For every record in both datasets we created:

- One dummy variable per category (e.g., *immigration*).
- A `reasoning` column capturing the model's explanation for each classification.

E.3.4 Category Definitions

The prompts identified each category by its name (Section E.5). In the analysis, and in the hand validation of the classification, the categories are defined as follows.

- **Ebola (EB):** the text refers to the Ebola virus, the outbreak, Ebola patients, or a policy explicitly about Ebola (travel restrictions, quarantine, CDC guidance), with or without the word "Ebola".
- **Negative sentiment (NS):** the dominant tone of the text is negative (criticism, anger, worry or alarm) about any subject.
- **Immigration (IM):** the text discusses immigration, border security, visas, deportation, refugees or asylum.
- **Republican-favorable (RF) / Democrat-favorable (DF):** the text promotes the positions or candidates of the party, or attacks the other party.
- **Ebola + immigration:** the same text is classified as both EB and IM. This is a co-mention measure: it does not require that the text connect the two topics.

- **President Obama (OB):** the text deals with President Obama. The code records that the text deals with the President, not whether it criticizes him.
- **Ebola + Obama:** the same text is classified as both EB and OB, a co-mention measure defined as for immigration.

The classification output also contains codes for fear (FE) and disgust (DI), which the paper does not use, and for health care (HC) and terrorism (TE), which we use only to describe the topics of candidate tweets after the election (Table A7).

E.4 Results: Category Totals

Table A12 reports the number of records assigned to each category in each dataset.

Table A12: Category totals by dataset.

Category	**Newsletters** ($n = 68{,}997$)	**Tweets** ($n = 229{,}464$)
Immigration	6,265	5,303
Republican	15,157	6,731
Democrat	6,082	5,144
Negative_sentiment	22,468	33,822
Ebola	516	3,467

E.5 Prompts Used

The listings below show the main categories the paper uses. The prompts as run also listed further codes: President Obama (OB), health care (HC) and terrorism (TE) in the two topic prompts, which we use as described in Section E.3.4, and fear (FE) and disgust (DI) in the two emotion prompts, which the paper does not use (Section E.3.4). The complete prompt files are part of the replication package.

Prompt 1: Topics / Twitter.

```
Context: We are classifying tweets from U.S. politicians into specific topics:
- Immigration (IM)
- Republican-favorable topics (RF)
```

```
- Democrat-favorable topics (DF)
A tweet may belong to multiple topics or none ("None").

Instructions:
* Read the tweet carefully.
* IMPORTANT: First provide a concise but explicit reasoning paragraph
  showing how you detected the topic(s).
* Classify the tweet only when its own textual content provides adequate
  evidence. If the post contains little or no substantive text and consists
  chiefly of a URL -- either shortened or full -- do not infer the webpage's
  content. In such cases, assign the category "None" and indicate that the
  available text is insufficient for reliable classification.
* Then output the chosen codes in the "categories" array.

Example
Tweet: "Fixing our broken immigration system must be Congress's top priority."
Expected classification:
{{"reasoning": "Explicit call for immigration reform.", "categories": ["IM"]}}

Now classify the following tweet by calling **classify_post**:
Tweet:
```

Prompt 2: Emotions & Ebola / Twitter.

```
Context: Classify tweets from U.S. politicians into emotion / topic categories:
- Negative sentiment (NS)
- Ebola topic (EB)
A tweet may belong to multiple categories or none ("None").

Instructions:
```

```
* Read the tweet carefully.
* IMPORTANT: First provide a concise but explicit reasoning paragraph
  showing how you detected the category(ies).
* Classify the tweet only when its own textual content provides adequate
  evidence. If the post contains little or no substantive text and consists
  chiefly of a URL -- either shortened or full -- do not infer the webpage's
  content. In such cases, assign the category "None" and indicate that the
  available text is insufficient for reliable classification.
* Then output the chosen codes in the "categories" array.

Now classify the following tweet by calling **classify_post**:
Tweet:
```

Prompt 3: Topics / Newsletters.

```
Context: We are classifying newsletters from U.S. politicians into specific
topics:
- Immigration (IM)
- Republican-favorable topics (RF)
- Democrat-favorable topics (DF)
A newsletter may belong to multiple topics or none ("None").

Instructions:
* Carefully read the subject **and** message.
* Classify the newsletter only when its own textual content provides adequate
  evidence. If the newsletter contains little or no substantive text and
  consists chiefly of a URL -- either shortened or full -- do not infer the
  webpage's content. In such cases, assign the category "None" and indicate
  that the available text is insufficient for reliable classification.
* IMPORTANT: First provide a concise but explicit reasoning paragraph showing
```

```
  how you detected the topic(s).
* Then output the chosen codes in the "categories" array.


Now classify the following newsletter by calling **classify_post**:
Newsletter:
```

Prompt 4: Emotions & Ebola / Newsletters.

```
Context: Classify newsletters from U.S. politicians into emotion / topic
categories:
- Negative sentiment (NS)
- Ebola topic (EB)
A newsletter can trigger multiple categories or none ("None").


Instructions:
* Read the subject **and** message carefully.
* Classify the newsletter only when its own textual content provides adequate
  evidence. If the newsletter contains little or no substantive text and
  consists chiefly of a URL -- either shortened or full -- do not infer the
  webpage's content. In such cases, assign the category "None" and indicate
  that the available text is insufficient for reliable classification.
* IMPORTANT: First give a concise but explicit reasoning paragraph that shows
  how you detected the category(ies).
* Then output only the selected codes in the "categories" array.


Example 1
Newsletter:
Subject: "A Dangerous Surge at the Border"
Message: "Criminal gangs are pouring into our communities -- your family is at
risk unless we act now."
```

```
Expected classification:
{{"reasoning": "Highlights personal danger and imminent threat, clearly aiming
to evoke fear.", "categories": ["NS"]}}

Example 2
Newsletter:
Subject: "Stopping Ebola at Our Borders"
Message: "The administration's weak response to the Ebola outbreak puts every
American at risk."
Expected classification:
{{"reasoning": "Talks explicitly about Ebola and conveys a strong warning
tone.", "categories": ["EB", "NS"]}}

Now classify the following newsletter by calling **classify_post**:
Newsletter:
```

F Robustness: Excluding the Communication Controls

The main specifications control for weekly and cumulative word count to absorb differences in overall communication intensity. Because these are themselves measures of communication, they could in principle be affected by the Ebola response (a "bad control" concern). Tables A13–A15 re-estimate Tables 1, 2, and 4 dropping these controls. The coefficients of interest are essentially unchanged: the main Republican response (Table A13) moves by at most a few percent on Twitter and is, if anything, slightly larger for newsletters; the electoral-advantage gradient (Table A14) and the distance terms (Table A15) are likewise stable. The headline results are therefore not artifacts of conditioning on communication volume.

Table A13: The Republican Strategic Response, Excluding Communication Controls

	(1) Any Ebola	(2) # Ebola	(3) Any Neg.	(4) # Neg.	(5) Any Immig.	(6) # Immig.
Panel A: Twitter						
Post × Republican	0.057***	0.308***	0.017***	0.030***	0.016***	0.022***
	(0.012)	(0.059)	(0.006)	(0.011)	(0.003)	(0.005)
Obs.	9,588	9,588	9,588	9,588	9,588	9,588
Panel B: Newsletters						
Post × Republican	0.084***	0.092***	0.080***	0.084***	0.016***	0.017***
	(0.013)	(0.015)	(0.012)	(0.012)	(0.005)	(0.005)
Obs.	4,908	4,908	4,908	4,908	4,908	4,908

Notes: As Table 1, but excluding the weekly and cumulative word-count controls. Candidate (or member) and week fixed effects throughout; standard errors clustered at the race level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A14: Electoral Advantage, Excluding Communication Controls

	Twitter		Newsletters	
	(1) Any Ebola	(2) # Ebola	(3) Any Ebola	(4) # Ebola
Post × Republican	0.054***	0.281***	0.084***	0.089***
	(0.011)	(0.053)	(0.024)	(0.025)
Post × Rep. × Advantage	0.027***	0.099***	0.016	0.019*
	(0.004)	(0.020)	(0.010)	(0.011)
Post × Advantage	−0.011***	−0.022***	−0.006	−0.007
	(0.003)	(0.008)	(0.005)	(0.005)
Republican advantage gradient	0.017***	0.077***	0.010	0.013
	(0.004)	(0.018)	(0.009)	(0.009)
Obs.	9,564	9,564	4,644	4,644

Notes: As Table 2, but excluding the word-count controls. The "Republican advantage gradient" is the within-Republican slope (Post × Advantage + Post × Republican × Advantage), delta-method SE. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A15: Distance to Ebola Cases, Excluding Communication Controls

	Twitter		Newsletters	
	(1) Any Ebola	(2) # Ebola	(3) Any Ebola	(4) # Ebola
Post × Republican	0.051***	0.295***	0.092***	0.101***
	(0.013)	(0.066)	(0.016)	(0.017)
Post × Rep. × Distance	0.010	0.066*	0.033**	0.037**
	(0.009)	(0.038)	(0.014)	(0.015)
Post × Distance	−0.027**	−0.138***	−0.020	−0.021
	(0.011)	(0.051)	(0.016)	(0.016)
Distance	0.013	0.060	0.001	0.002
	(0.010)	(0.046)	(0.015)	(0.015)
Republican distance gradient	−0.017	−0.072	0.013	0.016
	(0.013)	(0.067)	(0.017)	(0.017)
Obs.	8,832	8,832	4,896	4,896

Notes: As Table 4, but excluding the word-count controls. Distance is the log distance to the nearest case known as of that week, demeaned; the "Republican distance gradient" is the within-Republican slope (Post × Distance + Post × Republican × Distance), delta-method SE. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

G Ebola Messaging and the Vote: Suggestive Evidence

This appendix reports the correlation between candidates' Ebola messaging and their results in the 2014 House elections. We see this as suggestive evidence only, and it plays no role in the paper's argument: a candidate's decision to tweet about Ebola is obviously not randomly assigned, and candidates who campaign more actively may also be better positioned electorally.

We link the candidate-level Twitter measures to district returns for the 2014 House elections (from Dave Leip's Atlas of U.S. Elections, matched by state, district, and party). For each candidate, we count the Ebola tweets sent before election day, define an indicator for sending any, and relate both to the candidate's vote share and, alternatively, to the log of her vote count. We use Twitter rather than newsletters, since official e-newsletters can only be sent by sitting members. Table A16 reports three designs, all controlling for the candidate's party vote share in the 2010 House election: within race (race fixed effects, the two major-party candidates in races contested by both parties); within state (state fixed effects, Republicans only); and within media market (DMA fixed effects, Republicans in districts lying entirely within one DMA). Standard errors are clustered by race, state and DMA, respectively.

Candidates who tweeted about Ebola obtained higher vote shares in all three designs: about 13 percentage points within race, and about 6 percentage points within state and within market, for the extensive margin. These associations should not, however, be read as returns to the message. Within race, the estimate falls by more than half when we also control for incumbency, and becomes small and insignificant once we add overall tweeting volume; within state, it disappears once we add Cook-rating fixed effects or the district's partisan lean (PVI). In sum, the pattern is consistent with better-positioned Republicans both messaging more and winning by more, rather than with an electoral payoff to the Ebola frame itself.

Table A16: Ebola Tweeting and the Vote: Within Race, Within State, and Within Market

	Vote share (%)		Log votes	
	(1) Any Ebola	(2) # Ebola	(3) Any Ebola	(4) # Ebola
Panel A: Within race (race FE, Democrat vs. Republican)				
Any Ebola tweet (0/1)	13.310***		0.318***	
	(2.052)		(0.060)	
# Ebola tweets		0.483***		0.011***
		(0.156)		(0.003)
Party vote share, 2010	0.543***	0.600***	0.012***	0.014***
	(0.040)	(0.038)	(0.001)	(0.001)
Observations	694	694	694	694
Clusters (races)	347	347	347	347
Panel B: Within state, across Republicans (state FE)				
Any Ebola tweet (0/1)	6.198***		0.169	
	(2.257)		(0.113)	
# Ebola tweets		0.244**		0.005*
		(0.114)		(0.003)
Party vote share, 2010	0.560***	0.580***	0.017***	0.018***
	(0.084)	(0.084)	(0.003)	(0.003)
Observations	375	375	375	375
Clusters (states)	42	42	42	42
Panel C: Within DMA, across Republicans (media-market FE, single-DMA districts)				
Any Ebola tweet (0/1)	6.103**		0.317***	
	(2.497)		(0.097)	
# Ebola tweets		0.166		0.006
		(0.198)		(0.008)
Party vote share, 2010	0.558***	0.602***	0.019***	0.022***
	(0.072)	(0.067)	(0.003)	(0.003)
Observations	130	130	130	130
Clusters (DMAs)	30	30	30	30

Notes: The unit of observation is a candidate. The dependent variable is the candidate's share of the district vote (columns 1–2) or the natural log of the candidate's vote count (columns 3–4). Ebola tweets are identified by GPT-4o-mini and counted over the pre-election period; "Any Ebola tweet" is an indicator for at least one. Panel A includes race (district) fixed effects and covers the two major-party candidates in races contested by both parties; Panel B includes state fixed effects and covers Republican candidates only; Panel C includes media-market (DMA) fixed effects and covers Republican candidates in districts that lie entirely within a single DMA. All columns control for the candidate's party vote share in the 2010 House election. Standard errors, clustered by race (Panel A), state (Panel B), or DMA (Panel C), in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

H Illustrative Examples from Congressional Newsletters

This appendix supplements the quantitative results in the main text with concrete examples of the communications that our GPT-4o-mini coding procedure (Section 4) identifies. The figures in the main text establish that, following the first U.S. Ebola diagnosis in Dallas on September 30, 2014, Republican members of Congress sharply increased Ebola-related newsletter output and were disproportionately likely to frame the disease with negative sentiment and in explicit connection to immigration and border security (Table 1, Panel B). The excerpts below are drawn verbatim from the DCinbox corpus (Cormack, 2017) and are intended purely to illustrate the textual content underlying those coded measures. They are selected examples, not a representative sample, and inclusion is not a claim about any individual legislator's intent.

Two features of the corpus are worth noting. First, essentially no member of either party discussed Ebola before the Dallas diagnosis; all examples below fall within the six-week post-onset campaign window (weeks 40–45). Second, the immigration-linked framing is highly concentrated: a large share of Ebola newsletters discussed travel restrictions, screening, or appropriations in neutral public-health terms, while a smaller subset, illustrated here, explicitly tied the outbreak to the security of the U.S. border or to immigration enforcement. The latter is the content captured by our "Ebola + Immigration" indicator (columns 5–6 of Table 1).

H.1 Selected Excerpts Linking Ebola to Immigration and Border Security

Table B1 reproduces representative passages in which the Ebola outbreak is framed alongside immigration or border-security themes. Each row reports the sending member, the date and subject line of the newsletter, and the relevant verbatim passage.

Table B1: Representative Newsletter Excerpts Framing Ebola with Immigration and Border Security

Member (Party-State)	**Date**	**Newsletter subject**	**Excerpt**
Rep. Ron DeSantis (R-FL)	Oct 4	"A Message from Congressman DeSantis"	"The President also must enforce existing laws related to immigration and border security so that the American people are protected from this deadly disease."
Rep. Jeff Miller (R-FL)	Oct 5	"Miller Newsletter – 10/05/14"	"Reports emerged last week of the first confirmed human Ebola case on U.S. soil when Liberian citizen, Thomas Eric Duncan, was diagnosed with the virus days after arriving in Dallas, Texas."
Rep. Phil Roe (R-TN)	Oct 11	"Ebola"	"This outbreak is also a reminder that we must secure our borders... it will be easier to prevent the disease's spread with a secure border."
Rep. Jim Bridenstine (R-OK)	Oct 15	"Securing America Town Hall"	"How we respond to ISIS, Ebola, Russian aggression, and the crisis on our southern border is critical to both our national security and our sovereignty."
Rep. H. Morgan Griffith (R-VA)	Oct 20	"Griffith's Weekly E-Newsletter 10.20.14"	"[The strategy] should include actions to secure our nation's porous borders. It should include the additional training of health care workers... to properly identify and treat Ebola."
Rep. Steve Stockman (R-TX)	Oct 27	"The Hill Report – Weekly Newsletter"	"[He] asked how the countries can halt the sending of children and underage criminals to the US illegally, and how they can... prevent Ebola victims from entering their countries and then crossing our border."

Notes: Excerpts are reproduced verbatim from members' official e-newsletters in the DCinbox corpus (Cormack, 2017); ellipses denote omitted intervening text and emphasis is as in the original. All listed members are Republican. The passages illustrate the content that the GPT-4o-mini procedure of Section 4 flags as mentioning Ebola together with immigration or border themes (the indicator in columns 5–6 of Table 1, Panel B); several also carry negative sentiment toward the disease or its management (columns 3–4). The Miller passage foregrounds the foreign origin and arrival of the index patient without an explicit policy link and is shown for contrast. Examples are illustrative and were selected for clarity; they are not a random sample, and their inclusion carries no implication about an individual legislator's motives.

H.2 Discussion

These passages share a common rhetorical move: a public-health event originating in West Africa is reframed as a question of domestic border control. In several cases (Roe, Griffith, Bridenstine) the link is made even though the text elsewhere concedes there is no domestic transmission risk from neighboring countries, and the connection to the U.S. southern border is geographically unrelated to the actual (trans-Atlantic) route of the index case. This is the pattern that our placebo test in Section 6 helps interpret: the rise in immigration-tinged content is specific to Ebola framing rather than a general increase in immigration messaging, since pure immigration communication (mentions with no Ebola reference) does not change differentially post-onset.

Consistent with the timing evidence in Figure 1 and the event studies (Figures A2–A9), every excerpt falls between the Dallas diagnosis and election day. The decline of this content after November 4, visible in the post-election coefficients of the event studies and in Table A6, is consistent with a campaign-period communication strategy rather than a sustained public-health concern. The examples here put concrete language to that statistical pattern but, on their own, establish nothing causal; the identification rests on the differences-in-differences design of Section 4.2.

I Illustrative Examples from Candidate Tweets

This appendix mirrors Appendix H for the Twitter channel. It presents verbatim examples of the candidate tweets underlying the GPT-4o-mini-coded "Ebola + Immigration" measure (columns 5–6 of Table 1, Panel A). The main-text figures show that, after the first U.S. Ebola diagnosis in Dallas on September 30, 2014, Republican candidates sharply increased Ebola-related tweeting and were disproportionately likely to pair it with negative sentiment and with explicit immigration or border-security themes. The tweets below illustrate that textual content. They are selected, not representative, and inclusion implies no claim about any individual candidate's intent.

In the tweet corpus, 84 messages are flagged as jointly referencing Ebola and immigration; the largest single share are from Republican candidates. The passages below were drawn from that Republican subset and chosen to illustrate the recurring rhetorical move of treating border security as the remedy for an incoming epidemic. As in the newsletter data, the great majority of Ebola tweets discussed travel restrictions or screening without an immigration frame; the subset shown here is the content captured specifically by the immigration indicator.

I.1 Selected Tweets Linking Ebola to Immigration and Border Security

Table C1 reproduces representative tweets. Each row reports the candidate, state and party, the date, and the verbatim tweet text.

I.2 Discussion

The tweets exhibit the same core frame documented for newsletters in Appendix H: a West-African outbreak is recast as a U.S. border-control problem, often with an explicit causal claim that securing or "sealing" the border would stop the disease, and frequently paired with

Table C1: Representative Tweets Framing Ebola with Immigration and Border Security

Candidate (Party-State)	**Date**	**Tweet text**
Scott Brown (R-NH)	Oct 10	"ICYMI: In today's @ConMonitorNews, I renewed my call to secure the border to stop Ebola from spreading into the U.S."
Daniel Bongino (R-MD)	Oct 4	"The president is jumping through hoops to protect the 'rights' of illegal border crossers but won't act to protect us from #Ebola. Fair?"
Zach Dasher (R-LA)	Oct 16	"Solution for Ebola crisis: Close our borders. Stop inbound flights from infected countries. Fire the CDC head, Dr. Tom Frieden. #la05"
George Holding (R-NC)	Oct 17	"We need immediate action on the Ebola crisis: Secure our borders, restrict travel from affected nations, and work to find a cure. #ncpol"
David Williams (R-IL)	Oct 17	"To fix the #ebola issue all you got to do @BarackObama is secure the border & ban travel to West Africa. That simple"
Brian Babin (R-TX)	Oct 22	"Pres. Obama must stop the political correctness and protect the US by securing the border and stopping flights from Ebola infected countries"
James Hagedorn (R-MN)	Oct 29	"To protect America and Americans from Ebola, we need to quarantine the open borders policies of Obama-Walz on November 4th. #mn01 #mngop"
Rose Izzo (R-DE)	Oct 6	"*Warning* Reason to Seal the Borders Now! #Ebola scare in #Dover #Delaware"
Rose Izzo (R-DE)	Aug 3	"RT @realDonaldTrump: US must stop all flights from EBOLA infected countries or the plague will start & spread inside our borders >Act fast!" [retweet]

Notes: Tweets are reproduced verbatim from the candidate Twitter corpus; HTML entities have been decoded and URLs and trailing media links omitted for readability. All listed candidates are Republican, consistent with Appendix H. The final row is a retweet of a third party, labeled accordingly. Examples are illustrative of the immigration-linked content captured in columns 5–6 of Table 1, Panel A; they were selected for clarity, are not a random sample, and carry no implication about an individual candidate's motives.

criticism of the incumbent administration. The compressed Twitter format makes the fear appeal especially direct ("*Warning*", "Act fast!", "the plague will start"). Consistent with the weekly time series of immigration-linked Ebola tweeting in Figure 1, the examples cluster in October 2014 between the Dallas diagnosis and election day. The single pre-onset example (August 3) is a retweet calling for a halt to flights from Ebola-affected countries; it predates the first domestic case and echoes that summer's coverage of the West African outbreak rather than any contemporaneous border-crisis news cycle. As with the newsletter excerpts, these illustrations are descriptive: the causal claims of the paper rest on the differences-in-differences design of Section 4.2, not on any individual message.