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

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August 2026

Abstract

We study the supply of political communication highlighting perceived threats, using the 2014 Ebola scare as a natural experiment. Analyzing Twitter posts and congressional newsletters from US House and Senate candidates, we find Republicans increased Ebola-related communication, emphasizing negative sentiment and links to immigration. This response was strongest in safe Republican seats, consistent with base signaling. The supply side was active, not reactive: the Republican response did not vary with proximity to diagnosed cases despite concentrated voter anxiety, politician tweets predicted public Ebola activity but not vice-versa, and more intensive messaging correlated with better electoral outcomes, controlling for local conditions.

Keywords: political communication, electoral strategy, fear, anxiety, perceived threats, epidemics.

*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.

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"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. Candidates stand to gain from framing a salient threat in ways that align with their platform, and thereby activating voters' emotions. This prospect creates a strong incentive to exploit such threats strategically. The existence of fear-based political appeals is well-documented experimentally (Brader, 2005; Marcus, Neuman and MacKuen, 2000) and theorized extensively (Huddy, Feldman and Cassese, 2007).[2] What is less well understood is the supply side of this dynamic: which politicians choose to exploit it, why they do so, and how the content and framing of their communication varies with their electoral situation.

This paper investigates those questions using a natural experiment: the 2014 Ebola scare in the United States. 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). Campante, Depetris-Chauvin and Durante (2024) establish the demand-side consequences of this anxiety. Using the geographic variation in proximity to Ebola cases as an instrument for public anxiety, they show that Ebola concerns reduced the Democratic vote share and suppressed

[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`.

[2]We will use "fear" as shorthand for a range of emotions (fear, anxiety, disgust, anger) that can be triggered by politically salient threats. For an overview of the distinctions and overlap between them, see Brader and Marcus (2013).

turnout in the 2014 midterms, with voters expressing more anti-immigrant attitudes in the districts most exposed to the threat. Crucially, those demand-side effects are geographically concentrated: voter anxiety, and its electoral consequences, are strongest in the places closest to where Ebola cases were diagnosed.

We focus squarely on the supply side. Taking advantage of the plausible exogeneity of the timing and location of cases, 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.

We address these questions using panel data 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 (explicit linkage to 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 substantially increased their Ebola-related communication after the first U.S. case, while Democratic candidates did not. 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 – a doubling relative to the pre-onset baseline. The same pattern is evident in newsletters. The Republican response was specifically targeted: it featured elevated negative sentiment and a disproportionate tendency to link Ebola to immigration, the issue where Republicans had a clear competitive advantage and where Ebola anxiety actually moved voter attitudes

(Campante, Depetris-Chauvin and Durante, 2024).

We then turn to the role of electoral incentives in shaping politicians' response. We find that among Republicans (and especially on Twitter), the intensity of the response was strongest for candidates in the safest seats rather than those in competitive races. This suggests that the communication effort was driven not by an attempt at persuading swing voters, but rather by politicians signaling to their own base – presumably motivated by career concerns regarding future primary races, and more broadly, their prospects within the Republican coalition.

We next disentangle supply from demand drivers in the response of politicians 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. 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.

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. Finally, we find that, when comparing candidates within the same race or local media market (and hence controlling for demand characteristics), those with more intensive Ebola messaging obtained more votes in the election. Since the communication strategy around Ebola is evidently endogenous, we cannot make causal statements about its effectiveness; still, the correlational pattern suggests that it operated in ways that did not merely track the demand from constituents or the features of local media markets.

Taken together, our results establish that the Ebola threat was strategically exploited by Republicans, as they tried to raise the salience of the episode using a negative framing aligned to their preferred issues, such as immigration. This effort seems at least in part driven by base-signaling motives, as distinct to persuasion, and strategically deployed, as opposed to merely responding to voter sentiment.

Our paper contributes to several strands of literature. A rich experimental literature has documented that fear, anxiety and disgust shift political preferences and behavior in predictable ways (Brader, 2005; Jost et al., 2003; Thórisdóttir and Jost, 2011; Clifford and Jerit, 2018), 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, as discussed, Campante, Depetris-Chauvin and Durante (2024) show in the context of the 2014 Ebola shock that Republicans benefited electorally. We build on this work by examining the strategic production of fear-based political content in response to an exogenous anxiety shock. Closer to our setting, 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.[3] 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).[4] 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 incentives to signal to one's own base. This is consistent

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

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

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, 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). Our use of GPT-4o-mini for content coding also contributes to the growing literature on computational text analysis in political science (Grimmer and Stewart, 2013; Heseltine and Clemm von Hohenberg, 2024).

The remainder of this paper is organized as follows. Section 2 provides background on the Ebola episode and the 2014 elections, including a first descriptive look at the partisan communication patterns. Section 3 describes the data and empirical strategy. Section 4 reports the main results, and Section 5 examines robustness. Section 6 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 linked Ebola to immigration, separately for Republicans and Democrats, from August through three weeks after the election. The figure is striking in several respects. Until the week before the first U.S. case (week 40), neither party discussed Ebola to any meaningful degree. Immediately following 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. Upon the arrival of the election, the Republican signal collapses to near-zero, in a pattern evidently suggestive of strategic electoral behavior.

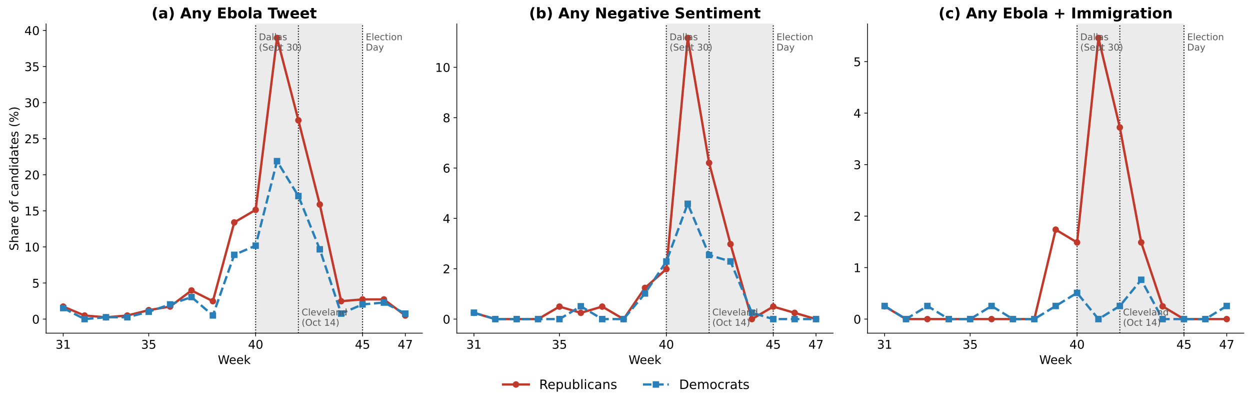

Figure 1: Weekly Ebola Communication by Party, August–November 2014

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). The shaded region covers the post-onset campaign period (weeks 40–45). Vertical dotted lines mark the first U.S. Ebola diagnosis in Dallas (week 40) and election day (week 45).

3 Data and Empirical Strategy

3.1 Data

3.1.1 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 (week 40, the week of September 30, 2014): the six weeks before the onset (weeks 34–39) and the six-week post-onset campaign period (weeks 40–45, running through election week). This covers 796 Republican and Democratic candidates with active Twitter accounts, each observed over all twelve weeks (9,552 candidate-weeks). 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 explicitly links Ebola to immigration or border-related themes. (Appendix A 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. 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 E reproduces a set of representative tweets that the GPT-4o-mini procedure flags as linking Ebola to 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. These excerpts are purely illustrative of the coded content and are not a representative sample.

3.1.2 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—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 D provides illustrative excerpts from the newsletter corpus, reproducing verbatim 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 E.

3.1.3 Electoral Competitiveness and Candidate Characteristics

We use data from the Cook Political Report (CPR), as of September 19, 2014—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.

3.1.4 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.

3.2 Empirical Strategy

We estimate the following differences-in-differences model:

$$Y_{p,t} = \alpha + \beta\,(\text{Post}_t \times \text{Republican}_p) + \delta_p + \lambda_t + \boldsymbol{\pi}' X_{p,t} + \varepsilon_{p,t}, \tag{1}$$

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 (from the week of the first U.S. Ebola case through the election). Republican_p is an indicator for the candidate's party affiliation. δ_p and λ_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.[5] 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. Given that virtually no candidates mentioned Ebola before week 40, this assumption is both plausible and testable in the pre-period.

To examine the role of geographic proximity, we augment equation (1) with the interaction:

$$\begin{aligned} Y_{p,t} = \alpha &+ \beta\,(\text{Post}_t \times \text{Republican}_p) + \gamma\,\text{Dist}_{p,t} + \rho\,(\text{Post}_t \times \text{Dist}_{p,t}) \\ &+ \mu\,(\text{Post}_t \times \text{Republican}_p \times \text{Dist}_{p,t}) + \delta_p + \lambda_t + \boldsymbol{\pi}' X_{p,t} + \varepsilon_{p,t}, \end{aligned} \tag{2}$$

[5] Because these controls are themselves measures of communication, they could in principle be affected by the Ebola response. Appendix C 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.

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 γ, 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 ρ captures whether Democratic candidates (the omitted category) respond more in proximate districts after the onset; μ captures the differential response by Republicans, so that the within-Republican distance gradient is $\rho+\mu$. 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 (1) 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 electoral position (far behind, competitive, far ahead). This design allows us to formally test the prediction of the standard persuasion account – that competitive races drive strategic communication more than safe seats – by comparing the cell estimates directly and testing whether the far-ahead and competitive cells are statistically distinguishable.

The validity of our design rests on three features. First, Ebola was essentially absent from domestic political discourse before September 30, 2014, so pre-trends are expected (and found) to be flat. 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, we observe a sharp collapse in Ebola-related communication around election day, consistent with strategic behavior and inconsistent with the hypothesis that Republicans simply cared more about the disease. Event-study estimates presented in Appendix

Figures A1-A8 validate these claims.

4 Results

4.1 The Republican Strategic Response

4.1.1 Main Results

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 a sample-period mean of approximately 2 percent for Democratic candidates. On the intensive margin, Republicans sent 0.32 additional Ebola-related tweets per week (column 2)—a doubling relative to the pre-onset baseline.

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 link Ebola explicitly to immigration (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.

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

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	0.059***	0.321***	0.018***	0.032***	0.017***	0.023***
	(0.013)	(0.063)	(0.006)	(0.011)	(0.004)	(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.	9,552	9,552	9,552	9,552	9,552	9,552
Panel B: Newsletters						
Post × Republican	0.076***	0.081***	0.072***	0.075***	0.014**	0.015***
	(0.013)	(0.014)	(0.011)	(0.012)	(0.006)	(0.006)
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 September 30, 2014). 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 linking Ebola to immigration. Controls include weekly and cumulative word count. Standard errors clustered at the race level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

reflects a genuine strategic decision rather than an idiosyncratic feature of any one medium.

4.1.2 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). Table 2 tests this prediction by interacting the post-onset Republican indicator with the continuous Cook electoral advantage score.

The key coefficient (Post × Republican × Advantage) is positive and statistically significant for both Twitter (columns 1–2) and newsletters (columns 3–4). This triple interaction measures the difference between the Republican and Democratic advantage gradients; the within-Republican gradient itself is the sum of the Post × Advantage and Post × Republican × Advantage coefficients, which we report (with delta-method standard errors) at the foot of the table. On Twitter this within-Republican gradient is 0.018 ($p < 0.01$) on the extensive margin and 0.083 ($p < 0.01$) tweets per week on the intensive margin: each one-unit increase in Republican electoral advantage (on the Cook 7-point scale) is associated with a further 1.8-percentage-point rise in the post-onset probability of Ebola tweeting. For newsletters the analogous within-Republican gradient is positive but smaller (0.007 on the extensive margin) and not statistically significant at conventional levels, even though the Republican–Democratic difference in slopes (the triple interaction, 0.022, $p < 0.05$) is itself significant—that is, Republicans' advantage gradient is distinguishable from the Democrats' (negative) gradient but not from zero on its own. Crucially, the direction is the opposite of what the persuasion story would predict: greater Republican advantage (i.e. a safer seat) is associated with a stronger Ebola response – though we note that electoral safety may proxy for other candidate or district attributes, so we read this gradient as consistent with, rather than dispositive of, a base-signaling mechanism.

Figure 2 further unpacks this pattern by plotting the predicted post-onset effects for six cells defined by party and electoral position (Republicans far behind, competitive, Republicans far ahead), separately for Twitter (panel a) and newsletters (panel b). (Democrats in competitive districts constitute the reference group.) Among Republicans, the estimated effect rises steeply from a statistically insignificant 3.1 percentage points for those far behind in safe Democratic seats, to 8.8 points for competitive Republicans, to 14.4 points for those far ahead in safe Republican seats. The Democratic cells show no comparable gradient: Democrats in competitive and solid-Republican districts are near zero, though Democrats in solid-Democratic districts do increase their Ebola communication on Twitter (8.2 percentage points, $p < 0.01$).

Again, we interpret this finding as consistent with a base-signaling logic. 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,

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***	0.106***	0.112***
	(0.012)	(0.055)	(0.025)	(0.027)
Post × Rep. × Advantage	0.028***	0.103***	0.022**	0.025**
	(0.005)	(0.021)	(0.009)	(0.010)
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***	0.007	0.009
	(0.004)	(0.019)	(0.007)	(0.007)
Candidate/Member FE	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Obs.	9,528	9,528	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). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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, for Republican politicians. Those running in heavily Democratic districts, in contrast, behave similarly to their opponents, possibly as they face a more moderate electorate even within their party.

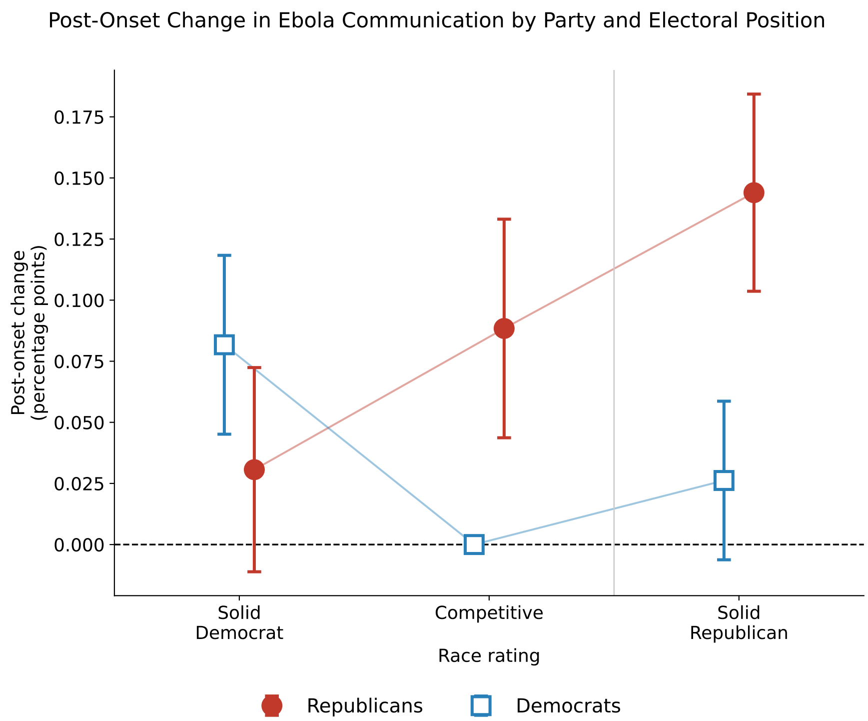

Figure 2: Post-Onset Change in Ebola Communication by Party and Electoral Position

Notes: Each dot shows the predicted post-onset change in the probability of an Ebola tweet for a given party-by-electoral-position cell, relative to competitive Democrats (the reference category, shown at zero without a confidence interval). Error bars are 95% confidence intervals. "Solid Democrat" = Republican advantage score of -3; "Solid Republican' = Republican advantage score of $+3$; "Competitive" comprises all intermediate ratings (scores -2 to $+2$, i.e. Likely and Lean seats and Toss Ups). Cell estimates are computed via the delta method from specifications with candidate and week fixed effects and controls as in Table 1.

4.2 Supply versus Demand

Having established that Republican candidates responded to the Ebola shock by increasing negative communication focused on the disease and linking it to immigration, we now ask how much of that response reflects supply rather than demand considerations. In other words: were politicians simply responding to the anxiety of their constituents, or were they instead taking the initiative in trying to fuel that anxiety?

To answer that question, we pursue three complementary approaches. First, we exploit how the response by politicians varied according to the distance to Ebola cases, which Campante, Depetris-Chauvin and Durante (2024) show predicts public anxiety. Second, 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. Finally, we study whether electoral outcomes vary with messaging, holding location, and hence demand conditions, fixed.

4.2.1 Did 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 3 reports estimates of equation (2), 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 × Distance coefficient is negative in both samples, statistically significantly so on Twitter (columns 1–2), though not in newsletters (columns 3–4). This indicates that Democrats' communication around Ebola 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 × Distance and Post × Republican × 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, the disproportionate Republican surge was essentially uniform across districts regardless of proximity.[6]

Table 3: Distance to Ebola Cases and the Strategic Response

	Twitter		Newsletters	
	(1) Any Ebola	(2) # Ebola	(3) Any Ebola	(4) # Ebola
Post × Republican	0.052***	0.301***	0.084***	0.090***
	(0.014)	(0.069)	(0.015)	(0.017)
Post × Rep. × Distance	0.011	0.071*	0.035**	0.039***
	(0.010)	(0.040)	(0.014)	(0.015)
Post × Distance	−0.031***	−0.157***	−0.023	−0.025
	(0.011)	(0.051)	(0.016)	(0.016)
Distance	0.017*	0.081*	0.002	0.003
	(0.010)	(0.046)	(0.015)	(0.015)
Republican distance gradient	−0.019	−0.085	0.012	0.015
	(0.013)	(0.068)	(0.016)	(0.017)
Candidate/Member FE	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Obs.	8,783	8,783	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). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

This null result 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. This

[6]Note that the Distance main coefficient, identified by the arrival of the later cases, is small and at most marginally significant, as well as positive. This indicates that the later cases did not occur near areas where politicians already happened to be communicating intensively about Ebola.

is consistent with a partisan supply-side strategy from Republicans, rather than a response to geographically concentrated demand.

4.2.2 Did Politician Behavior Follow Public Anxiety, or Vice Versa?

The distance null result in Section 4.2.1 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 Ebola activity to predict subsequent politician behavior. If instead politicians were actively trying to amplify the issue, their behavior should predict subsequent public activity.

The results are in Table 4, 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, Post-Onset $\times$ Politician Activity: 0.322^{***}). The same relationship holds for Google searches, a fully private behavior unaffected by partisan retweeting (column 4: 13.68^{***}). 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 prior-day public Ebola activity draws out Republican politician tweets. If anything the association runs the other way in the tweets column (column 3, Post-Onset $\times$ Public Activity: -2.81^{**}) and is statistically null for searches (column 6: 0.001); in neither case does public activity positively predict subsequent politician messaging.[7] Finally, the triple interaction between politician activity, the post-onset indicator, and (log) distance to the nearest case is negative and significant (column 1: -0.052^{***}; column 4: -1.97^{**}), indicating that Republican messaging predicts public anxiety more strongly in places already primed by 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 4.2.1, 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.

4.2.3 Ebola Communication and the Vote

We then turn to the electoral returns on the Ebola communication strategy: did more intensive messaging correlate with votes? We stop short of a causal claim, since a candidate's decision to tweet about Ebola is not randomly assigned, and better-positioned candidates may both campaign more actively and perform better at the polls. Our goal is to discern the imprint of the supply of Ebola messaging using specifications that hold fixed local conditions, and hence demand.

We link our candidate-level Twitter measures to district-level returns for the 2014 House elections.[8] For each candidate we compute the number of Ebola tweets sent before election

[7] The negative coefficient on the interaction Post-Onset $\times$ Distance may seem in tension with the result that distance does not predict behavior by Republican politicians, as in Table 3. 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.

[8] District-level vote returns are compiled from Dave Leip's Atlas of U.S. Elections; we match candidates

Table 4: Does Politician Behavior Predict Public Anxiety? (Daily DMA-Level Analysis)

	Public Ebola Tweets			Public Ebola Searches		
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable →	Public Tweets	Public Tweets	Rep. Politician Tweets	Public Searches	Public Searches	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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

day and an indicator for sending any such tweet, and relate these to the candidate's share of the district vote and, alternatively, to the log of their vote count. We deliberately focus on Twitter rather than newsletters here: official congressional e-newsletters can only be sent by sitting members, so a newsletter-based measure mechanically confounds messaging with incumbency, whereas tweeting is available to incumbents and challengers alike.

We use three complementary designs. The first augments the candidate-level regression with race (district) fixed effects and is estimated on the two major-party candidates in races contested by both parties. It thus compares a candidate to the specific opponent they faced, absorbing common factors within a race, such as district partisanship, turnout, competitiveness, and proximity to the diagnosed cases. The remaining within-race variation in the vote therefore cannot reflect differential exposure to the cases or other local characteristics, and instead reflect candidate characteristics and behavior, including their communication.

The second and third designs are meant to draw a different comparison: between Republican candidates with different levels of Ebola messaging within a given area. We do so by including state and DMA fixed effects, respectively. The advantage of the latter is that it narrows to a more specific geographical area, holding fixed the television news media environment. The downside is that it requires restricting attention to districts lying entirely within a single DMA, thus reducing the sample size. The specification with state fixed effects strikes a middle ground between these considerations. All three specifications control for the candidate's party vote share in the 2010 House election, as a measure of baseline local strength, and cluster standard errors by race, by state, and by DMA, respectively.

Table 5 reports the estimates, and the pattern is consistent across designs and outcomes. Within race (Panel A), a candidate who sent any Ebola tweet ran roughly 13.5 percentage points ahead of their opponent, and each additional Ebola tweet is associated with about 0.6 percentage points; in log votes, sending any Ebola tweet corresponds to about a third of a log point, on the order of 30 to 40 percent more votes.

to districts by state, district number, and party.

The within-Republican, within-state comparison (Panel B) yields the same broad patterns though with smaller magnitudes – about 6 percentage points on the extensive margin and a quarter of a point per tweet. This is to be expected, since the comparison is now between Republicans who messaged more and those who messaged less, rather than between a messaging Republican and a largely quiescent Democrat. Restricting the comparison to Republicans in the same media market (Panel C) leaves the extensive-margin return essentially intact at about 6 percentage points and, on log votes, even larger (roughly a third of a log point); the intensive margin, now estimated on just 130 candidates across 30 markets, stays positive but is no longer precisely estimated.

We read these results as suggestive rather than dispositive. The within-race, within-state, and within-market designs absorb a great deal of confounding variation, and the 2010 control further nets out persistent differences in local partisanship. Still, the estimates remain correlational, and part of the within-race magnitude reflects the national Republican tide of 2014, which the 2010 baseline cannot fully purge. With that caveat, the evidence is consistent with the strategic response from Republican politicians playing a role above and beyond local constituent demand for the Ebola framing.

5 Robustness

5.1 Pre-Trends and the Post-Election Collapse

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, re-centred on the pre-onset average (weeks 31–39). Figures A1–A8 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. The Republican differential emerges in week 41—the week after the

Table 5: 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)	13.502***		0.322***	
	(2.055)		(0.060)	
# Ebola tweets		0.564***		0.012***
		(0.182)		(0.004)
Party vote share, 2010	0.542***	0.594***	0.012***	0.014***
	(0.040)	(0.039)	(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	
	(2.230)		(0.111)	
# Ebola tweets		0.244**		0.005*
		(0.112)		(0.003)
Party vote share, 2010	0.560***	0.580***	0.017***	0.018***
	(0.083)	(0.083)	(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***	
	(2.455)		(0.095)	
# Ebola tweets		0.166		0.006
		(0.194)		(0.008)
Party vote share, 2010	0.558***	0.602***	0.019***	0.022***
	(0.071)	(0.066)	(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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

first Dallas case was confirmed on September 30 (week 40)—where it peaks; 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.

5.2 Which Case Drove the Supply-Side Response?

Our baseline specification defines Post_t as an indicator for the period following the first U.S. Ebola diagnosis (Dallas, September 30). However, the U.S. episode involved four distinct diagnoses of varying salience. Among these, the October 14 diagnosis of nurse Amber Vinson, who had flown commercially from Dallas to Cleveland days earlier, was particularly alarming, triggering contact-tracing across multiple cities and a second wave of public anxiety (Campante, Depetris-Chauvin and Durante, 2024). We assess the robustness of our results to this choice by estimating the baseline DiD separately around the three distinct case locations, using $\pm$3-week windows about each onset—Dallas in week 40, Cleveland (Vinson's travel) in week 42, and New York (the October 23 diagnosis of Craig Spencer) in week 43, so that the Cleveland and New York onsets fall in adjacent weeks rather than the same week—following the approach of Campante, Depetris-Chauvin and Durante (2024).

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 9.4 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 collapse in communication: because the Cleveland and NYC windows extend to weeks 45–46 (election day and after), we re-estimate each window ending at the last pre-election week (week 44), and the pattern is essentially unchanged (for any Ebola tweet, Cleveland -0.050 and NYC -0.097, 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.

5.3 Alternative Competitiveness Measures

Our advantage measure is derived from the Cook race ratings as of September 19, 2014, before the first Ebola case, which minimizes the risk of reverse causality. We verify that our results are stable when restricting the sample to candidates active on Twitter throughout the August–November period, and that the three-way breakdown in Figure 2 is not sensitive to the specific thresholds used to define "far behind," "competitive," and "far ahead."

Beyond robustness, we also provide a more formal test of the base-versus-persuasion distinction. The standard competitive-races account predicts that the Post × Republican × Advantage interaction in Table 2 should be negative – greater electoral safety reducing the incentive to deploy a fear-based frame. Our estimates show the opposite sign. To quantify this, we test the null hypothesis that the effect for Republicans far ahead in their races equals the effect for competitive Republicans, using the cell estimates underlying Figure 2 and the delta method. For Twitter, the difference between the far-ahead and competitive cells is 5.6 percentage points ($0.144 - 0.088 = 0.056$), which is statistically significant ($p < 0.05$). For

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	0.094***	−0.062***	−0.105***
	(0.022)	(0.019)	(0.022)
Any neg. sentiment	0.038***	−0.020**	−0.035***
	(0.011)	(0.009)	(0.011)
Any Ebola + Immig.	0.028***	−0.024***	−0.033***
	(0.007)	(0.007)	(0.007)
Panel B: Intensive margin (count)			
No. Ebola tweets	0.580***	−0.444***	−0.637***
	(0.115)	(0.098)	(0.125)
No. neg. sentiment	0.064***	−0.059***	−0.067***
	(0.022)	(0.022)	(0.020)
No. Ebola + Immig.	0.035***	−0.034***	−0.045***
	(0.009)	(0.012)	(0.011)
Candidate FE	Yes	Yes	Yes
Week FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	4,776	4,776	4,776
Clusters	460	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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

newsletters the point estimates order in the same direction, but the far-ahead − competitive difference is not statistically significant at conventional levels, mirroring the weaker within-Republican gradient in the newsletter columns of Table 2. The Twitter evidence thus rejects the prediction of the standard persuasion account in favor of a base-signaling interpretation, with the newsletter estimates pointing the same way more tentatively.

5.4 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—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 A9–A12 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.

6 Conclusion

This paper studies the supply of fear-based political communication using the 2014 Ebola scare as a natural experiment. 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 linking the disease to immigration. Democratic candidates displayed no analogous response.

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-signaling motive: 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 trying to fuel it? Three 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. Third, Republican candidates who tweeted more intensively about Ebola performed better at the polls within the same race, within the same state, and within the same media market – designs that absorb local demand conditions. While we stop short of a causal claim regarding the effects of communication strategies, the pattern suggests they operated above and beyond what local constituent anxiety can explain.

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 highlight a threat 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.

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Online Appendix

A Classification of Tweets and Newsletters

A.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*.

A.2 Data Description

Table A1: 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

A.3 Classification Methodology

A.3.1 Prompt Design & Categories

We designed and applied four prompts as summarized in Table A2. Each prompt employed function-calling to enforce a structured JSON response compatible with downstream processing.

A.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`

Table A2: Prompt design and categories evaluated.

Prompt	Dataset	Categories evaluated
Topics	Twitter	Immigration, Republican-favorable topics, Democrat-favorable topics
Emotions & Ebola	Twitter	Negative sentiment, Ebola
Topics	Newsletters	Same as first row
Emotions & Ebola	Newsletters	Same as second row

- **Storage:** responses stored in separate columns.

Classification was carried out through the API using batch processing.

A.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.

A.4 Results: Category Totals

Table A3 reports the number of records assigned to each category in each dataset.

Table A3: 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

A.5 Prompts Used

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:
```

B Event-Study Estimates

The figures in this appendix display event-study estimates of equation (1). 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 A1–A4 cover the Twitter sample; Figures A5–A8 cover the newsletter sample.

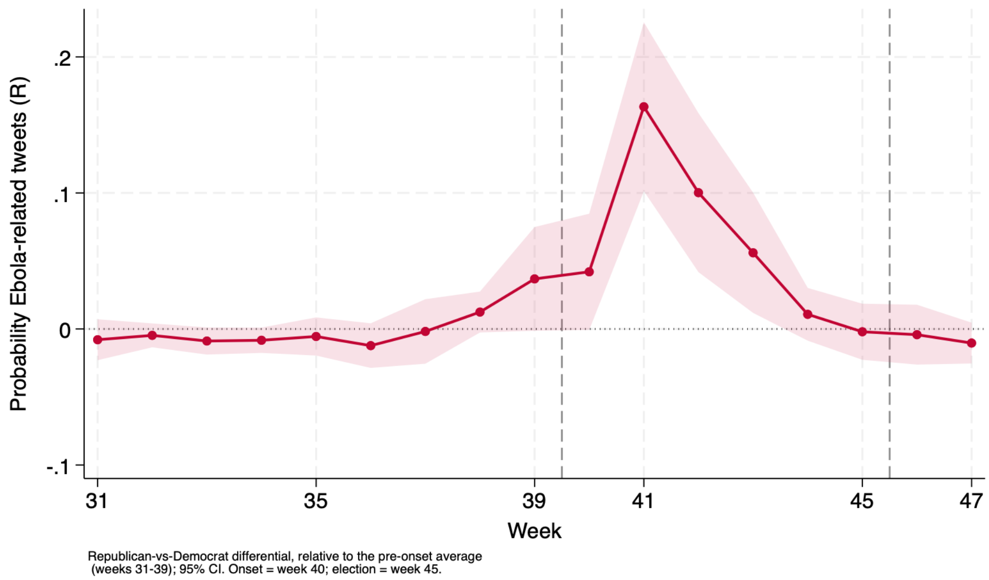

Figure A1: Event Study: Probability of Any Ebola Tweet (Twitter)

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.

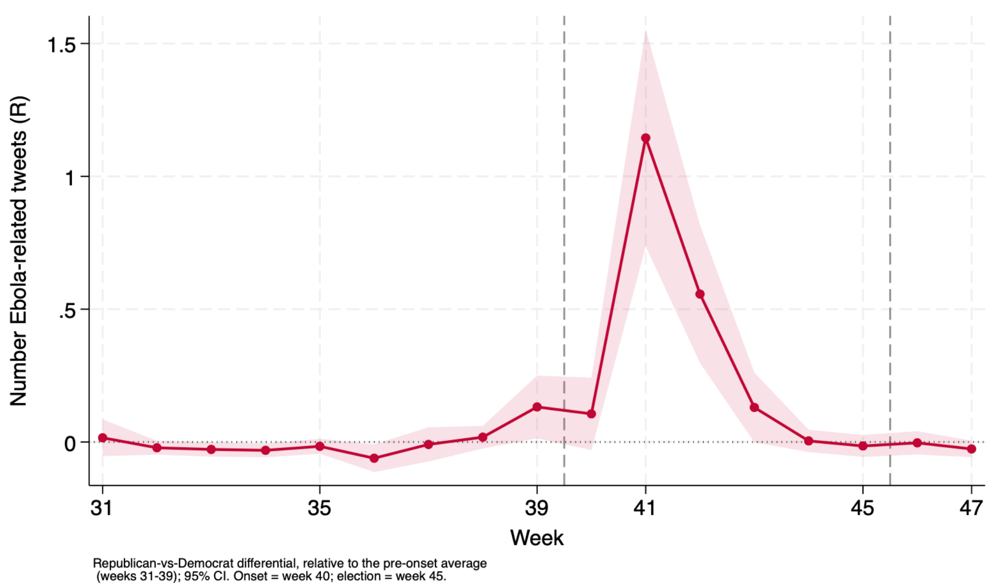

Figure A2: Event Study: Number of Ebola Tweets (Twitter)

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 A1.

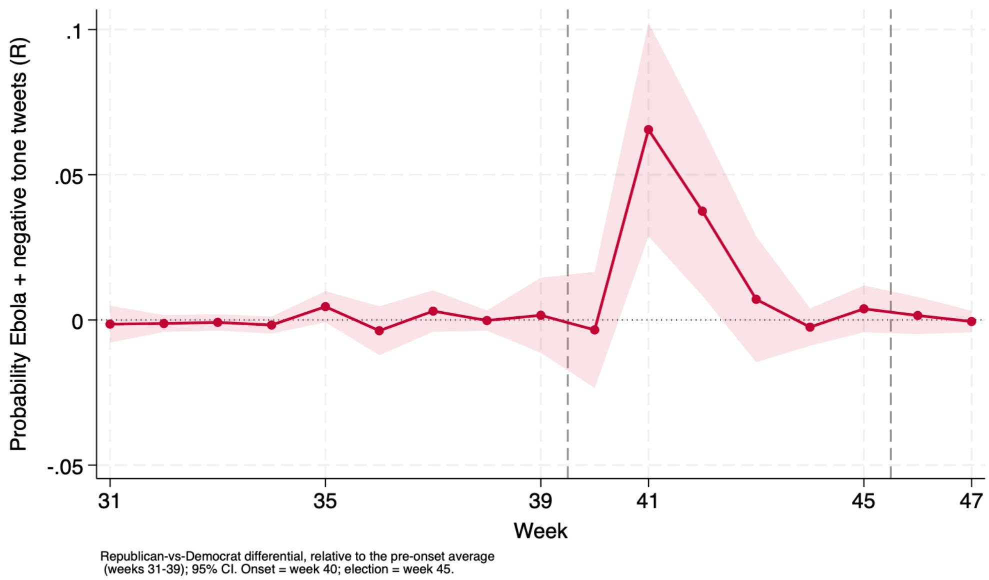

Figure A3: Event Study: Probability of Any Ebola Tweet with Negative Sentiment (Twitter)

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 A1.

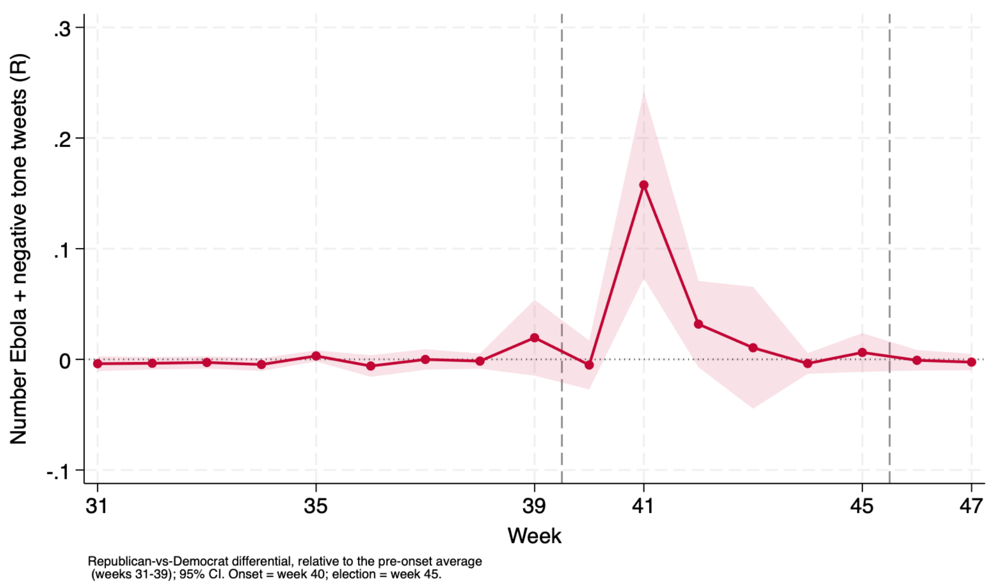

Figure A4: Event Study: Number of Ebola Tweets with Negative Sentiment (Twitter)

Notes: Week-by-week DiD coefficients for the count of Ebola tweets with negative sentiment. Specification as in Figure A1.

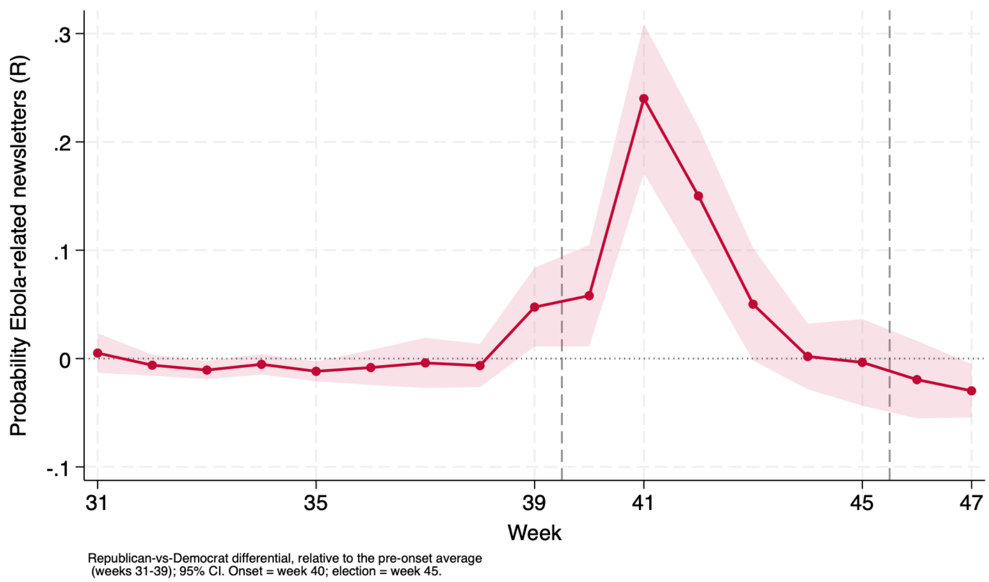

Figure A5: Event Study: Probability of Any Ebola Newsletter (Newsletters)

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.

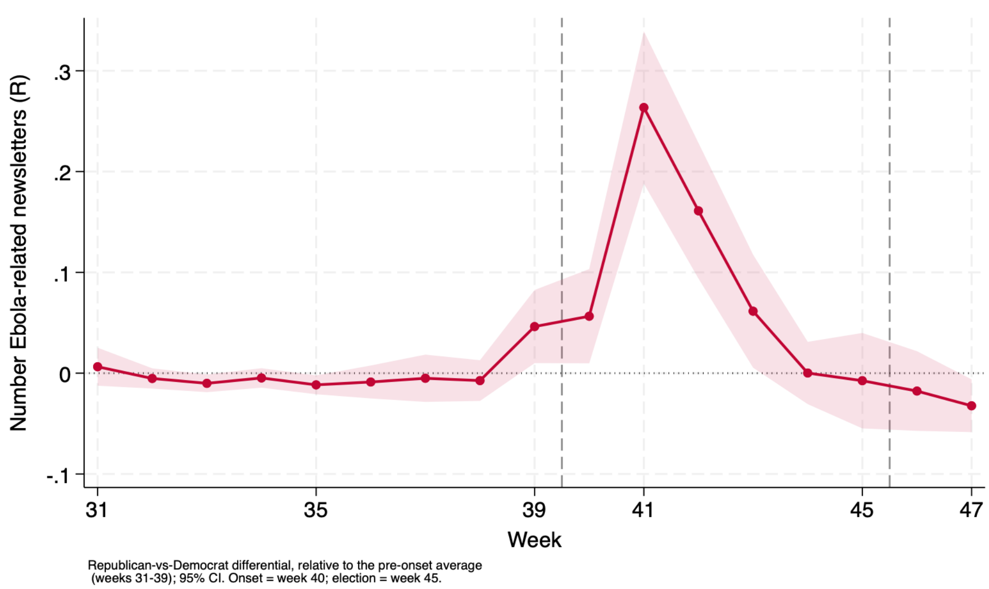

Figure A6: Event Study: Number of Ebola Newsletters (Newsletters)

Notes: Week-by-week DiD coefficients for the count of Ebola-related newsletters sent by Republican members relative to Democrats. Specification as in Figure A5.

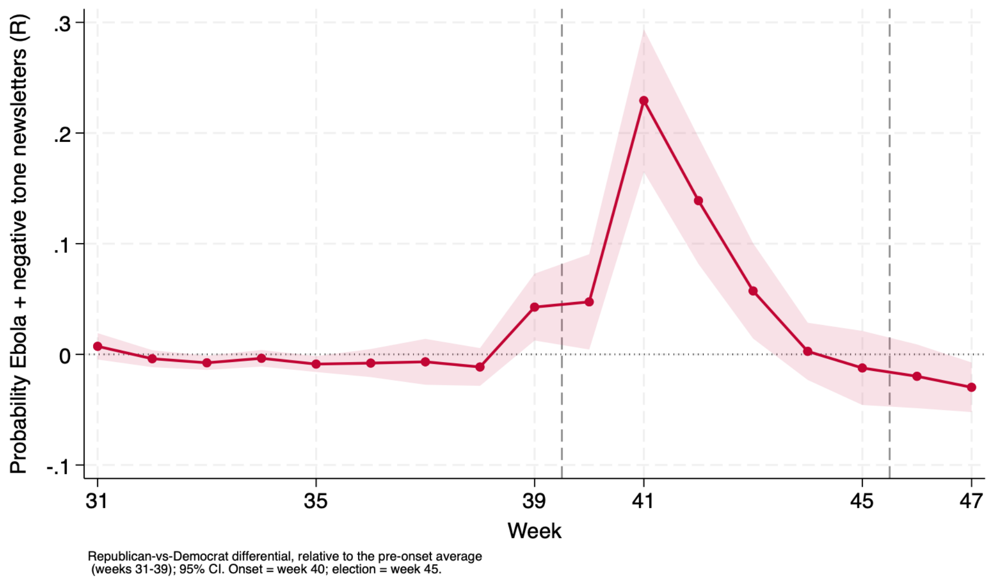

Figure A7: Event Study: Probability of Any Ebola Newsletter with Negative Sentiment (Newsletters)

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 A5.

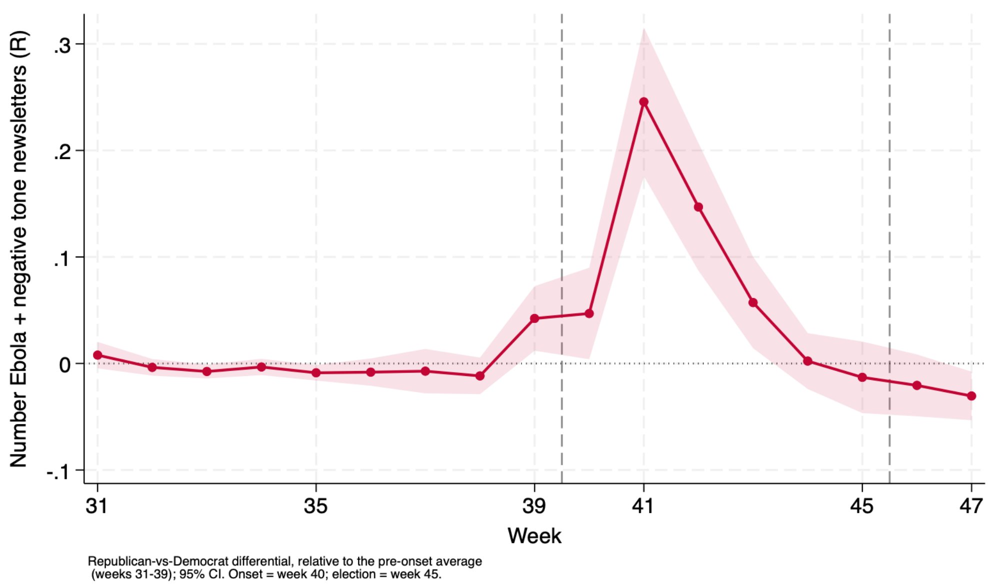

Figure A8: Event Study: Number of Ebola Newsletters with Negative Sentiment (Newsletters)

Notes: Week-by-week DiD coefficients for the count of Ebola newsletters with negative sentiment. Specification as in Figure A5.

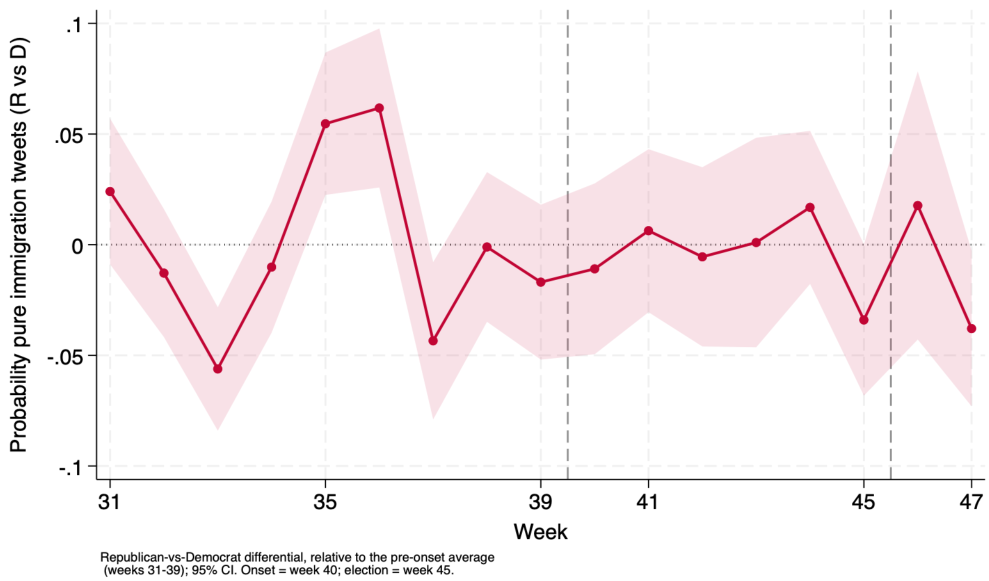

Figure A9: Event Study: Probability of Any Pure Immigration Tweet (Twitter)

Notes: Week-by-week DiD coefficients for the probability of a pure immigration tweet—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 A1.

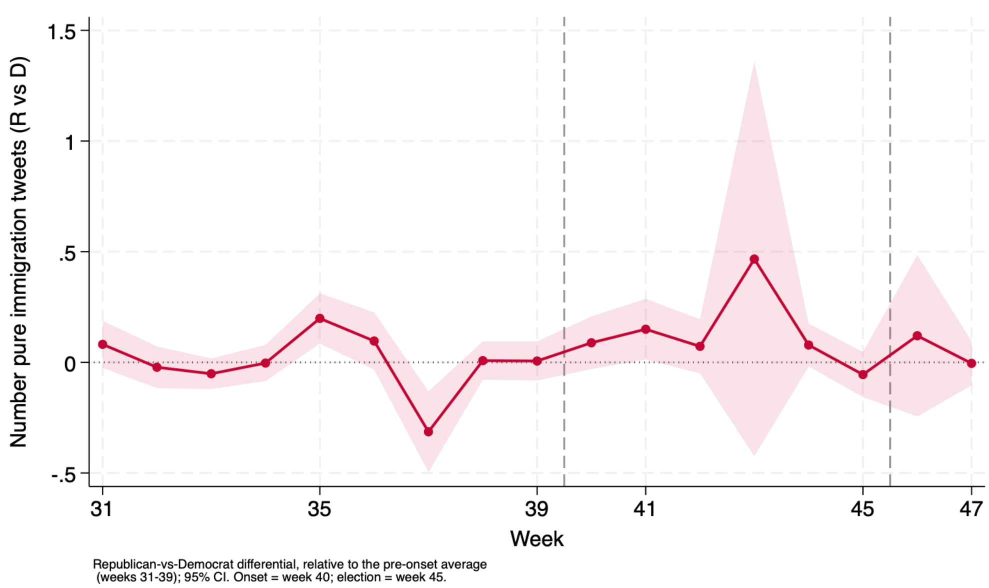

Figure A10: Event Study: Number of Pure Immigration Tweets (Twitter)

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 A1.

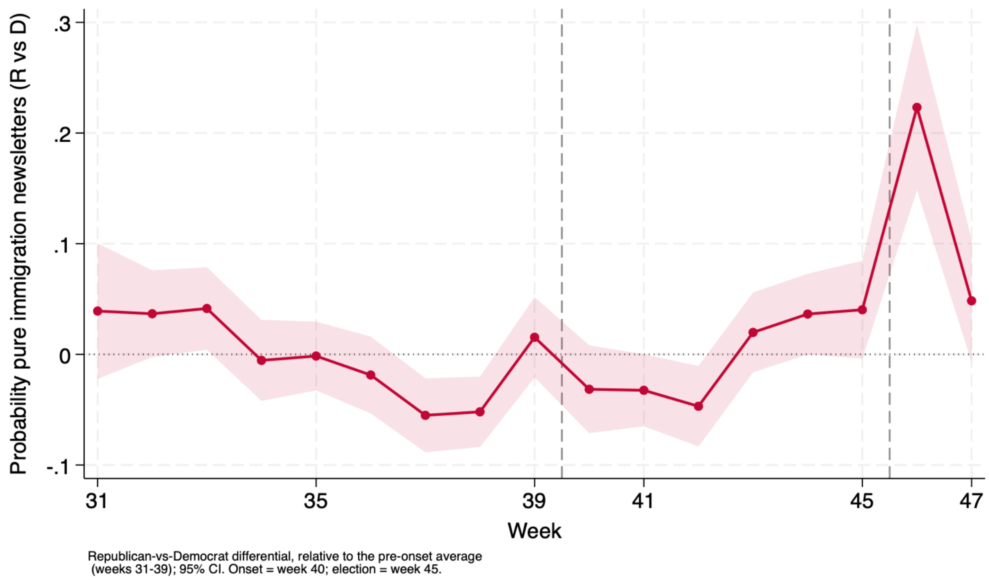

Figure A11: Event Study: Probability of Any Pure Immigration Newsletter (Newsletters)

Notes: Week-by-week DiD coefficients for the probability of a pure immigration newsletter—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 A5.

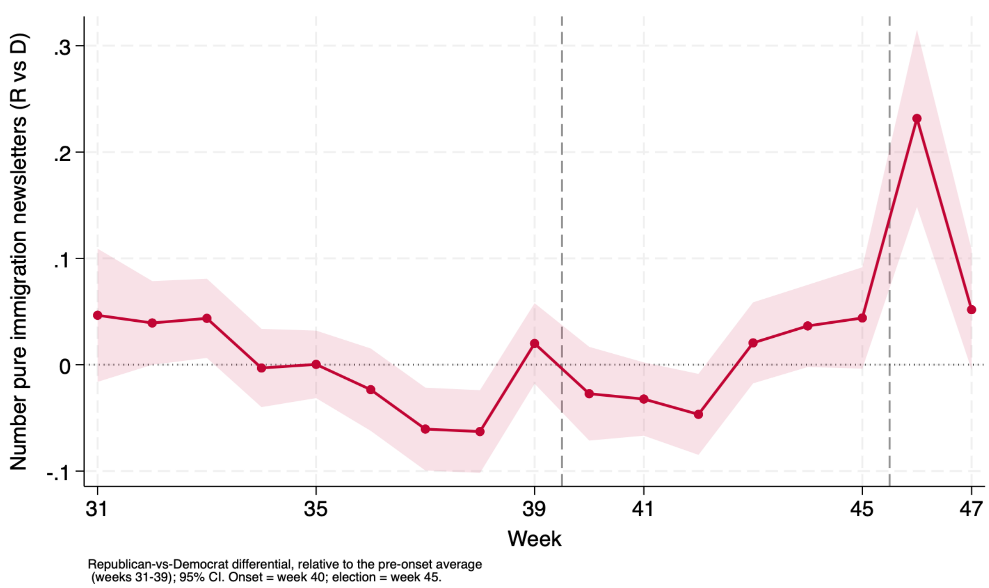

Figure A12: Event Study: Number of Pure Immigration Newsletters (Newsletters)

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 A5.

C 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 A4–A6 re-estimate Tables 1, 2, and 3 dropping these controls. The coefficients of interest are essentially unchanged: the main Republican response (Table A4) moves by at most a few percent on Twitter and is, if anything, slightly larger for newsletters; the electoral-advantage gradient (Table A5) and the distance terms (Table A6) are likewise stable. The headline results are therefore not artifacts of conditioning on communication volume.

Table A4: 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	0.056***	0.307***	0.017***	0.030***	0.016***	0.022***
	(0.013)	(0.062)	(0.006)	(0.011)	(0.004)	(0.005)
Obs.	9,552	9,552	9,552	9,552	9,552	9,552
Panel B: Newsletters						
Post × Republican	0.083***	0.091***	0.079***	0.083***	0.016***	0.017***
	(0.014)	(0.016)	(0.012)	(0.013)	(0.005)	(0.006)
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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

D 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 3) identifies. The

Table A5: Electoral Advantage, *Excluding* Communication Controls

	Twitter		Newsletters	
	(1) Any Ebola	(2) # Ebola	(3) Any Ebola	(4) # Ebola
Post × Republican	0.054***	0.280***	0.080***	0.085***
	(0.012)	(0.055)	(0.022)	(0.023)
Post × Rep. × Advantage	0.027***	0.099***	0.018**	0.021**
	(0.005)	(0.021)	(0.009)	(0.010)
Post × Advantage	−0.011***	−0.022**	−0.006	−0.007
	(0.003)	(0.009)	(0.005)	(0.005)
Republican advantage gradient	0.017***	0.077***	0.012	0.014*
	(0.004)	(0.019)	(0.008)	(0.008)
Obs.	9,528	9,528	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 A6: 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***	0.091***	0.100***
	(0.014)	(0.069)	(0.016)	(0.018)
Post × Rep. × Distance	0.011	0.067*	0.032**	0.036**
	(0.010)	(0.040)	(0.015)	(0.015)
Post × Distance	−0.027**	−0.138***	−0.020	−0.021
	(0.012)	(0.053)	(0.016)	(0.017)
Distance	0.013	0.060	0.001	0.002
	(0.010)	(0.048)	(0.015)	(0.016)
Republican distance gradient	−0.016	−0.071	0.012	0.016
	(0.013)	(0.070)	(0.018)	(0.018)
Obs.	8,783	8,783	4,896	4,896

Notes: As Table 3, 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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).

D.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.

D.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,

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 3 flags as linking Ebola to 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.

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 5 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 A1–A8), every excerpt falls between the Dallas diagnosis and election day. The near-instantaneous collapse of this content after November 4—documented in the main text and visible in the post-election coefficients of the event studies—is what distinguishes a campaign-period communication strategy from 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 3.2.

E Illustrative Examples from Candidate Tweets

This appendix mirrors Appendix D 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—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.

E.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.

E.2 Discussion

The tweets exhibit the same core frame documented for newsletters in Appendix D: 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 D. 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 3.2, not on any individual message.