The Virus of Fear:

The Political Impact of Ebola in the U.S.*

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Abstract

We study how fear can affect the behavior of voters and politicians by looking at the Ebola scare that hit the U.S. a month before the 2014 midterm elections. Exploiting the timing and location of the four cases diagnosed in the U.S., we show that heightened concern about Ebola, as measured by online activity, led to a lower vote share for the Democrats in congressional and gubernatorial elections, as well as lower turnout, despite no evidence of a general anti-incumbent effect (including on President Obama's approval ratings). We then show that politicians responded to the Ebola scare by mentioning the disease in connection with immigration, terrorism, and President Obama in newsletters, tweets and campaign ads. This response came only from Republicans, especially those facing competitive races, suggesting a strategic use of the issue in conjunction with topics perceived as favorable to them. Survey evidence suggests that voters responded with increasingly conservative attitudes on immigration but not on other ideologically-charged issues. Taken together, our findings indicate that emotional reactions associated with fear can have a strong electoral impact, that politicians perceive and act strategically in response to this, and that the process is mediated by issues that can be plausibly associated with the specific fear-triggering factor.

Keywords: Fear, Emotions, Elections, Immigration, Ebola.

JEL codes: D72, D91

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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

Emotions are widely recognized, both by practitioners and scholars, as a powerful force conditioning voter behavior.[2] Among those emotions, fear stands out as a particularly potent one. The idea that one can mobilize voters around perceived threats – from crime, conflict, terrorism, diseases, and often from people (e.g. immigrants or ethnic minorities) seen as associated with those threats – is a staple of political campaigns and discourse in many different contexts. At the same time, it is often difficult to isolate the impact of "fear itself" – that is, the emotional response – from policy judgments. Are voters indeed changing their behavior as a result of fear, or is the latter simply correlated with policy or ideological views that ultimately guide behavior?[3] If it indeed has an impact, is the strategic exploitation of fear by politicians a channel through which that takes place?

To help answer these questions, we exploit a natural experiment that affected perceptions of threat, while arguably having a negligible impact on the actual risk environment: the Ebola scare episode, as experienced in the US, in the fall of 2014. While the 2014 Ebola outbreak in West Africa was then the largest and most complex since the virus was first discovered in 1976 (WHO, 2017), it was well-understood by public health experts at the time that the likelihood of an outbreak of the disease in the U.S. was extremely low. Still, the episode triggered substantial fear and anxiety in the country, given the gruesome nature of the disease, its associated fatality risk, and the absence of effective prevention or treatment at the time.

The Ebola scare is particularly interesting because it took place during campaign season, on the weeks before the 2014 midterm elections, in which all U.S. House seats, as well as a number of U.S. Senate seats, and state- and local-level positions, were being chosen. Ebola was a prominent topic of media coverage at the time, and the idea that the episode was strategically used and had a political impact in favor of Republicans in those elections has often been mentioned in media reports (e.g. Gertz and Savillo (2014); Yglesias (2018)).[4]

This paper shows causal evidence that Ebola concerns indeed had a significant effect in worsening

[1] The quote is an extract from a televised debate held on October 7, 2014. The video of the debate is available at `https://www.c-span.org/video/?c4510790/user-clip-tillis-ebola&start=1567`.

[2] See for instance Brader (2005), and references therein.

[3] Research in political psychology has documented that threat is associated with political conservatism (e.g. Jost et al. (2003), Thórisdóttir and Jost (2011)), but this has typically been done in a lab via experimental manipulation, leaving open the question of to what extent this translates into practice in the context of an actual campaign with real stakes.

[4] In fact, studies have shown correlational evidence that voter intentions moved towards Republicans in places with more intense concerns about the disease (Beall et al., 2016) and that Republican candidates were more likely to raise the Ebola issue during the campaign (Cormack, 2014), as well as experimental evidence that partisan mentions of the topic were associated with more negative attitudes towards immigrants (Adida et al., 2018).

the electoral performance of Democrats in the 2014 midterm elections. Moreover, it shows that this did not happen because of a general anti-incumbent impact, whereby the perceived crisis may have, for instance, affected the perception of effectiveness of President Obama, either rationally or through misattribution. Instead, the effect seems associated with the strategic use of the crisis by Republicans, who mentioned Ebola in connection with topics typically perceived to be favorable to them. The response of voters in terms of reported attitudes, however, was only present when it comes to anti-immigrant sentiment, suggesting that not all of the attempted associations actually stuck with voters.

Our research design exploits the timing and geographical variation in the salience of the Ebola threat perception. Specifically, between September and October 2014, there were precisely four diagnosed cases of Ebola on U.S. soil. First, a Liberian national visiting the U.S. was diagnosed in Dallas, TX (September 30); then it was two nurses who had treated that patient, one of whom had then traveled to Akron, OH (October 14); and finally, an American doctor returning from Guinea was diagnosed in New York, NY (October 23). We show that distance to these places strongly predicts Ebola concerns, as captured by web searches and social media (Twitter) activity, with the timing consistent with the emergence of the cases, while not systematically associated with previous electoral patterns. This allows us to instrument Ebola concerns with the distance to the closest Ebola location, controlling for those previous patterns as well as a number of demographic characteristics.

We find that a one-standard-deviation increase in Ebola concerns, as expressed in tweets or searches, induced a lower Democratic vote share, by just over four percentage points in the House, and three and four percentage points in Senate and gubernatorial elections, respectively. This corresponds to just over 1/7 of the average margin of victory in House elections. Alternatively, 40 House races would have been swung by such a change – fifteen of which won by Republicans. Flipping those seats would have erased Republican majority gains between 2012 and 2014. It also depressed turnout, with a one-standard-deviation increase in Ebola searches associated with a drop of about 1.6 percentage points. Interestingly, the 2014 midterm elections registered the lowest turnout (36.7%) since 1942, and the effect corresponds to about one third of the drop relative to the preceding midterms in 2010 (40.8%) (McDonald, 2010).

In contrast, we find a precisely estimated zero response of presidential approval ratings, as measured by daily Gallup polls, to the timing of and distance to Ebola-related events, as well as no evidence of Republican incumbents being punished. This suggests that the electoral impact did not come from changes in the perception of incumbents and their performance in dealing with the threat of the disease.

We then look at the strategic response by politicians, using data on newsletters sent by members of Congress to their constituents (Cormack, 2017), and on tweets and TV campaign advertisement by candidates. We find that Republican members are more likely to mention Ebola and to appeal to fear-based content after the emergence of the U.S. cases. They do so in conjunction with mentions to Obama, and with traditionally Republican issues, such as immigration and terrorism, that can be associated with threats. Interestingly, Democrats did not respond by trying to tie Ebola to topics of their own: if anything, Republicans were also more likely to mention it in conjunction with healthcare, in an election where the latter was one of the key issues. By the same token, we find no evidence that

Republicans tried to link Ebola to other ideologically charged issues, such as guns, that can hardly be associated with the disease. We also show that the candidates that respond more strongly are those who are involved in races classified as competitive (as of before the Ebola episode), further establishing the strategic motives behind the increased mentions.

Last but not least, we look directly at the attitudes reported by voters, using data from the Cooperative Congressional Election Study (CCES).

We find that, compared to respondents interviewed in 2013, individuals more exposed to Ebola in 2014 (again, instrumenting exposure with geographical proximity) tend to display more negative attitudes towards immigrants.[5] We do not find, however, any evidence of an impact of Ebola concerns on other attitudes typically associated with conservatives in the context of the US, such as pro-gun rights or opposed to same-sex marriage, nor on self-reported conservatism.

In sum, we show evidence of fear being strategically exploited and having a meaningful impact on an actual election. The effect of fear is mediated by issues that can be plausibly associated with the specific fear-triggering factor, at least in the mind of the public, as opposed to a general move towards more conservative attitudes, or to the threat being blamed on an incumbent. This finding could certainly depend on the characteristics of the specific threat in question – for instance, the coronavirus (Covid-19) episode of 2019-20 has meaningfully affected the public health risk environment around the globe, and, as such, might have a different impact in terms of how voters evaluate the performance of incumbents. Yet, our findings suggest that the strategic possibilities available to politicians are constrained by the associations that can be plausibly drawn by voters: they must be able to establish a connection between the threat and a topic that favors them in the minds of voters.[6,7]

Our paper relates to several strands of literature. A number of papers have studied the political impact of threats such as terrorism in actual elections (Montalvo, 2011; Getmansky and Zeitzoff, 2014). Our context exploits a perceived threat that is not political in nature, and documents the strategic behavior of politicians in exploiting that perceived threat. Others have looked experimentally at the impact of emotions on political behavior (Jost et al., 2003; Brader, 2005; Thórisdóttir and Jost, 2011) or at correlations between emotions such as fear and disgust and conservative ideological views (Inbar et al., 2012; Shook et al., 2017). We show the causal impact of these emotional reactions in an actual election, and that this impact is not necessarily associated with more conservative attitudes in general.[8] A separate strand looks at the impact on incumbents of shocks unrelated to their actual performance, such as lottery winnings (Bagues and Esteve-Volart, 2016) or the death of a spouse (Liberini et al., 2017).[9] Our results very much differ, as we find no evidence of the evaluation of incumbents being

[5] This is consistent with the experimental findings in Adida et al. (2018).

[6] Note also that our empirical setting does not allow us to distinguish between the effect of the initial fear-triggering shock – in this case, the Ebola infection cases – and that of its strategic exploitation by politicians. One should interpret our results as identifying the causal impact of a fear shock that is in fact exploited by politicians.

[7] This is consistent with President Trump's habit of referring to the novel coronavirus associated with Covid-19 as the "China virus," or variants of that term.

[8] Bisbee and Honig (2020) show that localities with more early cases of Covid-19 tended to vote more conservative in the Democratic primary in 2020 (for Joe Biden over Bernie Sanders), consistent with a "flight to safety" but not necessarily associated with more conservative ideology.

[9] This general idea goes back to a longstanding debate in the literature on the effect of "shark attacks," starting from Achen and Bartels (2004). For a survey, see Healy and Malhotra (2013), as well as the discussions in Fowler and Hall (2018) and Achen and Bartels (2018).

affected, or of incumbents being generally punished.

Last but not least, we relate to the contributions that have studied the social, economic, and political effects of the Ebola crisis of 2014 (Beall et al., 2016; Adida et al., 2018; Maffioli, 2018; Kostova et al., 2019; Gonzalez-Torres and Esposito, 2017; Flückiger et al., 2019; Bandiera et al., 2019). To the best of our knowledge, our paper is the first to study the causal electoral impact of that crisis in a country largely unaffected by that outbreak, from an epidemiological perspective.

The remainder of the paper is organized as follows: Section 2 outlines the context and background of the Ebola crisis and the 2014 midterm elections, and Sections 3 and 4 present the data and empirical strategy, respectively. Section 5 discusses the results on voting and presidential approval ratings, and Section 6 examines the politicians' strategic response. Section 7 considers the impact on reported attitudes. Section 8 concludes.

2 Background

2.1 Ebola outbreak

The 2014-15 Ebola outbreak, the largest ever recorded for this virus, can be traced back to December 2013 when in a village in rural Guinea a 18-month boy suffered a bat-related infection. Following several additional cases, and after the disease reached the capital city Conakry, on March 13, 2014 the Guinea's Ministry of Health issued an official alert about an unidentified pathogen which would later be confirmed to be Ebola. Over the following months, the epidemic grew exponentially expanding to the rest of Guinea, Liberia and Sierra Leone. On August 8, the World Health Organization (WHO) declared the outbreak an international public health emergency (WHO, 2014). The vast majority of the Ebola-related deaths recorded worldwide were in Guinea (2,543), Liberia (4,809), and Sierra Leone (3,956 deaths). Yet, over the following months the virus spread to various other countries - including Italy, Mali, Nigeria, Senegal, Spain, and the UK - where, however, the death toll was much lower (i.e., between 3 and 20) (CDCP, 2019).

The first case of Ebola in the U.S. was confirmed on September 30, 2014 when the Centers for Disease Control and Prevention (CDC) announced that Thomas Eric Duncan, a Liberian national visiting the United States from Liberia, had been diagnosed in Dallas, Texas. Following an initial misdiagnosis, Duncan's conditions quickly deteriorated until he died on October 8. Two nurses that had assisted Duncan were later diagnosed with Ebola: Nina Pham, confirmed on October 11, and Amber Joy Vinson, confirmed on October 14. Vinson's case was particularly alarming since days before being diagnosed she had flown from Dallas to Cleveland, Ohio and visited her family in Akron, Ohio. Both nurses were declared Ebola free after a few days. The fourth case was diagnosed in New York city on October 23 and concerned Dr. Craig Spencer a physician who had just returned to the U.S. from working with Doctors Without Borders in Guinea. Dr. Spencer was declared Ebola free and released on November 11 (Bell et al., 2016).[10]

Despite the limited number of cases, the presence of Ebola in the U.S. caused a major public

[10]Seven additional people, mostly medical workers, became ill while in West Africa but were transported and cared for in the US. Six of them made full recovery, one passed away.

reaction. The issue rapidly attracted massive news coverage. In the five weeks following the first case, over 3,000 news segments mentioning Ebola were aired on the top five cable TV networks alone.[11] Indeed, according to a report by the Pew Research Center,[12] the Ebola outbreak generated more news interest than any previous public health crisis (including SARS, swine flu, and anthrax), and was comparable to some of the most important stories featured on U.S. media since 2010, such as the killing of Osama Bin Laden and Hurricane Sandy (Motel, 2014). Media coverage of the Ebola outbreak was criticized by many as excessively alarmist and even hysterical (Ihekweazu, 2017; Kelly et al., 2015).

Popular concern about the possible spread of the virus also raised rapidly. Polls conducted in late October indicated that 36% of Americans were worried or very worried that they or their family members might be exposed to the virus (SteelFisher et al., 2015), and that a staggering 16% perceived the probability of contracting the virus within six months to be above 10% (Carman et al., 2015). Furthermore, when asked to identify the most urgent health problem affecting the nation, respondents would rank Ebola above other diseases such as obesity, cancer, and diabetes, which are three of the main causes of death in the U.S. (SteelFisher et al., 2015). Fear of contagion was fueled by widespread misinformation about the way the disease spreads. Indeed, according to another poll, 85% of Americans believed that Ebola could be transmitted through sneezing or coughing and 48% that asymptomatic carriers could be contagious (SteelFisher et al., 2015), both claims with no scientific base.

2.2 The 2014 U.S. midterm elections

The 2014 elections were held on Tuesday November 4, 2014, halfway through Barack Obama's second presidential term. American voters were called to elect 435 House representatives, 36 senators in 36 states (including three special elections), and the governors of 36 states and three territories. According to data from the United States Elections Projects, nationwide turnout – computed as the ratio of total ballots cast to eligible voters – was 36.7%. This was about five percentage points lower than the previous midterm elections held in 2010, and arguably the lowest since 1942.[13] The 2014 election resulted in a large victory for the Republican party. In the House elections, Republicans won 247 seats (a net gain of 13 seats) against 188 for the Democrats, winning the popular vote by almost 6 percentage points and obtaining the largest House majority since 1928. Republicans also regained control of the Senate winning 24 of the 36 available seats, a net gain of 9 seats and the largest Senate gain in a midterm election since 1958. Similarly, in the gubernatorial elections, Republicans won 24 of the 36 state governorships, for a net gain of two seats, and two out of three in the territories.

The Ebola outbreak, and the way federal authorities responded to it, also generated a heated political debate, just a few weeks before the 2014 midterm elections. Republicans harshly criticized the Obama administration for not preventing the virus to enter the country, and demanded the President to ban all flights from affected West African countries, a measure that the administration opposed and

[11] According to data from the Internet TV News Archive (https://archive.org/details/tv), precisely 3,148 distinct news segments containing the word Ebola were aired between October 1, 2014 and November 4, 2014 on ABC, CBS, CNN, Fox News, and NBC.

[12] Link: http://pewrsr.ch/1t4aEFI

[13] Data are from the United States Elections Project available at: `http://www.electproject.org/2014g`.

that public health experts deemed as ineffective and even potentially harmful (Ferrel and Agarwal, 2018). Anecdotally, there has been a widespread perception that Ebola was an important campaign theme in the weeks leading up to the 2014 election (e.g. Gertz and Savillo (2014); Yglesias (2018)), backed up by correlational evidence that Republican candidates were more likely to raise the Ebola issue during the campaign (Cormack, 2014).

3 Data

3.1 Ebola concerns

We use two measures of popular concern about Ebola based on users' online activity. The first one is the volume of Google searches for the search topic "Ebola," available from the Google Trends website. We collect data by media Designated Market Area (DMA) and by week for the 5-week period between the first Ebola case and the elections, as well as for the month of August 2014 - i.e., when the World Health Organization declared Ebola as an International health crisis but prior to the first case in the U.S. - which we use for a placebo exercise. For each DMA, Google provides a measure of the search volume defined between 0 and 100 relative to the highest point in the time series. The second measure is the weekly number of messages containing the word "Ebola" or the hashtag "#Ebola" published on the Twitter platform over the five weeks before the elections and over the months between March and August 2014, which we use for a placebo exercise. Data were collected via the Twitter API. We focus on tweets that are geo-located, which we can attribute to a specific DMA, and divide their number by the DMA population.

Figure 1 shows the evolution of the volume of Google searches about Ebola between January to December 2014, and of the aggregate number of Ebola-related tweets from September to December 2014. The three vertical lines represent respectively: i) the day when the WHO declared Ebola an international public health emergency (August 8), (ii) the day when CDC announced the first Ebola case in the U.S. (September 30), and (iii) the day of the 2014 midterm elections (November 4). It is evident how both searches and tweets are extremely responsive to Ebola-related events, with a local peak after the WHO's declaration and global peak right after the first case. Furthermore, Ebola-related online activity remained relatively high in the weeks before the elections, losing intensity immediately afterwards.

3.2 Electoral results and presidential disapproval

For the analysis of the impact of Ebola concerns on voting, we use county-level data on turnout and candidates' vote share for all elections held on November 4th 2014 – i.e., House, Senate, and Governors – available from the Dave Leip's Electoral Atlas. To control for pre-trends in political preferences, we also use similar data for previous elections, i.e., 2012, 2010, 2008, 2006, and 2002 for the House, 2012, 2008, 2006, and 2002 for the Senate elections, and 2010, 2006 and 2002 for governors - available from the same source.

To explore the hypothesis that concerns for Ebola may have influenced voters' opinions about the

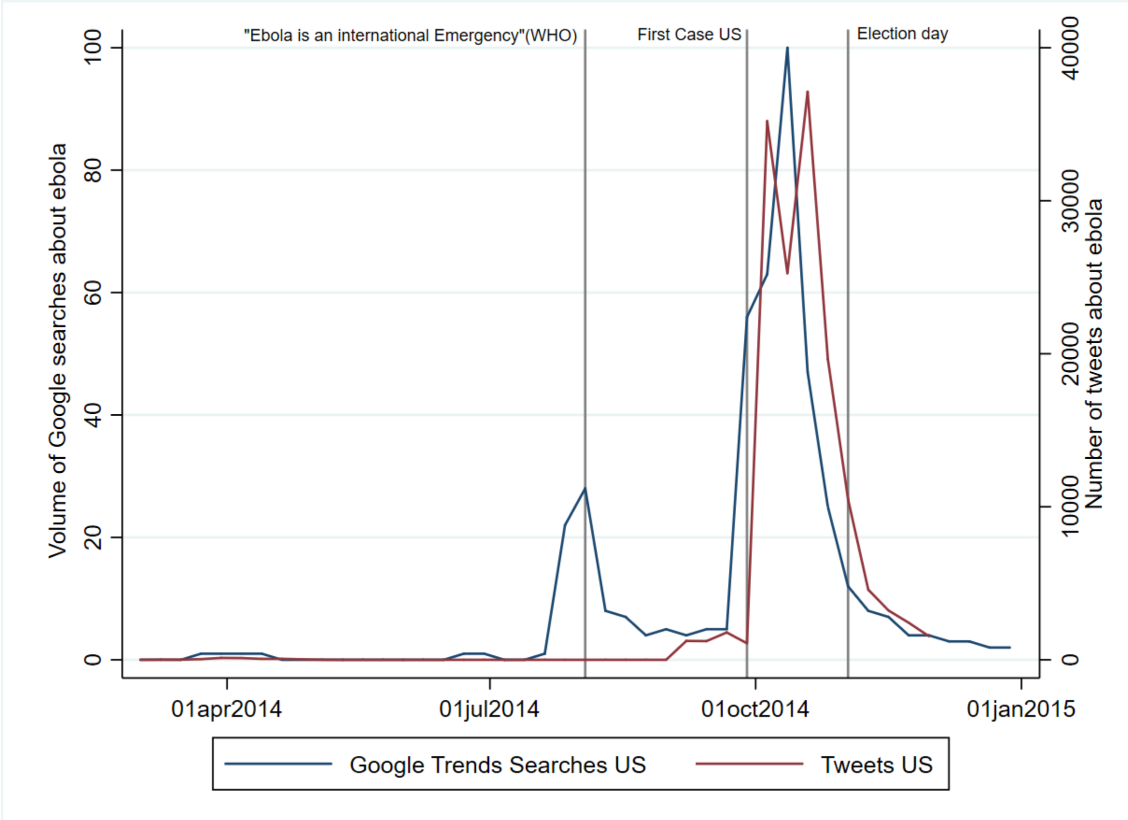


Figure 1: Google Searches and Ebola-Related Tweets

incumbent president, we use daily data on president Obama's (dis)approval ratings, available from the Gallup daily tracking. Specifically, we construct a dummy variable equal to 1 for all respondents that reported disapproving of the way Obama was handling his job as president at the time of the interview. Exploiting the daily nature of these data, we look at the evolution of Obama's disapproval in the 15 days before and after the occurrence of the three Ebola cases. We also perform our analysis for the entire period between September 1 and the day of the elections.

3.3 Politicians' newsletters, tweets, and campaign ads

To investigate whether and how candidates reacted strategically to Ebola, we analyze three components of their communication strategy via both online and traditional media: electronic newsletters, tweets, and campaign TV ads.

Comprehensive data on all e-newsletters sent by members of Congress are available from the DCinbox dataset, assembled by (Cormack, 2017). The data include every official e-newsletter sent by every sitting representative and senator to her/his constituents. For each newsletter, the data report: the name of the politician, the state of origin, the party affiliation, the congressional district, and the subject and the full text of the newsletter. We use data on all e-newsletters sent between August and December 2014, for a total of over 2,300 newsletters. We identify as Ebola-related all newsletters that contain the term "Ebola" either in the subject or in the body of the newsletter, which represent about 10% of the total. Based on this information we construct both an indicator variable for whether a given politician on a given week sent at least one Ebola-related newsletter and a variable for the number of such newsletters. Using keyword searches, we also code whether newsletters mention other topics, with different degrees of proximity to their mentions of Ebola.[14]

We also use data on all message published by candidates on the Twitter social media platform during the 2014 campaign. We start from a dataset collected by Evans et al. (2017) and kindly shared with us by the authors. The data include information on all tweets published by any active Twitter accounts associated with candidates for House and Senate elections between September 5, 2014 and November 4, 2014.[15] We extend the dataset to include all the tweets published between August 1, 2014 and September 4, 2014 (before the first Ebola case) and between November 5, 2014 and December 31, 2014 (i.e., after the election), which we collected through the Twitter API. We identify all the tweets containing the word "ebola", and those associated with immigration and terrorism, following the same keyword-based procedure used for newsletters.

Finally, we collect comprehensive data on the campaign ads aired on broadcast TV across 210 media markets by all the candidates running in the 2014 elections. These data are available from Kantar Media through the Wesleyan Media Project (WMP, Fowler et al. (2017)). The data cover over 5,550 ads accounting for over 2.6 million airings. For each airing the data reports the following information: date, time, media market, channel, length, sponsor (i.e., candidates, parties, or interest groups) and the estimated cost. The data also include several qualitative variables – coded by the WMP staff through a semi-automated procedure – regarding the content of each ad, such as the issue(s) mentioned in the ad, and the tone used in it. References to Ebola were coded as such, but only starting on October 14, when it had become clear that it was a topic of interest. Additional variables, however, indicate whether an ad – through its script, images, and/or music – appeals to specific sentiments such as fear, a measure which we employ in our analysis.

3.4 Other variables

To examine whether candidates competing in closes races are more likely to use the issue of Ebola in their campaign, we use information on the competitiveness of elections available from the Cook Political Report (CPR). In particular, for each congressional or senatorial race, the Cook Partisan Voting Index (PVI) indicates whether the election is likely to be close (i.e, "Toss Up", "Lean Republican" or "Lean Democrat") or not (i.e., "Likely Republican" or "Likely Democrat"). To make sure the measure of competitiveness is not itself affected by the Ebola episode, we use data from September 19, 2014, i.e., before the first case.

We also use data for a wide range of variables, both at the county and at the DMA level, which we use as controls in our regressions. County-level controls includes: population density, median age, the share of white population, the share of population with a college degree, income per capita, and

[14]The topics we consider are: president Obama (if they contain "Obama"), immigration ("immigrant", "immigration", "alien", "border", or "ICE"), terrorism ("terrorism", "terrorist", "ISIS", "Islamic State", or "Daesh'), guns ("gun", "weapon", "firearm", or "2nd amendment"), and health care ("ACA", "Affordable Care Act", "health care", "medicare", or "obamacare").

[15]These include candidates' official accounts, campaign accounts, and personal accounts.

unemployment rates all available from the U.S. Census Bureau. DMA-level controls include instead: the level of cable penetration in 2010 (Sood, 2016), and the volume of Google searches for the terms "virus" and "anxiety," which is meant to capture the general attitudes of the local population on issues related to infectious diseases. Finally, for our empirical analysis we compute the shortest-path distance of each county or DMA from the three locations of Ebola cases (i.e., Dallas, Cleveland/Akron, and New York City) as well as the distance to the nearest one of the three.

4 Empirical Strategy

In order to unpack the political impact of the Ebola crisis, we start by asking how it affected voting behavior. For that, we first implement the following basic specification:

$$Vote_{c,d}^{2014} = \alpha + \beta Ebola_d + \gamma Vote_{c,d}^{2010-06} + \lambda' X_c + \theta' D_d + \Lambda_r + \epsilon_{d,c}, \tag{1}$$

where $Vote_{c,d}^{2014}$ is the Democratic vote share in county c, located in DMA d. $Ebola_{d,}$ is the proxy for Ebola concerns (Google searches or tweets per capita) in DMA d, during the five weeks immediately before the 2014 election – that is, starting from the report of the first case diagnosed in the US. The vector $Vote_{c,d}^{2012-10}$ includes the Democratic vote share in 2010 house (midterm) election and its change between 2010 and 2006 elections. The vectors X_c and D_d include county- and DMA-level control variables, as described in the data section, and Λ_r stands for Census region dummies. Finally, $\epsilon_{d,c}$ is a heteroskedasticity-robust error term, clustered at the DMA level.

We are interested in the coefficient β, describing the impact of Ebola concerns on the Democratic vote share. Simply estimating (1) via OLS is not enough, however, as the coefficient of interest may still be biased for multiple reasons, even after conditioning on our control variables. First, Ebola concerns are not randomly assigned: searching information about Ebola on the Internet, or tweeting about it, are evidently endogenous decisions that may be affected by things such as access to information, susceptibility to biased news, or beliefs that may also shape voting preferences. This is not to mention the potential (arguably classical) measurement error in the main independent variable, which could introduce attenuation bias in the estimated effect of Ebola concerns on electoral results. To address these issues, we turn to the geographically uneven spread of Ebola cases, as a source of variation in the perception of potential exposure to the threat of the disease.

4.1 Proximity to Ebola Cases as a Source of Variation

We identify the three key locations within the US, as described in Section 2: (1) Dallas, TX, (2) the Cleveland-Akron area, in Ohio, and (3) New York City, NY. These were the only areas where the CDC and state public health officials implemented contact-tracing procedures to surveil 458 individuals who potentially had close personal contact with Ebola patients diagnosed in the U.S. (CDC 2014).

It seems natural that people living closer to those key locations would display a heightened concern with the potential threat. Figure 2, depicting the geographic variation in Ebola searches and the location (in red dots) of the aforementioned three critical locations, suggests that this was indeed the case. It is easy to see from inspection that Ebola concerns are associated with proximity to Dallas, Cleveland, and New York. [16]

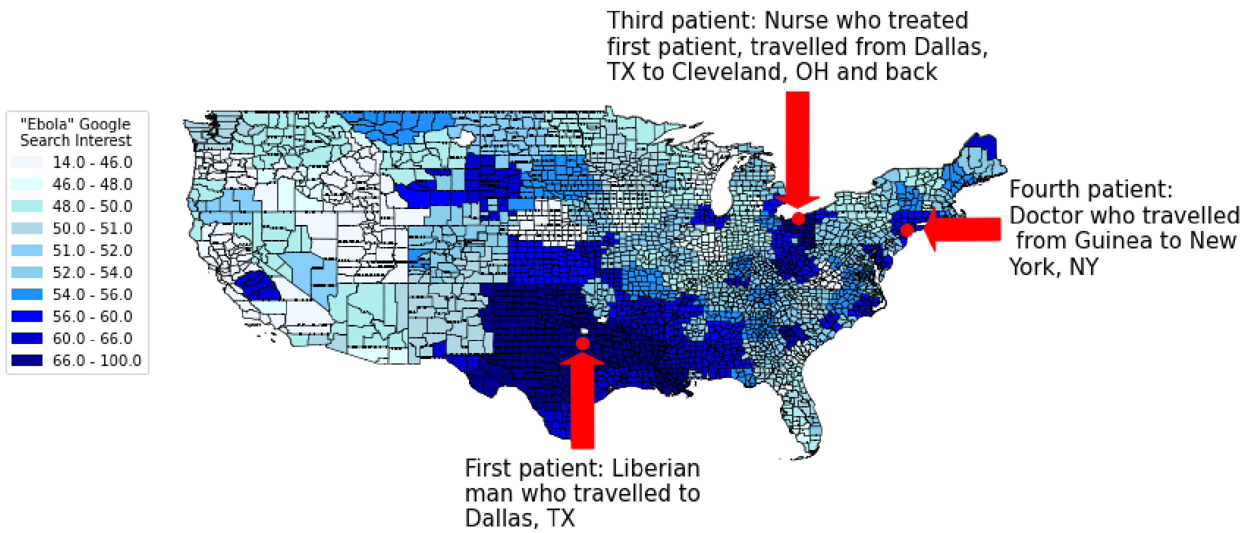


Figure 2: Geographic Distribution of Google Searches

The point is underscored by Figure 3, showing the evolution of Ebola-related Google searches and Twitter activity over time, for the three locations. The timing of the reactions to each case being public should mitigate concerns that the association suggested in Figure 2 was due to mere chance, or to other confounding factors unrelated to the perceived threat due to proximity.

We can show this pattern more systematically, for our entire sample, by estimating the following equation, exploiting the daily variation in Ebola-related tweets:

$$Tweets_{d,t(c)} = \gamma Post - Onset_{t(c)} \times ln(Dist.Ebola_c)_d + \lambda_d + \theta_t + \Gamma_t \times \lambda_d + \epsilon_{d,t}, \tag{2}$$

where $Tweets_{d,t(c)}$ are Ebola-related tweets (per 1,000 inhabitants) sent from DMA d, on date t. $Post{-}Onset_t(c)$ is an indicator taking the value of 1 after the diagnosis of Ebola case $c \in TX, OH, NY$. The variable $ln(Dist.Ebola_c)_d$ is the (log) distance (in miles) of DMA d from the location of Ebola case c. (λ_d and θ_t are DMA and day fixed effects, respectively, and Γ_t is a linear trend.) We will cluster the standard errors at the DMA-level.

Table 1 presents the main results. In columns 1 to 3, we first focus on the eve of each case, by looking at 15 days before and after the diagnosis of each case (i.e., Dallas, Cleveland, and NYC, following their chronological order). In each case, the coefficient for γ closely mirrors the usual interpretation in a standard multiple-period differences-in-differences (DD) specification with a continuous treatment. In all cases, the volume of Ebola-related tweets increases with the proximity to the case, upon its detection.[17] Column 4 then displays a staggered DD model, estimating the three coefficients together without restricting the sample to the eve of each case. Results suggest that the occurrence of and

[16] Figure A.1 shows the spatial distribution of the instrument.

[17] Figures A.2, A.3, and A.4 in the appendix show how point estimates in columns 1, 2, and 3 of Table 1 become even more negative as we constrain our regressions in terms of the proximity to Dallas, Cleveland, and NYC respectively.

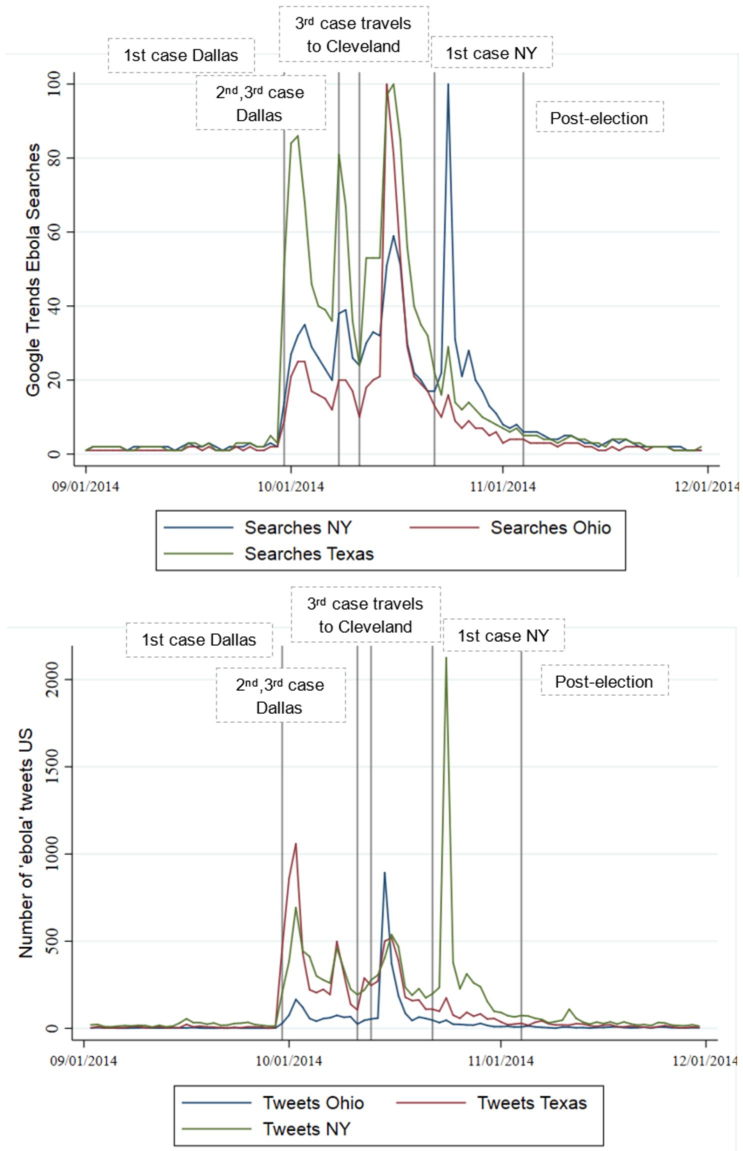


Figure 3: Timing of Ebola-Related Google Searches and Tweets

proximity to the first two cases strongly predicts the increase in Ebola tweeting.

To summarize the association between geographical proximity and Ebola concerns, we compute the distances (in miles) between the centroid of each DMA to each of the three locations, and then take the minimum value to compute a variable we refer to as *Distance to Nearest Case*. We will use it as an instrumental variable in the main regressions. As with any valid instrument, our variable must be correlated with Ebola concerns but, conditional on our full set of controls, uncorrelated with any unobserved characteristic of a locality that may affect voting behavior in a systematic way.[18]

We can examine the strength of the relationship between our instrument and the measures of Ebola

[18]Conditioning is, of course, important: for instance, our instrument quite obviously varies systematically with region.

Table 1: Ebola Tweets and Distance to Reported Ebola Cases

	Ebola Tweets				
	(1)	(2)	(3)	(4)	(5)
Post-Onset Dallas * Distance (in logs) to Dallas	-0.101***			-0.062***	
	(0.026)			(0.022)	
Post-Onset Cleveland * Distance (in logs) to Cleveland		-0.031***		-0.040***	
		(0.010)		(0.008)	
Post-Onset NYC * Distance (in logs) to NYC			-0.022**	0.020***	
			(0.010)	(0.007)	
Post-Onset First Case * Distance (in logs) to Nearest Case					-0.068***
					(0.013)
Mean Tweets per 10,000 inhab.	0.085	0.125	0.088	0.05	0.05
Day FE	Yes	Yes	Yes	Yes	Yes
DMA FE	Yes	Yes	Yes	Yes	Yes
DMA-specific Linear Trends	Yes	Yes	Yes	Yes	Yes
Adjusted-R^2	0.61	0.50	0.49	0.55	0.56
Observations	6177	6177	6177	19596	19596
Number of Clusters (DMA)	213	213	213	213	213

Notes: the table reports the coefficient of the interaction between the distance (in logs) to an Ebola Case and a dummy indicating the post-onset of that case. The dependent variable is the number of ebola related tweets per 10,000 inhabitants in DMA (using 2010 census population). The unit observation is a DMA-day. Samples in columns 1 to 3 include daily data by DMA 15 days before and 15 days after the ebola diagnosis of the case. Samples in columns 4 and 5 include all daily data from September 1st to November 30th. Heteroskedasticity robust standard error estimates clustered at the DMA-level are reported in parentheses.

concerns, by estimating the first-stage regression:

$$Ebola_{c,d} = \pi_0 + \pi_1 ln(DistanceNearestCase)_d + \pi_2 Vote_{c,d}^{2010-06} + \pi_3' X_c + \pi_4' D_d + \Lambda_r + \epsilon_{d,c}. \quad (3)$$

Table 2 presents different specifications estimating equation (3) and shows that, indeed, proximity to the nearest reported Ebola case is a strong predictor of Ebola concerns. Column 1 establishes the basic result using the search measure. Adding the full set of DMA controls (column 2), pre-trends in voting (column 3), or regional dummies (column 4) does not substantially change the point estimate for the instrument. The implied F-statistics for the first stage suggest that our setting is not subject to a weak instrument problem: all F-statistics are substantially larger than the standard Stock-Yogo critical values. Further, removing population weights in column 5 does not alter our results. Columns 6 and 7 of Table 2 then confirm the results using the Twitter measure.[19]

We also want to ensure that we are picking up something specific to the location of Ebola cases – and not, say, about proximity to large urban centers. On that, it is reassuring that the distance to the nearest Ebola case is largely uncorrelated with observable variables, as can be seen in Table A.9 in the Appendix. To further assuage concerns, we also conduct a placebo exercise: we randomly select three out of the top 100 cities in the US by population (excluding the three with Ebola cases), and compute for all counties and DMAs the minimum distance among the randomly selected cities. We then run a regression of Ebola concerns on this distance, with and without controlling for distance to the nearest Ebola case. Figure 4 plots the kernel estimation of the probability density function for the coefficients obtained from 1000 random draws. It is apparent that our coefficient of interest is an

[19]Table A.8 in the Appendix shows that these first-stage results are robust to allowing for spatial autocorrelation in the computation of the standard errors.

Table 2: Ebola Concerns and Distance to Nearest Case (First-Stage)

	Ebola Searches					Ebola Tweets	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Distance (in logs) to Nearest Case	-5.475**	-8.434***	-7.974***	-7.866***	-7.309***	-1.766***	-1.609***
	(2.438)	(1.821)	(1.288)	(1.261)	(1.292)	(0.311)	(0.347)
Mean Value Dep. Var.	54.9	54.9	54.9	54.9	54.1	5.6	4.2
County-Level Controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	No	Yes	Yes	Yes	Yes	Yes	Yes
DMA-Level Controls	No	No	Yes	Yes	Yes	Yes	Yes
Previous Election Controls	No	No	No	Yes	Yes	Yes	Yes
Population Weights	Yes	Yes	Yes	Yes	No	Yes	No
Adjusted-R^2	0.38	0.62	0.66	0.68	0.49	0.80	0.64
Observations	3068	3067	3062	3062	3062	3064	3064
Number of Clusters (DMA)	203	203	202	202	202	203	203

Notes: The variable Ebola Searches accounts for the google search volume of the term 'ebola' during the 5 weeks before the 2014 election. The variable Ebola Tweets accounts for the number of tweets about 'ebola' per 10,000 inhabitants in DMA during the same period. Heteroskedasticity robust standard error estimates clustered at the DMA-level are reported in parentheses; *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level, all for two-sided hypothesis tests. County-level controls are population density, median age, share of white population, share of population with college degree, income per capita, and unemployment. DMA-level controls are cable TV penetration 2010, Ebola Searches/Tweets before first case in the US, and google searches for the terms 'anxiety' and 'virus', both in 2013. Previous election controls include the Democratic vote share for House in the midterm election of 2010 and its change with respect to the 2006 midterm election.

extreme outlier in the distribution of randomly generated coefficients. In addition, the distribution of the coefficient on distance to nearest Ebola case that comes from the "horse race" regressions is far to the left of the distribution of the random distance coefficients, which is roughly centered near zero.[20]

As for the exclusion restriction, Table 3 presents a few checks. We can see that distance to the nearest Ebola case does not predict Ebola-related searches before the first diagnosed case in the U.S. (column 1), and its correlation with Ebola tweets before the first case is a precisely estimated zero (column 2). Nor does it strongly predict Google searches during the swine flu pandemic of 2009. In short, our instrument does not seem to be picking up some general interest in Ebola unrelated to the perception of threat, or geographical variation in some persistent characteristic related to reactions to infection-related risky situations in general.[21] Similarly, and importantly, it does not predict political outcomes prior to 2014: it is uncorrelated with the vote share of Democratic candidates for the preceding House, Senate, or gubernatorial elections (columns 4-7).

[20] Alternatively, Table A.10 in the Appendix shows first-stage regressions controlling for the distance to the nearest (non-Ebola) large city, for several definitions of what constitutes a "large city." The coefficient on distance to the nearest case is barely affected when we include that alternative distance, and is substantially larger in magnitude than coefficient on the latter. We find the same pattern when looking at Ebola-related Twitter activity in Table A.11

[21] This is an important check since there is evidence that psychological mechanisms that have evolved to promote disease-avoidance may encourage the endorsement of socially conservative beliefs (Terrizzi et al., 2013).

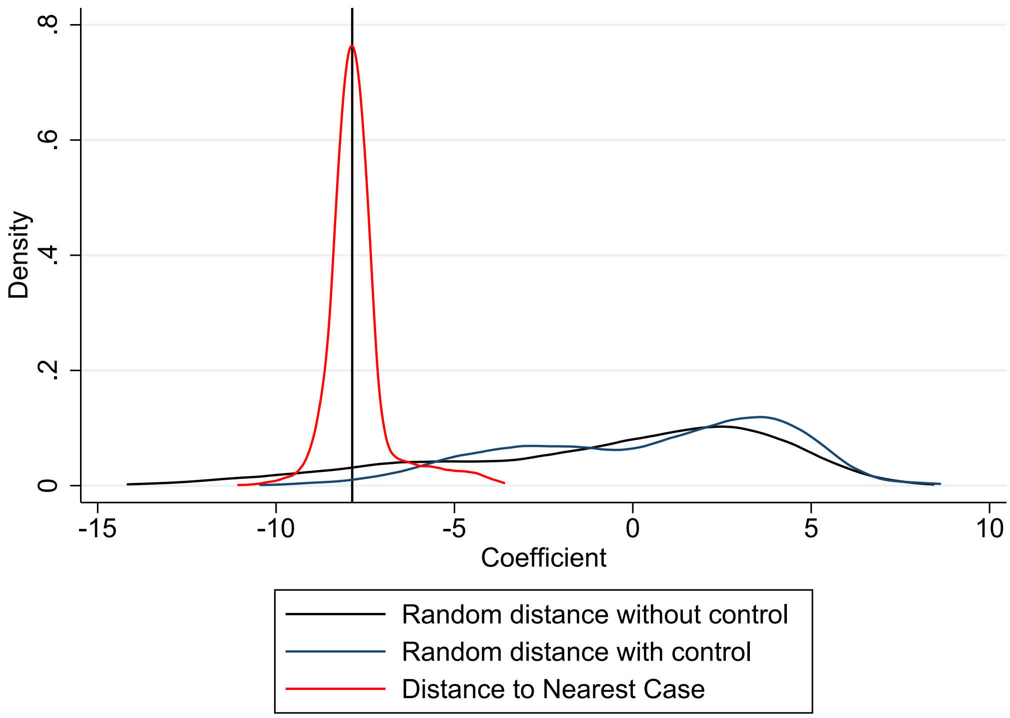


Figure 4: Placebo First-Stage

Note: The figure shows kernel density estimations for three pdf of: (1) coefficient of minimum distance to 3 randomly drawn cities out of the largest 100 cities (excluding Ebola locations) obtained from regressing Ebola Concerns on random distance and full set of controls described in equation (1) (1000 random draws) -pdf labelled as random distance without control-, (2) coefficient of random minimum distance as before but controlling for the minimum distance to nearest ebola case -pdf labelled as random distance with control-, and (3) coefficient of distance to nearest ebola case in each horse race with random distance. Black vertical line denotes point estimate in our baseline specification (column 4 in Table 2)

5 The Political Impact of Ebola

5.1 Ebola and Voting: Baseline OLS Results

We first look at the basic correlation patterns, by estimating (1) via OLS. Table 4 presents the results for U.S. House election outcomes, in order to maximize coverage and sample size, since not all states had Senate or gubernatorial elections that year. (We will discuss those elections later.)[22] We weigh regressions by DMA population, which does not qualitatively affect the results, as we will show, but generally improves the precision of our estimates.

We start by showing, in Column 1, that Ebola searches before the first case in the U.S. do not predict the Democratic vote share in the 2014 midterm election. In contrast, column 2 shows a strong unconditional correlation between Ebola concerns after the first case and the vote share for Democratic candidates. This remains true even after controlling for possible confounding factors, captured by regional dummies and by our county- and DMA-level variables (columns 3 and 4), which include demographic characteristics, as well as media access (cable TV) and intensity of Google searches for

[22] All analyses are based on continental United States (i.e., we exclude Alaska and Hawaii).

Table 3: Distance to Ebola Cases and Selected Outcomes

	Pre-treatment		Swine flu	Previous Elections: Democratic Vote Share			
	Ebola Searches	Ebola Tweets	Searches	House 2010	House 2012	Senate 2012	Gubern. 2010
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Distance (in logs) to Nearest Case	1.132	-0.002**	-0.476*	0.560	0.512	-0.084	-0.307
	(1.984)	(0.001)	(0.278)	(0.444)	(0.530)	(0.728)	(0.478)
Mean Value Dep. Var	57.7	0.021	34.7	38.5	39.7	47.5	40.9
Effect of Std Dev Δ in Distancee	1.52	-0.00	-0.64	0.75	0.69	-0.13	-0.42
County-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
DMA-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Previous Election Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted-R^2	0.43	0.44	0.44	0.76	0.70	0.77	0.70
Observations	3062	3064	3062	3060	3019	1865	2136

Notes: All specifications are weighted by DMA population. The variable Ebola Searches accounts for the google search volume of the term 'ebola' during the 5 weeks before the 2014 election. The variable Ebola Tweets accounts for the number of tweets about 'ebola' per 10,000 inhabitants in DMA during the same period. Heteroskedasticity robust standard error estimates clustered at the DMA-level are reported in parentheses; *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level, all for two-sided hypothesis tests. County-level controls are population density, median age, share of white population, share of population with college degree, income per capita, and unemployment. DMA-level controls are cable TV penetration 2010, Ebola Searches/Tweets before first case in the US, and google searches for the terms 'anxiety' and 'virus', both in 2013. Previous election controls vary depending on the corresponding election for each outcome variable: For House 2010, it includes the Democratic vote share for the 2006 midterm House election and its change with respect to the 2002 midterm election. For House 2012, it includes the Democratic vote share for the previous House election (i..e, 2010) and its change with respect to the previous house election (i.e., 2008). For Senate 2012, it includes the Democratic vote share for the previous senatorial election (i..e, 2006) and its change with respect to the previous senatorial election (i.e., 2000). For 2010 gubernatorial election, it includes the Democratic vote share for the 2006 gubernatorial election and its changes from the 2002 election.

"anxiety" and "virus" (as of 2013), all of which might correlate with Ebola concerns and information, as well as political views. The point estimate suggests that Democratic vote share is significantly negatively associated with Ebola concerns: a one-standard-deviation increase in Ebola searches is associated with a decrease in vote share of one fifth of a standard deviation (about four percentage points).

Democrats thus did poorly in areas that display greater Ebola concerns. This, however, could be partly explained by selection: it could be that areas where Democrats had been doing poorly would also be disproportionately concerned about Ebola. Column 5 suggests that this is indeed the case: the coefficient of interest drops substantially once we control for the Democratic vote share in 2010 (the previous midterm election), as well as the change between 2006 and 2010.[23] A similar pattern is present, if somewhat less starkly, when it comes to Ebola concerns as measured by tweets (columns 6-7).

In sum, the basic OLS results show a correlation between Ebola concerns and the electoral performance of Democrats, but also that selection on pre-existing political patterns is an important issue. In order to establish a causal effect, we need a source of variation in Ebola concerns that does not suffer from such selection. Table 3 has shown that the geographical patterns of Ebola cases provide

[23]Results are remarkably similar if we look at presidential election years as well, namely controlling for 2012 vote share and the change between 2010 and 2012.

Table 4: Ebola Concerns and Democratic Vote Share (OLS)

	Democratic Vote Share in 2014 House Reps. Election						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Ebola Searches before First Case US	-0.007						
	(0.182)						
Ebola Searches		-0.352**	-0.361***	-0.301***	-0.170***		
		(0.169)	(0.101)	(0.089)	(0.058)		
Ebola Tweets						-1.297***	-0.937***
						(0.365)	(0.177)
Std Dev Vote Share	20.61	20.61	20.61	20.61	20.61	20.61	20.61
Std Dev Ebola (Searches or Tweets)	14.14	11.86	11.86	11.86	11.86	2.75	2.75
Effect of Std Dev Δ in Searches/Tweets	-0.10	-4.17	-4.28	-3.57	-2.01	-3.56	-2.57
County-Level Controls	No	No	Yes	Yes	Yes	Yes	Yes
Region FE	No	No	Yes	Yes	Yes	Yes	Yes
DMA-Level Controls	No	No	No	Yes	Yes	Yes	Yes
Previous Elections Controls	No	No	No	No	Yes	No	Yes
Adjusted-R^2	-0.00	0.04	0.50	0.56	0.74	0.55	0.74
Observations	3062	3062	3061	3056	3056	3058	3058
Number of Clusters (DMA)	203	203	203	202	202	203	203

Notes: All specifications are weighted by DMA population. The variable Ebola Searches accounts for the google search volume of the term 'ebola' during the 5 weeks before the 2014 election. The variable Ebola Tweets accounts for the number of tweets about 'ebola' per 10,000 inhabitants in DMA during the same period. Heteroskedasticity robust standard error estimates clustered at the DMA-level are reported in parentheses; *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level, all for two-sided hypothesis tests. County-level controls are population density, median age, share of white population, share of population with college degree, income per capita, and unemployment. DMA-level controls are cable TV penetration 2010, Ebola Searches/Tweets before first case in the US, and google searches for the terms 'anxiety' and 'virus', both in 2013.

us with such a source.

5.2 Ebola and Voting: Instrumental Variable Results

The nature of the variation behind our IV strategy is quite apparent from Figure 5, which plots the residuals of the Democratic share of the House vote in 2014 (regressed on our full set of control variables described in equation (1)) on a map of U.S. counties marked with our three key Ebola locations. It is apparent that Democrats seem to have performed relatively poorly in the areas around the latter, especially for the Texas and Ohio cases.

This basic intuition is confirmed by Table 5, which presents the main IV results for U.S. House elections. Columns 1-2 show the reduced-form results, with distance to the nearest Ebola case strongly predicting Democratic electoral performance.[24] Columns 3-6 then show the population-weighted and unweighted IV estimates, implying a negative and highly significant effect of Ebola concerns on the Democratic vote share, whether they are measured by Google searches or tweets.[25]

[24] Alternatively, in Table A.12 in appendix we show that reduced-form results do not change when controlling for the distance to the nearest (non-Ebola) large city, for several definitions of what constitutes a "large city." The coefficient on distance to the nearest case is barely affected when we include that alternative distance, and is substantially larger in magnitude than coefficient on the latter.

[25] These results are robust to different combinations and permutations of our sets of control variables, as can be seen in Figures A.5 and A.6 in the Appendix. They are also robust to accounting for spatial correlation in the standard errors, as shown in Table A.13 in the Appendix.

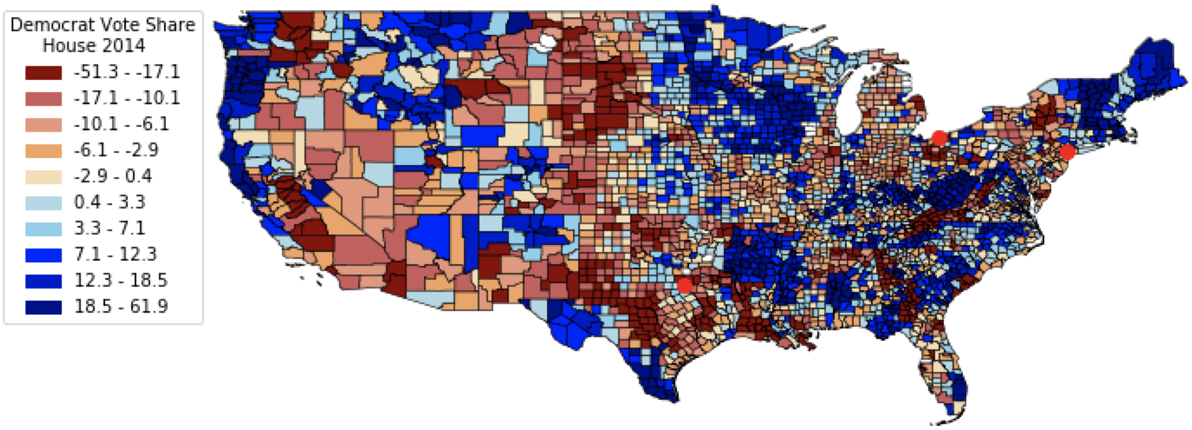


Figure 5: Democrat Vote Shares in House Election

Note: The figure shows the geographical distribution of the residuals obtained from a regression of Democratic vote share in 2014 House election on the full set of controls described in equation (1). Red dots denote the location of Dallas, Cleveland, and New York.

Broadly speaking, we estimate a quantitatively large impact of Ebola concerns on Democratic vote shares: from column 3, a one-standard-deviation increase in Ebola concerns leads to a decrease in vote share of about 4.5 percentage points (just over one fifth of a standard deviation). This is indeed a meaningful effect: 40 House of Representatives races were defined by a margin of nine percentage points or less, which would have been flipped by that change. Fifteen of those were won by the Republican candidate, and flipping those seats to the Democratic column would have completely wiped out the Republican majority's increase relative to 2012.[26]

Note that the IV coefficient is larger than the comparable OLS coefficient (see column 5 in Table 4). This could be due to a combination of measurement error in the variables capturing Ebola concerns, omitted variable bias in OLS – for instance, if Ebola concerns are stronger in areas with many swing voters, which presumably correlates with Democratic vote losses – and/or the nature of the local average treatment effect – perhaps the type of place where Ebola concerns would be more sensitive to the distance to a case are also those with more swing voters.

As a placebo exercise, we can use the previously described approach of randomly drawing a group of three cities out of the largest 100 cities (excluding Ebola locations), repeating the procedure 1000 times, and comparing the distribution of reduced-form coefficients obtained for the minimum distance to the randomly drawn cities and for the distance to the nearest Ebola case. As we can see in Figure 6, the latter is far to the right of the former. Quite interestingly, this pattern is not present for the 2010 election (Figure A.7 in the Appendix), which provides further reassurance that our instrumental variable is not picking up something unrelated to the unfolding of the Ebola episode.

We can also look at the impact of Ebola on other electoral outcomes. Table 6 shows results for senatorial and gubernatorial races, as well as overall turnout rates, with odd (even) columns using the Google search (Twitter) measure. We find that Democrats are also negatively affected by Ebola concerns in the senatorial and gubernatorial races. The magnitude of the standardized effects is again

[26]The Republican majority went from 234-201 in 2012 to 247-188 in 2014.

Table 5: Ebola Concerns and Democratic Vote Share (IV)

	Democratic Vote Share in 2014 House Reps. Election					
	(1)	(2)	(3)	(4)	(5)	(6)
Distance (in logs) to Nearest Case	2.918***	2.492***				
	(0.455)	(0.641)				
Ebola Searches			-0.373***	-0.342***		
			(0.097)	(0.094)		
Ebola Tweets					-1.644***	-1.485***
					(0.479)	(0.436)
Std Dev Vote Share	20.61	18.69	20.61	18.69	20.61	18.69
Std Dev Ebola (Searches or Tweets)	1.34	0.82	11.86	10.45	2.75	2.11
Effect of Std Dev Δ in Searches/Tweets	3.90	2.04	-4.42	-3.58	-4.52	-3.13
County-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
DMA-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Previous Election Controls	Yes	Yes	Yes	Yes	Yes	Yes
Population Weight	Yes	No	Yes	No	Yes	No
Effective F Statistic	-	-	38.57	32.537	31.433	21.57
Adjusted-R^2	0.75	0.63	0.73	0.61	0.73	0.62
Observations	3056	3056	3056	3056	3058	3058
Number of Clusters (DMA)	202	202	202	202	203	203

Notes: The variable Ebola Searches accounts for the google search volume of the term 'ebola' during the 5 weeks before the 2014 election. The variable Ebola Tweets accounts for the number of tweets about 'ebola' per 10,000 inhabitants in DMA during the same period. All regressions but those on columns (4) and (6) are weighted by DMA population. Heteroskedasticity robust standard error estimates clustered at the DMA-level are reported in parentheses; *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level, all for two-sided hypothesis tests. Effective F Statistic reports Montiel-Pflueger robust weak instrument F-Statistics. County-level controls are population density, median age, share of white population, share of population with college degree, income per capita, and unemployment. DMA-level controls are cable TV penetration 2010, Ebola Searches/Tweets before first case in the US, and google searches for the terms 'anxiety' and 'virus', both in 2013. Previous election controls include the Democratic vote share for House in the midterm election of 2010 and its change with respect to the 2006 midterm election.

quite substantial: a one-standard-deviation increase in Ebola concerns reduces the Democratic vote share by just about one fifth of a standard deviation. Put differently, those increases in Ebola concerns translate into a 2.9 percentage-point (4.3 p.p.) decrease in vote share for the Senate (gubernatorial) election. Extrapolating the results for the gubernatorial election can convey this magnitude quite starkly: this hypothetical loss in vote share would have been decisive in eight gubernatorial elections in which Republican candidates won by less than six percentage points.[27].

Columns 5 and 6 of Table 6 showcase a substantial negative impact of Ebola concerns on total voter turnout. In fact, the magnitude is such that a one-standard-deviation increase in Ebola searches would have led to a drop of about 1.6 percentage points. Interestingly, the 2014 midterm elections registered the lowest turnout (36.7%) since 1942, and the 1.4 percentage points corresponds to about one third of the drop relative to the preceding midterms in 2010 (40.8%) (McDonald 2010). This suggests that the decline in the Democratic vote share may have been to an important extent due to potential supporters being induced to abstain from voting. Nonetheless, the negative impact on democratic vote share is not entirely explained by lower turnouts. In columns 7 and 8, we use as dependent variable the share of democratic votes relative to the total number of eligible voters (which is very much stable over time) and identify, again, a strongly negative impact of Ebola concerns.

[27]These eight toss-up races were (vote margin for Republican candidate in parenthesis): Florida (1%), Illinois (5%), Kansas (4%), Massachusetts (1%), Maryland (5%), Maine (5%), Michigan (4%), and Wisconsin (5%),

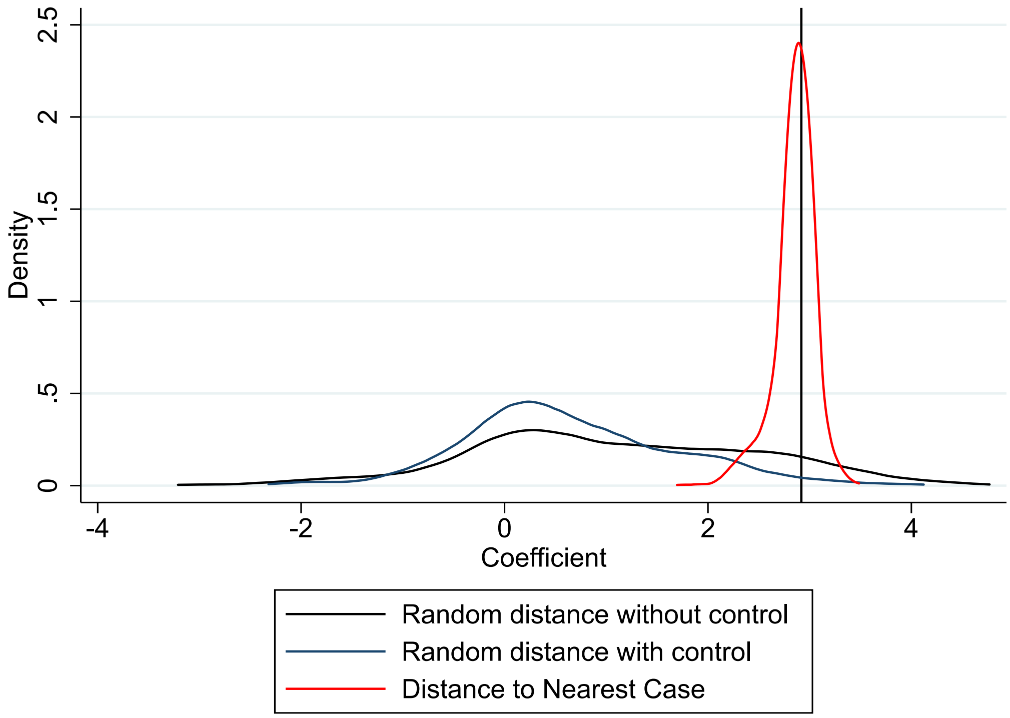


Figure 6: Placebo Reduced-Form 2014 Vote Share and Distance

Note: The figure shows kernel density estimations for three pdf of: (1) coefficient of minimum distance to 3 randomly drawn cities out of the largest 100 cities (excluding Ebola locations) obtained from regressing Democratic vote share in 2014 House election on random distance and full set of controls described in equation (1) (1000 random draws) -pdf labelled as random distance without control-, (2) coefficient of random minimum distance as before but controlling for minimum distance to nearest ebola case -pdf labelled as random distance with control-, and (3) coefficient of distance to nearest ebola case in each horse race with the random distance. Black vertical line denotes point estimate in our baseline specification (column 1 in Table 5)

In sum, the Ebola threat had a substantial negative impact on the electoral fortunes of Democrats in the 2014 midterms, across congressional and gubernatorial races.

5.3 Were Voters Blaming Incumbents?

One possible mechanism underlying our results could be an anti-incumbent effect, whereby the perceived crisis may have affected the perception of effectiveness of incumbent officials, both at the national and local level, either rationally or through misattribution. After all, it is possible that voters could be making inferences about incumbent performance based on their perception of the government's response to the Ebola crisis, not to mention that there is substantial evidence that voters may punish or reward incumbents for outcomes over which they have little influence.

We first consider the possibility of a general anti-incumbent channel, looking at voting results by incumbency status. Table 7 shows that, for all types of election, we do not find that incumbents faced a reduction in vote shares due to Ebola concerns (columns 1, 3, 5). It was only Democratic incumbents who experienced a substantial a reduction in their vote share as a result of those concerns (columns 2, 4, 6). Similarly, if we only consider races in which the incumbent was not a Democrat (columns 7-9),

Table 6: Democratic Vote Share in Other Races and Turnout in 2014 (IV)

	Democratic Vote Share				Turnout		Dem. Vote Share	
	Senatorial		Gubernatorial		2014		Elegible Voters	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ebola Searches	-0.213**		-0.330***		-0.133***		-0.224***	
	(0.102)		(0.110)		(0.048)		(0.077)	
Ebola Tweets		-1.054**		-1.545***		-0.617***		-0.993***
		(0.487)		(0.538)		(0.199)		(0.370)
Std Dev Vote Share	17.68	17.68	15.68	15.67	10.50	10.50	7.89	7.89
Std Dev Ebola (Searches or Tweets)	13.49	3.03	13.09	2.92	11.99	2.76	11.86	2.75
Effect of Std Dev Δ in Searches/Tweets	-2.87	-3.19	-4.32	-4.52	-1.59	-1.70	-2.65	-2.73
County-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
DMA-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Previous Election Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Effective F Statistic	55.64	46.12	114.40	69.28	42.46	30.71	38.37	31.43
Adjusted-R^2	0.76	0.75	0.80	0.80	0.74	0.75	0.56	0.60
Observations	2274	2276	2136	2138	3093	3095	3056	3058
Number of Clusters (DMA)	153	154	172	173	202	203	202	203

Notes: All regressions are weighted by DMA population. The dependent variable in columns 7 and 8 is the democratic vote share in 2014 house election computed as total votes normalized by county's eligible voting population. The variable Ebola Searches accounts for the google search volume of the term 'ebola' during the 5 weeks before the 2014 election. Heteroskedasticity robust standard error estimates clustered at the DMA-level are reported in parentheses; *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level, all for two-sided hypothesis tests. Effective F Statistic reports Montiel-Pflueger robust weak instrument F-Statistics. County-level controls are population density, median age, share of white population, share of population with college degree, income per capita, and unemployment. DMA-level controls are cable TV penetration 2010, Ebola Searches before first case in the US, and google searches for the terms 'anxiety' and 'virus', both in 2013.

we still detect a negative impact on the vote share of the Democratic challengers.

Table 7: Ebola Searches and Incumbent Vote Share (IV)

	Incumbent Vote Share in 2014 Election						Democratic Vote Share House		
	House		Senatorial		Gubernatorial		House	Senatorial	Gubernatorial
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Ebola Searches	0.216*	-0.960***	0.017	-0.649***	0.351***	-0.655**	-0.279***	-0.113	-0.230***
	(0.120)	(0.322)	(0.182)	(0.233)	(0.097)	(0.316)	(0.055)	(0.074)	(0.081)
Incumbents	All	Democrat	All	Democrat	All	Democrat	Exclude Democrat Incumbents		
Std Dev Vote Share	16.64	15.93	18.18	13.49	16.53	14.97	14.73	15.52	13.77
Std Dev Ebola Searches	12.16	7.50	13.49	8.44	13.09	7.88	13.11	16.14	14.83
Effect of Std Dev Δ in Searches	2.62	-7.20	0.23	-5.48	4.60	-5.16	-3.66	-1.82	-3.41
County-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
DMA-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Previous Election Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Effective F Statistic	39.01	25.26	36.49	13.46	91.53	17.80	80.39	539.50	224.57
Adjusted-R^2	0.33	0.28	0.20	0.63	0.24	0.66	0.51	0.72	0.77
Observations	2916	663	2274	1093	2136	548	2348	1181	1588
Number of Clusters (DMA)	202	143	153	94	172	66	192	85	131

Notes: All regressions are weighted by DMA population. The variable Ebola Searches accounts for the google search volume of the term 'ebola' during the 5 weeks before the 2014 election. Heteroskedasticity robust standard error estimates clustered at the DMA-level are reported in parentheses; *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level, all for two-sided hypothesis tests. Effective F Statistic reports Montiel-Pflueger robust weak instrument F-Statistics. County-level controls are population density, median age, share of white population, share of population with college degree, income per capita, and unemployment. DMA-level controls are cable TV penetration 2010, Ebola Searches before first case in the US, and google searches for the terms 'anxiety' and 'virus', both in 2013.

While this pattern rules out a general anti-incumbent effect, it is still consistent with the possibility of voters punishing Democrats, at all levels, due to an attribution of responsibility to President Obama. If that were the case, we would expect to see Obama's approval ratings negatively affected by the timing of and distance to Ebola-related events. We explore that possibility by exploiting individual-level (daily) Gallup data on presidential approval ratings to estimate the following model:

$$Disapprove_{i,d,t(c)} = \gamma Post - Case_{t(c)} \times ln(Dist.Ebola_c)_d + \delta' X_i + \lambda_d + \theta_t + \epsilon_{d,t}, \tag{4}$$

where $Disapprove_{i,d,t(c)}$ is an indicator taking value 1 if individual i living in DMA d disapproves of Obama's job as president, and 0 otherwise. $PostCase_t(c)$ is an indicator taking value 1 after the diagnosis of Ebola case c. The variable $ln(Dist.Ebola_c)_d$ is the distance (in logs) of DMA d from Ebola case c. The vector X_i includes individual level controls (e.g., age, gender, race, etc), λ_d is a collection of DMA fixed effects, and θ_t is a collection of day fixed effects.

The results are in Table 8. In columns 1-3, we focus on a window of 15 days before and after the diagnosis of the first Ebola case in the three different locations (Texas, Ohio, and New York). Results suggest that the timing of the events and proximity to the cases do not affect Obama's disapproval rates – in fact, we find a very precisely estimated zero effect.. We then exploit, in column 4, all the daily data from September 1st to November 30th 2014, and estimate the three interaction terms. Again, we find no evidence of an association. In column 5 we test whether the proximity to any of the three locations predicted Obama's disapproval after the first case in the US, and find no evidence of that either. Finally, the result is not an artifact of the Gallup data: column 6 shows no impact on Obama's disapproval as measured by the CCES survey.

In sum, we find no evidence of a general anti-incumbent effect of the Ebola crisis, nor of an impact on President Obama's approval ratings. This suggests that the political impact of Ebola was not about voters being disappointed with a policy response, or irrationally misattributing responsibility, and punishing politicians as a result. To shed additional light on the nature of that impact, we now turn to look at the strategic response by politicians.

6 The Strategic Response to Ebola

We now ask whether the widely perceived role of Ebola as an important campaign theme, in the weeks leading up to the 2014 election, is borne out more systematically in the data. In particular, we are interested in whether it responded to strategic considerations, and in understanding systematic differences across parties and over time, in response to Ebola-related events.

We use data on three dimensions of politician behavior. First, there is the textual analysis of the content of the weekly e-newsletters sent by members of Congress to their constituents, from which we obtain information on mentions to the term "Ebola," as well as other terms of interest. Second, we look at Twitter activity by all Republican and Democratic candidates for House, and Senate races, aggregating weekly mentions to "Ebola" and "#Ebola." Last but not least, we have weekly variation in the number and content of ads that candidates in House, Senate, and gubernatorial races placed on TV. We can also look directly at whether fear was an important component of politicians' strategy,

Table 8: Disapprove Barack Obama's job as president

	Disapproves Barack Obama's job as president					
	(1)	(2)	(3)	(4)	(5)	(6)
Post-Onset Dallas x Distance (in logs) to Dallas	-0.002			0.006		
	(0.018)			(0.011)		
Post-Onset Cleveland x Distance (in logs) to Cleveland		0.006		-0.002		
		(0.012)		(0.008)		
Post-Onset NYC x Distance (in logs) to NYC			-0.003	0.001		
			(0.010)	(0.007)		
Post-Onset First-Case x Distance (in logs) to Nearest Case					-0.003	0.005
					(0.007)	(0.004)
Mean Value Dep. Var.	0.57	0.59	0.59	0.58	0.58	0.53
Survey	Gallup	Gallup	Gallup	Gallup	Gallup	CCES
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
DMA FE	Yes	Yes	Yes	Yes	Yes	No
County FE	No	No	No	No	No	Yes
Individual-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted-R^2	0.14	0.14	0.14	0.14	0.14	0.17
Observations	8037	7984	7591	24168	24168	71931
Number of Clusters	183	184	183	184	184	2370

Notes: Samples in Columns 1 to 3 include Gallup' daily individual data 15 days before and 15 days after the ebola diagnosis of each case. Samples in columns 4 and 5 include all daily data between September 1st, 2014 and the midterm election. Sample in column includes CCES's daily data between November 2013 and the midterm election. The dependent variable takes value of 1 if the individual disapproves Barack Obama's job as president, 0 otherwise. Heteroskedasticity robust standard error estimates clustered at the DMA-level are reported in parentheses (county-level in columns 6); *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level, all for two-sided hypothesis tests. For specifications in columns 1 to 5, Individual-level controls are age and indicators for gender, employed, married, black, and hispanic.In column 6 Individual-level controls are are age and a set of indicators variables for male, white, hispanic, college or higher education, married, and annual income above US median (i.e., usd 59,000)

as the dataset codes whether ads feature an appeal to fear, based on the use of ominous music or on the text of the ad, as explained in Section 3.[28]

We implement the following general specification:

$$Strategy_{p,c,t} = \gamma PostOnset_t \times Politician_p + \pi' X_{p,t} + \lambda_t + \theta_p + \Gamma_t \times \lambda_c + \epsilon_{c,t}, \tag{5}$$

where $Strategy_{p,c,t}$ is one of the several measures of communication strategies (i.e., newsletters, tweets, or campaign ads) by a politician p, as of week t. In particular, we look at an indicator of whether at least one newsletter was sent, the weekly total number of tweets, and the weekly total number of campaign ads. Our main coefficient of interest captures the effect of the interaction between

[28]When it comes to the content, one limitation is that we only have information on whether ads mentioned Ebola for the sub-period between October 14 and November 4, since that was when the term was tracked by the Wesleyan Media Project. Interestingly, for that sub-period, 95% of the ads mentioning "Ebola" were aired by Republicans and 100% of those ads were coded as appealing to fear and 47% also mentioned immigration, underscoring the connection. None of the (few) Ebola-related ads by Democrats appealed to fear or were connected to immigration. See Table A.4 in the appendix.

$PostOnset_t$ (an indicator taking value 1 in the period after the onset Ebola cases) and C_p, which is a cross-sectional characteristic of the politician p or her electoral district, capturing the differential change in behavior, upon the onset of Ebola cases, by politicians with that characteristic. The vector $X_{p,t}$ accounts for the length of the newsletters/tweets/ads in terms of number of words (aired time for ads), λ_t is a collection of week fixed effects, and θ_p is a collection of politician fixed effects. Finally, $\Gamma_t \times \lambda_c$ accounts for linear trends specific to a race (or constituency, in the case of newsletters). We cluster the standard errors at the level of race (or constituency, for newsletters).

Figure 7 displays the evolution of newsletters (Panel A) and tweets (Panel B) by Republicans and Democrats. It is immediately apparent that mentions to Ebola in newsletters and tweets increased dramatically upon the occurrence of the first U.S. case. There is also a clear difference across parties: Republicans respond much more strongly. Moreover, the share of newsletters and tweets discussing Ebola in conjunction with immigration is substantially larger among Republicans. Note that, by the very constrained nature of Twitter content, it is quite apparent that joint mentions of Ebola with another topic are likely to be purposeful attempts at connecting them. A similar message emerges when we analyze the proximity between mentions to Ebola and immigration in newsletters, as we can see in Figure A.8 in the Appendix. [29]

The evolution of campaign ads appealing to fear (Panel C) in turn suggests two patterns. First, Republicans and Democrats seem to appeal to fear at similar rates throughout the period, which may be surprising in light of the literature that shows that priming fear in an experimental environment leads to more conservative political views (e.g. Jost et al. (2003), Thórisdóttir and Jost (2011)). However, ads appealing to fear while mentioning immigration are substantially more prevalent in Republican ads, and that combination increases substantially after the occurrence of the first Ebola case in the US.

We confirm these results more systematically, starting in Table 9. Republicans were more likely to send Ebola-related content in their newsletters, tweet about Ebola, and air fear-appealing campaign ads, upon the emergence of cases in the US (columns 1-3). The magnitudes are quite important: the relative increase in newsletters and tweets mentioning Ebola by Republicans, after the first case, is roughly twice as large as the average likelihood of newsletter mentions and the average number of Ebola tweets in a given week during the sample period of August-November 2014. The estimated relative increase in fear-based ads is smaller in magnitude, but still substantial at about 20% of its mean value.

This pattern begs the question of whether the response by Republican politicians was in fact strategic. After all, it could be the case that they were simply more likely to care about the Ebola threat themselves, or to represent voters who cared disproportionately. One piece of relevant evidence is already apparent in Figure 7, which shows a precipitous drop in Ebola mentions in newsletters and tweets immediately after the election, consistent with strategic considerations.[30]

[29] In 50% of the newsletters in which ebola and immigration were mentioned by Republicans the two terms were either in the same or in the adjacent sentence.

[30] This is confirmed in Table A.14 in the appendix. In the appendix, we also exploit the timing of different cases. Tables A.17 and A.18 shows that the second case, associated with Ohio, caused an especially larger reaction from Republican members. The pattern for fear-based ads, in Table A.19 is similar but imprecisely estimated, perhaps because our variable is a noisier proxy for an Ebola strategy, or because producing and airing a TV ad is costlier than a newsletter or tweet.

Figure 7: Communication Strategies Used by Politicians

Figure A: Evolution of Newsletters by Party

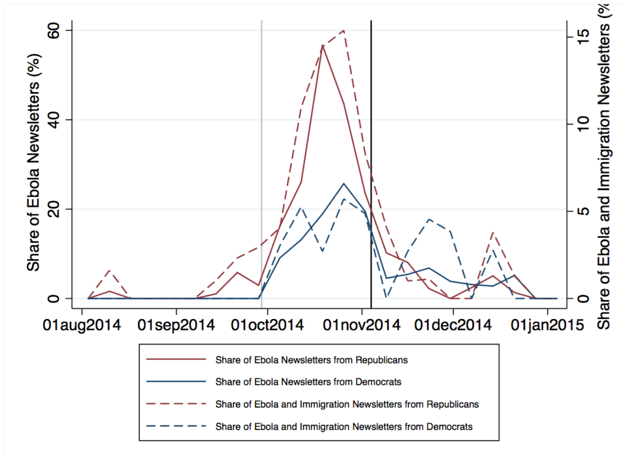


Figure B: Evolution of Candidates' Tweets by Party

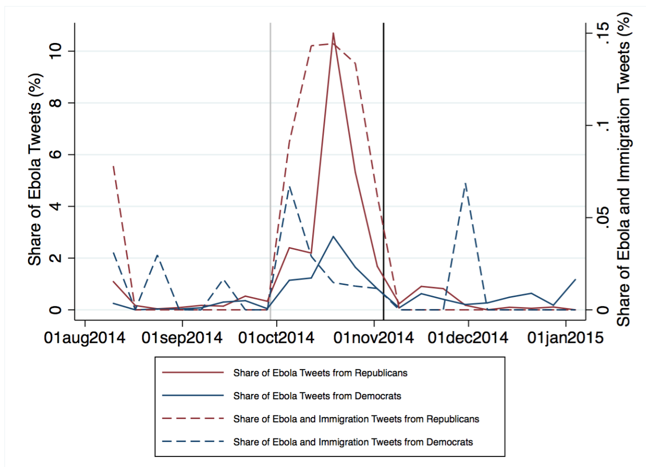
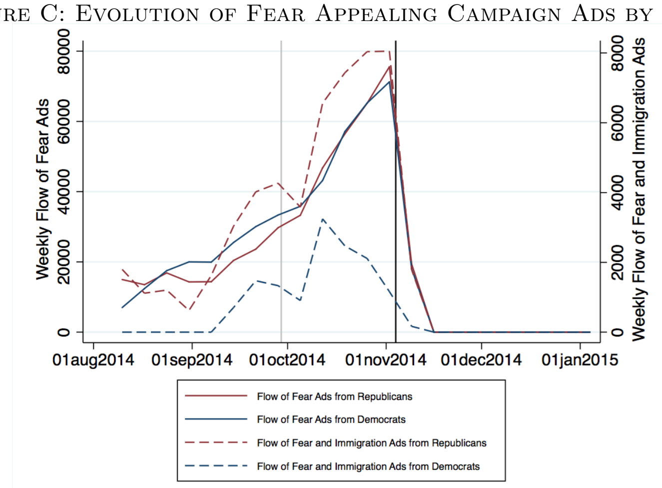


Figure C: Evolution of Fear Appealing Campaign Ads by Party



Note: The three figures plot the evolution of Newsletters (Fig. A), Tweets (Fig. B), and Campaign Ads (Fig. C) by party from early August to December 2014. Red lines denote Republicans whereas Blue lines denote Democrats. Solid lines denote ebola (fear for Ads)-related newsletters, tweets, and ads while dashed lines denote newsletters, tweets, and ads in which ebola (fear for Ads) is mentioned in conjunction with immigration. Vertical grey and black lines denote timing of first ebola case and midterm elections, respectively. Fig. A is based on 367 member of the congress who sent at least one official e-newsletters between August 2014 and the midterm elections. Fig. B focuses on 796 candidates for congress with twitter activity between August and November of 2014. Fig. C focuses on 575 candidates for congress and state governor who aired at least one campaign ad between August 2014 and the midterm elections.

Table 9: The Strategic Response to Ebola

	Ebola related		Fear	Ebola related		Fear	Ebola related		Fear
	Newsletter	Tweets	Ads	Newsletter	Tweets	Ads	Newsletter	Tweets	Ads
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Post-Onset First-Case x Republican	0.058***	0.414***	23.178*	0.054***	0.428***	-5.107	0.060***	0.419***	21.571*
	(0.016)	(0.077)	(12.139)	(0.017)	(0.086)	(9.874)	(0.016)	(0.077)	(11.633)
Post-Onset First-Case x Republican x Competitive Race				0.223***	-0.103	60.433**			
				(0.063)	(0.135)	(24.855)			
Post-Onset First-Case x Competitive Race				-0.015	-0.150**	-7.553			
				(0.013)	(0.069)	(24.581)			
Post-Onset First-Case x Republican x Distance to Nearest Case							-0.048**	-0.123**	32.793**
							(0.022)	(0.057)	(13.172)
Post-Onset First-Case x Distance to Nearest Case							0.004	-0.005	-4.017
							(0.009)	(0.026)	(8.260)
Mean Dep.Var.	0.03	0.19	108.30	0.03	0.19	108.30	0.03	0.19	108.30
Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Politician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Race/Constituency-Specific Linear Trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Newsletter/Tweet/Ad-level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted-R^2	0.23	0.27	0.68	0.23	0.27	0.77	0.23	0.27	0.77
Observations	5505	11144	8316	5505	11144	8316	5505	11144	8316
Number of Clusters (Race/Constituency)	285	460	227	285	460	227	285	460	227

Notes: The unit of observation is a politician - week. Newsletter sample focuses on 367 member of the congress (i.e., senators and house representatives) who sent sent at least one official e-newsletters between August 2014 and the midterm election. Twitter sample focuses on 796 democratic and republican candidates for congress with twitter activity between August and November of 2014. Campaign ads sample focuses on 575 democratic and republican candidates for congress (house or senate) and state governor who aired at least one campaign ad between August 2014 and the midterm election. The dependent variables are (1) an indicator variable if a member of Congress sent at least one official e-newsletter containing the term 'ebola' that week (Ebola Newsletter), (2) the weekly number of ebola-related tweets posted by each candidate (Ebola Tweets), and (3) the weekly number of TV campaign ads appealing to fear aired by candidates (Fear Ads). The coding of a fear-appealing ad is based on coding by Political Advertising in 2014 (Wesleyan Media Project) in two dimensions: 1) whether any ominous/tense music is played during the ad, or 2) there is direct appeal to fear in ads regardless of the music. Newsletter and Tweet-level controls are the weekly and accumulated wordcounts. Ad-level controls are the weekly and accumulated airing time length and number of ads. To ease the interpretation of the uninteracted coefficients, distance variables in the interaction terms were demeaned. Heteroskedasticity robust standard errors estimates clustered at the race (constituency for newsletters)-level are reported in parentheses; *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level, all for two-sided hypothesis tests.

Still, columns 4-6 of Table 9 address the issue more directly, by considering whether there was a differential response in races rated as competitive prior to the Ebola episode.[31] We can see that it was Republicans in competitive races who responded more strongly, and by a large margin: for instance, the relative increase in likelihood of mentioning Ebola in a newsletter was more than four times larger for a Republican involved in such a race, compared to those holding safe seats.[32]

Finally, columns 7-9 in Table 9 show that Republicans running for office in constituencies closer to the Ebola cases also responded more sharply, at least when it comes to the cheaper actions of newsletters and tweets, indicating that the strategic response was in line with the salience of the Ebola threat as perceived by voters.[33],[34] However, Democrats did not respond to that distance, indicating that the pattern is not simply driven by voter concerns.

Table 10 then turns to the issues exploited by politicians in conjunction with Ebola. We see quite clearly that Republican candidates were disproportionately inclined to mention Ebola (or appeal to

[31] By September 19, 2014, 36 (resp. 12) House (resp. Senate) races are classified as competitive by the Cook Political Report.

[32] While the point estimate for tweets is small and insignificant, and negative, this can be attributed to a small set of nine Republican candidates in non-competitive races who sent out an extremely large number of Ebola tweets (22 times more than average during the period of analysis). As shown in Table A.15 in the appendix, if we exclude this small set of candidates, the point estimate of interest reverses its sign. We find similar results if we exclusively focus on twitter activity by candidates for the US senate race. Further, we find a stronger positive effect when focused on the extensive margin (i.e. the likelihood of sending at least one Ebola tweet).

[33] Tables A.28 to A.38 in appendix present a detailed documentation of the role of distance to and the timing of each case.

[34] Table A.40 in the appendix suggests that the positive sign for the interaction term Post-Onset x Republican x Distance to Nearest Ebola Case for Fear-ads in Table 9 is driven by Republican ads aired after the occurrence of the case associated to NYC in places that were distant to that city.

fear) in newsletters, tweets, and ads that also mentioned themes like immigration, terrorism, and President Obama. For a sense of the magnitudes, after the first case Republicans were respectively 2.3 and 2.9 percentage points more likely to mention immigration (column 5) and Obama (column 6) in the same newsletters in which they mentioned Ebola. This represents an increase of about one-third over the average probability of receiving a newsletter mentioning immigration and President Obama during the sample period August-November 2014.[35]

Table 10: Ebola, Fear and Other Issues

	Ebola-Related Newsletter			Ebola-Related Tweets			Fear Appealing Ads		
	Terrorism	Immigration	Obama	Terrorism	Immigration	Obama	Terrorism	Immigration	Obama
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Post-Onset First-Case x Republican	0.011	0.023**	0.029***	0.012***	0.016***	0.061***	7.803***	9.266*	56.050***
	(0.007)	(0.009)	(0.011)	(0.004)	(0.005)	(0.011)	(2.613)	(4.920)	(11.648)
Mean Dep.Var.	0.01	0.01	0.02	0.01	0.00	0.01	2.43	8.02	24.36
Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Politician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Race/Constituency-Specific Linear Trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Newsletter/Tweet/Ad-level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted-R^2	0.10	0.11	0.16	0.02	0.04	0.09	0.16	0.34	0.46
Observations	5505	5505	5505	11144	11144	11144	8316	8316	8316
Number of Clusters (Race/Constituency)	285	285	285	460	460	460	227	227	227

Notes: The unit of observation is a politician - week. Newsletter sample focuses on 367 member of the congress (i.e., senators and house representatives) who sent sent at least one official e-newsletters between August 2014 and the midterm election. Twitter sample focuses on 796 democratic and republican candidates for congress with twitter activity between August and November of 2014. Campaign ads sample focuses on 575 democratic and republican candidates for congress (house or senate) and state governor who aired at least one campaign ad between August 2014 and the midterm election. The dependent variables are (1) an indicator variable if a member of Congress sent that week at least one official e-newsletter containing the term 'ebola' in conjunction with the issue listed in column (Ebola-Related Newsletter), (2) the weekly number of ebola-related tweets in conjunction with the issue listed in column posted by each candidate (Ebola-Related Tweets), and (3) the weekly number of TV campaign ads appealing to fear in conjunction with the issue listed in column aired by candidates (Fear Ads). The coding of a fear-appealing ad is based on codding by Political Advertising in 2014 (Wesleyan Media Project) in two dimensions: 1) whether any ominous/tense music is played during the ad, or 2) there is direct appeal to fear in ads regardless of the music. Newsletter and Tweet-level controls are the weekly and accumulated wordcounts. Ad-level controls are the weekly and accumulated airing time length and number of ads. To ease the interpretation of the uninteracted coefficients, distance variables in the interaction terms were demeaned. Heteroskedasticity robust standard errors estimates clustered at the race (constituency for newsletters)-level are reported in parentheses; *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level, all for two-sided hypothesis tests.

It is worth noting that, across all three measures, the response is quantitatively stronger when it comes to mentions of Ebola in conjunction with President Obama. In other words, Republican politicians seem to have tried especially hard to associate the Ebola threat with the president, which is interesting in light of the fact that his approval ratings were unaffected. This is also underscored by the sheer number of mentions to "Obama" and "Ebola" in a single tweet or in close proximity in a newsletter, as we can see in Figure A.8 in the Appendix. [36]

Interestingly, we find no evidence of an Ebola-related response by Republicans related to other Republican-friendly topics less plausibly related to the crisis. In particular, as shown in Table A.16 and Figure Figure A.9 in the Appendix, there is no evidence of an increase in joint mentions of "Ebola" and terms related to guns. This underscores that the responses we detect are indeed driven by strategic considerations.

Last but not least, these results also beg the question of whether Democrats may have responded strategically, perhaps by trying to associate Ebola with other themes more favorable to their message. This does not seem to have been the case, at least taking the example of healthcare – which seems a natural example of such a theme, as related to a public health threat. As we can see, again in Table

[35] In Tables A.29 to A.37 we again exploit the timing of each case when looking to the conjunction of ebola (or fear) with other issues discussed above. Again, the second case, associated with Ohio, appeared to cause an especially larger reaction from Republican members.

[36] In 50 (out of 82) newsletters in which republicans mentioned "Obama" and "Ebola", the two terms appeared in the same sentence.

A.16 and Figure Figure A.9, if anything it was Republican candidates who were more likely to mention healthcare-related words in proximity with Ebola.[37]

7 Did Ebola Make Voters More Conservative?

We have shown that the Ebola-related episodes in the U.S. triggered a strategic response by Republican politicians, and that they benefited the latter in the ballot box. In the absence of a separate source of exogenous variation for the behavior of politicians, we cannot establish whether the electoral effect was caused by that behavior.[38] However, we can look at whether voters changed their views in response to the Ebola threat. This is particularly important as it allows us to ascertain the extent to which the electoral impact was related to a broad threat-induced conservative shift in attitudes, as opposed to something more specific.

For that we resort to the CCES data, with which we replicate the exact same approach as in (5.3). As dependent variables of interest, we look at five attitudinal measures of surveyed individuals, which we can tie to conservative views: anti-immigration, pro-gun, religious, opposition to same sex marriage, and self-reported conservatism. Table 11 presents the main results. Point estimates suggest that the proximity to an Ebola case after the first Ebola does not explain disagreement with gun control measures, beliefs regarding the importance of religion, opposition towards gay marriage, or self-reported conservatism.

There is one dimension that does seem to be impacted by Ebola: attitudes towards immigration. Specifically, individuals leaving closer to an Ebola case tend to have stronger anti-immigration attitudes, after the occurrence of the first case.[39]

These findings have two important implications. First, the impact of the concerns regarding Ebola was not necessarily associated with more conservative attitudes in general, which was a possibility suggested by the previous experimental literature. Second, the results suggest that not all associations drawn by politicians were able to change voters' minds: as already documented in Section 5, our treatment does not explain disapproval rates of Obama, even though Republicans tried to push this connection, as established in Section 6. Instead, the strategic exploitation of the Ebola threat by politicians seems to have been constrained by those associations that can be more readily drawn by voters in regard to that threat.

[37] Healthcare was one of the major issues in the 2014 elections, coming on the heels of the initial implementation of the Affordable Care Act (aka, "Obamacare").

[38] In the Appendix Table A.41 we show estimates from a version of equation (1) that replaces our indicator of Ebola concerns with an indicator for whether at least one Ebola-related newsletter had been sent to a county, and exploits within-DMA variation in our treatment for the House election. Even after accounting for DMA-level unobservables, counties that received Ebola-related newsletters from Republican members of Congress experienced a large drop in Democratic vote shares, which is suggestive that Republicans may have benefited from priming Ebola concerns to their constituents, but certainly not dispositive.

[39] Reassuringly, we find the same patterns when we estimate the three distances interaction after each case in Table A.42 in the appendix.

Table 11: Proximity to Ebola Cases and Attitudes in CCES

	Anti-Immigration	Pro-Gun	Religious	Anti-gay Marriage	Conservative
	(1)	(2)	(3)	(4)	(5)
Post-Onset First-Case x Distance (in logs) to Nearest Case	-0.034**	0.003	-0.005	-0.000	-0.002
	(0.014)	(0.014)	(0.014)	(0.005)	(0.004)
Day FE	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes	Yes
Sample Weights	Yes	Yes	Yes	Yes	Yes
Adjusted-R^2	0.17	0.15	0.14	0.14	0.12
Observations	71931	71931	71931	71931	71866
Number of Clusters	2370	2370	2370	2370	2369

Notes: Sample includes all CCES's respondents for years 2013 and 2014. The variable Anti-Immigration (pro-gun)[religious] corresponds to the first principal component of responses to 5 (5)[3] questions regarding immigration (disagreement with gun-control measures)[importance of religion]. The variable Anti-gay Marriage takes value of 1 if respondent is against gay marriage. The variable conservative takes value of 1 if respondent is conservative or very conservative, 0 otherwise. The variable disapprove Obama takes value 1 if the respondent strongly disapproves or disapproves Obama, 0 otherwise. (all related questions are described in the appendix) The main independent variable accounts for the interaction between the distance (in logs) to the nearest Ebola Case and a dummy indicating the onset of that case. Individual-levels control are age and a set of indicators variables for male, white, hispanic, college or higher education, married, and annual income above US median (i.e., usd 59,000). Heteroskedasticity robust standard error estimates clustered at the county-level are reported in parentheses; *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level, all for two-sided hypothesis tests.

8 Concluding Remarks

Our investigation of the political consequences of the 2014 Ebola episode in the U.S. has uncovered a number of important effects. First, Ebola concerns caused a decrease in the Democratic vote share in that year's midterm elections, which was not related to a general or Obama-specific anti-incumbent reaction. Second, Republican candidates exploited the episode in their campaign strategy, by emphasizing the topic in conjunction with themes such as immigration, terrorism, and anti-Obama rhetoric. Finally, the salience of the Ebola threat also affected views on a subset of those themes, particularly related to increased anti-immigration sentiment.

Generally speaking, our results establish that fear of threats can indeed be a potent electoral force, in a high-stakes context in which we can isolate an exogenous shock to that fear that is relatively disconnected from the extent of the actual threat. They also suggest, however, that this force cannot be freely molded by politicians. Instead, the impact of the threat in changing voters' minds seems predicated on there being easily drawn connections between the threat and specific issues. In the case of Ebola, a gruesome disease originating abroad, the association with immigration seems to have stuck with voters.

The extent to which the lessons from Ebola apply to other salient threats is an open question, but we can nevertheless identify some dimensions that are worth considering. For instance, shocks that actually affect the risk environment – such as Ebola itself in the context of West Africa, or the recent coronavirus (COVID-19) pandemic – could well lead to a stronger updating of views on incumbent performance. As another example, we must consider which kinds of issues can be plausibly associated with the threat – shark attacks, to use a well-known example, are unlikely to lead to changed views on immigration. Finally, the timing could well matter: the Ebola crisis happened to reach the U.S. just a few weeks before an election, and had more time elapsed it could well be that effects would be more muted.

Last but not least, it would also be interesting to assess the role that the media may play in amplifying the impact of a perceived threat. We have seen evidence that the media gave extensive coverage to the handful of Ebola cases in the US, and that coverage dropped precipitously after the midterm elections. The extent to which this mattered for the effects we find remains a question for future research.

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Appendix

Figure A.1: Distance to Nearest Case

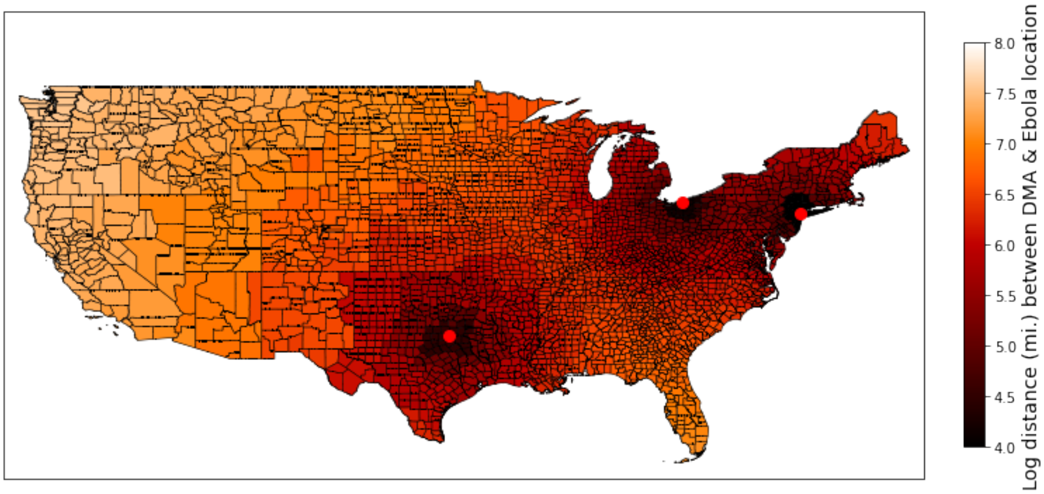
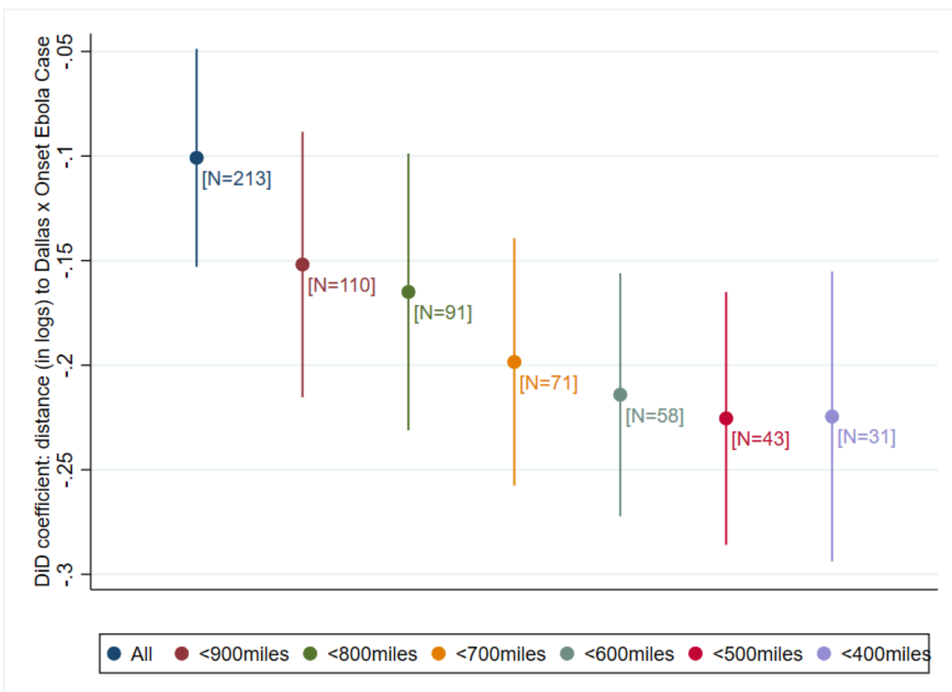
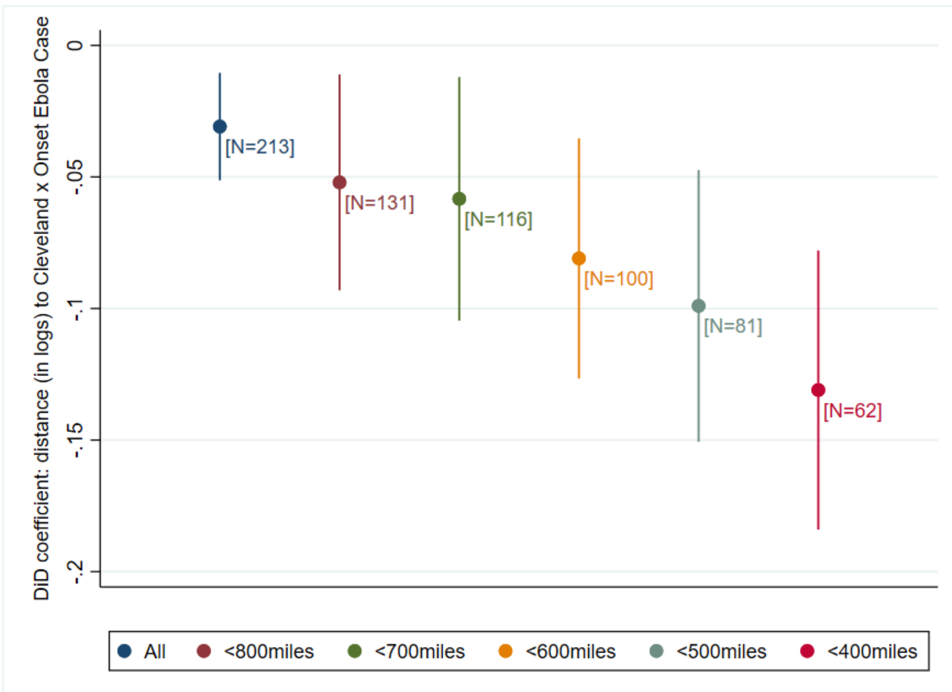


Figure A.2: Ebola-Related Twitter Activity (Dallas)



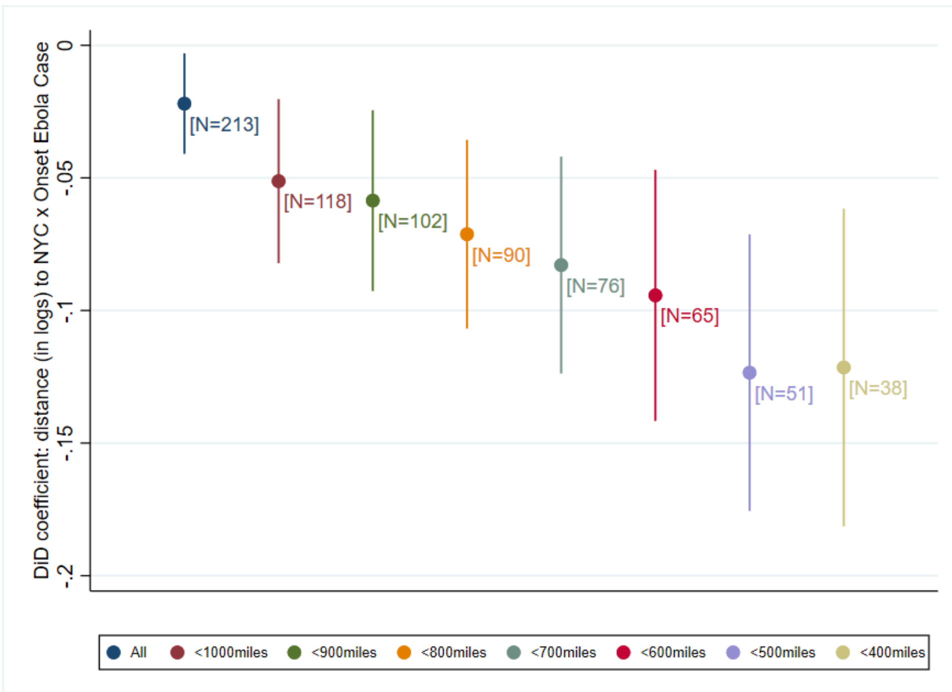
Note: The figure plots the coefficients and the 95% confidence intervals for the interaction between distance (in logs) to Dallas and a dummy indicating the onset of the first ebola case in Dallas. The dependent variable is the number of ebola related tweets per 10,000 inhabitants in DMA (using 2010 census population). The unit observation is a DMA-day. The coefficients are estimated from separate regressions in which we control for DMA fixed effect, day fixed effect, and DMA-specific linear trends while restricting the sample as a function of the proximity to Dallas. The sample includes daily data by DMA 15 days before and 15 days after the ebola diagnosis of the case. Confidence intervals are based on heteroskedasticity-robust standard errors clustered by DMA.The number of DMAs for each regression (clusters) are reported in brackets.

Figure A.3: Ebola-Related Twitter Activity (Cleveland)



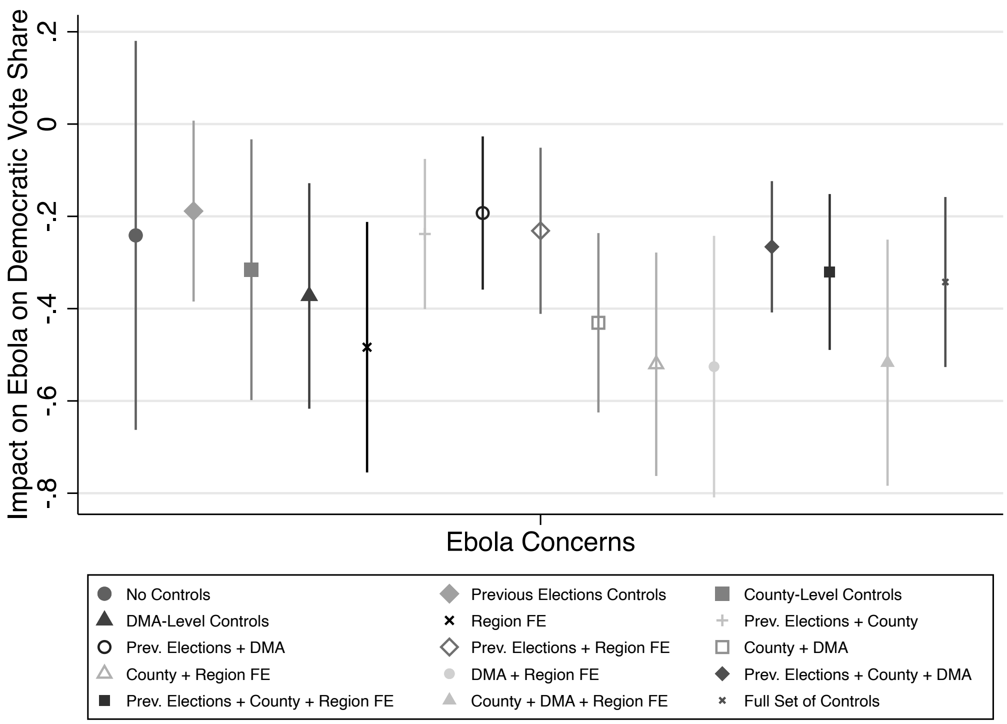
Note: The figure plots the coefficients and the 95% confidence intervals for the interaction between distance (in logs) to Cleveland and a dummy indicating the onset of the first ebola case in Cleveland. The dependent variable is the number of ebola related tweets per 10,000 inhabitants in DMA (using 2010 census population). The unit observation is a DMA-day. The coefficients are estimated from separate regressions in which we control for DMA fixed effect, day fixed effect, and DMA-specific linear trends while restricting the sample as a function of the proximity to Cleveland. The sample includes daily data by DMA 15 days before and 15 days after the ebola diagnosis of the case. Confidence intervals are based on heteroskedasticity-robust standard errors clustered by DMA.The number of DMAs for each regression (clusters) are reported in brackets.

Figure A.4: Ebola-Related Twitter Activity (NYC)



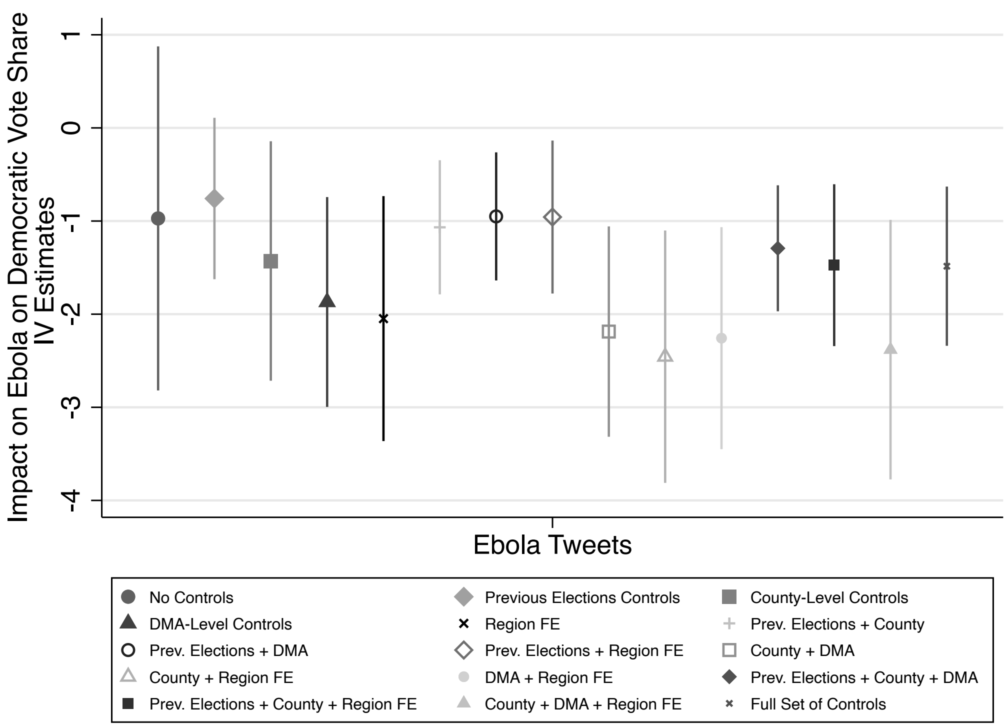
Note: The figure plots the coefficients and the 95% confidence intervals for the interaction between distance (in logs) to NYC and a dummy indicating the onset of the first ebola case in NYC. The dependent variable is the number of ebola related tweets per 10,000 inhabitants in DMA (using 2010 census population). The unit observation is a DMA-day. The coefficients are estimated from separate regressions in which we control for DMA fixed effect, day fixed effect, and DMA-specific linear trends while restricting the sample as a function of the proximity to NYC. The sample includes daily data by DMA 15 days before and 15 days after the ebola diagnosis of the case. Confidence intervals are based on heteroskedasticity-robust standard errors clustered by DMA.The number of DMAs for each regression (clusters) are reported in brackets.

Figure A.5: Permutation of Controls - Ebola Concerns



Note: The figure plots the coefficients and the 95% confidence intervals for Ebola Searches for all the different combinations of the set of controls listed in equation 1. Confidence intervals are based on heteroskedasticity-robust standard errors clustered by DMA.

Figure A.6: Permutation of Controls - Ebola Tweets



Note: The figure plots the coefficients and the 95% confidence intervals for Ebola Tweets for all the different combinations of the set of controls listed in equation 1. Confidence intervals are based on heteroskedasticity-robust standard errors clustered by DMA.

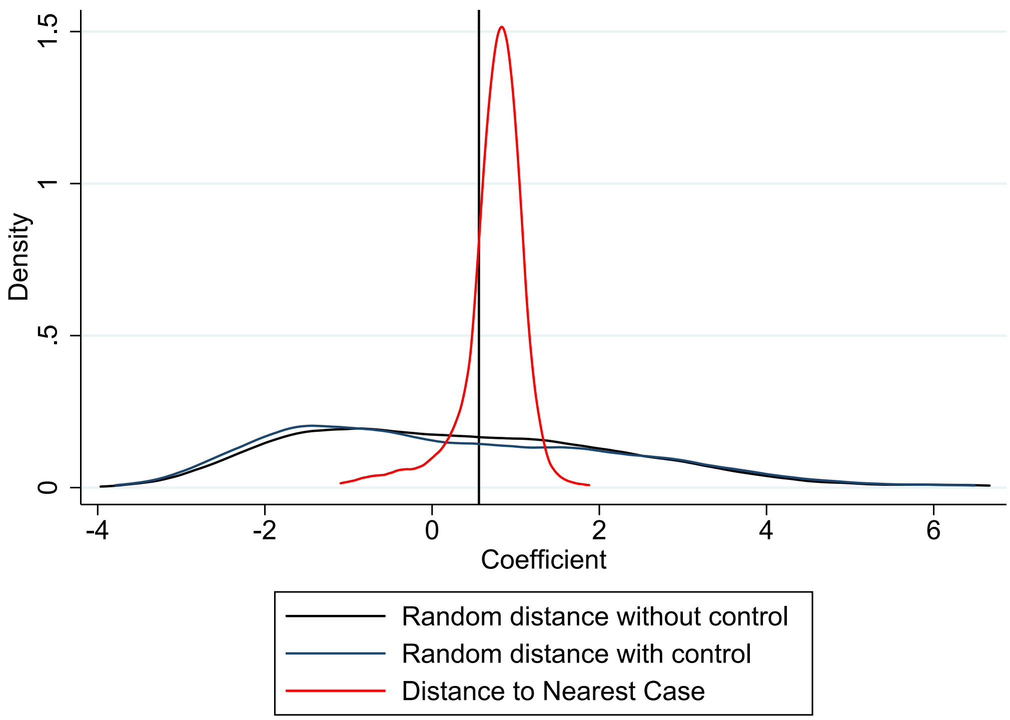


Figure A.7: Placebo Reduced-Form 2010 Vote Share and Distance

Note: The figure shows kernel density estimations for three pdf of: (1) coefficient of minimum distance to 3 randomly drawn cities out of the largest 100 cities (excluding Ebola locations) obtained from regressing Democratic vote share in 2010 House election on random distance and full set of controls described in equation (1) (1000 random draws) -pdf labelled as random distance without control-, (2) coefficient of random minimum distance as before but controlling for the minimum distance to nearest ebola case -pdf labelled as random distance with control-, and (3) coefficient of distance to nearest ebola case in each horse race with the random distance. Black vertical line denotes point estimate in our baseline specification (column 4 in Table 3)

Figure A.8: Communication Strategies Used by Politicians: Newsletters

Figure A: Ebola and Terrorism

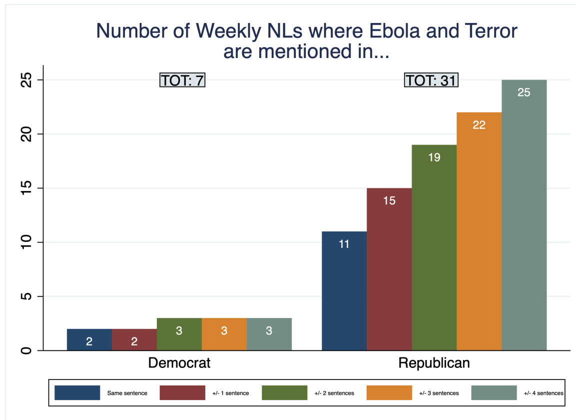


Figure B: Ebola and Immigration

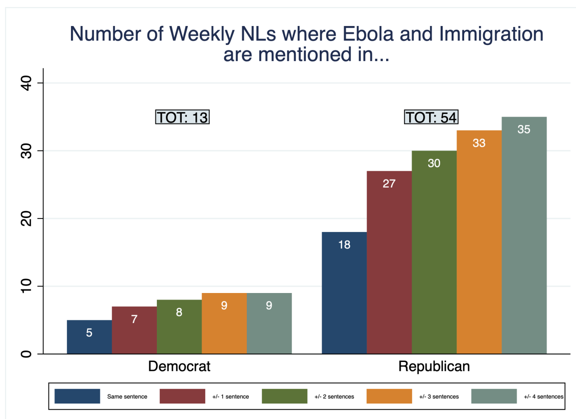


Figure C: Ebola and Obama

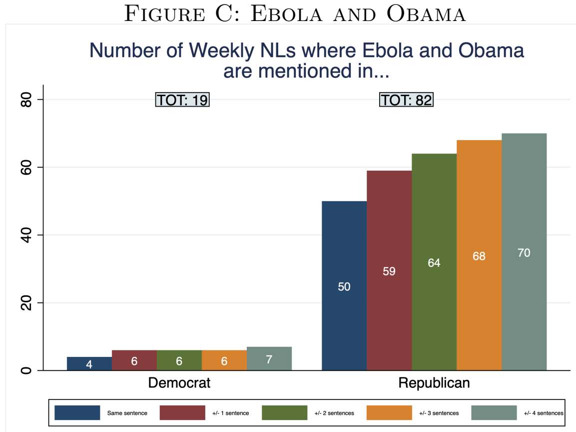


Figure A.9: Communication Strategies Used by Politicians: Newsletters

FIGURE A: EBOLA AND HEALTH CARE

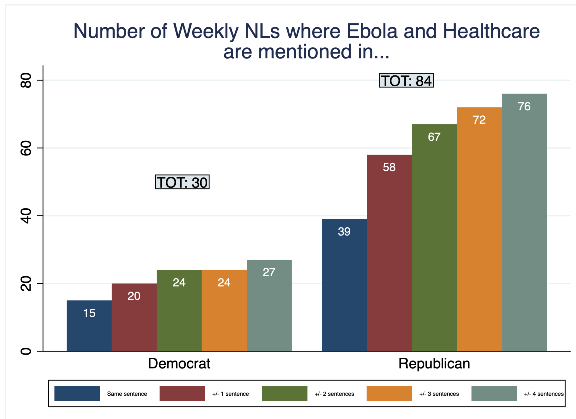


FIGURE B: EBOLA AND GUNS

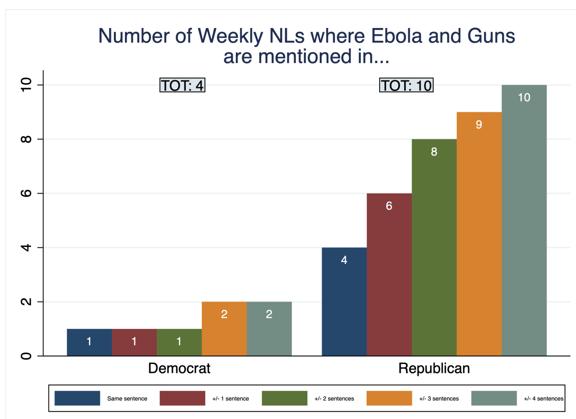


Table A.1: Summary Statistics - Voting Sample

County-level variables	Obs	Mean	Std. Dev.	Min	Max
2014 Democratic Voting Share - HOUSE	3103	33.029	18.685	0	100
2012 Democratic Voting Share - HOUSE	3112	35.632	19.399	0	99.526
2010 Democratic Voting Share - HOUSE	3090	35.553	17.489	0	90.292
2014 Incumbent Vote Share - HOUSE	2962	66.47	15.796	0	100
Δ Democratic Voting Share 2010-2006 - HOUSE	3076	-10.877	14.393	-69.813	75.226
Δ Democratic Voting Share 2010-2008 - HOUSE	3033	-10.904	13.779	-78.253	43.803
Δ Democratic Voting Share 2012-2010 - HOUSE	3088	.128	13.162	-79.932	58.386
Δ Democratic Voting Share 2006-2002 - HOUSE	3094	7.458	19.374	-73.054	89.296
2014 Democratic Voting Share - GOVERNOR	2146	35.228	14.213	1.075	88.153
2010 Democratic Voting Share - GOVERNOR	2176	37.844	14.524	8.562	87.93
2006 Democrat Vote Share - GOVERNOR	2149	45.269	16.878	3.909	89.39
2014 Incumbent Vote Share - GOVERNOR	2145	57.8	16.793	0	96.774
Δ Democrat Vote Share 2010-2006 - GOVERNOR	2145	-7.259	14.748	-57.535	26.345
Δ Democrat Vote Share 2006-2002 - GOVERNOR	2149	3.925	13.512	-40.646	49.533
2014 Democrat Voting Share - SENATE	2287	32.897	17.188	0	87.765
2012 Democrat Voting Share - SENATE	1873	42.571	16.44	0	93.092
2006 Democrat Voting Share - SENATE	1875	45.454	18.889	0	90.375
2008 Democrat Voting Share - SENATE	2289	46.401	17.741	6.09	94.884
2002 Democrat Voting Share - SENATE	2404	38.455	20.593	0	91.597
2014 Incumbent Vote Share - SENATE	2287	55.765	19.597	7.692	99.282
Δ Democrat Voting Share 2012 - 2006 - SENATE	1873	-2.862	15.684	-45.906	69.286
Δ Democrat Voting Share 2006 - 2000 - SENATE	1875	4.122	12.092	-57.043	60.769
Ebola Newsletter Sent by Republican (House)	3153	.206	.404	0	1
Population Density	3143	255.481	1708.543	.039	69357.68
Median Age	3143	39.862	4.922	18	62.5
Share of white population	3143	.787	.198	.012	1
Share of college population	3143	.19	.087	.037	.71
Income per capita	3142	22505.45	5409.365	7772	64381
Share of unemployed population	3143	.075	.034	0	.309
DMA-level variables	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Ebola Concerns (Google Trends)	203	53.963	9.476	14	100
Ebola Concerns (Tweets per capita)	206	3.987	2.076	0	15.447
Cable penetration	203	58.138	11.276	29	84
Anxiety (Google Trend, 2013)	204	70.848	8.405	44	100
Virus (Google Trend, 2013)	205	77.298	8.904	58	100
2009 Swine Flu Concerns (Google Trends, 2009)	203	41.111	9.973	16	100
Placebo Ebola Searches (Google Trends, Aug.2014)	203	52.944	12.656	25	100
Placebo Ebola Tweets (Twitter, Aug.2014)	206	.013	.017	0	.116
Distance to Nearest case (miles, in logs)	206	5.997	.844	2.311	7.73

Table A.2: Summary Statistics - Newsletters

Variable	Obs	Mean	Std. Dev.	Min	Max
Ebola Newsletter (Indicator)	5505	.032	.175	0	1
Num. of Times of Ebola is Mentioned	5505	.156	1.158	0	25
Number of Ebola Newsletters (flow)	5505	.033	.184	0	2
Number of Ebola Newsletters (stock)	5505	.128	.471	0	6
Any Newsletter (Indicator)	5505	.256	.437	0	1
Number of Newsletters	5505	.282	.525	0	7
Terrorism Newsletter	5505	.049	.217	0	1
Immigration Newsletter	5505	.068	.251	0	1
Obama Newsletter	5505	.076	.265	0	1
Ebola and Terrorism Newsletter	5505	.006	.077	0	1
Ebola and Immigration Newsletter	5505	.011	.102	0	1
Ebola and Obama Newsletter	5505	.015	.123	0	1
Republican	5505	.594	.491	0	1
Competitive Race	5505	.044	.204	0	1
Distance to Nearest case (miles, in logs)	5505	5.797	1.112	.385	7.458
Distance to Dallas (miles, in logs)	5505	6.577	.797	2.568	7.458
Distance to Cleveland (miles, in logs)	5505	6.51	.774	2.172	7.683
Distance to New York (miles, in logs)l	5505	6.565	1.164	.385	7.854

The unit of observation is member of congress - week. The sample focuses on 367 member of the congress (i.e., senators and house representatives) who sent sent at least one official e-newsletters between August 2014 and the midterm election.

Table A.3: Summary Statistics - Campaign Ads

Variable	Obs	Mean	Std. Dev.	Min	Max
Terrorism Ad (Indicator)	12255	.016	.125	0	1
Number of Terrorism Ads	12255	2.615	32.651	0	1106
Immigration Ad (Indicator)	12255	.044	.205	0	1
Number of Immigration Ads	12255	9.174	72.506	0	3388
Anti-Obama Ad (Indicator)	12255	.09	.286	0	1
Number of Anti-Obama Ads	12255	27.788	143.18	0	3403
Religion Ad (Indicator)	12255	.027	.163	0	1
Number of Religion Ads	12255	4.54	54.727	0	2303
Number of Ads Appealing to Fear (flow)	12255	82.603	253.173	0	4766
Number of Ads Appealing to Fear (stock)	12255	541.638	1700.07	0	23172
Number of Fear and Terrorism Ads (flow)	12255	1.71	24.146	0	865
Number of Fear and Terrorism Ads (stock)	12255	8.259	78.299	0	2278
Number of Fear and Immigration Ads (flow)	12255	5.911	56.295	0	1692
Number of Fear and Immigration Ads (stock)	12255	37.131	279.155	0	9443
Number of Fear and Anti-Obama Ads (flow)	12255	18.841	108.887	0	2263
Number of Fear and Anti-Obama Ads (stock)	12255	123.114	643.559	0	12990
Republican	12255	.505	.5	0	1
Competitive Race	12255	.392	.488	0	1
Distance to Nearest case (miles, in logs)	12255	6.039	.919	2.416	8.242
Distance to Dallas (miles, in logs)	12255	6.822	.561	4.912	8.242
Distance to Cleveland (miles, in logs)	12255	6.492	.811	3.549	8.426
Distance to New York (miles, in logs)	12255	6.822	.561	4.912	8.242

The unit of observation is a candidate - week. The sample focuses on 575 democratic and republican candidates for congress (house or senate) and state governor who aired at least campaign ad between August 2014 and the midterm election.

Table A.4: Campaign Ads on Ebola (21 Oct 14 - 04 Nov 14)

	Total	Fear	Immigration	Terrorism	Healthcare	Guns
Republicans	1,845	1,845 (100%)	847 (45.9%)	1,635 (88.6%)	1,330 (72.1%)	0
Democrats	91	0	0	0	0	0

This table characterizes campaign ads mentioning ebola during the two weeks before the election as coded by Political Advertising in 2014 (Wesleyan Media Project). Data for the House are complete while data for Senate and Governor races are either incomplete or have not been collected. Hence we focus on the former. The coding of a fear-appealing ad is based on coding by Political Advertising in 2014 (Wesleyan Media Project) in two dimensions: 1) whether any ominous/tense music is played during the ad, or 2) there is direct appeal to fear in ads regardless of the music.

Table A.5: Summary Statistics - Candidates' Twitter Activity

Variable	Obs	Mean	Std. Dev.	Min	Max
Ebola Tweet (Indicator)	11144	.073	.259	0	1
Number of Ebola Tweets (flow)	11144	.193	1.136	0	38
Number of Ebola Tweets (stock)	11144	.845	3.72	0	95
Num. Times of Ebola is Mentioned	11144	.202	1.181	0	38
Any Tweet (Indicator)	11144	.761	.426	0	1
Number of Tweets	11144	13.582	25.032	0	456
Terrorism Tweet (Indicator)	11144	.094	.291	0	1
Immigration Tweet (Indicator)	11144	.083	.276	0	1
Obama Tweet (Indicator)	11144	.158	.364	0	1
Ebola and Terrorism Tweet (Indicator)	11144	.005	.071	0	1
Ebola and Immigration Tweet (Indicator)	11144	.003	.059	0	1
Ebola and Obama Tweet (Indicator)	11144	.011	.104	0	1
Republican	11144	.506	.5	0	1
Competitive Race	11144	.114	.318	0	1
Distance to Nearest case (miles, in logs)	11144	5.808	1.152	.385	7.458
Distance to Dallas (miles, in logs)	11144	6.706	.672	2.107	7.458
Distance to Cleveland (miles, in logs)	11144	6.442	.829	2.172	7.683
Distance to New York (miles, in logs)	11144	6.472	1.251	.385	7.854

The unit of observation is candidate - week. The sample focuses on 796 democrat and republican candidates for congress with twitter activity between August and November of 2014.

Table A.6: Summary Statistics - CCES Sample

Variable	Obs	Mean	Std. Dev.	Min	Max
Anti-Immigration (1st PC)	71931	-.001	1.636	-2.331	2.796
Pro-Gun (1st PC)	71931	-.003	1.578	-1.609	3.31
Religious (1st PC) 1	71931	-.001	1.39	-1.689	2.013
Against Gay Marriage	71931	.409	.492	0	1
Conservative	71867	.325	.468	0	1
Disapprove Obama	71931	.532	.499	0	1
Male	71931	.466	.499	0	1
Age	71931	49.928	16.706	18	102
College Education or Higher	71931	.682	.466	0	1
White	71931	.741	.438	0	1
Hispanic	71931	.071	.257	0	1
Income Above Median US (USD59,000)	71931	.361	.48	0	1
Married	71931	.534	.499	0	1
Distance to Nearest case (miles, in logs)	71931	5.744	1.28	.203	7.475
Distance to Dallas (miles, in logs)	71931	6.708	.84	.203	7.479
Distance to Cleveland (miles, in logs)	71931	6.388	.89	2.965	7.697
Distance to New York (miles, in logs)	71931	6.434	1.261	1.394	7.865

Sample includes all CCES's respondents for years 2013 and 2014

Table A.7: Summary Statistics - Gallup Sample

Variable	Obs	Mean	Std. Dev.	Min	Max
Disapprove Obama	24936	.583	.493	0	1
Age	24398	54.738	18.309	18	99
Male	24935	.5	.5	0	1
Employed	24859	.478	.5	0	1
Married	24680	.546	.498	0	1
Black	24936	.097	.295	0	1
Hispanic	24936	.085	.28	0	1
Distance to Nearest case (miles, in logs)	24936	6.01	.896	3.243	8.244
Distance to Dallas (miles, in logs)	24936	6.697	.568	4.078	8.244
Distance to Cleveland (miles, in logs)	24936	6.459	.896	3.243	8.427
Distance to New York (miles, in logs)	24936	6.699	.896	3.853	8.512

Sample includes Gallup's daily between September 1st, 2014 and the midterm election.

Table A.8: First-Stage (Standard Errors Adjustment for Spatial Autocorrelation)

	Ebola Searches					Ebola Tweets	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Distance (in logs) to Nearest Case	-5.475***	-8.434***	-7.974***	-7.866***	-7.309***	-1.766***	-1.609***
100 km	(1.756)	(1.142)	(0.808)	(0.793)	(0.852)	(0.201)	(0.216)
200 km	(2.403)	(1.738)	(1.213)	(1.190)	(1.298)	(0.302)	(0.316)
300 km	(2.579)	(1.991)	(1.395)	(1.362)	(1.507)	(0.348)	(0.347)
400 km	(2.615)	(2.096)	(1.500)	(1.467)	(1.592)	(0.374)	(0.351)
500 km	(2.629)	(2.137)	(1.568)	(1.531)	(1.652)	(0.386)	(0.354)
1000 km	(2.569)	(2.217)	(1.755)	(1.713)	(1.770)	(0.406)	(0.380)
Mean Value Dep. Var.	54.9	54.9	54.9	54.9	54.1	5.6	4.2
County-Level Controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	No	Yes	Yes	Yes	Yes	Yes	Yes
DMA-Level Controls	No	No	Yes	Yes	Yes	Yes	Yes
Previous Election Controls	No	No	No	Yes	Yes	Yes	Yes
Population Weights	Yes	Yes	Yes	Yes	No	Yes	No
Observations	3068	3067	3062	3062	3062	3064	3064
Number of Clusters (DMA)	203	203	202	202	202	203	203

Notes: The variable Ebola Searches accounts for the google search volume of the term 'ebola' during the 5 weeks before the 2014 election. The variable Ebola Tweets accounts for the number of tweets about 'ebola' per 10,000 inhabitants in DMA during the same period. Spatial auto-correlation corrected standard errors (Conley, 1999) are reported in parentheses (cutoff distances reported on the left); *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level, all for two-sided hypothesis tests. County-level controls are population density, median age, share of white population, share of population with college degree, income per capita, and unemployment. DMA-level controls are cable TV penetration 2010, Ebola Searches/Tweets before first case in the US, and google searches for the terms 'anxiety' and 'virus', both in 2013.

Table A.9: Balance Test

	Distance (in logs) to Nearest Case					
	Panel A: Unweighted			Panel A: Weighted		
Covariate	Coef.	P-value	BH Q-value	Coef.	P-value	BH Q-value
Population	-33854.598	0.194	0.609	-50595.871	0.444	0.730
Density	-393.475	0.160	0.609	-1114.365	0.063	0.472
Median Age	0.354	0.073	0.556	0.204	0.107	0.472
Share with College Degree	-0.004	0.542	0.925	-0.020	0.105	0.472
Share White	-0.002	0.881	0.953	0.015	0.344	0.666
Share Black	-0.007	0.320	0.714	-0.007	0.170	0.472
Share Hispanic	0.000	0.960	0.960	-0.007	0.465	0.730
Share Foreign	-0.003	0.692	0.953	-0.018	0.179	0.472
Income per Capita	-661.407	0.232	0.612	-1775.540	0.063	0.472
Share Owners	-0.003	0.466	0.845	-0.008	0.217	0.525
Share Married	0.007	0.046	0.556	0.005	0.160	0.472
Ebola GT pre-treatment	-1.855	0.108	0.556	-3.147	0.068	0.472
Ebola tweets pc pre-treatment	-0.003	0.042	0.556	-0.003	0.000	0.001
Anxiety GT 2013	-1.509	0.210	0.609	-0.155	0.853	0.884
Virus GT 2013	-0.383	0.699	0.953	0.427	0.589	0.743
Swineflu GT 2009	-0.157	0.812	0.953	-0.218	0.585	0.743
Cable TV Penetration 2010	-2.785	0.115	0.556	-4.204	0.126	0.472
Dem. Vote Share House 2012	0.426	0.788	0.953	-1.860	0.478	0.730
Dem. Vote Share House 2010	0.487	0.722	0.953	-0.988	0.663	0.770
Dem. Vote Share House 2006	0.196	0.882	0.953	-1.567	0.436	0.730
Δ Dem. Vote Share House 2010-2006	0.291	0.602	0.953	0.579	0.152	0.472
Dem. Vote Share Pres. 2012	0.486	0.755	0.953	-1.178	0.638	0.770
Dem. Vote Share Pres. 2008	-0.126	0.920	0.953	-1.248	0.543	0.743
Dem. Vote Share Sen. 2012	0.231	0.899	0.953	-0.841	0.766	0.823
Dem. Vote Share Sen. 2006	2.165	0.188	0.609	-0.107	0.962	0.962
Δ Dem. Vote Share Sen. 2006-2000	0.816	0.349	0.723	-0.235	0.751	0.823
Dem. Vote Share Gov. 2010	-1.329	0.261	0.631	-2.281	0.330	0.666
Dem. Vote Share Gov. 2006	-1.747	0.440	0.845	-1.981	0.539	0.743
Δ Dem. Vote Share Gov. 2006-2002	-3.207	0.102	0.556	-3.593	0.248	0.554

Notes: This table reports point estimates, p-values (standard errors clustered at the DMA level), and False Discovery Rate (FDR) adjusted p-values (Anderson, 2008) for 30 OLS county-level regressions of a covariate (listed at the left) on our instrument (Distance (in logs) to Nearest Case). Regressions in Panel B are weighted by DMA population.

Table A.10: Ebola Searches and Distances to Large Cities (First-Stage)

	Ebola Searches				
	(1)	(2)	(3)	(4)	(5)
Distance (in logs) to Nearest Case	-7.866***	-7.802***	-7.765***	-7.988***	-8.245***
	(1.261)	(1.212)	(1.120)	(1.280)	(1.197)
Distance (in logs) to Nearest Non-Ebola Large City		-0.493	-1.020	0.359	1.919**
		(0.689)	(0.729)	(0.588)	(0.796)
Definition of Nearest Large City		Top 100	Top 50	More than 500k	More than 1 million
Std Dev Vote Share	11.96	11.96	11.96	11.96	11.96
Std Dev Distance Nearest Case	1.23	1.23	1.23	1.23	1.23
Effect of Std Dev Δ in Distance	-10.54	-10.46	-10.41	-10.71	-11.05
County-Level Controls	Yes	Yes	Yes	Yes	Yes
DMA-Level Controls	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes
Previous Election Controls	Yes	Yes	Yes	Yes	Yes
Adjusted-R^2	0.68	0.68	0.68	0.68	0.69
Observations	3062	3062	3062	3062	3062
Number of Clusters (DMA)	202	202	202	202	202

Notes: All regressions are weighted by DMA population. Heteroskedasticity robust standard error estimates clustered at the DMA-level are reported in parentheses; *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level, all for two-sided hypothesis tests. County-level controls are population density, median age, share of white population, share of population with college degree, income per capita, and unemployment. DMA-level controls are cable TV penetration 2010, Ebola Searches/Tweets before first case in the US, and google searches for the terms 'anxiety' and 'virus', both in 2013.

Table A.11: Ebola-Related Twitter Activity and Distances to Large Cities (First-Stage)

	Ebola Tweets				
	(1)	(2)	(3)	(4)	(5)
Distance (in logs) to Nearest Case	-1.766***	-1.759***	-1.736***	-1.708***	-1.760***
	(0.311)	(0.303)	(0.268)	(0.311)	(0.330)
Distance (in logs) to Nearest Non-Ebola Large City		-0.056	-0.314**	-0.162	-0.032
		(0.143)	(0.150)	(0.131)	(0.153)
Definition of Nearest Large City		Top 100	Top 50	More than 500k	More than 1 million
County-Level Controls	Yes	Yes	Yes	Yes	Yes
DMA-Level Controls	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes
Previous Election Controls	Yes	Yes	Yes	Yes	Yes
Std Dev Vote Share	2.76	2.76	2.76	2.76	2.76
Std Dev Distance Nearest Case	1.34	1.34	1.34	1.34	1.34
Effect of Std Dev Δ in Distance	-2.37	-2.36	-2.33	-2.29	-2.36
Adjusted-R^2	0.80	0.80	0.81	0.80	0.80
Observations	3064	3064	3064	3064	3064
Number of Clusters (DMA)	203	203	203	203	203

Notes: All regressions are weighted by DMA population. Heteroskedasticity robust standard error estimates clustered at the DMA-level are reported in parentheses; *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level, all for two-sided hypothesis tests. County-level controls are population density, median age, share of white population, share of population with college degree, income per capita, and unemployment. DMA-level controls are cable TV penetration 2010, Ebola Searches/Tweets before first case in the US, and google searches for the terms 'anxiety' and 'virus', both in 2013.

Table A.12: Democrat Vote Share and Distances to Large Cities

	Democrat Vote Share in 2014 House Reps. Election				
	(1)	(2)	(3)	(4)	(5)
Distance (in logs) to Nearest Case	2.918***	2.862***	2.840***	2.726***	2.612***
	(0.455)	(0.472)	(0.505)	(0.500)	(0.377)
Distance (in logs) to Nearest Non-Ebola Large City		0.444	0.821**	0.570	1.546***
		(0.396)	(0.377)	(0.391)	(0.460)
Definition of Nearest Large City		Top 100	Top 50	More than 500k	More than 1 million
County-Level Controls	Yes	Yes	Yes	Yes	Yes
DMA-Level Controls	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes
Previous Election Controls	Yes	Yes	Yes	Yes	Yes
Std Dev Vote Share	20.61	20.61	20.61	20.61	20.61
Std Dev Distance Nearest Case	1.22	1.22	1.22	1.22	1.22
Effect of Std Dev Δ in Distance	3.90	3.83	3.80	3.65	3.49
Adjusted-R^2	0.75	0.75	0.75	0.75	0.75
Observations	3056	3056	3056	3056	3056
Number of Clusters (DMA)	202	202	202	202	202

Notes: All regressions are weighted by DMA population. Heteroskedasticity robust standard error estimates clustered at the DMA-level are reported in parentheses; *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level, all for two-sided hypothesis tests. County-level controls are population density, median age, share of white population, share of population with college degree, income per capita, and unemployment. DMA-level controls are cable TV penetration 2010, Ebola Searches/Tweets before first case in the US, and google searches for the terms 'anxiety' and 'virus', both in 2013.

Table A.13: Ebola Searches/Tweets and Democrat Vote Share (IV - Standard Errors Adjustment for Spatial Autocorrelation)

	Democrat Vote Share in 2014 House Reps. Election					
	(1)	(2)	(3)	(4)	(5)	(6)
Distance (in logs) to Nearest Case	2.918***	2.492***				
100km	(0.582)	(0.663)				
200km	(0.547)	(0.758)				
300km	(0.387)	(0.777)				
400km	(0.401)	(0.839)				
500km	(0.335)	(0.885)				
1000km	(.)	(0.804)				
Ebola Searches			-0.373***	-0.342***		
100km			(0.088)	(0.092)		
200km			(0.099)	(0.103)		
300km			(0.093)	(0.092)		
400km			(0.099)	(0.085)		
500km			(0.096)	(0.084)		
1000km			(0.077)	(0.055)		
Ebola Tweets					-1.644***	-1.485***
100km					(0.410)	(0.434)
200km					(0.485)	(0.486)
300km					(0.480)	(0.433)
400km					(0.508)	(0.414)
500km					(0.493)	(0.381)
1000km					(0.391)	(.)
Std Dev Vote Share	18.66		18.66	18.66	18.66	18.66
Std Dev Ebola (Searches or Tweets)	0.80	0.80	10.48	10.48	2.12	2.12
Effect of Std Dev Δ in Searches/Tweets	2.32	2.32	-3.88	-4.15	-3.29	-3.98
County-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
DMA-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Previous Election Controls	Yes	Yes	Yes	Yes	Yes	Yes
Population Weight	Yes	No	Yes	No	Yes	No
Observations	3056	3056	3056	3056	3058	3058

Notes: The variable Ebola Searches accounts for the google search volume of the term 'ebola' during the 5 weeks before the 2014 election. The variable Ebola Tweets accounts for the number of tweets about 'ebola' per 10,000 inhabitants in DMA during the same period. All regressions but those on columns (4) and (6) are weighted by DMA population. Spatial auto-correlation corrected standard errors (Conley, 1999) are reported in parentheses (cutoff distances reported on the left); *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level, all for two-sided hypothesis tests. County-level controls are population density, median age, share of white population, share of population with college degree, income per capita, and unemployment. DMA-level controls are cable TV penetration 2010, Ebola Searches/Tweets before first case in the US, and google searches for the terms 'anxiety' and 'virus', both in 2013.

Table A.14: Post-Election Newsletters and Twitter Activity

	Newsletter		Tweets	
	Ebola	Any	Ebola	Any
	(1)	(2)	(3)	(4)
Post-Election x Republican	-0.069***	-0.039	-0.197***	-0.142
	(0.016)	(0.024)	(0.037)	(0.180)
Mean Dep.Var.	0.02	0.25	0.13	10.12
Std Dev Indep. Variable	0.40	0.40	0.39	0.39
Effect of Std Dev Δ in Indep. Variable	-0.03	-0.02	-0.08	-0.05
Week FE	Yes	Yes	Yes	Yes
Politician FE	Yes	Yes	Yes	Yes
Race/Constituency-Specific Linear Trends	Yes	Yes	Yes	Yes
Newsletter/Tweet-level Controls	Yes	Yes	Yes	Yes
Adjusted-R^2	0.13	0.56	0.16	0.99
Observations	8441	8441	17512	17512
Number of Clusters (Race/Constituency)	285	285	460	460

Notes: The unit of observation is a politician - week. The sample of columns 1 and 2 focuses on 367 members of the congress (i.e., senators and house representatives) who sent at least one official e-newsletter between August 2014 and the midterm election. The sample on columns 3 and 4 focuses on 796 democratic and republican candidates for Congress with twitter activity during the same period. The dependent variables are (1) Newsletters (Ebola and Any): an indicator variable if a member of Congress sent at least one official ebola-related (any e-newsletter) during the week; (2) Tweets (Ebola and Any): the number of ebola related (any) tweets posted by each candidate. The main independent variable accounts for the interaction between a dummy indicating the post-election period and an indicator taking value 1 if the politician is republican, 0 otherwise. Newsletter and Tweet-level controls are the weekly and accumulated wordcounts. Ad-level controls are the weekly and accumulated airing time length and number of ads. Heteroskedasticity robust standard errors estimates clustered at the race (constituency for newsletters)-level are reported in parentheses; *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level, all for two-sided hypothesis tests.

Table A.15: Twitter Activity and Competitive Races (Restricted Sample)

	Number of Tweets			At least 1 Ebola Tweet
	(1)	(2)	(3)	(4)
Post-Onset First-Case x Republican	0.428***	0.251***	0.772*	0.137*
	(0.086)	(0.056)	(0.409)	(0.069)
Post-Onset First-Case x Republican x Competitive Race	-0.103	0.039	0.366	0.199**
	(0.135)	(0.118)	(0.418)	(0.082)
Post-Onset First-Case x Competitive Race	-0.150**	-0.110*	0.125	0.011
	(0.069)	(0.065)	(0.207)	(0.065)
Mean Dep.Var.	0.19	0.15	0.33	0.11
Sample	Full	Exc. Top 10 Ebola-Tweet	Senate Race	Senate Race
Week FE	Yes	Yes	Yes	Yes
Politician FE	Yes	Yes	Yes	Yes
Race-Specific Linear Trends	Yes	Yes	Yes	Yes
Tweets-Level Controls	Yes	Yes	Yes	Yes
Adjusted-R^2	0.27	0.23	0.32	0.34
Observations	11144	11004	882	882
Number of Clusters (Race)	460	458	31	31

Notes: The unit of observation is a politician - week. Twitter sample focuses on 796 democratic and republican candidates for congress with twitter activity between August and November of 2014. In column 2, 10 candidates with a disproportionate number of ebola-related tweets are excluded. In columns 3 and 4, the sample exlusively focus in candidates in the US Senate race. The dependent variables are (1) the weekly number of ebola-related tweets posted by each candidate in columns 1 to 3, and (2) an indicator variable if the candidate tweeted at least once the term 'ebola' that week. Heteroskedasticity robust standard errors estimates clustered at the race-level are reported in parentheses; *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level, all for two-sided hypothesis tests. Tweets controls are the weekly and accumulated wordcounts.

Table A.16: Ebola and Other Issues

	Ebola-Related Newsletters		Ebola-Related Tweets	
	Health	Guns	Health	Guns
	(1)	(2)	(3)	(4)
Post-Onset First-Case x Republican	0.029***	0.004	0.007*	-0.000
	(0.011)	(0.003)	(0.004)	(0.001)
Week FE	Yes	Yes	Yes	Yes
Politician FE	Yes	Yes	Yes	Yes
Race/Constituency-Specific Linear Trends	Yes	Yes	Yes	Yes
Newsletter/Tweets-Level Controls	Yes	Yes	Yes	Yes
Adjusted-R^2	0.15	0.03	0.03	-0.01
Observations	5505	5505	11144	11144
Number of Clusters (Race)	285	285	460	460

Notes: The unit of observation is a politician - week. Newsletter sample focuses on 367 member of the congress (i.e., senators and house representatives) who sent sent at least one official e-newsletters between August 2014 and the midterm election. Twitter sample focuses on 796 democratic and republican candidates for congress with twitter activity between August and November of 2014. The dependent variables are (1) an indicator variable if a member of Congress sent that week at least one official e-newsletter containing the term 'ebola' in conjunction with the issue listed in column (Ebola-Related Newsletter) and (2) the weekly number of ebola-related tweets in conjunction with the issue listed in column posted by each candidate (Ebola-Related Tweets). Health indicates whether at least one of the following keywords was mentioned in the message: Affordable Care Act, ACA, health care, medicare or obamacare. Guns indicates whether at least one of the following keywords was mentioned in the message: gun, firearm, weapon or second amendment. Heteroskedasticity robust standard errors estimates clustered at the race-level are reported in parentheses; *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level, all for two-sided hypothesis tests. Newsletters and Tweets controls are the weekly and accumulated wordcounts.

Table A.17: Ebola Newsletters and Timing of Each Case

	Ebola Newsletter							
	Indicator	Stock	Indicator	Stock	Indicator	Stock	Indicator	Stock
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post-Onset Dallas x Republican	0.080***	0.134***					0.036	0.059**
	(0.020)	(0.030)					(0.025)	(0.025)
Post-Onset Cleveland x Republican			0.070***	0.209***			0.068**	0.218***
			(0.023)	(0.036)			(0.030)	(0.039)
Post-Onset NYC x Republican					-0.090***	0.049*	-0.113***	0.062**
					(0.022)	(0.028)	(0.026)	(0.030)
Mean Dep.Var.	0.06	0.13	0.09	0.22	0.09	0.41	0.02	0.27
Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Politician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constituency-Specific Linear Trends	No	No	No	No	No	No	Yes	Yes
Newsletter-level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted-R^2	0.29	0.66	0.32	0.77	0.37	0.93	0.24	0.77
Observations	1468	1468	1468	1468	1468	1468	5505	5505
Number of Clusters (Constituency)	285	285	285	285	285	285	285	285

Notes: The unit of observation is a politician - week. The sample focuses on 367 member of the congress (i.e., senators and house representatives) who sent at least one official e-newsletter. The analysis restricts to: (1) 2 weeks before and 2 weeks after the ebola diagnosis of each case in columns 1 to 6, and (2) period between August 2014 and the midterm election in columns 7 and 8. The variable Ebola Newsletter 'Indicator' takes value 1 if the member of Congress sent at least one official ebola-related newsletter during the week, 0 otherwise.The variable Ebola Newsletter 'Stock' accounts for the accumulated number of ebola-related newsletters that were sent up to that week by the member of Congress. The main independent variables account for the interaction between a dummy indicating the post-onset of each ebola case and an indicator taking value 1 if the member of the Congress is republican, 0 otherwise. Newsletter-level controls are the weekly and accumulated wordcounts. Heteroskedasticity robust standard error estimates clustered at the constituency-level are reported in parentheses; *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level, all for two-sided hypothesis tests.

Table A.18: Ebola Tweets and Timing of Each Case

	Ebola Tweets							
	Flow	Stock	Flow	Stock	Flow	Stock	Flow	Stock
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post-Onset Dallas x Republican	0.590***	0.869***					0.634***	1.000***
	(0.113)	(0.186)					(0.125)	(0.249)
Post-Onset Cleveland x Republican			0.105	1.484***			-0.070	1.177***
			(0.104)	(0.264)			(0.108)	(0.213)
Post-Onset NYC x Republican					-0.824***	0.493***	-0.474***	0.226***
					(0.145)	(0.107)	(0.124)	(0.076)
Mean Dep.Var.	0.41	0.82	0.56	1.38	0.49	2.43	0.13	1.56
Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Politician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Race-Specific Linear Trends	No	No	No	No	No	No	Yes	Yes
Tweet-level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted-R^2	0.34	0.62	0.45	0.71	0.36	0.97	0.27	0.70
Observations	3184	3184	3184	3184	3184	3184	11144	11144
Number of Clusters (Race)	460	460	460	460	460	460	460	460

Notes: The unit of observation is a candidate - week. The sample focuses on 796 democratic and republican candidates for congress with twitter activity. The analysis restricts to: (1) 2 weeks before and 2 weeks after the ebola diagnosis of each case in columns 1 to 6, and (2) period between August 2014 and the midterm election in columns 7 and 8. The dependent variables are the weekly flow and accumulated stock of ebola-related tweets posted by each candidate. The main independent variable accounts for the interaction between a dummy indicating the post-onset of each ebola case and an indicator taking value 1 for the republican candidate, 0 otherwise. Tweet-level controls are the weekly and accumulated wordcounts. Heteroskedasticity robust standard error estimates clustered at the race-level are reported in parentheses; *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level, all for two-sided hypothesis tests.

Table A.19: Fear Appealing Ads and Timing of Each Case

	Fear Ads							
	Flow	Stock	Flow	Stock	Flow	Stock	Flow	Stock
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post-Onset Dallas x Republican	12.477	42.747					19.914*	12.001
	(15.022)	(30.161)					(11.142)	(66.171)
Post-Onset Cleveland x Republican			5.810	32.866			-10.072	1.863
			(20.009)	(34.987)			(18.039)	(25.294)
Post-Onset NYC x Republican					16.973	50.030	19.990	33.902
					(17.654)	(36.992)	(17.397)	(30.807)
Mean Dep.Var.	141.26	877.35	202.29	1249.24	180.17	1429.41	108.30	752.32
Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Politician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Race-Specific Linear Trends	No	No	No	No	No	No	Yes	Yes
Ad-level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted-R^2	0.79	0.98	0.84	0.98	0.83	0.98	0.77	0.94
Observations	2376	2376	2376	2376	2376	2376	8316	8316
Number of Clusters (Race)	227	227	227	227	227	227	227	227

Notes: The unit of observation is a candidate - week. The sample focuses on 575 democratic and republican candidates for congress that aired at least one campaign TV ads. The analysis restricts to: (1) 2 weeks before and 2 weeks after the ebola diagnosis of each case in columns 1 to 6, and (2) period between August 2014 and the midterm election in columns 7 and 8. The dependent variables are the number of fear-appealing ads (weekly flow and accumulated stock). The coding of a fear-appealing ad is based on codding by Political Advertising in 2014 (Wesleyan Media Project) in two dimensions: 1) whether any ominous/tense music is played during the ad, or 2) there is direct appeal to fear in ads regardless of the music. The main independent variable accounts for the interaction between a dummy indicating the post-onset of each ebola case and an indicator taking value 1 for the republican candidate, 0 otherwise. Ad-level controls are the weekly and accumulated airing time length and number of ads. Heteroskedasticity robust standard error estimates clustered at the race-level are reported in parentheses; *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level, all for two-sided hypothesis tests.

Table A.20: Ebola and Terrorism Newsletters,Timing and Distance To Cases

	Ebola and Terrorism Newsletters							
	Flow	Stock	Flow	Stock	Flow	Stock	Flow	Stock
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post-Onset Dallas x Republican	0.022**	0.039***					0.021	0.023*
	(0.010)	(0.015)					(0.014)	(0.013)
Post-Onset Dallas x Republican x Distance Dallas (logs)	-0.005	-0.005					-0.001	0.006
	(0.010)	(0.015)					(0.007)	(0.016)
Post-Onset Dallas x Distance Dallas (logs)	0.003	0.006					0.004	0.008
	(0.004)	(0.008)					(0.003)	(0.008)
Post-Onset Cleveland x Republican			0.002	0.039***			-0.006	0.029**
			(0.010)	(0.014)			(0.015)	(0.014)
Post-Onset Cleveland x Republican x Distance Cleveland (logs)			0.004	-0.014			-0.001	0.000
			(0.010)	(0.015)			(0.009)	(0.015)
Post-Onset Cleveland x Distance Cleveland (logs)			-0.006	0.005			-0.002	0.009
			(0.008)	(0.008)			(0.006)	(0.009)
Post-Onset NYC x Republican					-0.020*	0.004	-0.023*	0.007
					(0.010)	(0.015)	(0.012)	(0.017)
Post-Onset NYC x Republican x Distance NYC (logs)					0.014	-0.025	0.017	-0.048
					(0.013)	(0.022)	(0.012)	(0.040)
Post-Onset NYC x Distance NYC (logs)					0.001	0.002	-0.001	0.003
					(0.003)	(0.005)	(0.003)	(0.005)
Mean Dep.Var.	0.01	0.03	0.01	0.04	0.01	0.07	0.01	0.02
Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Politician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constituency-Specific Linear Trends	No	No	No	No	No	No	Yes	Yes
Newsletter-level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted-R^2	0.08	0.58	0.19	0.66	0.18	0.91	0.11	0.71
Observations	1468	1468	1468	1468	1468	1468	5505	5505
Number of Clusters (Constituency)	285	285	285	285	285	285	285	285

Notes: The unit of observation is member of congress - week. The sample focuses on 367 member of the congress (i.e., senators and house representatives) who sent at least one official e-newsletter. The analysis restricts to: (1) 2 weeks before and 2 weeks after the ebola diagnosis of each case in columns 1 to 6, and (2) period between August 2014 and the midterm election in columns 7 and 8. The dependent variables are the number of ebola & terrorism - related newsletters (weekly flow and accumulated stock). The main independent variables account for the interaction between a dummy indicating the post-onset of each ebola case, an indicator taking value 1 if the member of the congress is republican and 0 otherwise, and the distance (in logs) to the correspondent ebola case. Newsletter-level controls are the weekly and accumulated content wordcounts. To ease the interpretation of the uninteracted coefficients, distance variables in the interaction terms were demeaned. Heteroskedasticity robust standard error estimates clustered at the constituency-level are reported in parentheses; *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level, all for two-sided hypothesis tests.

Table A.21: Ebola and Terrorism Tweets, Timing and Distance To Cases

	Ebola-Terrorism Tweets							
	Flow	Stock	Flow	Stock	Flow	Stock	Flow	Stock
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post-Onset Dallas x Republican	0.009	0.014					0.014*	0.027*
	(0.009)	(0.009)					(0.007)	(0.015)
Post-Onset Dallas x Republican x Distance Dallas (logs)	-0.005	-0.006					-0.008	-0.055*
	(0.010)	(0.011)					(0.006)	(0.028)
Post-Onset Dallas x Distance Dallas (logs)	-0.003	-0.003					0.001	0.024
	(0.008)	(0.013)					(0.005)	(0.016)
Post-Onset Cleveland x Republican			0.012	0.048***			0.008	0.043***
			(0.012)	(0.014)			(0.013)	(0.012)
Post-Onset Cleveland x Republican x Distance Cleveland (logs)			0.001	-0.017			0.002	-0.015
			(0.010)	(0.012)			(0.006)	(0.023)
Post-Onset Cleveland x Distance Cleveland (logs)			-0.006*	0.002			-0.004	0.004
			(0.003)	(0.004)			(0.004)	(0.010)
Post-Onset NYC x Republican					-0.026***	0.023**	-0.017	0.012*
					(0.010)	(0.009)	(0.011)	(0.007)
Post-Onset NYC x Republican x Distance NYC (logs)					0.001	0.004	0.001	0.000
					(0.006)	(0.006)	(0.004)	(0.012)
Post-Onset NYC x Distance NYC (logs)					0.004	0.000	0.004	0.002
					(0.003)	(0.003)	(0.003)	(0.005)
Mean Dep.Var.	0.01	0.03	0.01	0.04	0.01	0.07	0.00	0.05
Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Politician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Race-Specific Linear Trends	No	No	No	No	No	No	Yes	Yes
Tweet-level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted-R^2	0.04	0.70	-0.01	0.70	0.00	0.93	0.02	0.62
Observations	3184	3184	3184	3184	3184	3184	11144	11144
Number of Clusters (Race)	460	460	460	460	460	460	460	460

Notes: The unit of observation is a candidate - week. The sample focuses on 796 democratic and republican candidates for congress with twitter activity. The analysis restricts to: (1) 2 weeks before and 2 weeks after the ebola diagnosis of each case in columns 1 to 6, and (2) period between August 2014 and the midterm election in columns 7 and 8. The dependent variables are the weekly flow and accumulated stock of ebola & terrorism -related tweets posted by each candidate. The main independent variables account for the interaction between a dummy indicating the post-onset of each ebola case, an indicator taking value 1 if the member of the congress is republican and 0 otherwise, and the distance (in logs) to the correspondent ebola case. Tweet-level controls are the weekly and accumulated content wordcounts. To ease the interpretation of the uninteracted coefficients, distance variables in the interaction terms were demeaned. Heteroskedasticity robust standard error estimates clustered at the race-level are reported in parentheses; *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level, all for two-sided hypothesis tests.

Table A.22: Fear Appealing Ads with Terrorism, Timing and Distance To Cases

	Fear-Terrorism Ads							
	Flow	Stock	Flow	Stock	Flow	Stock	Flow	Stock
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post-Onset Dallas x Republican	4.269	13.780**					7.247**	26.811***
	(2.735)	(5.346)					(3.099)	(8.198)
Post-Onset Dallas x Republican x Distance Dallas (logs)	-6.520	-1.752					-5.213	-8.899
	(5.073)	(8.046)					(5.074)	(19.028)
Post-Onset Dallas x Distance Dallas (logs)	-0.579	0.892					-1.395	4.264
	(1.889)	(3.291)					(1.537)	(6.351)
Post-Onset Cleveland x Republican			3.058	21.962***			2.553	16.997***
			(4.103)	(7.703)			(2.937)	(5.692)
Post-Onset Cleveland x Republican x Distance Cleveland (logs)			-1.301	3.505			0.913	8.974
			(2.847)	(7.318)			(2.915)	(11.116)
Post-Onset Cleveland x Distance Cleveland (logs)			-0.927	-0.779			-1.001	-2.280
			(1.711)	(1.383)			(1.579)	(2.704)
Post-Onset NYC x Republican					-3.198	18.175**	-2.791	14.388**
					(4.018)	(7.715)	(3.146)	(5.755)
Post-Onset NYC x Republican x Distance NYC (logs)					-2.383	4.376	-0.854	4.828
					(2.233)	(4.649)	(2.093)	(5.772)
Post-Onset NYC x Distance NYC (logs)					-0.291	-1.429	-0.429	-1.497
					(0.609)	(1.304)	(0.862)	(2.141)
Mean Dep.Var.	4.15	13.13	5.90	24.12	5.00	29.12	2.43	11.72
Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Politician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Race-Specific Linear Trends	No	No	No	No	No	No	Yes	Yes
Ad-level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted-R^2	0.27	0.75	0.29	0.78	0.26	0.82	0.16	0.53
Observations	2376	2376	2376	2376	2376	2376	8316	8316
Number of Clusters (Race)	227	227	227	227	227	227	227	227

Notes: The unit of observation is a candidate - week. The sample focuses on 575 democratic and republican candidates for congress that aired at least one campaign TV ads. The analysis restricts to: (1) 2 weeks before and 2 weeks after the ebola diagnosis of each case in columns 1 to 6, and (2) period between August 2014 and the midterm election in columns 7 and 8. The dependent variables are the number of fear-appealing ads mentioning terrorism (weekly flow and accumulated stock). The coding of a fear-appealing ad r is based on codding by Political Advertising in 2014 (Wesleyan Media Project) in two dimensions: 1) whether any ominous/tense music is played during the ad, or 2) there is direct appeal to fear in ads regardless of the music. The main independent variables account for the interaction between a dummy indicating the post-onset of each ebola case, an indicator taking value 1 if the member of the congress is republican and 0 otherwise, and the distance (in logs) to the correspondent ebola case. Ad-level controls are the weekly and accumulated airing time length and number of ads. To ease the interpretation of the uninteracted coefficients, distance variables in the interaction terms were demeaned. Heteroskedasticity robust standard error estimates clustered at the race-level are reported in parentheses; *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level, all for two-sided hypothesis tests.

Table A.23: Ebola and Immigration Newsletters,Timing and Distance To Cases

	Ebola and Immigration Newsletters							
	Flow	Stock	Flow	Stock	Flow	Stock	Flow	Stock
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post-Onset Dallas x Republican	0.031**	0.046**					0.019	0.013
	(0.012)	(0.019)					(0.016)	(0.018)
Post-Onset Dallas x Republican x Distance Dallas (logs)	0.002	-0.003					-0.004	-0.005
	(0.013)	(0.018)					(0.009)	(0.023)
Post-Onset Dallas x Distance Dallas (logs)	-0.002	0.009					0.004	0.016
	(0.008)	(0.012)					(0.006)	(0.014)
Post-Onset Cleveland x Republican			0.028**	0.067***			0.021	0.063***
			(0.014)	(0.020)			(0.020)	(0.020)
Post-Onset Cleveland x Republican x Distance Cleveland (logs)			0.005	-0.028			0.001	-0.013
			(0.016)	(0.024)			(0.013)	(0.024)
Post-Onset Cleveland x Distance Cleveland (logs)			-0.006	-0.002			-0.003	0.002
			(0.010)	(0.011)			(0.007)	(0.010)
Post-Onset NYC x Republican					-0.035**	0.031*	-0.041**	0.032*
					(0.015)	(0.017)	(0.016)	(0.019)
Post-Onset NYC x Republican x Distance NYC (logs)					0.004	-0.027	0.009	-0.043
					(0.018)	(0.026)	(0.017)	(0.042)
Post-Onset NYC x Distance NYC (logs)					0.008	-0.005	0.004	-0.006
					(0.007)	(0.008)	(0.006)	(0.009)
Mean Dep.Var.	0.02	0.05	0.03	0.07	0.03	0.13	0.01	0.09
Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Politician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constituency-Specific Linear Trends	No	No	No	No	No	No	Yes	Yes
Newsletter-level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted-R^2	0.15	0.59	0.19	0.68	0.15	0.90	0.10	0.68
Observations	1468	1468	1468	1468	1468	1468	5505	5505
Number of Clusters (Constituency)	285	285	285	285	285	285	285	285

Notes: The unit of observation is member of congress - week. The sample focuses on 367 member of the congress (i.e., senators and house representatives) who sent at least one official e-newsletter. The analysis restricts to: (1) 2 weeks before and 2 weeks after the ebola diagnosis of each case in columns 1 to 6, and (2) period between August 2014 and the midterm election in columns 7 and 8. The dependent variables are the number of ebola & immigration - related newsletters (weekly flow and accumulated stock). The main independent variables account for the interaction between a dummy indicating the post-onset of each ebola case, an indicator taking value 1 if the member of the congress is republican and 0 otherwise, and the distance (in logs) to the correspondent ebola case. Newsletter-level controls are the weekly and accumulated content wordcounts. To ease the interpretation of the uninteracted coefficients, distance variables in the interaction terms were demeaned. Heteroskedasticity robust standard error estimates clustered at the constituency-level are reported in parentheses; *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level, all for two-sided hypothesis tests.

Table A.24: Ebola and Immigration Tweets, Timing and Distance To Cases

	Ebola-Immigration Tweets							
	Flow	Stock	Flow	Stock	Flow	Stock	Flow	Stock
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post-Onset Dallas x Republican	0.017*	0.031**					0.020***	0.034*
	(0.009)	(0.014)					(0.007)	(0.020)
Post-Onset Dallas x Republican x Distance Dallas (logs)	-0.008	0.012					-0.006	-0.001
	(0.011)	(0.018)					(0.011)	(0.043)
Post-Onset Dallas x Distance Dallas (logs)	0.006	-0.005					0.000	-0.000
	(0.006)	(0.007)					(0.005)	(0.017)
Post-Onset Cleveland x Republican			0.007	0.043***			0.003	0.033***
			(0.010)	(0.013)			(0.010)	(0.010)
Post-Onset Cleveland x Republican x Distance Cleveland (logs)			0.014	-0.023*			-0.001	-0.051**
			(0.010)	(0.014)			(0.005)	(0.023)
Post-Onset Cleveland x Distance Cleveland (logs)			-0.002	0.004			0.005	0.016**
			(0.005)	(0.004)			(0.004)	(0.007)
Post-Onset NYC x Republican					-0.015**	0.022**	-0.016*	0.011
					(0.007)	(0.009)	(0.009)	(0.008)
Post-Onset NYC x Republican x Distance NYC (logs)					0.003	-0.003	0.001	-0.005
					(0.004)	(0.006)	(0.004)	(0.012)
Post-Onset NYC x Distance NYC (logs)					0.000	0.003	0.000	0.007*
					(0.001)	(0.002)	(0.002)	(0.004)
Mean Dep.Var.	0.01	0.03	0.01	0.04	0.01	0.06	0.00	0.02
Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Politician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Race-Specific Linear Trends	No	No	No	No	No	No	Yes	Yes
Tweet-level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted-R^2	0.04	0.67	0.09	0.82	0.04	0.94	0.04	0.67
Observations	3184	3184	3184	3184	3184	3184	11144	11144
Number of Clusters (Race)	460	460	460	460	460	460	460	460

Notes: The unit of observation is a candidate - week. The sample focuses on 796 democratic and republican candidates for congress with twitter activity. The analysis restricts to: (1) 2 weeks before and 2 weeks after the ebola diagnosis of each case in columns 1 to 6, and (2) period between August 2014 and the midterm election in columns 7 and 8. The dependent variables are the weekly flow and accumulated stock of ebola & immigration -related tweets posted by each candidate. The main independent variables account for the interaction between a dummy indicating the post-onset of each ebola case, an indicator taking value 1 if the member of the congress is republican and 0 otherwise, and the distance (in logs) to the correspondent ebola case. Tweet-level controls are the weekly and accumulated content wordcounts. To ease the interpretation of the uninteracted coefficients, distance variables in the interaction terms were demeaned. Heteroskedasticity robust standard error estimates clustered at the race-level are reported in parentheses; *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level, all for two-sided hypothesis tests.

Table A.25: Fear Appealing Ads with Immigration, Timing and Distance To Cases

	Fear-Immigration Ads							
	Flow	Stock	Flow	Stock	Flow	Stock	Flow	Stock
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post-Onset Dallas x Republican	2.962	21.676**					7.329	57.498***
	(6.310)	(10.622)					(5.637)	(16.342)
Post-Onset Dallas x Republican x Distance Dallas (logs)	-9.084	-8.309					-11.977	-69.754
	(8.394)	(20.529)					(10.079)	(52.175)
Post-Onset Dallas x Distance Dallas (logs)	-3.289	-15.649					4.734	26.987
	(6.967)	(28.362)					(7.987)	(21.751)
Post-Onset Cleveland x Republican			8.051	38.581**			5.995	28.725**
			(8.530)	(16.317)			(8.549)	(13.634)
Post-Onset Cleveland x Republican x Distance Cleveland (logs)			3.392	17.316			8.423	15.355
			(7.395)	(16.767)			(6.036)	(27.591)
Post-Onset Cleveland x Distance Cleveland (logs)			1.713	6.295			-1.211	2.069
			(5.234)	(6.480)			(4.988)	(11.654)
Post-Onset NYC x Republican					-3.005	34.697***	-3.943	28.545***
					(6.565)	(12.506)	(6.840)	(8.924)
Post-Onset NYC x Republican x Distance NYC (logs)					-3.870	17.295**	-2.829	18.859*
					(5.268)	(8.762)	(3.757)	(10.973)
Post-Onset NYC x Distance NYC (logs)					-1.933	0.974	-3.639*	-3.495
					(2.566)	(2.265)	(2.160)	(4.177)
Mean Dep.Var.	12.54	63.43	16.44	94.33	13.14	107.47	8.02	52.99
Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Politician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Race-Specific Linear Trends	No	No	No	No	No	No	Yes	Yes
Ad-level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted-R^2	0.50	0.88	0.58	0.90	0.51	0.93	0.34	0.73
Observations	2376	2376	2376	2376	2376	2376	8316	8316
Number of Clusters (Race)	227	227	227	227	227	227	227	227

Notes: The unit of observation is a candidate - week. The sample focuses on 575 democratic and republican candidates for congress that aired at least one campaign TV ads. The analysis restricts to: (1) 2 weeks before and 2 weeks after the ebola diagnosis of each case in columns 1 to 6, and (2) period between August 2014 and the midterm election in columns 7 and 8. The dependent variables are the number of fear -appealing ads mentioning immigration (weekly flow and accumulated stock). The coding of a fear-appealing ad is based on codding by Political Advertising in 2014 (Wesleyan Media Project) in two dimensions: 1) whether any ominous/tense music is played during the ad, or 2) there is direct appeal to fear in ads regardless of the music. The main independent variables account for the interaction between a dummy indicating the post-onset of each ebola case, an indicator taking value 1 if the member of the congress is republican and 0 otherwise, and the distance (in logs) to the correspondent ebola case. Ad-level controls are the weekly and accumulated airing time length and number of ads. To ease the interpretation of the uninteracted coefficients, distance variables in the interaction terms were demeaned. Heteroskedasticity robust standard error estimates clustered at the race-level are reported in parentheses; *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level, all for two-sided hypothesis tests.

Table A.26: Ebola and Obama Newsletters,Timing and Distance To Cases

	Ebola and Obama Newsletters							
	Flow	Stock	Flow	Stock	Flow	Stock	Flow	Stock
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post-Onset Dallas x Republican	0.039**	0.067***					0.014	0.005
	(0.016)	(0.022)					(0.015)	(0.020)
Post-Onset Dallas x Republican x Distance Dallas (logs)	0.010	0.019					0.001	0.022
	(0.018)	(0.023)					(0.014)	(0.031)
Post-Onset Dallas x Distance Dallas (logs)	-0.018	-0.018					-0.019**	-0.035
	(0.011)	(0.014)					(0.009)	(0.023)
Post-Onset Cleveland x Republican			0.035**	0.102***			0.039**	0.106***
			(0.015)	(0.025)			(0.020)	(0.027)
Post-Onset Cleveland x Republican x Distance Cleveland (logs)			-0.024	-0.051			-0.040*	-0.043
			(0.024)	(0.036)			(0.022)	(0.044)
Post-Onset Cleveland x Distance Cleveland (logs)			-0.017	-0.015			-0.002	-0.011
			(0.015)	(0.020)			(0.013)	(0.027)
Post-Onset NYC x Republican					-0.057***	0.034*	-0.070***	0.037*
					(0.017)	(0.020)	(0.019)	(0.022)
Post-Onset NYC x Republican x Distance NYC (logs)					0.041**	-0.038	0.046***	-0.074*
					(0.018)	(0.024)	(0.016)	(0.043)
Post-Onset NYC x Distance NYC (logs)					0.006	0.009	0.000	0.017**
					(0.005)	(0.007)	(0.005)	(0.007)
Mean Dep.Var.	0.03	0.06	0.04	0.10	0.04	0.19	0.01	0.13
Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Politician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constituency-Specific Linear Trends	No	No	No	No	No	No	Yes	Yes
Newsletter-level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted-R^2	0.23	0.60	0.26	0.72	0.27	0.92	0.16	0.74
Observations	1468	1468	1468	1468	1468	1468	5505	5505
Number of Clusters (Constituency)	285	285	285	285	285	285	285	285

The unit of observation is member of congress - week. The sample focuses on 367 member of the congress (i.e., senators and house representatives) who sent at least one official e-newsletter. The analysis restricts to: (1) 2 weeks before and 2 weeks after the ebola diagnosis of each case in columns 1 to 6, and (2) period between August 2014 and the midterm election in columns 7 and 8. The dependent variables are the number of ebola & Obama - related newsletters (weekly flow and accumulated stock). The main independent variables account for the interaction between a dummy indicating the post-onset of each ebola case, an indicator taking value 1 if the member of the congress is republican and 0 otherwise, and the distance (in logs) to the correspondent ebola case. Newsletter controls are the weekly and accumulated content wordcounts. To ease the interpretation of the uninteracted coefficients, distance variables in the interaction terms were demeaned. Heteroskedasticity robust standard error estimates clustered at the constituency-level are reported in parentheses; *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level, all for two-sided hypothesis tests.

Table A.27: Ebola and Obama Tweets, Timing and Distance To Cases

	Ebola-Obama Tweets							
	Flow	Stock	Flow	Stock	Flow	Stock	Flow	Stock
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post-Onset Dallas x Republican	0.084***	0.106***					0.088***	0.113***
	(0.018)	(0.021)					(0.018)	(0.025)
Post-Onset Dallas x Republican x Distance Dallas (logs)	-0.032	-0.026					-0.018	-0.069
	(0.024)	(0.026)					(0.018)	(0.061)
Post-Onset Dallas x Distance Dallas (logs)	0.000	-0.001					0.003	0.024
	(0.004)	(0.006)					(0.005)	(0.023)
Post-Onset Cleveland x Republican			0.022	0.202***			-0.006	0.164***
			(0.021)	(0.035)			(0.023)	(0.029)
Post-Onset Cleveland x Republican x Distance Cleveland (logs)			-0.005	-0.067**			-0.004	-0.064
			(0.024)	(0.034)			(0.013)	(0.046)
Post-Onset Cleveland x Distance Cleveland (logs)			-0.006	0.002			0.000	0.006
			(0.009)	(0.010)			(0.006)	(0.013)
Post-Onset NYC x Republican					-0.106***	0.085***	-0.062***	0.045***
					(0.021)	(0.017)	(0.021)	(0.012)
Post-Onset NYC x Republican x Distance NYC (logs)					0.018	-0.023	-0.001	-0.037
					(0.020)	(0.016)	(0.011)	(0.040)
Post-Onset NYC x Distance NYC (logs)					-0.002	-0.001	0.005	0.009
					(0.004)	(0.004)	(0.005)	(0.009)
Mean Dep.Var.	0.03	0.05	0.04	0.09	0.04	0.18	0.01	0.06
Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Politician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Race-Specific Linear Trends	No	No	No	No	No	No	Yes	Yes
Tweet-level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted-R^2	0.07	0.41	0.13	0.50	0.16	0.93	0.10	0.58
Observations	3184	3184	3184	3184	3184	3184	11144	11144
Number of Clusters (Race)	460	460	460	460	460	460	460	460

Notes: The unit of observation is a candidate - week. The sample focuses on 796 democratic and republican candidates for congress with twitter activity. The analysis restricts to: (1) 2 weeks before and 2 weeks after the ebola diagnosis of each case in columns 1 to 6, and (2) period between August 2014 and the midterm election in columns 7 and 8. The dependent variables are the weekly flow and accumulated stock of ebola & Obama -related tweets posted by each candidate. The main independent variables account for the interaction between a dummy indicating the post-onset of each ebola case, an indicator taking value 1 if the member of the congress is republican and 0 otherwise, and the distance (in logs) to the correspondent ebola case. Tweet-level controls are the weekly and accumulated content wordcounts. To ease the interpretation of the uninteracted coefficients, distance variables in the interaction terms were demeaned. Heteroskedasticity robust standard error estimates clustered at the race-level are reported in parentheses; *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level, all for two-sided hypothesis tests.

Table A.28: Fear Appealing Ads with Obama, Timing and Distance To Cases

	Fear-Obama Ads							
	Flow	Stock	Flow	Stock	Flow	Stock	Flow	Stock
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post-Onset Dallas x Republican	23.364**	138.909***					50.305***	307.221***
	(11.410)	(25.887)					(11.131)	(54.149)
Post-Onset Dallas x Republican x Distance Dallas (logs)	-41.510**	-77.953*					-46.142**	-284.392*
	(20.621)	(43.209)					(21.547)	(147.857)
Post-Onset Dallas x Distance Dallas (logs)	0.843	37.045					0.407	151.946*
	(3.340)	(25.933)					(12.174)	(81.878)
Post-Onset Cleveland x Republican			32.010***	201.495***			29.185***	158.907***
			(10.940)	(38.843)			(10.741)	(30.116)
Post-Onset Cleveland x Republican x Distance Cleveland (logs)			6.145	32.602			11.039	-12.808
			(10.961)	(34.735)			(10.370)	(87.023)
Post-Onset Cleveland x Distance Cleveland (logs)			-0.260	-7.695			-0.306	14.084
			(2.554)	(13.419)			(5.337)	(39.322)
Post-Onset NYC x Republican					-24.178*	176.057***	-31.400**	136.307***
					(13.088)	(34.561)	(12.857)	(24.800)
Post-Onset NYC x Republican x Distance NYC (logs)					-12.509	48.955**	-7.421	71.543*
					(9.565)	(19.438)	(7.850)	(37.679)
Post-Onset NYC x Distance NYC (logs)					2.700	-8.110	-0.405	-22.735
					(3.038)	(8.437)	(2.685)	(16.765)
Mean Dep.Var.	32.70	193.21	48.27	281.12	43.61	324.73	24.36	170.19
Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Politician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Race-Specific Linear Trends	No	No	No	No	No	No	Yes	Yes
Ad-level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted-R^2	0.52	0.86	0.66	0.88	0.60	0.90	0.46	0.80
Observations	2376	2376	2376	2376	2376	2376	8316	8316
Number of Clusters (Race)	227.00	227.00	227.00	227.00	227.00	227.00	227.00	227.00

Notes: The unit of observation is a candidate - week. The sample focuses on 575 democratic and republican candidates for congress that aired at least one campaign TV ads. The analysis restricts to: (1) 2 weeks before and 2 weeks after the ebola diagnosis of each case in columns 1 to 6, and (2) period between August 2014 and the midterm election in columns 7 and 8. The dependent variables are the number of fear-appealing ads mentioning Obama (weekly flow and accumulated stock). The coding of a fear-appealing ad is based on codding by Political Advertising in 2014 (Wesleyan Media Project) in two dimensions: 1) whether any ominous/tense music is played during the ad, or 2) there is direct appeal to fear in ads regardless of the music. The main independent variables account for the interaction between a dummy indicating the post-onset of each ebola case, an indicator taking value 1 if the member of the congress is republican and 0 otherwise, and the distance (in logs) to the correspondent ebola case. Ad-level controls are the weekly and accumulated airing time length and number of ads. To ease the interpretation of the uninteracted coefficients, distance variables in the interaction terms were demeaned. Heteroskedasticity robust standard error estimates clustered at the race-level are reported in parentheses; *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level, all for two-sided hypothesis tests.

Table A.29: Ebola and Terrorism Newsletters and Timing of Each Case

	Ebola and Terrorism Newsletter							
	Indicator	Stock	Indicator	Stock	Indicator	Stock	Indicator	Stock
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post-Onset Dallas x Republican	0.021**	0.037**					0.019	0.020
	(0.009)	(0.015)					(0.014)	(0.013)
Post-Onset Cleveland x Republican			0.002	0.039***			-0.006	0.029**
			(0.010)	(0.014)			(0.016)	(0.014)
Post-Onset NYC x Republican					-0.017*	0.001	-0.020*	0.001
					(0.010)	(0.013)	(0.011)	(0.014)
Mean Dep.Var.	0.01	0.03	0.01	0.04	0.01	0.07	0.00	0.05
Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Politician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constituency-Specific Linear Trends	No	No	No	No	No	No	Yes	Yes
Newsletter-level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted-R^2	0.08	0.58	0.19	0.66	0.18	0.91	0.11	0.71
Observations	1468	1468	1468	1468	1468	1468	5505	5505
Number of Clusters (Constituency)	285	285	285	285	285	285	285	285

Notes: The unit of observation is member of congress - week. The sample focuses on 367 member of the congress (i.e., senators and house representatives) who sent at least one official e-newsletter. The analysis restricts to: (1) 2 weeks before and 2 weeks after the ebola diagnosis of each case in columns 1 to 6, and (2) period between August 2014 and the midterm election in columns 7 and 8. The variable Ebola Newsletter 'Indicator' takes value 1 if the member of Congress sent at least one official ebola & terrorism-related newsletter during the week, 0 otherwise.The variable Ebola Newsletter 'Stock' accounts for the accumulated number of ebola & terrorism-related newsletters sent up to that week by the member of Congress. The main independent variables account for the interaction between a dummy indicating the post-onset of each ebola case and an indicator taking value 1 if the member of the Congress is republican, 0 otherwise. Newsletter-level controls are the weekly and accumulated wordcounts. Heteroskedasticity robust standard error estimates clustered at the constituency-level are reported in parentheses; *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level, all for two-sided hypothesis tests.

Table A.30: Ebola and Terrorism Tweets and Timing of Each Case

	Ebola and Terrorism Tweets							
	Flow	Stock	Flow	Stock	Flow	Stock	Flow	Stock
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post-Onset Dallas x Republican	0.009	0.015					0.013*	0.025*
	(0.009)	(0.009)					(0.007)	(0.015)
Post-Onset Cleveland x Republican			0.012	0.048***			0.008	0.043***
			(0.012)	(0.014)			(0.013)	(0.012)
Post-Onset NYC x Republican					-0.025**	0.493***	-0.016	0.012*
					(0.010)	(0.107)	(0.011)	(0.007)
Mean Dep.Var.	0.01	0.03	0.01	0.04	0.01	2.43	0.00	0.05
Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Politician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Race-Specific Linear Trends	No	No	No	No	No	No	Yes	Yes
Tweet-level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted-R^2	0.04	0.70	-0.01	0.70	0.00	0.97	0.02	0.62
Observations	3184	3184	3184	3184	3184	3184	11144	11144
Number of Clusters (Race)	460	460	460	460	460	460	460	460

Notes: The unit of observation is a candidate - week. The sample focuses on 796 democratic and republican candidates for congress with twitter activity. The analysis restricts to: (1) 2 weeks before and 2 weeks after the ebola diagnosis of each case in columns 1 to 6, and (2) period between August 2014 and the midterm election in columns 7 and 8. The dependent variables are the weekly flow and accumulated stock of ebola & terrorism -related tweets posted by each candidate. The main independent variable accounts for the interaction between a dummy indicating the post-onset of each ebola case and an indicator taking value 1 for the republican candidate, 0 otherwise. Tweet-level controls are the weekly and accumulated content wordcounts. Heteroskedasticity robust standard error estimates clustered at the race-level are reported in parentheses; *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level, all for two-sided hypothesis tests.

Table A.31: Fear Appealing Ads with Terrorism and Timing of Each Case

	Fear-Terrorism Ads							
	Flow	Stock	Flow	Stock	Flow	Stock	Flow	Stock
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post-Onset Dallas x Republican	4.636	13.773**					7.456**	26.720***
	(2.817)	(5.358)					(3.150)	(8.154)
Post-Onset Cleveland x Republican			3.046	21.972***			2.505	16.994***
			(4.095)	(7.719)			(2.923)	(5.676)
Post-Onset NYC x Republican					-3.327	18.231**	-2.914	14.427**
					(4.009)	(7.789)	(3.172)	(5.790)
Mean Dep.Var.	4.15	13.13	5.90	24.12	5.00	29.12	2.43	11.72
Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Politician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Race-Specific Linear Trends	No	No	No	No	No	No	Yes	Yes
Ad-level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted-R^2	0.27	0.75	0.29	0.78	0.26	0.82	0.16	0.53
Observations	2376	2376	2376	2376	2376	2376	8316	8316
Number of Clusters (Race)	227	227	227	227	227	227	227	227

Notes: The unit of observation is a candidate - week.The sample focuses on 575 democratic and republican candidates for congress that aired at least one campaign TV ads. The analysis restricts to: (1) 2 weeks before and 2 weeks after the ebola diagnosis of each case in columns 1 to 6, and (2) period between August 2014 and the midterm election in columns 7 and 8. The dependent variables are the number of fear-appealing ads mentioning terrorism (weekly flow and accumulated stock). The coding of a fear-appealing ad is based on codding by Political Advertising in 2014 (Wesleyan Media Project) in two dimensions: 1) whether any ominous/tense music is played during the ad, or 2) there is direct appeal to fear in ads regardless of the music. The main independent variable accounts for the interaction between a dummy indicating the post-onset of each ebola case and an indicator taking value 1 for the republican candidate, 0 otherwise. Ad-level controls are the weekly and accumulated airing time length and number of ads. Heteroskedasticity robust standard error estimates clustered at the race-level are reported in parentheses; *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level, all for two-sided hypothesis tests.

Table A.32: Ebola and Immigration Newsletters and Timing of Each Case

	Ebola and Immigration Newsletter							
	Indicator	Stock	Indicator	Stock	Indicator	Stock	Indicator	Stock
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post-Onset Dallas x Republican	0.031***	0.043**					0.018	0.009
	(0.012)	(0.019)					(0.016)	(0.018)
Post-Onset Cleveland x Republican			0.028**	0.068***			0.021	0.064***
			(0.014)	(0.021)			(0.020)	(0.020)
Post-Onset NYC x Republican					-0.031**	0.024	-0.038**	0.023
					(0.014)	(0.016)	(0.015)	(0.017)
Mean Dep.Var.	0.02	0.05	0.03	0.07	0.03	0.13	0.01	0.09
Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Politician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constituency-Specific Linear Trends	No	No	No	No	No	No	Yes	Yes
Newsletter-level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted-R^2	0.15	0.59	0.20	0.68	0.15	0.90	0.10	0.68
Observations	1468	1468	1468	1468	1468	1468	5505	5505
Number of Clusters (Constituency)	285	285	285	285	285	285	285	285

Notes: The unit of observation is member of congress - week. TThe sample focuses on 367 member of the congress (i.e., senators and house representatives) who sent at least one official e-newsletter. The analysis restricts to: (1) 2 weeks before and 2 weeks after the ebola diagnosis of each case in columns 1 to 6, and (2) period between August 2014 and the midterm election in columns 7 and 8. The variable Ebola Newsletter 'Indicator' takes value 1 if the member of Congress sent at least one official ebola & immigration-related newsletter during the week, 0 otherwise.The variable Ebola Newsletter 'Stock' accounts for the accumulated number of ebola & immigration-related newsletters sent up to that week by the member of Congress. The main independent variables account for the interaction between a dummy indicating the post-onset of each ebola case and an indicator taking value 1 if the member of the Congress is republican, 0 otherwise. Newsletter-level controls are the weekly and accumulated content wordcounts. Heteroskedasticity robust standard error estimates clustered at the constituency-level are reported in parentheses; *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level, all for two-sided hypothesis tests.

Table A.33: Ebola and Immigration Tweets and Timing of Each Case

	Ebola and Immigration Tweets							
	Flow	Stock	Flow	Stock	Flow	Stock	Flow	Stock
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post-Onset Dallas x Republican	0.017*	0.031**					0.020***	0.034*
	(0.009)	(0.014)					(0.007)	(0.020)
Post-Onset Cleveland x Republican			0.007	0.043***			0.003	0.033***
			(0.010)	(0.013)			(0.010)	(0.010)
Post-Onset NYC x Republican					-0.015**	0.022**	-0.016*	0.011
					(0.007)	(0.009)	(0.009)	(0.008)
Mean Dep.Var.	0.01	0.03	0.01	0.04	0.01	0.06	0.00	0.04
Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Politician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Race-Specific Linear Trends	No	No	No	No	No	No	Yes	Yes
Tweet-level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted-R^2	0.04	0.67	0.09	0.82	0.04	0.94	0.04	0.67
Observations	3184	3184	3184	3184	3184	3184	11144	11144
Number of Clusters (Race)	460	460	460	460	460	460	460	460

Notes: The unit of observation is a candidate - week. The sample focuses on 796 democratic and republican candidates for congress with twitter activity. The analysis restricts to: (1) 2 weeks before and 2 weeks after the ebola diagnosis of each case in columns 1 to 6, and (2) period between August 2014 and the midterm election in columns 7 and 8. The dependent variables are the weekly flow and accumulated stock of ebola & immigration -related tweets posted by each candidate. The main independent variable accounts for the interaction between a dummy indicating the post-onset of each ebola case and an indicator taking value 1 for the republican candidate, 0 otherwise. Tweet-level controls are the weekly and accumulated content wordcounts. Heteroskedasticity robust standard error estimates clustered at the race-level are reported in parentheses; *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level, all for two-sided hypothesis tests.

Table A.34: Fear Appealing Ads with Immigration and Timing of Each Case

	Fear-Immigration Ads							
	Flow	Stock	Flow	Stock	Flow	Stock	Flow	Stock
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post-Onset Dallas x Republican	3.724	23.649**					7.448	57.519***
	(6.367)	(10.301)					(5.727)	(16.647)
Post-Onset Cleveland x Republican			8.076	38.693**			6.021	28.669**
			(8.530)	(16.530)			(8.601)	(13.673)
Post-Onset NYC x Republican					-3.347	35.526***	-4.387	28.849***
					(6.733)	(12.897)	(7.002)	(8.938)
Mean Dep.Var.	12.54	63.43	16.44	94.33	13.14	107.47	8.02	52.99
Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Politician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Race-Specific Linear Trends	No	No	No	No	No	No	Yes	Yes
Ad-level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted-R^2	0.50	0.88	0.58	0.90	0.51	0.93	0.34	0.73
F-Statistic	1.22	1.52	2.22	2.86	3.30	6.08	3.44	2.64
Observations	2376	2376	2376	2376	2376	2376	8316	8316
Number of Clusters (Race)	227	227	227	227	227	227	227	227

Notes: The unit of observation is a candidate - week. The sample focuses on 575 democratic and republican candidates for congress that aired at least one campaign TV ads. The analysis restricts to: (1) 2 weeks before and 2 weeks after the ebola diagnosis of each case in columns 1 to 6, and (2) period between August 2014 and the midterm election in columns 7 and 8. The dependent variables are the number of fear-appealing ads mentioning immigration (weekly flow and accumulated stock). The coding of a fear-appealing ad is based on codding by Political Advertising in 2014 (Wesleyan Media Project) in two dimensions: 1) whether any ominous/tense music is played during the ad, or 2) there is direct appeal to fear in ads regardless of the music. The main independent variable accounts for the interaction between a dummy indicating the post-onset of each ebola case and an indicator taking value 1 for the republican candidate, 0 otherwise. Ad-level controls are the weekly and accumulated airing time length and number of ads. Heteroskedasticity robust standard error estimates clustered at the race-level are reported in parentheses; *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level, all for two-sided hypothesis tests.

Table A.35: Ebola and Obama Newsletters and Timing of Each Case

	Ebola and Obama Newsletter							
	Indicator	Stock	Indicator	Stock	Indicator	Stock	Indicator	Stock
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post-Onset Dallas x Republican	0.043***	0.071***					0.020	0.016
	(0.015)	(0.020)					(0.015)	(0.018)
Post-Onset Cleveland x Republican			0.034**	0.106***			0.036*	0.109***
			(0.015)	(0.026)			(0.019)	(0.027)
Post-Onset NYC x Republican					-0.044***	0.031	-0.059***	0.032*
					(0.016)	(0.019)	(0.017)	(0.019)
Mean Dep.Var.	0.03	0.06	0.04	0.10	0.04	0.19	0.01	0.13
Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Politician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constituency-Specific Linear Trends	No	No	No	No	No	No	Yes	Yes
Newsletter-level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted-R^2	0.23	0.61	0.26	0.72	0.27	0.92	0.15	0.73
Observations	1468	1468	1468	1468	1468	1468	5505	5505
Number of Clusters (Constituency)	285	285	285	285	285	285	285	285

Notes: The unit of observation is member of congress - week. The sample focuses on 367 member of the congress (i.e., senators and house representatives) who sent at least one official e-newsletter. The analysis restricts to: (1) 2 weeks before and 2 weeks after the ebola diagnosis of each case in columns 1 to 6, and (2) period between August 2014 and the midterm election in columns 7 and 8. The variable Ebola Newsletter 'Indicator' takes value 1 if the member of Congress sent at least one official ebola & Obama-related newsletter during the week, 0 otherwise. The variable Ebola Newsletter 'Stock' accounts for the accumulated number of ebola & Obama-related newsletters sent up to that week by the member of Congress. The main independent variables account for the interaction between a dummy indicating the post-onset of each ebola case and an indicator taking value 1 if the member of the Congress is republican, 0 otherwise. Newsletter-level controls are the weekly and accumulated wordcounts. Heteroskedasticity robust standard error estimates clustered at the member of constituency-level are reported in parentheses; *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level, all for two-sided hypothesis tests.

Table A.36: Ebola and Obama Tweets and Timing of Each Case

	Ebola and Obama Tweets							
	Flow	Stock	Flow	Stock	Flow	Stock	Flow	Stock
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post-Onset Dallas x Republican	0.086***	0.108***					0.088***	0.113***
	(0.017)	(0.021)					(0.018)	(0.026)
Post-Onset Cleveland x Republican			0.022	0.202***			-0.006	0.164***
			(0.021)	(0.035)			(0.023)	(0.029)
Post-Onset NYC x Republican					-0.105***	0.083***	-0.062***	0.043***
					(0.021)	(0.017)	(0.021)	(0.012)
Mean Dep.Var.	0.03	0.05	0.04	0.09	0.04	0.18	0.01	0.11
Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Politician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Race-Specific Linear Trends	No	No	No	No	No	No	Yes	Yes
Tweet-level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted-R^2	0.07	0.41	0.13	0.50	0.16	0.93	0.10	0.58
Observations	3184	3184	3184	3184	3184	3184	11144	11144
Number of Clusters (Race)	460	460	460	460	460	460	460	460

Notes: The unit of observation is a candidate - week. The sample focuses on 796 democratic and republican candidates for congress with twitter activity. The analysis restricts to: (1) 2 weeks before and 2 weeks after the ebola diagnosis of each case in columns 1 to 6, and (2) period between August 2014 and the midterm election in columns 7 and 8. The dependent variables are the weekly flow and accumulated stock of ebola & Obama -related tweets posted by each candidate. The main independent variable accounts for the interaction between a dummy indicating the post-onset of each ebola case and an indicator taking value 1 for the republican candidate, 0 otherwise. Tweet-level controls are the weekly and accumulated content wordcounts. Heteroskedasticity robust standard error estimates clustered at the race-level are reported in parentheses; *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level, all for two-sided hypothesis tests.

Table A.37: Fear Appealing Ads with Obama and Timing of Each Case

	Fear-Obama Ads							
	Flow	Stock	Flow	Stock	Flow	Stock	Flow	Stock
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post-Onset Dallas x Republican	25.245**	138.864***					51.417***	305.996***
	(11.875)	(26.643)					(11.515)	(55.287)
Post-Onset Cleveland x Republican			32.033***	201.579***			28.961***	159.226***
			(10.945)	(38.956)			(10.739)	(30.281)
Post-Onset NYC x Republican					-24.466*	177.409***	-32.034**	137.380***
					(13.158)	(35.125)	(12.936)	(25.263)
Mean Dep.Var.	32.70	193.21	48.27	281.12	43.61	324.73	24.36	170.19
Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Politician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Race-Specific Linear Trends	No	No	No	No	No	No	Yes	Yes
Ad-level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted-R^2	0.52	0.86	0.66	0.88	0.60	0.90	0.46	0.79
Observations	2376	2376	2376	2376	2376	2376	8316	8316
Number of Clusters (Race)	227	227	227	227	227	227	227	227

Notes: The unit of observation is a candidate - week. The sample focuses on 575 democratic and republican candidates for congress that aired at least one campaign TV ads. The analysis restricts to: (1) 2 weeks before and 2 weeks after the ebola diagnosis of each case in columns 1 to 6, and (2) period between August 2014 and the midterm election in columns 7 and 8. The dependent variables are the number of fear-appealing ads mentioning Obama (weekly flow and accumulated stock). The coding of a fear-appealing ad is based on codding by Political Advertising in 2014 (Wesleyan Media Project) in two dimensions: 1) whether any ominous/tense music is played during the ad, or 2) there is direct appeal to fear in ads regardless of the music. The main independent variable accounts for the interaction between a dummy indicating the post-onset of each ebola case and an indicator taking value 1 for the republican candidate, 0 otherwise. Ad-level controls are the weekly and accumulated airing time length and number of ads. Heteroskedasticity robust standard error estimates clustered at the race-level are reported in parentheses; *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level, all for two-sided hypothesis tests.

Table A.38: Ebola Newsletters,Timing and Distance To Cases

	Ebola Newsletters							
	Indicator	Stock	Indicator	Stock	Indicator	Stock	Indicator	Stock
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post-Onset Dallas x Republican	0.083***	0.119***					0.034	0.033
	(0.023)	(0.030)					(0.025)	(0.027)
Post-Onset Dallas x Republican x Distance Dallas (logs)	-0.039	-0.006					-0.051	-0.053
	(0.043)	(0.047)					(0.038)	(0.070)
Post-Onset Dallas x Distance Dallas (logs)	0.007	-0.038					0.011	-0.053*
	(0.032)	(0.026)					(0.028)	(0.031)
Post-Onset Cleveland x Republican			0.075***	0.203***			0.078**	0.214***
			(0.023)	(0.035)			(0.031)	(0.038)
Post-Onset Cleveland x Republican x Distance Cleveland (logs)			-0.028	-0.087*			-0.046	-0.113*
			(0.033)	(0.050)			(0.028)	(0.065)
Post-Onset Cleveland x Distance Cleveland (logs)			-0.022	-0.019			-0.002	-0.003
			(0.019)	(0.024)			(0.016)	(0.035)
Post-Onset NYC x Republican					-0.107***	0.052*	-0.131***	0.069**
					(0.023)	(0.030)	(0.027)	(0.033)
Post-Onset NYC x Republican x Distance NYC (logs)					0.029	-0.017	0.043**	-0.052
					(0.023)	(0.035)	(0.021)	(0.053)
Post-Onset NYC x Distance NYC (logs)					0.017**	0.000	0.004	0.007
					(0.009)	(0.011)	(0.008)	(0.014)
Mean Dep.Var.	0.07	0.13	0.10	0.22	0.09	0.41	0.03	0.13
Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Politician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constituency-Specific Linear Trends	No	No	No	No	No	No	Yes	Yes
Newsletter-level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted-R^2	0.31	0.66	0.33	0.77	0.39	0.93	0.25	0.77
Observations	1468	1468	1468	1468	1468	1468	5505	5505
Number of Clusters (Constituency)	285	285	285	285	285	285	285	285

Notes: The unit of observation is member of congress - week. The sample focuses on 367 member of the congress (i.e., senators and house representatives) who sent at least one official e-newsletter. The analysis restricts to: (1) 2 weeks before and 2 weeks after the ebola diagnosis of each case in columns 1 to 6, and (2) period between August 2014 and the midterm election in columns 7 and 8. The dependent variables are the number of ebola-related newsletters (weekly flow and accumulated stock). The main independent variables account for the interaction between a dummy indicating the post-onset of each ebola case, an indicator taking value 1 if the member of the congress is republican and 0 otherwise, and the distance (in logs) to the correspondent ebola case. Newsletter-level controls are the weekly and accumulated content wordcounts. To ease the interpretation of the uninteracted coefficients, distance variables in the interaction terms were demeaned. Heteroskedasticity robust standard error estimates clustered at the constituency-level are reported in parentheses; *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level, all for two-sided hypothesis tests.

Table A.39: Ebola Tweets, Timing and Distance To Cases

	Ebola Tweets							
	Flow	Stock	Flow	Stock	Flow	Stock	Flow	Stock
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post-Onset Dallas x Republican	0.560***	0.782***					0.635***	0.978***
	(0.111)	(0.180)					(0.125)	(0.255)
Post-Onset Dallas x Republican x Distance Dallas (logs)	-0.301*	-0.394					-0.240	-1.330*
	(0.170)	(0.399)					(0.153)	(0.743)
Post-Onset Dallas x Distance Dallas (logs)	-0.106*	-0.549**					0.037	-0.057
	(0.056)	(0.261)					(0.058)	(0.378)
Post-Onset Cleveland x Republican			0.106	1.485***			-0.067	1.196***
			(0.104)	(0.261)			(0.108)	(0.214)
Post-Onset Cleveland x Republican x Distance Cleveland (logs)			-0.069	-0.770**			-0.003	-1.055***
			(0.120)	(0.302)			(0.059)	(0.381)
Post-Onset Cleveland x Distance Cleveland (logs)			-0.088*	0.051			-0.019	0.165
			(0.049)	(0.089)			(0.048)	(0.138)
Post-Onset NYC x Republican					-0.829***	0.505***	-0.473***	0.243***
					(0.146)	(0.107)	(0.124)	(0.078)
Post-Onset NYC x Republican x Distance NYC (logs)					0.026	-0.030	-0.052	0.109
					(0.094)	(0.085)	(0.060)	(0.190)
Post-Onset NYC x Distance NYC (logs)					0.023	-0.076*	0.037	-0.060
					(0.036)	(0.046)	(0.029)	(0.076)
Mean Dep.Var.	0.41	0.82	0.56	1.38	0.49	2.43	0.13	1.56
Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Politician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Race-Specific Linear Trends	No	No	No	No	No	No	Yes	Yes
Tweet-level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted-R^2	0.34	0.63	0.45	0.71	0.36	0.97	0.27	0.70
Observations	3184	3184	3184	3184	3184	3184	11144	11144
Number of Clusters (Race)	460	460	460	460	460	460	460	460

Notes: The unit of observation is a candidate - week. The sample focuses on 796 democratic and republican candidates for congress with twitter activity. The analysis restricts to: (1) 2 weeks before and 2 weeks after the ebola diagnosis of each case in columns 1 to 6, and (2) period between August 2014 and the midterm election in columns 7 and 8. The dependent variables are the weekly flow and accumulated stock of ebola-related tweets posted by each candidate. The main independent variables account for the interaction between a dummy indicating the post-onset of each ebola case, an indicator taking value 1 if the member of the congress is republican and 0 otherwise, and the distance (in logs) to the correspondent ebola case. Tweet-level controls are the weekly and accumulated content wordcounts. To ease the interpretation of the uninteracted coefficients, distance variables in the interaction terms were demeaned. Heteroskedasticity robust standard error estimates clustered at the race-level are reported in parentheses; *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level, all for two-sided hypothesis tests.

Table A.40: Fear Appealing Ads, Timing and Distance To Cases

	Fear Ads							
	Flow	Stock	Flow	Stock	Flow	Stock	Flow	Stock
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post-Onset Dallas x Republican	11.897	45.550					18.977*	9.556
	(15.079)	(29.572)					(10.964)	(67.484)
Post-Onset Dallas x Republican x Distance Dallas (logs)	-51.127	13.545					-20.286	290.651
	(45.845)	(69.824)					(23.138)	(257.729)
Post-Onset Dallas x Distance Dallas (logs)	18.255	21.420					-6.787	-194.470
	(26.117)	(40.652)					(18.217)	(165.436)
Post-Onset Cleveland x Republican			5.795	32.781			-9.918	2.598
			(19.992)	(34.650)			(18.069)	(24.996)
Post-Onset Cleveland x Republican x Distance Cleveland (logs)			-18.312	55.827			3.137	30.811
			(23.975)	(45.581)			(22.603)	(97.707)
Post-Onset Cleveland x Distance Cleveland (logs)			13.722	-21.909			2.808	20.212
			(13.570)	(33.901)			(13.814)	(57.355)
Post-Onset NYC x Republican					17.704	51.721	20.841	36.202
					(17.755)	(36.640)	(17.544)	(31.047)
Post-Onset NYC x Republican x Distance NYC (logs)					-9.339	37.425	7.468	136.339***
					(11.971)	(23.524)	(11.753)	(51.292)
Post-Onset NYC x Distance NYC (logs)					-3.635	-36.060**	-10.865	-79.935***
					(8.915)	(15.482)	(8.652)	(30.029)
Mean Dep.Var.	141.26	877.35	202.29	1249.24	180.17	1429.41	108.30	752.32
Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Politician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Race-Specific Linear Trends	No	No	No	No	No	No	Yes	Yes
Ad-level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted-R^2	0.79	0.98	0.84	0.98	0.83	0.98	0.77	0.94
Observations	2376	2376	2376	2376	2376	2376	8316	8316
Number of Clusters (Race)	227	227	227	227	227	227	227	227

Notes: The unit of observation is a candidate - week. The sample focuses on 575 democratic and republican candidates for congress that aired at least one campaign TV ads. The analysis restricts to: (1) 2 weeks before and 2 weeks after the ebola diagnosis of each case in columns 1 to 6, and (2) period between August 2014 and the midterm election in columns 7 and 8. The dependent variables are the number of fear-appealing ads (weekly flow and accumulated stock). The coding of a fear-appealing ad is based on codding by Political Advertising in 2014 (Wesleyan Media Project) in two dimensions: 1) whether any ominous/tense music is played during the ad, or 2) there is direct appeal to fear in ads regardless of the music. The main independent variables account for the interaction between a dummy indicating the post-onset of each ebola case, an indicator taking value 1 if the member of the congress is republican and 0 otherwise, and the distance (in logs) to the correspondent ebola case. Ad-level controls are the weekly and accumulated airing time length and number of ads. To ease the interpretation of the uninteracted coefficients, distance variables in the interaction terms were demeaned. Heteroskedasticity robust standard error estimates clustered at the race-level are reported in parentheses; *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level, all for two-sided hypothesis tests.

Table A.41: Ebola Newsletters and Democratic Vote Share (OLS)

	Democratic Vote Share in 2014 House Election			
	(1)	(2)	(3)	(4)
Ebola Newsletters	-5.765***	-5.568***	-5.259***	-4.417**
	(1.610)	(1.553)	(1.608)	(1.894)
Std Dev Vote Share	20.61	20.61	20.61	20.61
Std Dev Ebola Letters	0.41	0.41	0.41	0.41
Effect of Std Dev Δ in Letters	-2.33	-2.25	-2.13	-1.79
County-Level Controls	Yes	Yes	Yes	Yes
DMA-Level Controls	Yes	Yes	Yes	No
Previous Election Controls	Yes	Yes	Yes	Yes
Region FE	No	Yes	No	No
State FE	No	No	Yes	No
DMA FE	No	No	No	Yes
Adjusted-R^2	0.73	0.74	0.79	0.80
Observations	3056	3056	3056	3065
Number of Clusters (DMA)	202	202	202	205

Notes: All specifications are weighted by DMA population. The variable Ebola Newsletters is a dummy equal to 1 if the term 'ebola' is mentioned in a political newsletter sent a by Republican House Representative in Congressional District during Aug.-Dec.2014. All regressions but the one in column (5) are weighted by DMA population. Heteroskedasticity robust standard error estimates clustered at the DMA-level are reported in parentheses; *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level, all for two-sided hypothesis tests. County-level controls are population density, median age, share of white population, share of population with college degree, income per capita, and unemployment. DMA-level controls are cable TV penetration 2010, Ebola Searches before first case in the US, and google searches for the terms 'anxiety' and 'virus', both in 2013.

Table A.42: Attitudes in CCES and Proximity to Ebola Cases

	Anti-Immigration	Pro-Gun	Religious	Anti-gay Marriage	Conservative
	(1)	(2)	(3)	(4)	(5)
Onset Dallas Case x Distance (in logs) to Dallas	-0.035**	-0.014	-0.013	-0.004	-0.013**
	(0.015)	(0.021)	(0.018)	(0.005)	(0.005)
Onset Cleveland Case x Distance (in logs) to Cleveland	-0.065***	-0.009	0.022	-0.004	-0.008
	(0.020)	(0.022)	(0.019)	(0.007)	(0.006)
Onset NYC Case x Distance (in logs) to NYC	0.016	0.026	0.035	0.009	0.006
	(0.028)	(0.025)	(0.023)	(0.009)	(0.008)
County FE	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes	Yes
Sample Weights	Yes	Yes	Yes	Yes	Yes
Adjusted-R^2	0.17	0.15	0.14	0.14	0.12
Observations	2370	2370	2370	2370	2369

Notes: Sample includes all CCES's respondents for years 2013 and 2014. The variable Anti-Immigration (pro-gun)[religious] corresponds to the first principal component of responses to 5 (5)[3] questions regarding immigration (disagreement with gun-control measures)[importance of religion]. The variable Anti-gay Marriage takes value of 1 if respondent is against gay marriage. The variable conservative takes value of 1 if respondent is conservative or very conservative, 0 otherwise (all related questions are described in the appendix) The main independent variable accounts for the interaction between the distance (in logs) to an Ebola Case and a dummy indicating the onset of that case. Individual-levels control are age and a set of indicators variables for male, white, hispanic, college or higher education, married, and annual income above US median (i.e., usd 59,000). Heteroskedasticity robust standard error estimates (two-way) clustered at the county and day level are reported in parentheses; *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level, all for two-sided hypothesis tests.