The Virus of Fear:
The Political Impact of Ebola in the U.S.*

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Abstract

We study how public anxiety related to the threat of a disease outbreak can affect the behavior of voters, by looking at the Ebola scare that hit the U.S. right 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 led to a lower vote share for the Democrats, as well as lower turnout, despite no evidence of a general anti-incumbent effect (including for President Obama). Voters displayed increasingly conservative attitudes on immigration but not on other ideologically-charged issues. Our findings indicate that emotional reactions can have a strong electoral impact, and that this is mediated by issues that can be plausibly associated with the specific triggering factor.

Keywords: Anxiety, Fear, Disgust, Emotions, Elections, Immigration, Pandemics, Ebola.

JEL codes: D72, D91

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1 Introduction

Emotions are widely recognized, both by practitioners and scholars, as a powerful force conditioning voter behavior.[1] The idea that voters can be affected by negative emotional reactions such as fear, anxiety or disgust, in response to 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 the emotional response itself from policy judgments. Are voters indeed changing their behavior as a result of, say, fear, anxiety or disgust, or are these simply correlated with policy or ideological views that ultimately guide behavior?[2]

To help answer these questions, we exploit a natural experiment that significantly affected perceptions of threat, while arguably having a relatively small impact on the actual environment faced by the population in their daily lives: 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 a major outbreak of the disease in the U.S. was relatively low – as underscored by the fact that no significant Ebola outbreak has ever been recorded outside of Sub-Saharan Africa.[3] 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.[4] Importantly, unlike in a case such as the Covid-19 pandemic that emerged in 2020, at no point was daily life affected by public health interventions regarding Ebola, allowing us to focus on the impact of the public's anxiety (justified or otherwise), without such confounders.[5]

[1]See for instance Brader and Marcus (2013), and references therein.

[2]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.

[3]According to the World Health Organization (WHO), since 1976, instances of outbreaks with more than ten Ebola cases have only been recorded in Sudan, Zaire/DRC, Gabon, Uganda, Republic of Congo, as well as Sierra Leone, Guinea, and Liberia, which were the countries affected in 2014. The 2014 episode was by far the worst ever recorded, with a total of more than 28,000 cases and 11,000 deaths (WHO 2017).

[4]Relatedly, the Ebola shock may arguably have also triggered other emotional reactions, such as disgust. While some of our analysis will allow us to focus specifically on fear, and we will often refer to "fear" as shorthand, our results can be interpreted as pertaining to the broader mix of negative emotions.

[5]Note that we do not argue that fear or anxiety were unreasonable or unjustified: there may have been a small risk of an outbreak, but a small probability of a disastrous event could still trigger a rational response of

The Ebola episode is particularly interesting because it took place during campaign season, in the weeks before the 2014 midterm elections, in which all U.S. House seats were being chosen, along with a number of U.S. Senate seats and state- and local-level positions. 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)).[6] In addition, the episode was sufficiently close to the election date that any repercussion on candidate selection can be ruled out.

We show causal evidence that Ebola concerns indeed had a significant effect in worsening the electoral performance of Democrats in the 2014 midterm elections, as well as lowering voter turnout. Moreover, we show 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. However, in terms of reported attitudes, the only response from voters we detect is on anti-immigrant sentiment, suggesting that there was no broader trend towards conservative attitudes among the electorate.

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

increased concern. The point is that there were no public health interventions meaningfully affecting all but a very small number of individuals at the time. As a result, changes in behavior can be attributed to the threat of a disease outbreak, as opposed to its materialization or a policy-induced reaction.

[6] 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).

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. To give a sense of magnitudes, flipping those seats would have erased Republican majority gains between 2012 and 2014 – though we should note that our estimates capture a local average treatment effect, for places induced by proximity to Ebola cases into greater concern with the disease, and hence cannot speak to the counterfactual question of what election outcomes would have been in the absence of the Ebola episode. Ebola concerns 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). That said, under reasonable assumptions the drop in turnout is unlikely to explain the full magnitude of the decrease in Democratic vote share, while survey data suggests that concerns with Ebola were associated with an increased likelihood of cross-party vote by registered Democrats.[7]

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.

Finally, 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.[8] 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. This suggests that the political response triggered by negative emotions need not be favorable to conservative politicians, but is instead

[7]The drop in turnout is unlikely to be associated with individual concerns with an increased risk of infection from turning out to vote: we show that, in survey data, at the time it was Republican voters who were significantly more worried about contracting the virus.

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

issue-dependent.

In sum, we show evidence of public anxiety – in this case, driven by a contagious disease – having a meaningful impact on an actual election. While we cannot pin down the specific channels through which the anxiety affects voter behavior – there could be a role for strategic actions by politicians, media exposure, etc. – the evidence suggests that the effect is mediated by issues that can be plausibly associated with the specific 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 Covid-19 pandemic constituted a huge shock to the public health risk environment around the globe, and, as such, might have had 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.[9,10]

Our paper relates to several strands of literature. A number of papers have studied the political impact of perceived threats such as terrorism or immigration in actual elections (Montalvo, 2011; Getmansky and Zeitzoff, 2014; Hangartner et al., 2019). Our context exploits a perceived threat that is not political in nature, and as such it relates to a separate strand looking 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), and going back to the debate on the political implications of "shark attacks" (Achen and Bartels, 2004, 2017).[11] Our results differ from this latter body of work, as we find no evidence of the evaluation of incumbents being affected, or of incumbents being generally punished. Most importantly, we extend the broad literature by zooming into the behavior of politicians in response to the perceived threat: we show that they exploit it strategically, but face limitations in their ability to influence voters.

Others have looked experimentally at the impact of emotions on political behavior (Jost

[9]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 shock that is in fact exploited by politicians.

[10]This is consistent with President Donald Trump's habit of referring to the coronavirus associated with Covid-19 as the "China virus," or variants of that term, during the 2020 campaign.

[11]For a survey of this literature, see Healy and Malhotra (2013), as well as the discussions in Fowler and Hall (2018) and Achen and Bartels (2018).

et al., 2003; Brader, 2005; Thórisdóttir and Jost, 2011) or at correlations between emotions such as fear and disgust and conservative ideological views and voting behavior (Inbar et al., 2008, 2012b,a; 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.[12]

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, presidential approval ratings, and voter attitudes. Section 6 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,

[12]Bisbee and Honig (2021) 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.

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).[13]

Despite the limited number of cases, the presence of Ebola in the U.S. caused a major public 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.[14] Indeed, according to a report by the Pew Research Center,[15] 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,

[13] 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.

[14] 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.

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

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.[16] 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 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).

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

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 months of August and September 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.[17] To study the evolution of Ebola concerns over time across DMAs, we also construct a longitudinal dataset of Ebola-related Google searches by DMA/day.[18] 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

[17] Media market definition comes from *Broadcasting cable yearbook.* (1993 - 2010) based on Nielsen DMA Market Atlas for the year 2000. The crosswalk between counties and DMAs was kindly provided by Leopoldo Fergusson.

[18] To create such panel we use the following procedure. First, we download daily data on the volume of Ebola-related searches for each DMA over the period September, 1 2014 - November, 30 2014. Second, for the same period we download the cross-section of Ebola-related searches for all DMAs which we use to construct a relative measure of the intensity of interest in Ebola in each DMA. Finally, to obtain a time-variant comparable measure at the DMA level, we multiply the DMA-specific daily measure by this weighting factor.

weeks before the elections, losing intensity immediately afterwards.

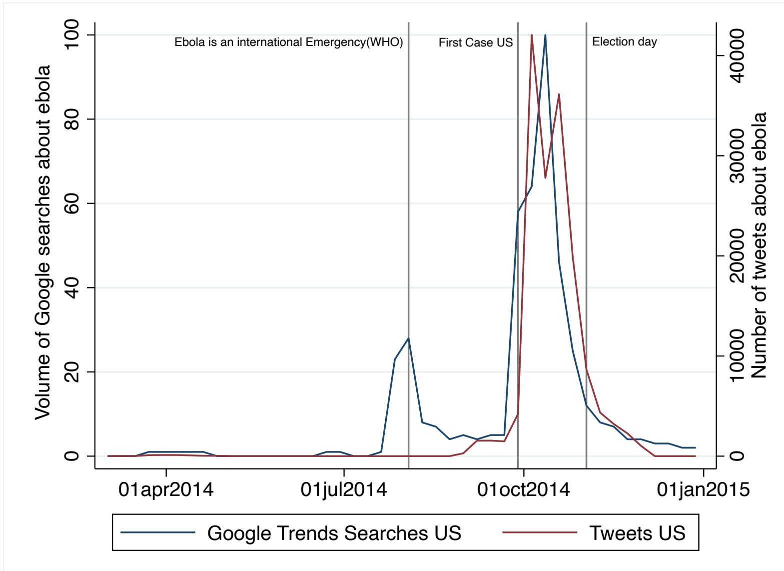


Figure 1: Google Searches and Ebola-Related Tweets

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 (Leip, 2017). To control for pre-trends in political preferences, we also use similar data for previous elections held during all even years between 1996 and 2014 -including House, gubernatorial, and senatorial elections available from the same source.

To explore the hypothesis that concerns for Ebola may have influenced voters' opinions about the incumbent president, we use daily data on president Obama's (dis)approval ratings, available from the Gallup daily tracking (Gallup, 2015). 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 Survey data

To further test the relationship between Ebola concerns and voters' attitudes, we use survey data from the Cooperative Congressional Election Study, (CCES) a large scale electoral survey conducted on a yearly basis by a consortium of universities led by Harvard and administered by YouGov. The CCES surveys include a battery of questions about respondents' political views, party identification, and attitudes on a wide range of issues. First, to study the link between proximity to Ebola cases, voters attitudes, and support for the president we use data from the 2014 wave of the CCES conducted in October and November 2014 and involving a sample of 56,200 respondents (Schaffner and Ansolabehere, 2015b). To examine how voters attitudes evolved between the pre-Ebola and the post-Ebola period depending on the distance to Ebola cases we combine this information with data from the 2013 CCES wave, conducted in November 2013 and involving 16,400 respondents (Ansolabehere and Schaffner, 2019). Finally, we also use data from the third wave of a panel study conducted by the CCES between 2010, 2012, and 2014 and involving 9,500 respondents (Schaffner and Ansolabehere, 2015a). Although the sample is much smaller than the cross-section for 2014, this survey has the advantage to include some explicit questions regarding concerns about Ebola and support for different policies aimed at limiting the spread of the virus (i.e., banning flights from Africa, quarantine for people coming from Africa, increase funding for Ebola-related research).

3.4 Other variables

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 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.[19]

[19]Table A.1 reports summary statistics for the complete set of variables exploited in the main analysis.

4 Empirical Strategy: Proximity to Ebola Cases as a Source of Variation

We want to study the impact of the Ebola crisis on voting behavior. For that, we first implement the following basic specification:

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

where $Vote^{2014}_{c,d}$ 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 $Vote^{2010-06}_{c,d}$ 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.

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).

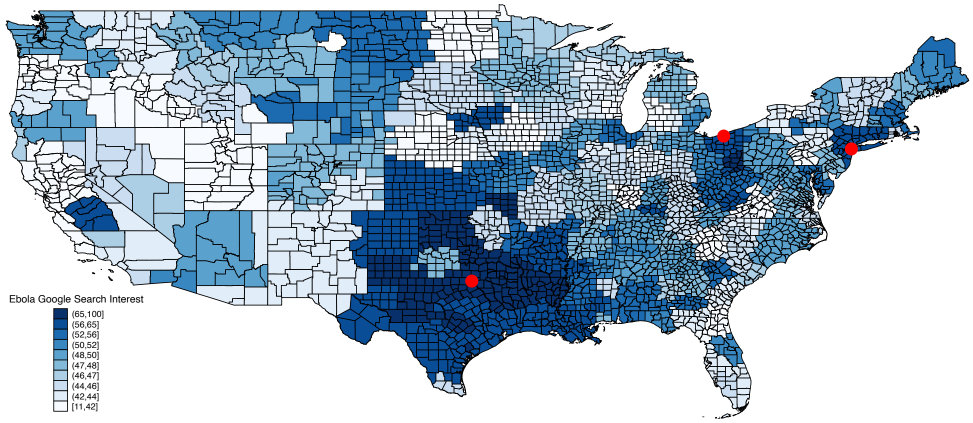


Figure 2: Geographic Distribution of Google Searches
Note: Red dots denote the three locations of Ebola cases (i.e., Dallas, Cleveland, and New York City).

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 of the three critical locations (in red dots), 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. Similarly, the CCES survey from October/November 2014, which included specific questions on Ebola concerns, shows that distances to those locations are significantly negative predictors of whether respondents were worried about the virus and whether they supported banning flights and quarantining people coming from Ebola-affected countries (Table A.2).

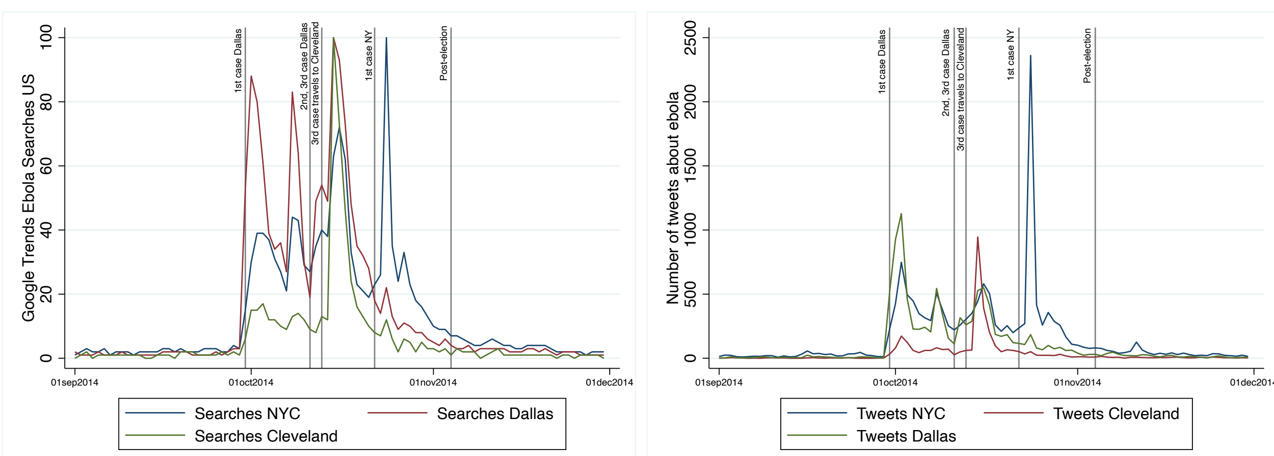


Figure 3: Timing of Ebola-Related Google Searches and Tweets

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. 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 can show this pattern more systematically, for our entire sample, exploiting the daily variation in our measures of Ebola-related concerns and following a event-study approach:

$$Ebola_{d,t} = \sum_{\substack{\tau=-25 \\ \tau\neq-1}}^{25} \gamma_\tau ln(DistanceNearestCase)_d \times 1[\Upsilon_t = \tau] + \lambda_d + \theta_t + \epsilon_{d,t}, \qquad (2)$$

where $Ebola_{d,}$ are Ebola-related tweets (per 1,000 inhabitants) or Google searches sent from DMA d, on date t. The variable $ln(DistanceNearestCase)_d$ is the (log) distance (in miles) of DMA d from the nearest location of one of the Ebola cases and Υ_t is a relative time indicator defined as days from the first case in September 30, 2014. For our analysis, we restrict our attention to 25 days before and after that date. λ_d and θ_t are DMA and day fixed effects, respectively. We will cluster standard errors at both DMA and day level.

Figure 4 displays the resulting patterns, for Google searches and tweets. Prior to the emergence of the first case, we see no pattern with respect to distance to the nearest key location. After the first case, that distance becomes negatively predictive of both measures of Ebola concerns. The relationship is strongest immediately after the emergence of a new case, but remains predictive throughout, especially on Twitter – the more expressive, public-facing medium. Google search activity is less precisely estimated, but consistent with a pattern of an immediate rush to search for information.[20] The overall picture underscores that distance to Ebola cases is a driving force behind Ebola concerns.[21]

[20]Figures A.1, A.2, and A.3 show the same pattern when we focus on the period surrounding each case, by looking separately at 7 days before and after the diagnosis of each case (i.e., Dallas, Cleveland, and NYC, following their chronological order). For the cases of Cleveland and New York, we additionally perform the same analysis focusing on internet activity from a sample of the 100 closest DMA to each case.

[21]In the appendix we alternatively estimate the following equation:

$$Ebola_{d,t(c)} = \gamma PostOnset_{t(c)} \times ln(Dist.Ebola_c)_d + \lambda_d + \theta_t + \Gamma_t \times \lambda_d + \epsilon_{d,t}, \qquad (3)$$

where $PostOnset_t(c)$ 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 cluster the standard errors at the DMA-level. Table A.5 presents the main results, for tweets (Panel A) and searches (Panel B), showing that the pattern is present for all three cases, evaluated separately or jointly.

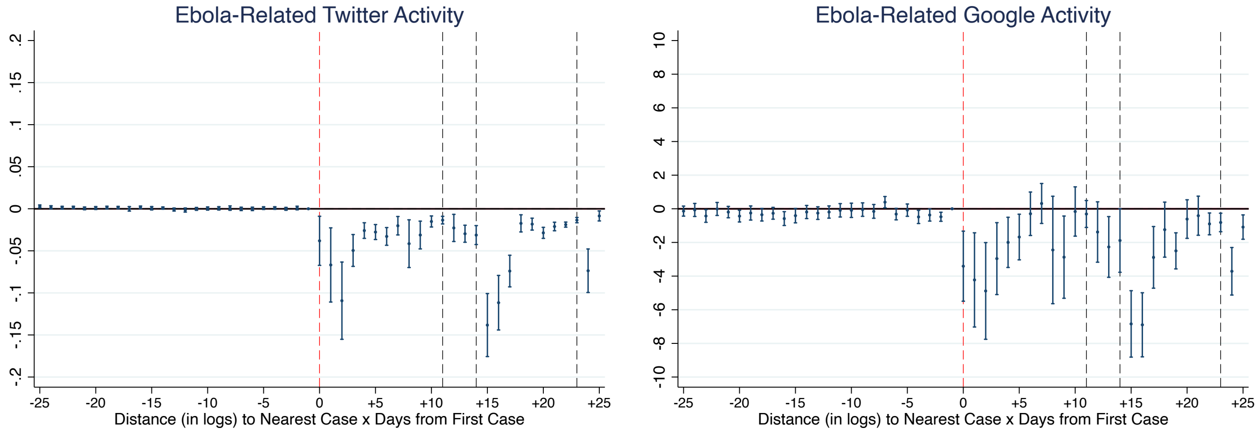


Figure 4: Event Study for Ebola-Related Google Searches and Tweets

Note: These figures show point estimates and 95% confidence intervals of coefficients for relative time indicators (days) with respect to the first reported ebola case (i.e., September 30th 2014 in Dallas) interacted with distance (in logs) to nearest ebola case (i.e., our main instrument). The coefficient for the day immediately before the first ebola case is normalized to zero. The unit observation is a DMA-day. The sample covers 25 days before and after the first case. The dependent variable in the left panel is the number of ebola related tweets per 10,000 inhabitants in DMA (using 2010 census population). The dependent variable in the right panel accounts for the daily google search volume of the term 'ebola' in DMA. Each DMA google searches time series is scaled by a DMA-specific weight based on the relative geographic distribution of ebola searches between September 1st and November 30th. The specifications includes both DMA and day fixed effects. Standard errors are clustered at both DMA and day level. Red vertical lines denote the timing of the first case whereas the black vertical lines denote the timing of the three other cases.

We will thus use *Distance to Nearest Case* as an instrumental variable in our main regressions with election results, summarizing the variation in a context in which the timing of different cases cannot be directly exploited.[22] 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.[23]

We can examine the strength of the relationship between our instrument and the measures of Ebola concerns, by estimating the first-stage regression:

$$Ebola_{c,d} = \pi_0 + \pi_1 ln(DistanceNearestCase)_d + \pi_2 Vote_{c,d}^{2010-06} + \pi_3' X_c + \pi_4' D_d + \Lambda_r + \epsilon_{d,c}. \quad (4)$$

Table 1 presents different specifications estimating equation (4) and shows that proximity to the nearest reported Ebola case is indeed a strong predictor of Ebola concerns. Column 1

[22]Figure A.4 depicts the histogram of distance to nearest case both in level and in logs.

[23]Conditioning is, of course, important: for instance, our instrument quite obviously varies systematically with region, as can be readily seen from Figure A.5, showing the spatial distribution of the variable.

establishes the basic result using the search measure. Adding the full set of county-level controls and regional dummies (colum 2), DMA controls (column 3), or pre-trends in voting (column 4) does not substantially change the point estimate for the instrument.[24] Further, removing population weights in column 5 does not alter our results. Columns 6 and 7 of Table 1 then confirm the results using the Twitter measure.[25] We can also see this pattern in less parametric fashion, by plotting (the residuals of) Ebola searches and tweets against (the residuals of) the distance to the nearest case. Figure 5 shows a largely monotonic and close to (log)linear decline. This underscores that the relationship is not being overly influenced by places in the near vicinity or very far from the key locations.[26]

Table 1: 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	-6.546***	-9.381***	-8.824***	-8.687***	-7.389***	-1.451***	-1.418***
	(2.205)	(1.953)	(1.492)	(1.475)	(1.749)	(0.285)	(0.297)
Mean Value Dep. Var.	51.86	51.86	51.87	51.87	50.35	4.73	3.69
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	0.47	0.64	0.69	0.70	0.50	0.76	0.60
Observations	3069	3068	3059	3059	3059	3061	3061
Number of Clusters (DMA)	204	204	200	200	200	201	201

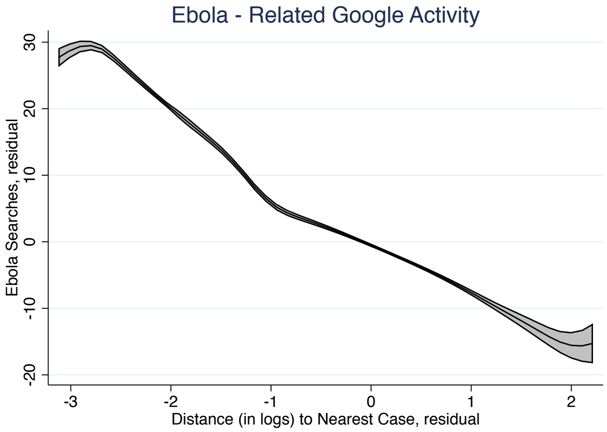
Notes: The variable Ebola Searches accounts for the google search volume of the term 'ebola' during the 5 weeks before the 2014 election. The variable Ebola Tweets accounts for the number of tweets about 'ebola' per 10,000 inhabitants in DMA during the same period. The instrument Distance to Nearest Case is computed by taking the logarithm of the minimum distance (in miles) between the centroid of each DMA to each of the three Ebola locations. 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.

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

[24]The first stage results suggest that our setting is not particularly subject to a weak instrument problem: the implied robust weak instrument F-Statistics (i.e., Olea and Pflueger (2013)'s effective F-Statistics) are above 30. Still, for all our instrumental variable results we report the effective F-Statistic (Olea and Pflueger, 2013) as well as the Anderson-Rubin 95% confidence sets which are robust to weak identification and are efficient in the just-identified case (Andrews et al., 2019).

[25]Table A.7 shows that the first-stage results are robust to allowing for spatial autocorrelation in the computation of the standard errors using several cutoff-distances from 100km to 1,000km.

[26]Figure A.6 depicts the non-parametric first-stage relationships for the unweighted cases.



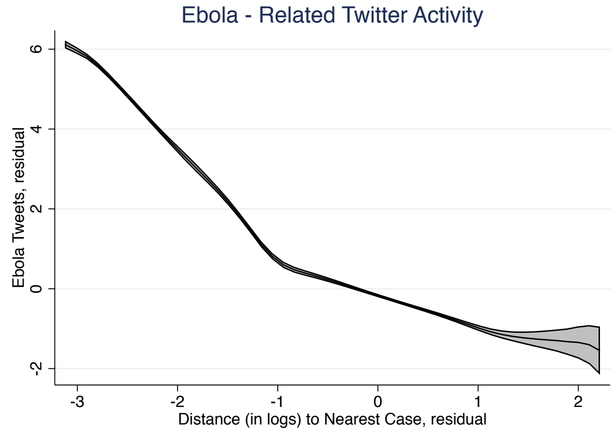


Figure 5: First-Stage Relationship (Non-Parametric Estimation)

Note: These figures non-parametrically plot the relationship between our instrument (i.e., distance (in logs) to nearest case) and our two measures of Ebola concerns (based on google searches on the left and based on ebola-related tweets on the right). To account for the full set of controls discussed in equation (4), we separately regress both our instrument and the measures of Ebola concerns on these set of controls, generate the residuals, and then estimate non-parametric regressions using these residuals. Local linear regressions with bandwidth of 0.7 are displayed. Regressions are weighted using DMA population. The black lines show the fitted values from those local lineal regressions whereas gray shading areas represent 95 percent confidence intervals.

can be seen in Table A.6 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 6 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 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. By the same token, Tables A.8 and A.9 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.

In sum, proximity to an Ebola case induced increased concern with the virus, as proxied by web searches and social media activity. Armed with this source of variation, we now turn to the estimation of the impact of Ebola concerns on the outcomes of the subsequent election.

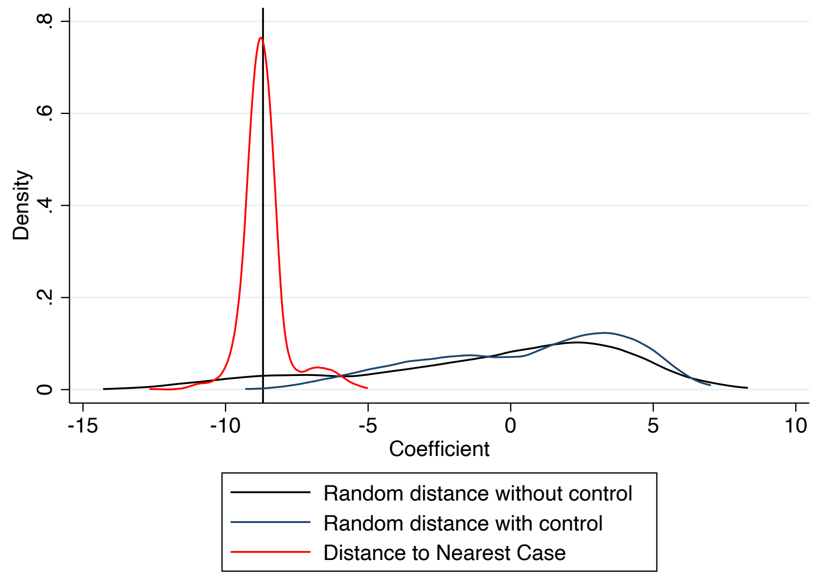


Figure 6: Placebo First-Stage

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 1)

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 2 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.)[27] 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 large unconditional association between Ebola concerns after the first case and the vote share for Democratic candidates. This remains true, and becomes more precisely estimated, even after controlling for possible confounding factors, captured by regional dummies and by

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

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 "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).

Table 2: 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	-0.048						
	(0.270)						
Ebola Searches		-0.242	-0.333***	-0.304***	-0.163***		
		(0.211)	(0.082)	(0.066)	(0.044)		
Ebola Tweets						-1.176***	-0.767***
						(0.408)	(0.270)
Std Dev Vote Share	20.61	20.61	20.61	20.61	20.61	20.61	20.61
Std Dev Ebola (Searches or Tweets)	7.20	12.69	12.69	12.69	12.69	2.33	2.33
Effect of Std Dev Δ in Searches/Tweets	-0.35	-3.08	-4.23	-3.86	-2.07	-2.74	-1.79
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	3061	3063	3062	3053	3053	3055	3055
Number of Clusters (DMA)	203	204	204	200	200	201	201

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 specifications 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.

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.[28] A similar pattern is present, if somewhat less starkly, when it comes to Ebola concerns

[28]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. We will elaborate on that later, when discussing our main results.

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.

5.2 Ebola and Voting: Instrumental Variable Results

The nature of the variation behind our IV strategy can be seen Figure 7, 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.

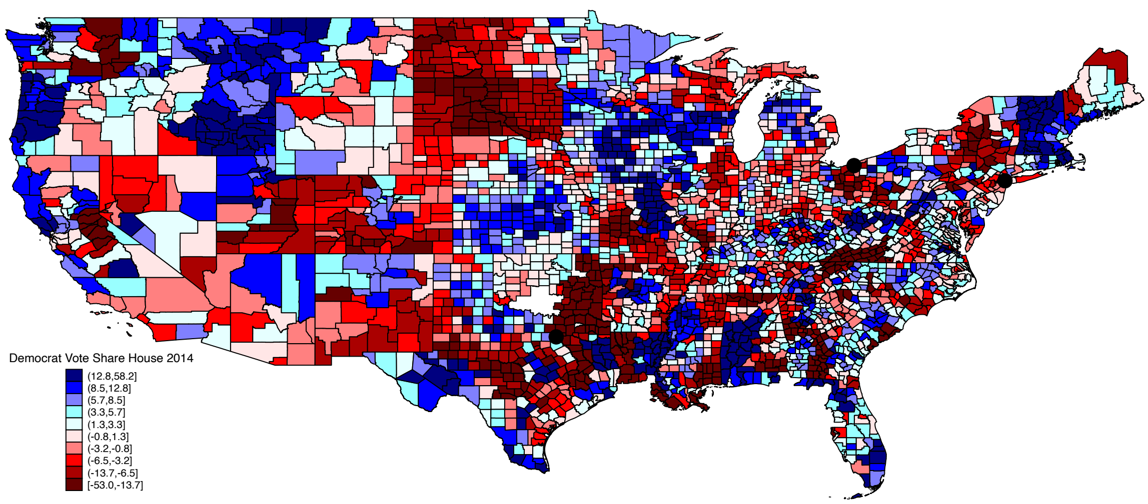


Figure 7: Democratic Vote Shares in House Elections

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). Black dots denote the location of Dallas, Cleveland, and New York.

We confirm this pattern more systematically, in columns 1-2 in Table 3, which show the reduced-form results: distance to the nearest Ebola case strongly predicts Democratic electoral performance in House elections in 2014.This can also be seen in non-parametric fashion, by plotting the residuals of the Democratic House vote share, after accounting for the full set of control variables in Table 2, against the residuals of our instrument, $DistanceNearestCase$. This non-parametric reduced form is in Figure 8, for the unweighted and weighted cases (by

DMA population). We see a clear pattern where Democrats got fewer votes in places closest to Ebola cases, relative to what they would be expected to have obtained given demographic characteristics and, most importantly, previous voting patterns. We once again see that this is close to a (log)linear relationship, not driven by specific distances.[29]

Table 3: 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	2.928***	2.569***				
	(0.439)	(0.624)				
Ebola Searches			-0.339***	-0.350***		
			(0.091)	(0.111)		
Ebola Tweets					-2.014***	-1.629***
					(0.593)	(0.506)
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	12.69	10.73	2.33	1.82
Effect of Std Dev Δ in Searches/Tweets	3.92	2.10	-4.30	-3.75	-4.70	-2.97
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	-	-	34.09	18.12	25.30	22.94
Anderson-Rubin CI	-	-	[-0.60, -0.20]	[-0.69, -0.18]	[-3.77, -1.15]	[-2.97, -0.77]
tF adjusted 95% CI	-	-	[-0.55, -0.13]	[-0.65, -0.05]	[-3.45, -0.58]	[-2.89, -0.36]
Adjusted-R^2	0.74	0.63	0.73	0.61	0.72	0.61
Observations	3053	3053	3053	3053	3055	3055
Number of Clusters (DMA)	200	200	200	200	201	201

Notes: This table reports instrumental variable estimates. 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. The instrument Distance to Nearest Case is computed by taking the logarithm of the minimum distance (in miles) between the centroid of each DMA to each of the three Ebola locations. 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. Anderson-Rubin CI reports the 95% confidence set which is robust to weak identification and efficient in the just-identified case (Andrews et al., 2019). Effective F Statistic reports Olea and Pflueger (2013) robust weak instrument F-Statistics. tF adjusted 95% CI reports (Lee et al., 2022)'s valid confidence intervals for IV. 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 importantly, the reduced form linking distance to key Ebola locations and Democratic House vote share is not present in previous electoral cycles. Figure 9 displays the reduced-form coefficients estimated from (weighted) regressions following the specification in column 1 in Table 3, for all ten House elections between 1996 and 2014. We see that the 2014 coefficient

[29] In Figure A.10 we plot reduced-form coefficients for Distance (in logs) to Nearest Case excluding observations beyond different distance thresholds to show that these results are not driven by observations from places far from the Ebola cases.

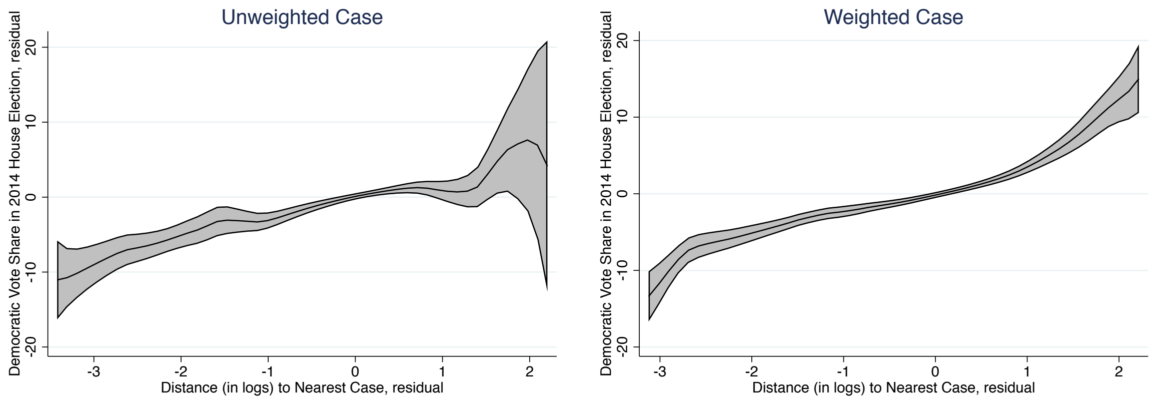


Figure 8: Reduced-Form (Non-Parametric Estimation)

Note: These figures non-parametrically plots the relationship between our instrument (i.e., Distance to Nearest Case) and Democratic vote share in 2014 House election. To account for the full set of controls discussed in equation (1), we separately regress both our instrument and the outcome variable, generate the residuals, and then estimate a non-parametric regression using these residuals. The panel on the left does not use weights whereas the panel uses DMA population as weights. Left (Right) panel displays a local linear regression with bandwidth of 0.62 (0.71). The black line shows the fitted values from this local linear regression whereas the gray shading area represents 95 percent confidence intervals.

is the largest in magnitude, and no other election displays a statistically significant coefficient. In short, distance to the key Ebola locations was not predictive of the Democratic vote share in any election other than 2014.

The remainder of Table 3 then presents the main IV results for U.S. House elections.[30] Columns 3-6 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. Reassuring, all the identification-robust Anderson-Rubin confidence intervals reported in Table 3 safely exclude zero.[31]

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: in 2014, 40 House 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

[30]Table A.10 in the Appendix shows results for senatorial and gubernatorial races, confirming that Democrats were also negatively affected by Ebola concerns in those elections.

[31]We find similar results using CCES data on voting intentions at the individual level(as of October 2014): Ebola concerns (instrumented by distance to nearest Ebola case) have a negative impact on the intention to vote for the Democrats., as can be seen in Table A.11.

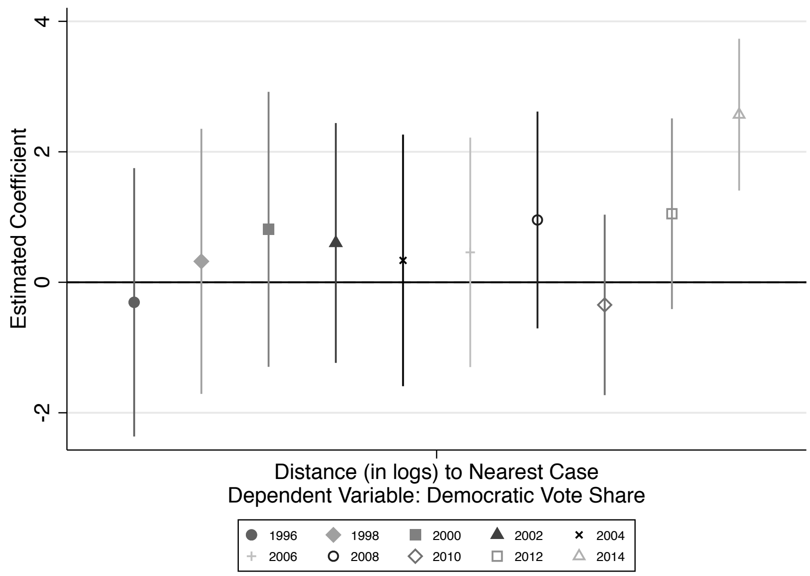


Figure 9: Distance to Nearest Case and Democratic Vote Shares in Previous Elections
Note: This figure plots point estimates and 95% confidence intervals for 10 separate regressions of democratic vote shares on distance (in logs) to nearest ebola case (i.e., our main instrument). We use data for all house, senatorial, and gubernatorial elections taken place in all even years from 1996 to 2014 (the year of election is listed next to each coefficient marker). All estimates are based on OLS regression (weighted by DMA population) in which we control for the set of county-level and DMA-level controls discussed in equation (1), region fixed effects, and type of election fixed effects (i.e., house, senatorial, or gubernatorial). Standard errors are clustered at the DMA-level.

(from 234-201 to 247-188).[32]

The IV coefficient is larger than the comparable OLS coefficient (see column 5 in Table 2). This could be due to a combination of measurement error in the variables capturing Ebola concerns and 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. The difference could also be related to the nature of the local average treatment effect, and for this it is instructive to look at the individual CCES survey data on Ebola concerns. It is noticeable (Table A.4) that Ebola concerns are much more sensitive to distance for registered Democrats than for registered Republicans. To the extent that this suggests that the typical "complier"

[32]The magnitude of the standardized effects is also quite substantial for Senate and gubernatorial elections, as per Table A.10 in the Appendix: a one-standard-deviation increase in Ebola concerns reduces the Democratic vote share by just about one fifth of a standard deviation. Specifically, 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. That the magnitude of the effect for House voting intentions is slightly smaller (about 2 p.p., as per Table A.11) is not surprising, as there we are looking at all CCES respondents in the month of October, over which the Ebola situation was playing out.

in the natural experiment induced by the geographical location of Ebola cases is a relatively Democratic area, it may be the case that the IV estimates are larger partly because the impact of Ebola concerns is stronger for Democratic voters.

To shed additional light on the nature of the electoral impact of Ebola, we look at voter turnout. Table 4 shows a substantial negative impact of Ebola concerns on total voter turnout (columns 1 and 2). 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 1.6 percentage points corresponds to about 40% 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.[33]

Still, the negative impact on the Democratic vote share is unlikely to be entirely explained by lower turnout. Consider that, as per columns 3 and 4, we also detect a strongly negative impact of Ebola concerns when using as dependent variable the share of Democratic votes relative to the total number of eligible voters – a number that is very much stable between elections. The magnitude of this decline is such that a one-standard-deviation increase in Ebola searches would have led to a drop of about 2.6 percentage points in that share. A simple back-of-the-envelope calculation, considering turnout of about 40%, evenly split between Democrats and Republicans, shows that this drop would by itself lead to about a 3.5 percentage-point decline in the Democratic share of the vote – compared to the 4.5 percentage-point magnitude we find in our comparable weighted regressions in Table 3. More direct, if correlational, evidence of switching votes across parties can be seen from the CCES survey responses: Table A.4 shows that registered Democrats who report individual concern with Ebola are more than twice as likely to report an intention to vote for a Republican candidate.

In any case, the pattern is clear: the Ebola threat had a substantial negative causal impact on the electoral fortunes of Democrats in the 2014 midterms.

[33]Could this be partly explained by Democratic voters being more likely to be concerned with the possibility of contracting the virus by turning out to vote, as may be suggested by the widely reported differences in partisan attitudes towards Covid-19 risk in 2020? It is a possibility, but in fact the Ebola context was rather different: in the CCES data, it was Republican voters who reported significantly higher levels of personal concern with Ebola, as shown in Table A.3 in the Appendix, suggesting that lower turnout due to fear of contagion would have pushed in the opposite direction of our findings. Moreover, the context in 2014 was very different from that of 2020, when it comes to turnout, as the Covid-19 pandemic led to massive changes in voting procedures, such as the expansion of access to mail voting.

Table 4: Ebola Concerns and Turnouts

	Turnout 2014		Democratic House Votes as Share of Elegible Voters	
	(1)	(2)	(3)	(4)
Ebola Searches	-0.111**		-0.197***	
	(0.048)		(0.073)	
Ebola Tweets		-0.698***		-1.166**
		(0.247)		(0.472)
Std Dev Vote Share	10.50	10.50	7.84	7.84
Std Dev Ebola (Searches or Tweets)	12.82	2.35	12.69	2.33
Effect of Std Dev Δ in Searches/Tweets	-1.42	-1.64	-2.50	-2.72
County-Level Controls	Yes	Yes	Yes	Yes
DMA-Level Controls	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Previous Election Controls	Yes	Yes	Yes	Yes
Effective F Statistic	35.92	25.84	34.15	25.31
Anderson-Rubin CI	[-0.23, -0.03]	[-1.31, -0.26]	[-0.40, -0.09]	[-2.60, -0.51]
tF adjusted 95% CI	[-0.22, -0.00]	[-1.30, -0.10]	[-0.36, -0.03]	[-2.31, -0.02]
Adjusted-R^2	0.75	0.75	0.58	0.58
Observations	3091	3093	3052	3054
Number of Clusters (DMA)	200	201	200	201

Notes: This table reports instrumental variable estimates. The dependent variable in columns 3 and 4 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. The instrument Distance to Nearest Case is computed by taking the logarithm of the minimum distance (in miles) between the centroid of each DMA to each of the three Ebola locations. 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. Anderson-Rubin CI reports the 95% confidence set which is robust to weak identification and efficient in the just-identified case (Andrews et al., 2019). Effective F Statistic reports Olea and Pflueger (2013) robust weak instrument F-Statistics. tF adjusted 95% CI reports (Lee et al., 2022)'s valid confidence intervals for IV. 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.

5.3 Robustness

We check the robustness of our results along several dimensions. First, we experiment with different combinations and permutations of our control variables, for county- and DMA-level characteristics, as well as results from previous elections. The results are robust – as can be seen in Figures A.9 and A.8 in the Appendix, for the reduced form and the IV coefficients respectively – underscoring that the finding is a robust pattern in the data, and not the result of mere happenstance or a "false positive." They also hold when we include as previous elections controls the Democratic vote share in all of the House elections between 2006 and 2012 – that is to say, including both midterm and presidential years – as well as in the 2008 and 2012 presidential elections. These results can be seen in Table A.12.

In addition, 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”, as can be seen in Table A.13. The coefficient on distance to the nearest case is barely affected when we include that alternative distance, and is substantially larger in magnitude than the coefficient on the latter. For further reassurance, we can use the previously described placebo 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 10, 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.

Last but not least, we also check robustness with respect to the spatial nature of our variation. The results still hold when we account for spatial autocorrelation in the error term in the computation of the standard errors(Table A.14), following Conley (1999). They also remain in place if we exclude the Dallas, Cleveland, and NYC’s DMAs or even the whole states of Texas, Ohio, and New York (Tables A.15 and A.16), showing that they are not driven by unrelated factors in these regions. Additionally, Figure A.11 depicts IV coefficients from specifications excluding observations beyond different distance thresholds to show that our results are not driven by observations from place far from the locations with Ebola cases. As a final check, we consider a linear instrument for distance to nearest case, instead of its logarithm transformation, to make the variation in the narrow proximity of the cases less disproportionately salient, and the results still hold (Table A.17).

5.4 Were Voters Blaming Incumbents?

One possible explanation for the patterns we have uncovered could be an anti-incumbent effect: 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,

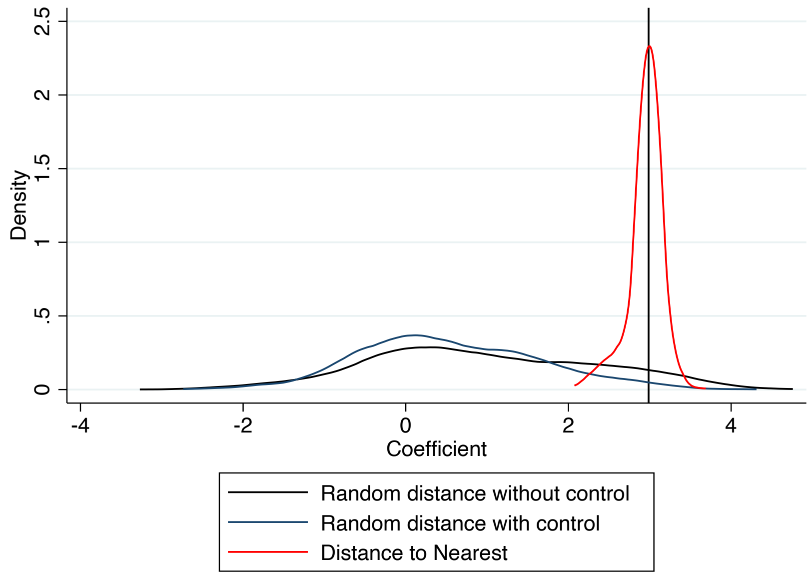


Figure 10: Placebo Reduced-Form 2014 Vote Share and Distance
Note: The figure shows kernel density estimations for three pdf of: (1) coefficient of minimum distance to 3 randomly drawn cities out of the largest 100 cities (excluding Ebola locations) obtained from regressing Democratic vote share in 2014 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 3)

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 (Healy and Malhotra, 2013).

We first consider the possibility of a general anti-incumbent channel, looking at voting results by incumbency status. Table 5 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), we still detect a negative impact on the vote share of the Democratic challengers.

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

Table 5: 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	0.175*	-0.570*	-0.038	-0.377*	0.160***	-0.421***	-0.291***	-0.147**	-0.197**
	(0.099)	(0.345)	(0.108)	(0.218)	(0.038)	(0.136)	(0.057)	(0.071)	(0.084)
Incumbents	All	Democrat	All	Democrat	All	Democrat	Exclude Democrat Incumbents		
Std Dev Vote Share	15.64	15.91	16.21	14.19	13.04	15.12	15.73	13.28	10.80
Std Dev Ebola Searches	13.40	9.58	14.34	9.18	13.94	9.32	14.24	16.72	15.39
Effect of Std Dev Δ in Searches	2.34	-5.47	-0.55	-3.46	2.24	-3.92	-4.15	-2.45	-3.03
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	37.41	32.65	53.79	12.95	70.13	42.18	53.53	275.6	112.2
Anderson-Rubin CI	[-0.07, 0.34]	[-1.40, 0.02]	[-0.29, 0.15]	[-0.90, 0.10]	[0.09, 0.24]	[-0.76, -0.20]	[-0.43, -0.20]	[-0.28, -0.00]	[-0.39, -0.05]
tF adjusted 95% CI	[-0.05, 0.40]	[-1.34, 0.21]	[-0.27, 0.19]	[-1.03, 0.28]	[0.08, 0.24]	[-0.72, -0.12]	[-0.41, -0.17]	[-0.29, -0.00]	[-0.36, -0.03]
Adjusted-R^2	0.35	0.33	0.38	0.60	0.69	0.84	0.55	0.69	0.61
Observations	2665	501	2273	1027	2134	497	2302	1246	1637
Number of Clusters (DMA)	198	99	152	118	170	113	182	115	151

Notes: This table reports instrumental variable estimates. The variable Ebola Searches accounts for the google search volume of the term 'ebola' during the 5 weeks before the 2014 election. All regressions are weighted by DMA population. The instrument Distance to Nearest Case is computed by taking the logarithm of the minimum distance (in miles) between the centroid of each DMA to each of the three Ebola locations. 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. Anderson-Rubin CI reports the 95% confidence set which is robust to weak identification and efficient in the just-identified case (Andrews et al., 2019). Effective F Statistic reports Olea and Pflueger (2013) robust weak instrument F-Statistics. tF adjusted 95% CI reports (Lee et al., 2022)'s valid confidence intervals for IV. 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.

negatively affected by the timing of and distance to Ebola-related events. We explore that possibility using daily individual-level data from Gallup surveys on presidential approval ratings, to estimate the following event-study specification:

$$Disapprove_{i,d,t} = \sum_{\substack{\tau=-25 \\ \tau\neq -1}}^{25} \gamma_\tau ln(DistanceNearestCase)_d \times 1[\Upsilon_t = \tau] + \delta' X_i + \lambda_d + \theta_t + \epsilon_{d,t}, \quad (5)$$

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. The variable $ln(DistanceNearestCase)_d$ is the (log) distance (in miles) of DMA d from the nearest location of one of the Ebola cases and Υ_t is a relative time indicator defined as days from the first case in September 30, 2014. The vector X_i includes individual level controls (e.g., age, gender, race, etc), λ_d and θ_t are DMA and day fixed effects, respectively. We will cluster standard errors at the DMA level. For our analysis, we restrict our attention to 25 days before and after September 30, 2014. We estimate equation (5.4) for the whole sample of individuals and for subsets based on ideology – namely, whether individuals declare being (registered) Republicans or Democrats.

Figure 11 depicts the estimated coefficients for the three groups. Regardless of the sample, there is no evidence of a systematic disapproval of Barack Obama in places close to any of the

Ebola cases after the occurrence of the first case. 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.[34]

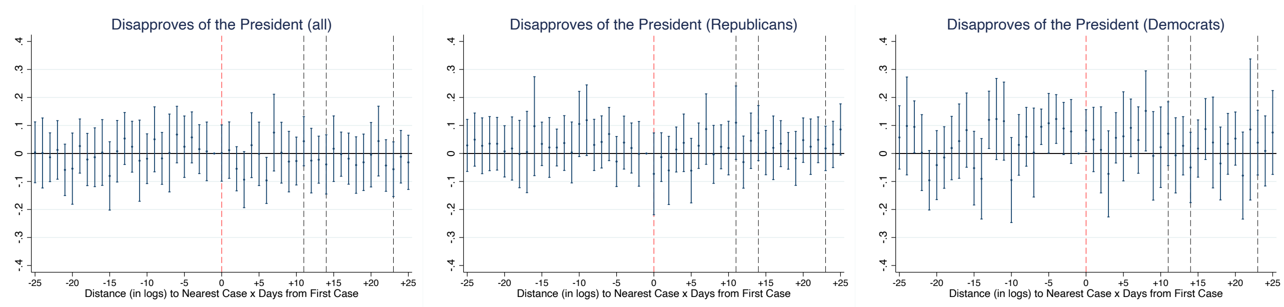


Figure 11: Event Study for President Obama's approval ratings (by ideology)

Note: These figures show point estimates and 95% confidence intervals of coefficients for relative time indicators (days) with respect to the first reported ebola case (i.e., September 30th 2014 in Dallas) interacted with distance (in logs) to nearest ebola case (i.e., our main instrument). The coefficient for the day immediately before the first ebola case is normalized to zero. The unit observation is an individual. The dependent variable the three panel is an indicator taking value 1 if individual disapproves of Obama's job as president, and 0 otherwise. Sample is based on Gallup's daily individual data and covers 25 days before and after the first case. The first panel on the left focuses on all individuals whereas the middle panel focuses on registered republicans and the one on the right focuses on registered democrats. The specifications includes day and DMA fixed effects as well as age and indicators for gender, employed, married, black, and hispanic as individual-level controls. Standard errors are clustered at the DMA level. Red vertical lines denote the timing of the first case whereas the black vertical lines denote the timing of the three other cases.

5.5 Did Ebola Make Voters More Conservative?

We can also look more directly 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.

[34]We again present in the Appendix an alternative approach by estimating:

$$Disapprove_{i,d,t(c)} = \gamma PostCase_{t(c)} \times ln(Dist.Ebola_c)_d + \delta' X_i + \lambda_d + \theta_t + \epsilon_{d,t}, \tag{6}$$

$PostCase_t(c)$ 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 A.18, with no evidence of any impact on Obama's approval ratings: we find a precisely estimated zero effect. The same table shows that the result is not an artifact of the Gallup data: we see no impact on Obama's disapproval as measured by the CCES survey.

For that we turn again to the CCES data, with which we will compare respondents interviewed in October/November 2014 to those interviewed in 2013 – we do not have pre-Ebola interviews in 2014, given the timing of the survey. Specifically, we estimate the following specification:

$$Y_{i,d,t} = \gamma PostOnset_t \times ln(DistanceNearestCase)_d + \delta' X_i + \lambda_d + \theta_t + \epsilon_{d,t}, \qquad (7)$$

where $PostOnset_t$ is an indicator taking the value of 1 after the diagnosis of the first Ebola case – that is to say, individuals surveyed in 2014. Y_{idt} stands for one of 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. The vector X_i includes individual level controls (e.g., age, gender, race, education, and income), λ_d and θ_t are DMA fixed effects and day fixed effects, respectively. Our geographical unit d is a DMA and the level at which we cluster the standard errors. The γ coefficient captures the reduced-form relationship in which the onset of the Ebola episode may have affected individual attitudes.

Table 6 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, however, 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.[35]

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, it illustrates the potential scope for the political impact of episodes such as the Ebola shock in the US. In fact, the working version of this paper [(Campante et al., 2020) showed evidence that Republican politicians tried to draw connections, in their messaging to voters, between Ebola and Obama, as well as immigration. While we cannot draw conclusions about the actual impact of that strategic response, the results here suggest that not all associations drawn by politicians would have resonated in voters' minds. Instead, any impact might have been constrained by those

[35]Reassuringly, we find the same patterns when we estimate the three distances interaction after each case in Table A.19.

Table 6: 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	-0.019**	-0.004	-0.007	-0.001	-0.002
	(0.009)	(0.013)	(0.015)	(0.004)	(0.004)
Day FE	Yes	Yes	Yes	Yes	Yes
DMA FE	Yes	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes	Yes
Sample Weights	Yes	Yes	Yes	Yes	Yes
Adjusted-R^2	0.13	0.11	0.11	0.10	0.08
Observations	72209	72209	72209	72209	72145
Number of Clusters (DMA)	204	204	204	204	204

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 4 (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 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.

associations that can be more readily drawn by voters in regard to that threat.

6 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, it also reduced voter turnout. Finally, the salience of the Ebola threat also affected views on a subset of those themes, particularly related to increased anti-immigration sentiment, but had no broader impact on conservative views.

Generally speaking, our results establish that public anxiety induced by threats, such as that of a deadly disease outbreak, can indeed be a potent electoral force, in a high-stakes context in which we can isolate an exogenous shock to that anxiety that is largely disconnected from the materialization 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, threats that materialize or otherwise directly affect daily lives – such as Ebola itself in the context of West Africa, or the 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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Online Appendix - Not Intended for Publication

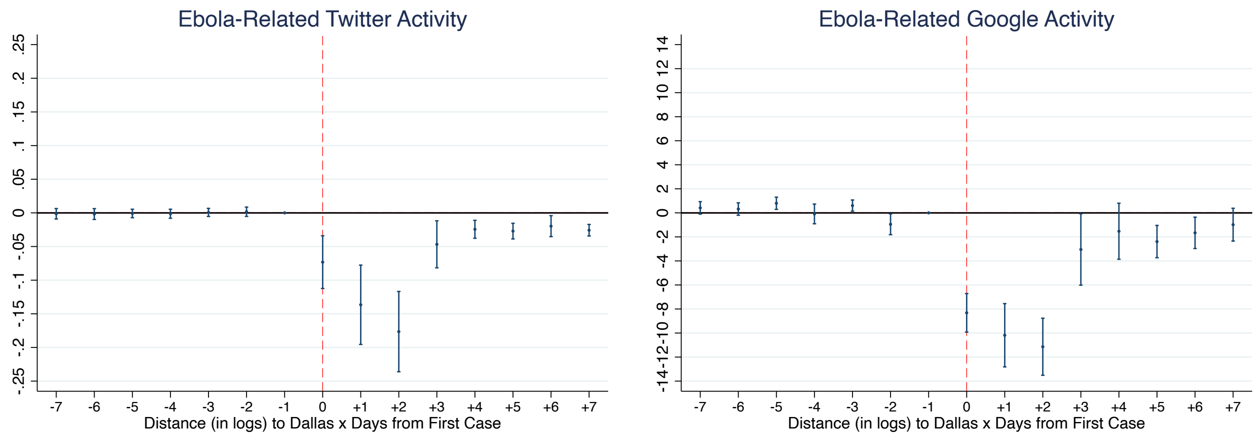


Figure A.1: Event Study for Ebola-Related Google Searches and Tweets (Dallas)

Note: These figures show point estimates and 95% confidence intervals of coefficients for relative time indicators (days) with respect to the first reported ebola case (i.e., September 30th 2014 in Dallas) interacted with distance (in logs) to Dallas. The coefficient for the day immediately before the first ebola case is normalized to zero. The unit observation is a DMA-day. The sample covers 7 days before and after Dallas case. The dependent variable in the left panel is the number of ebola related tweets per 10,000 inhabitants in DMA (using 2010 census population). The dependent variable in the right panel accounts for the daily google search volume of the term 'ebola' in DMA. Each DMA google searches time series is scaled by a DMA-specific weight based on the relative geographic distribution of ebola searches between September 1st and November 30th. The specifications includes both DMA and day fixed effects. Standard errors are clustered at both DMA and day level.

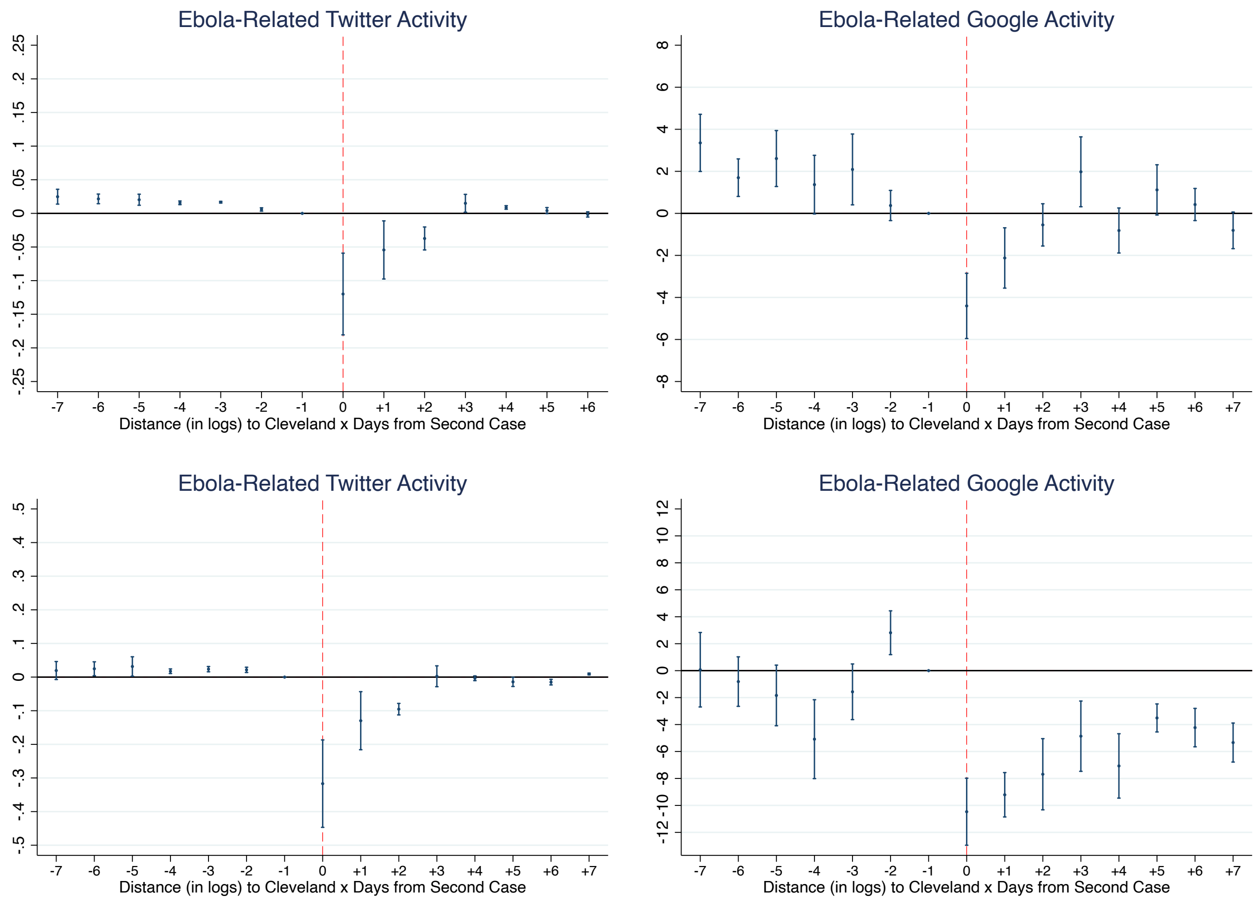


Figure A.2: Event Study for Ebola-Related Google Searches and Tweets (Cleveland)

Note: These figures show point estimates and 95% confidence intervals of coefficients for relative time indicators (days) with respect to the second reported ebola case (i.e., October 14th 2014) interacted with distance (in logs) to Cleveland. The coefficient for the day immediately before the first ebola case is normalized to zero. The unit observation is a DMA-day. The sample covers 7 days before and after Dallas case. The dependent variable in the left panels is the number of ebola related tweets per 10,000 inhabitants in DMA (using 2010 census population). The dependent variable in the right panels accounts for the daily google search volume of the term 'ebola' in DMA. Each DMA google searches time series is scaled by a DMA-specific weight based on the relative geographic distribution of ebola searches between September 1st and November 30th. The specifications includes both DMA and day fixed effects. Standard errors are clustered at both DMA and day level. Top panels focus on the whole sample of DMA while bottom panels focus on the sample of the 100 closest DMA to Cleveland (approximately within 670 miles).

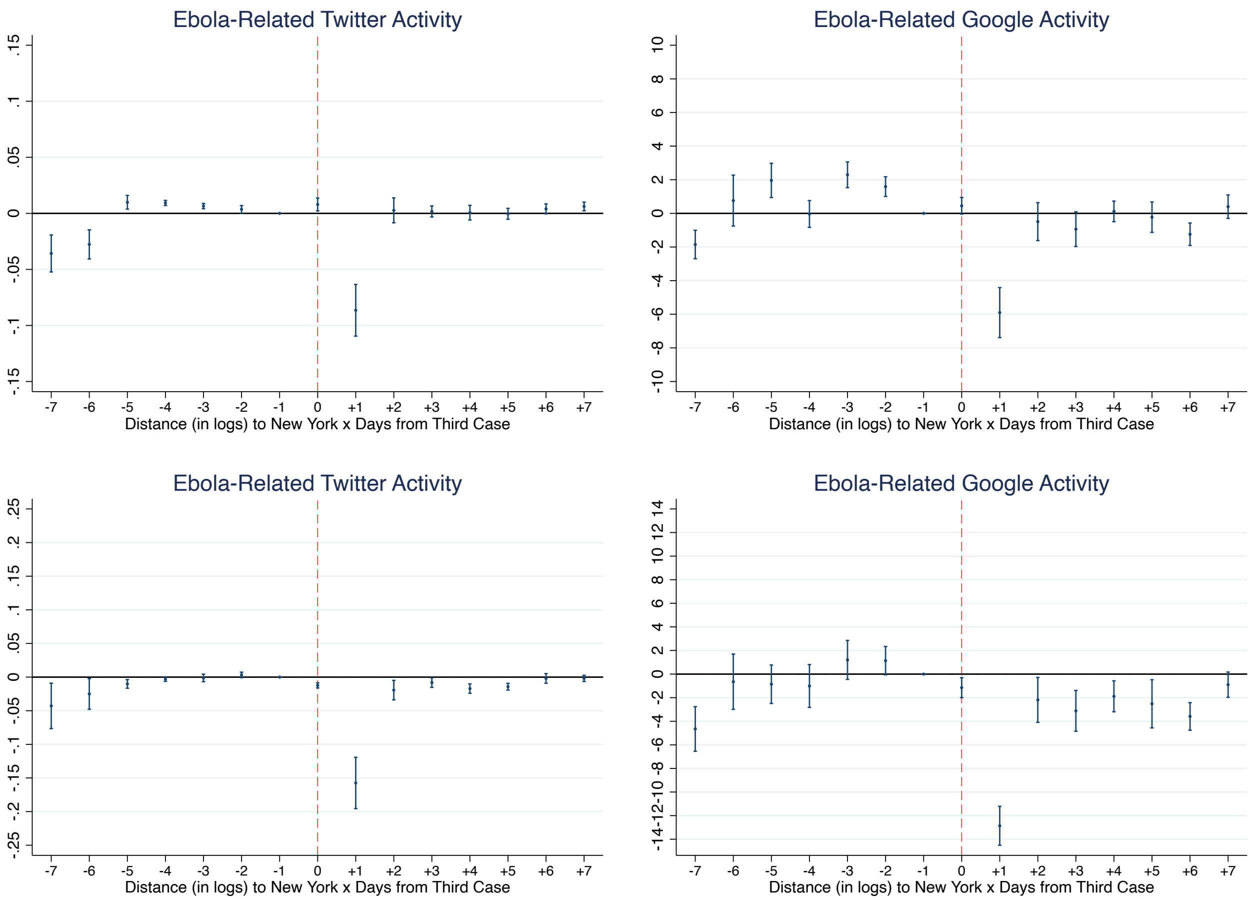


Figure A.3: Event Study for Ebola-Related Google Searches and Tweets (New York)

Note: These figures show point estimates and 95% confidence intervals of coefficients for relative time indicators (days) with respect to the last reported ebola case (i.e., October 23th 2014) interacted with distance (in logs) to New York. The coefficient for the day immediately before the first ebola case is normalized to zero. The unit observation is a DMA-day. The sample covers 7 days before and after Dallas case. The dependent variable in the left panels is the number of ebola related tweets per 10,000 inhabitants in DMA (using 2010 census population). The dependent variable in the right panels accounts for the daily google search volume of the term 'ebola' in DMA. Each DMA google searches time series is scaled by a DMA-specific weight based on the relative geographic distribution of ebola searches between September 1st and November 30th. The specifications includes both DMA and day fixed effects. Standard errors are clustered at both DMA and day level. Top panels focus on the whole sample of DMA while bottom panels focus on the sample of the 100 closest DMA to New York (approximately within 930 miles).

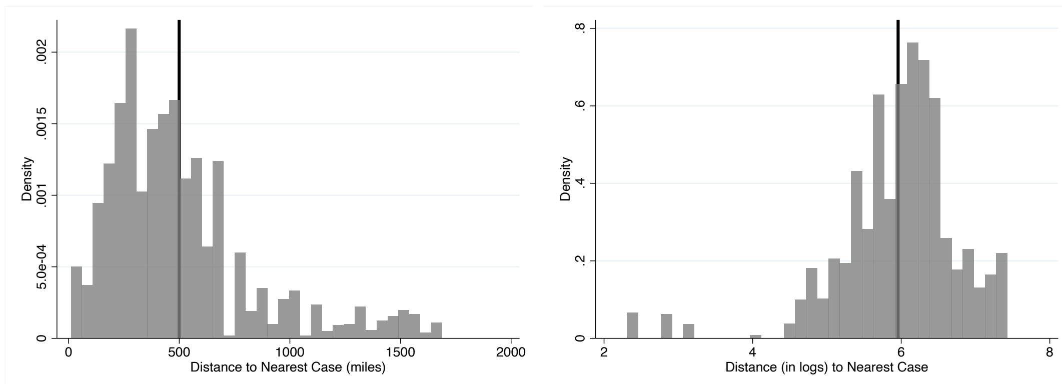
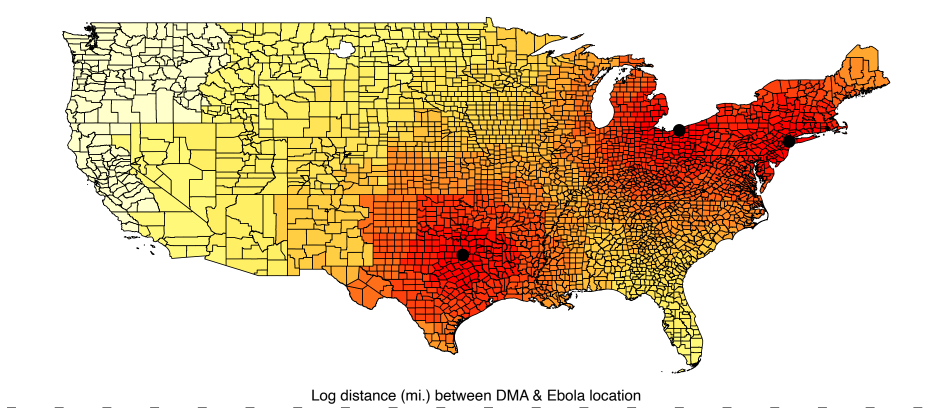


Figure A.4: Histogram Distance to Nearest Case (in miles)

Note: These figures show the histogram of Distance to Nearest Case (in miles) both in level (on the left) and in logs (on the right). Grey vertical lines denote mean values of the variables (499 and 6, respectively).

Figure A.5: Distance to Nearest Case



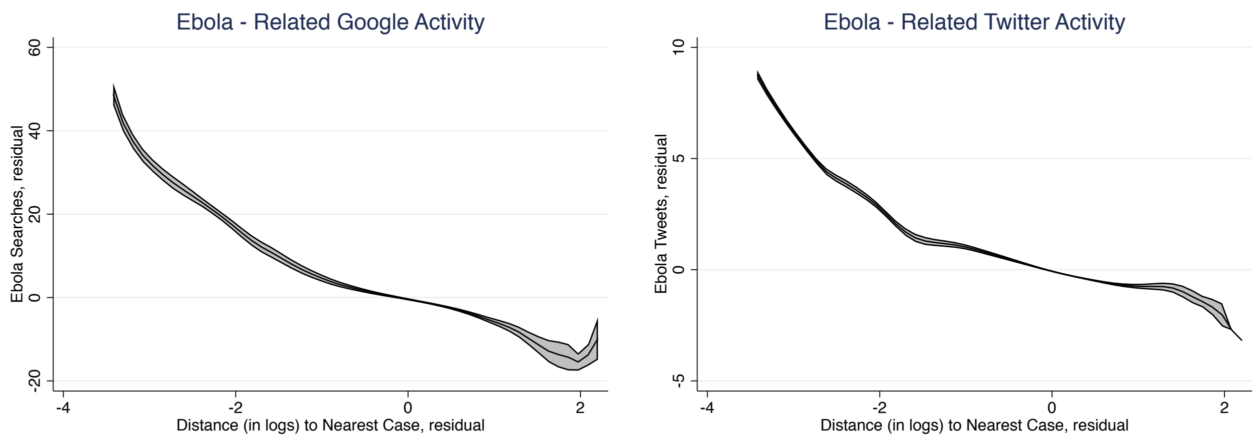


Figure A.6: First-Stage Relationship (Non-Parametric Estimation)

Note: These figures non-parametrically plot the relationship between our instrument (i.e., distance (in logs) to nearest case) and our two measures of ebola concerns (based on google searches on the left and based on ebola-related tweets on the right). To account for the full set of controls discussed in equation (4), we separately regress both our instrument and the measures of ebola concerns on these set of controls, generate the residuals, and then estimate non-parametric regressions using these residuals. Local linear regressions with bandwidth of 0.7 are displayed. The black lines show the fitted values from those local lineal regressions whereas gray shading areas represent 95 percent confidence intervals. As opposed to Figure 5, no weights are used in the regressions.

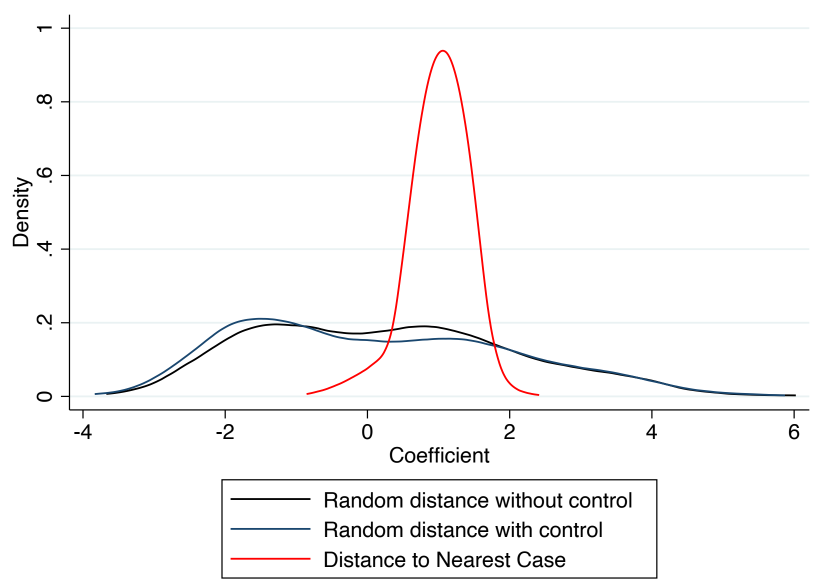
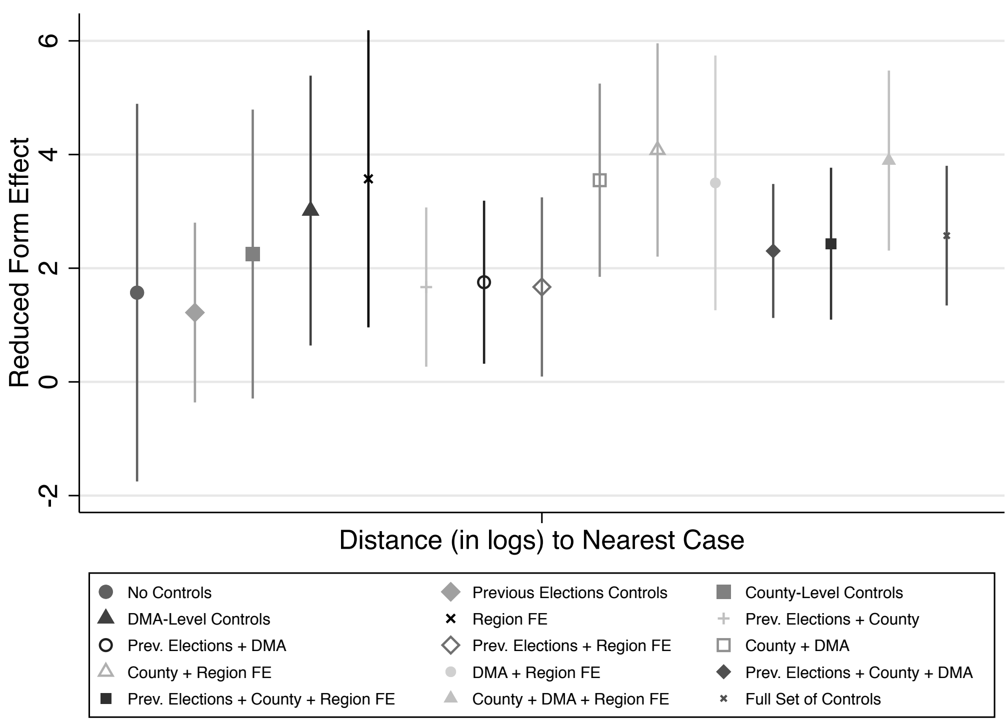


Figure A.7: Placebo Reduced-Form 2010 Vote Share and Distance

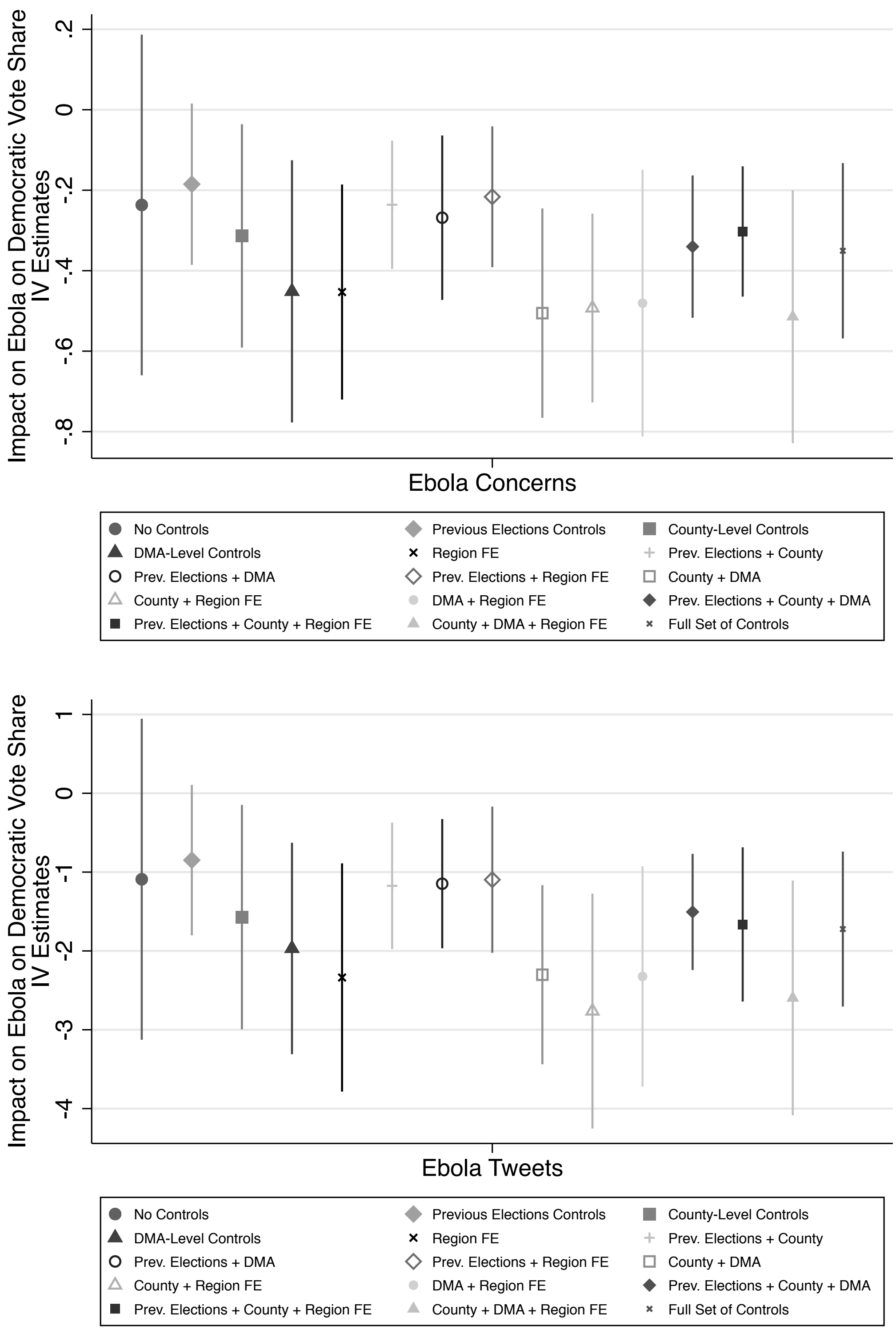
Note: The figure shows kernel density estimations for three pdf of: (1) coefficient of minimum distance to 3 randomly drawn cities out of the largest 100 cities (excluding Ebola locations) obtained from regressing Democratic vote share in 2010 House election on random distance and full set of controls 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.

Figure A.8: Permutation of Controls - Reduced Form



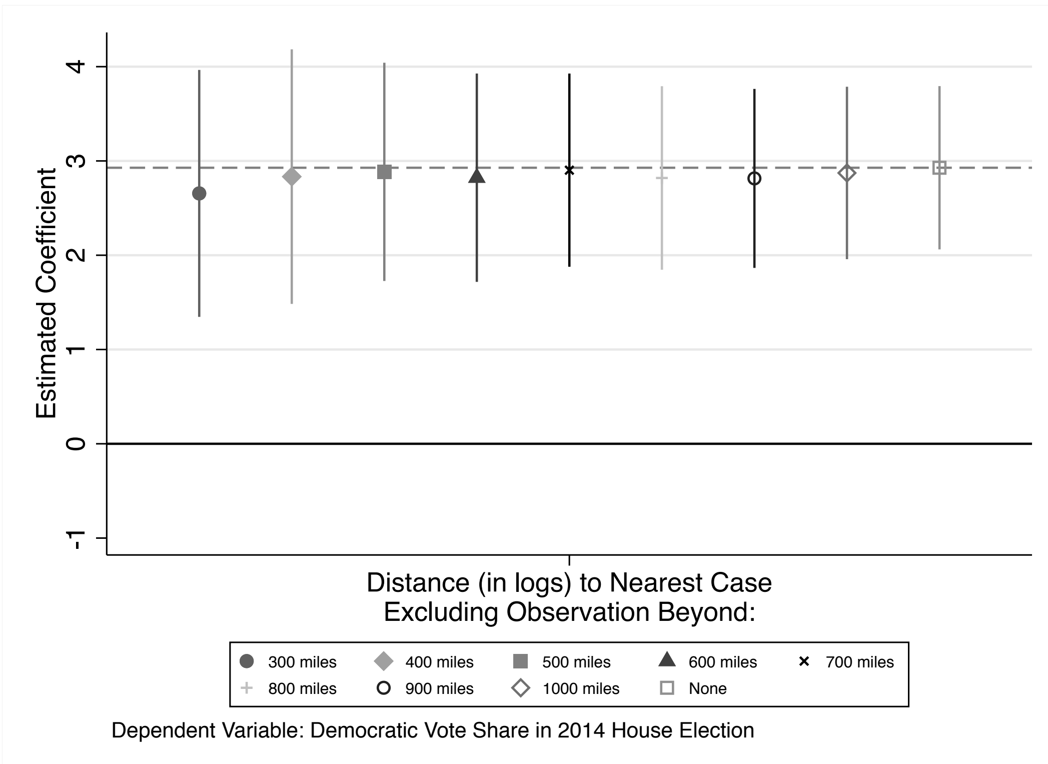
Note: This figure plots the reduced-form coefficients and the 95% confidence intervals for Distance (in logs) to Nearest Case for all the different combinations of the set of controls listed in equation 1. Confidence intervals are based on heteroskedasticity-robust standard errors clustered by DMA.

Figure A.9: Permutation of Controls - Ebola and Democratic Vote Share (IV)



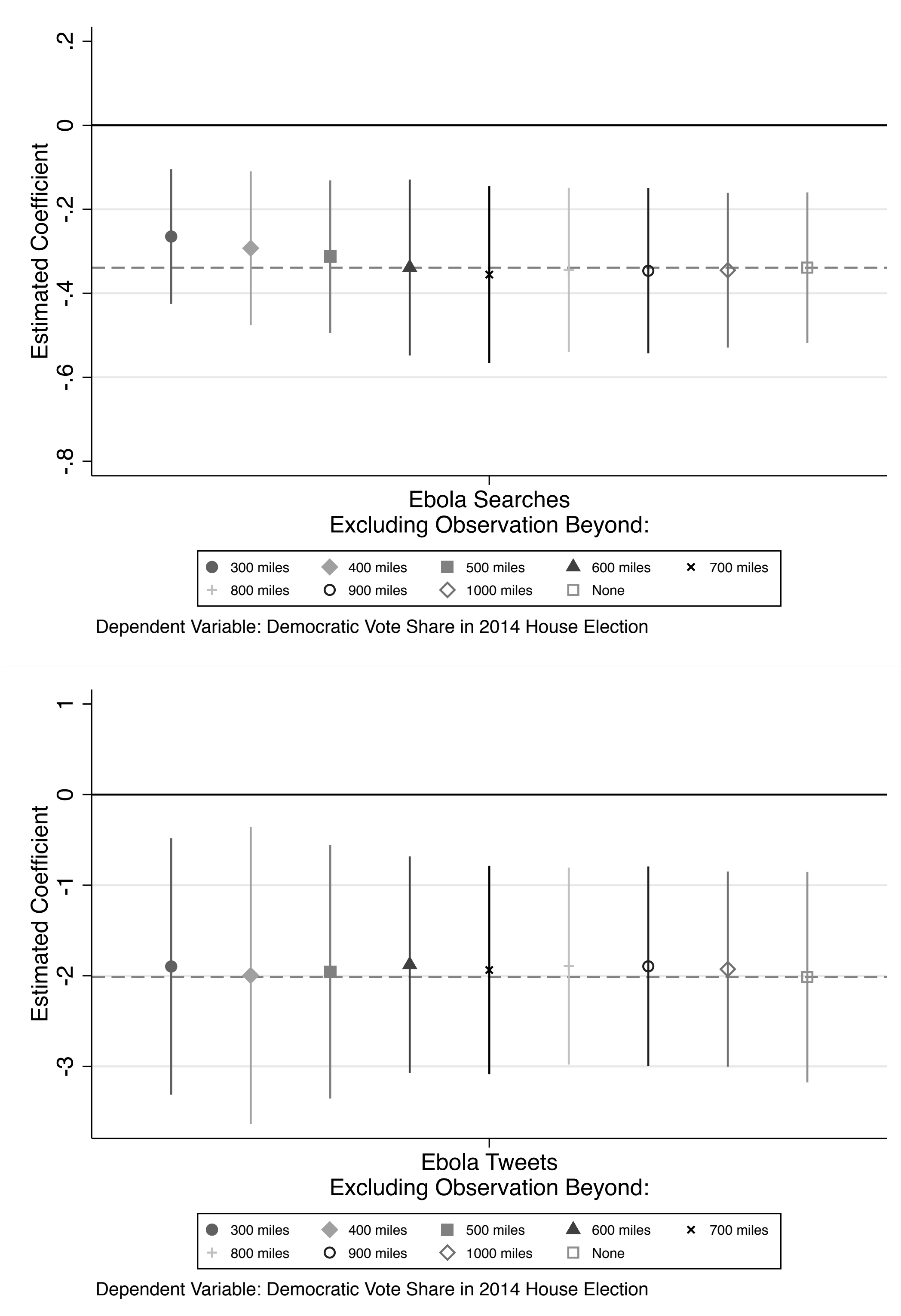
Note: These figures plot the IV coefficients and the 95% confidence intervals for Ebola Searches (Tweets) for all the different combinations of the set of controls listed in equation 1. Confidence intervals are based on heteroskedasticity-robust standard errors clustered by DMA.

Figure A.10: Omitting Distant Locations (Reduced Form)



Note: This figure plots the reduced-form coefficients and the 95% confidence intervals for Distance (in logs) to Nearest Case excluding observations beyond different distance thresholds. Confidence intervals are based on heteroskedasticity-robust standard errors clustered by DMA.

Figure A.11: Omitting Distant Locations (IV)



Note: These figures plot the IV coefficients and the 95% confidence intervals for Ebola Searches (Tweets) excluding observations beyond different distance thresholds. Confidence intervals are based on heteroskedasticity-robust standard errors clustered by DMA.

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	3092	35.605	17.514	0	90.292
Δ Democratic Voting Share 2010-2006 - HOUSE	3079	-10.849	14.393	-69.813	75.226
Δ Democratic Voting Share 2010-2008 - HOUSE	3036	-10.888	13.767	-78.253	43.803
Δ Democratic Voting Share 2012-2010 - HOUSE	3091	.127	13.16	-79.932	58.386
Δ Democratic Voting Share 2006-2002 - HOUSE	3098	7.454	19.363	-73.054	89.296
2014 Democrat Vote Share - GOVERNOR	2149	35.246	14.21	1.075	88.153
2010 Democrat Vote Share - GOVERNOR	2178	37.884	14.544	8.562	87.93
2006 Democrat Vote Share - GOVERNOR	2149	45.269	16.878	3.909	89.39
Δ Democrat Vote Share 2010-2006 - GOVERNOR	2149	-7.208	14.782	-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	32.902	17.178	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	46.462	17.702	6.09	94.884
2002 Democrat Voting Share - SENATE	2404	38.455	20.593	0	91.597
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
2014 Incumbent Vote Share - HOUSE	2962	66.47	15.796	0	100
2014 Incumbent Vote Share - GOVERNOR	2149	61.929	13.356	14.927	96.774
2014 Incumbent Vote Share - SENATE	2287	58.358	18.426	0	99.282
Population Density (per sq. mile)	3103	254.482	1715.588	.061	69357.68
Median Age	3103	39.896	4.855	21.7	61.4
Share of white population	3103	.791	.194	.012	1
Share of college population	3103	.19	.087	.037	.71
Income per capita	3102	22438.58	5361.509	7772	64381
Share of unemployed population	3103	.075	.033	0	.309
DMA-level variables	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Ebola Concerns (Google Trends)	204	50.382	9.517	11	100
Ebola Concerns (Tweets per capita)	204	3.519	1.752	.063	13.477
Cable penetration	203	58.138	11.276	29	84
Anxiety (Google Trend, 2013)	204	68.863	9.231	38	100
Virus (Google Trend, 2013)	204	66.26	8.949	46	100
Placebo Ebola Searches (Google Trends)	203	28.35	6.289	9	67
Placebo Ebola Tweets (Twitter)	204	.01	.014	0	.084
Distance to Nearest case (miles, in logs)	204	5.983	.836	2.311	7.431

Table A.2: Characterization People Concerned about Ebola - Demographics

		Worried about Ebola			Agreed on Ebola Measures		
	Mean	Coeff.	Std. Err.	N	Coeff.	Std. Err.	N
Age (in log)	4.068	.056	.024	9436	.103	.022	9457
Female	.445	.065	.01	9436	.035	.01	9457
Not white	.156	.062	.014	9436	.022	.013	9457
Child aged 18	.141	.035	.015	9416	.038	.013	9437
Married	.685	.027	.011	9436	.055	.01	9457
High-school	.213	.162	.012	9436	.191	.01	9457
Employed	.476	-.038	.01	9436	-.049	.01	9457
TV use	.749	.06	.012	9436	.09	.011	9457
Radio use	.437	-.019	.01	9436	.014	.01	9457
Newspaper readership	.614	-.113	.01	9436	-.118	.01	9457
Ebola Searches (Google)	.499	.104	.048	9436	.227	.043	9457
Nearest dist. to Ebola case	.539	-.046	.011	9436	-.049	.011	9457
Distance to Cleveland	.831	-.039	.008	9436	-.032	.008	9457
Distance to Dallas	.971	-.054	.013	9436	-.1	.012	9457
Distance to NYC	1.026	-.028	.007	9436	-.018	.006	9457

Notes: This table reports point estimates, robust standard errors, and the number of observations for 30 OLS individual-level regressions of one of the two measures of ebola concerns on a covariate (listed at the left). The ebola concern measures are an indicator taking value of 1 if the individual states to be worried about ebola, 0 otherwise; and an indicator taking value 1 if the individual agrees with at least one of the two control measures regarding ebola (i.e.,. banning flights from Africa and requiring a quarantine for people who have been in countries where there was a major Ebola outbreak). 54% of the individuals stated to be at least somewhat worried about ebola while 68% agreed with at least of the two restrictive ebola measures. Distance measures are expressed in thousands of kilometers and age in logs to ease the exposition of coefficients. Data comes from the 2014 CCES Panel Study.

Table A.3: Characterization People Concerned about Ebola - Political Preferences

		Worried about Ebola			Agreed Ebola Measures		
	Mean	Coeff.	Std. Err.	N	Coeff.	Std. Err.	N
Registered with Rep. party	.336	.212	.01	9436	.33	.008	9457
Registered with Dem. party	.375	-.195	.01	9436	-.325	.01	9457
Democrat	.364	-.214	.01	9436	-.34	.01	9457
Preference for Rep. House	.505	.322	.011	7489	.481	.009	7505
Preference for Rep. Senate	.505	.323	.015	3811	.483	.013	3820
Preference for Rep. Governor	.503	.313	.012	6232	.488	.01	6243
Any preference for Rep.	.807	.36	.016	5504	.538	.015	5512

Notes: This table reports point estimates, robust standard errors, and the number of observations for 14 OLS individual-level regressions of one of the two measures of ebola concerns on a covariate (listed at the left). The ebola concern measures are an indicator taking value of 1 if the individual states to be worried about ebola, 0 otherwise; and an indicator taking value 1 if the individual agrees with at least one of the two control measures regarding ebola (i.e.,. banning flights from Africa and requiring a quarantine for people who have been in countries where there was a major Ebola outbreak). 57% of the individuals stated to be at least somewhat worried about ebola while 68% agreed with at least one of the two restrictive ebola measures. Distance measures are expressed in thousands of kilometers and age in logs to ease the exposition of coefficients. Preference measures refer to vote intentions in 2014 election. Data comes from the 2014 CCES Panel Study.

Table A.4: Characterization People Concerned about Ebola -By Party Affiliation

Panel A: Registered Democrats

		Worried about Ebola			Agreed Ebola Measures		
	Mean	Coeff.	Std. Err.	N	Coeff.	Std. Err.	N
Nearest dist. to Ebola case	.543	-.068	.017	3535	-.086	.017	3546
Distance to Cleveland	.836	-.055	.012	3535	-.066	.012	3546
Distance to Dallas	1.013	-.065	.022	3535	-.098	.022	3546
Distance to NYC	1.015	-.043	.01	3535	-.044	.01	3546
Preference for Rep. House	.093	.33	.03	2864	.381	.026	2874
Preference for Rep. Senate	.076	.398	.044	1367	.494	.031	1371
Preference for Rep. Governor	.086	.331	.033	2450	.446	.026	2455

Panel B: Registered Republicans

		Worried about Ebola			Agreed Ebola Measures		
	Mean	Coeff.	Std. Err.	N	Coeff.	Std. Err.	N
Nearest dist. to Ebola case	.536	-.004	.019	3170	.005	.012	3175
Distance to Cleveland	.842	-.015	.013	3170	.004	.008	3175
Distance to Dallas	.923	0	.022	3170	-.004	.014	3175
Distance to NYC	1.049	-.012	.011	3170	.004	.007	3175
Preference for Rep. House	.929	.194	.037	2674	.273	.035	2679
Preference for Rep. Senate	.938	.172	.057	1327	.28	.053	1331
Preference for Rep. Governor	.931	.248	.042	2196	.305	.04	2200

Notes: This table reports point estimates, robust standard errors, and the number of observations for 28 OLS individual-level regressions of one of the two measures of ebola concerns on a covariate (listed at the left). The ebola concern measures are an indicator taking value of 1 if the individual states to be worried about ebola, 0 otherwise; and an indicator taking value 1 if the individual agrees with at least one of the two control measures regarding ebola (i.e.,. banning flights from Africa and requiring a quarantine for people who have been in countries where there was a major Ebola outbreak). 57% of the individuals stated to be at least somewhat worried about ebola while 68% agreed with at least one of the two restrictive ebola measures. Distance measures are expressed in thousands of kilometers and age in logs to ease the exposition of coefficients. Preference measures refer to vote intentions in 2014 election. Panel A focuses on registered democrats while Panel B focuses on republicans. Data comes from the 2014 CCES Panel Study.

Table A.5: Internet Activity and Distance to Reported Ebola Cases

	Panel A: Ebola Tweets				
	(1)	(2)	(3)	(4)	(5)
Post-Onset Ebola Case in Dallas * Distance (in logs) to Dallas	-0.102***			-0.066***	
	(0.023)			(0.017)	
Post-Onset Ebola Case in Cleveland * Distance (in logs) to Cleveland		-0.047***		-0.037***	
		(0.012)		(0.006)	
Post-Onset Ebola Case in NYC * Distance (in logs) to NYC			-0.017*	0.022***	
			(0.009)	(0.007)	
Post-Onset First-Case*Distance (in logs) to Nearest Case					-0.062***
					(0.011)
Mean Tweets per 10,000 inhab.	0.08	0.11	0.08	0.04	0.04
Adjusted-R^2	0.61	0.51	0.49	0.58	0.58
Observations	5916	5916	5916	18564	18564
Number of Clusters (DMA)	204	204	204	204	204

	Panel B: Ebola Searches				
	(1)	(2)	(3)	(4)	(5)
Post-Onset Ebola Case in Dallas * Distance (in logs) to Dallas	-6.934***			-6.377***	
	(1.253)			(1.358)	
Post-Onset Ebola Case in Cleveland * Distance (in logs) to Cleveland		-3.124***		-2.472***	
		(0.678)		(0.415)	
Post-Onset Ebola Case in NYC * Distance (in logs) to NYC			-2.604***	0.164	
			(0.746)	(0.796)	
Post-Onset First-Case*Distance (in logs) to Nearest Case					-2.971**
					(1.291)
Mean Google Searches	14.25	21.18	15.83	8.66	8.66
Adjusted-R^2	0.70	0.59	0.67	0.70	0.69
Observations	5945	5945	5945	18655	18655
Number of Clusters (DMA)	205	205	205	205	205
Day FE	Yes	Yes	Yes	Yes	Yes
DMA FE	Yes	Yes	Yes	Yes	Yes
DMA-specific Linear Trends	Yes	Yes	Yes	Yes	Yes

Notes: The table reports estimated coefficients for the interaction between the distance (in logs) to an Ebola Case and a dummy indicating the post-onset of that case. 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. All regressions include DMA fixed effect, day fixed effect, and DMA-specific linear trends. The dependent variable in Panel A is the number of ebola related tweets per 10,000 inhabitants in DMA (using 2010 census population). The dependent variable in Panel B accounts for the daily google search volume of the term 'ebola' in DMA. Each DMA google searches time series is scaled by a DMA-specific weight based on the relative geographic distribution of ebola searches between September 1st and November 30th. Heteroskedasticity robust standard error estimates clustered at the DMA-level are reported in parentheses.

Table A.6: 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	-33800.67	.1957206	.667	-50592.69	.44365	.669
Density	-393.6457	.1597416	.667	-1114.356	.0625827	.502
Median Age	.3453058	.0809848	.667	.2037484	.106698	.502
Share with college degree	-.0044776	.5435809	.896	-.020035	.1046121	.502
Share White	-.0019501	.8697342	.955	.0150195	.343929	.602
Share Black	-.0072363	.326338	.747	-.0069161	.1701815	.502
Share Hispanic	.000477	.9543527	.955	-.0073043	.4649828	.669
Share Foreign	-.0028855	.6951545	.954	-.0181007	.1789297	.502
Inc per capita	-662.9529	.2316825	.667	-1775.446	.0631582	.502
Share Owners	-.0026506	.4728829	.828	-.0076579	.2174723	.554
Share Married	.0072376	.0481708	.667	.0049522	.1605208	.502
Ebola Google pre-treatment	.4651346	.3799791	.76	-.7012599	.2764136	.596
Ebola tweets pc pre-treatment	-.0033845	.002833	.08	-.0034639	3.17e-07	.001
Anxiety(Google Trends 2013)	-1.357864	.2616906	.667	-.9579886	.3293444	.602
Virus (Google Trends 2013)	-.3987127	.6290445	.928	-.2661722	.6690644	.75
Cable TV Penetration 2010	-2.425295	.1653199	.667	-4.142688	.1390849	.502
Dem. VS. House 2012	.4304276	.7859803	.955	-1.859988	.4776745	.669
Dem. VS. House 2010	.4956484	.7175273	.954	-.9859933	.6634526	.75
Dem. VS. House 2006	.214254	.8715251	.955	-1.566396	.4362493	.669
Δ Dem. VS. House 2010–2006	.2813944	.6153322	.928	.5804024	.1504509	.502
Dem. VS. Pres. 2012	.4991127	.7491025	.954	-1.178181	.6381507	.75
Dem. VS. Pres. 2008	-.11815	.9251394	.955	-1.247805	.5428623	.691
Dem. VS. Sen. 2012	.2424339	.8944495	.955	-.8412964	.7658349	.795
Dem. VS. Sen. 2006	2.181718	.1857687	.667	-.1065143	.9616309	.962
Δ Dem. VS. Sen. 2006–2000	.8219855	.3465185	.747	-.2349463	.7510035	.795
Dem. VS. Gov. 2010	-1.328832	.2611646	.667	-2.281008	.3301771	.602
Dem. VS. Gov. 2006	-1.746999	.4403731	.823	-1.980682	.5393807	.691
Δ Dem. VS. Gov. 2006–2002	-3.207152	.1023821	.667	-3.593376	.2480314	.579

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 29 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.7: 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	-6.546***	-9.381***	-8.824***	-8.687***	-7.389***	-1.451***	-1.418***
100km	(1.534)	(1.203)	(0.922)	(0.914)	(1.102)	(0.187)	(0.184)
200 km	(2.157)	(1.828)	(1.377)	(1.365)	(1.652)	(0.276)	(0.263)
500 km	(2.375)	(2.174)	(1.641)	(1.627)	(1.956)	(0.340)	(0.287)
1000 km	(2.338)	(2.249)	(1.773)	(1.752)	(1.987)	(0.341)	(0.312)
Mean Value Dep. Var.	50.34	50.34	50.34	50.34	50.34	3.68	3.68
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	3069	3068	3059	3059	3059	3061	3061

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.8: Ebola Searches and Distances to Large Cities (First-Stage)

	Ebola Searches				
	(1)	(2)	(3)	(4)	(5)
Distance (in logs) to Nearest Case	-8.687***	-8.663***	-8.650***	-8.783***	-9.023***
	(1.475)	(1.454)	(1.321)	(1.494)	(1.440)
Distance (in logs) to Nearest Non-Ebola Large City		-0.184	-1.284*	0.347	1.580**
		(0.714)	(0.765)	(0.622)	(0.673)
Definition of Nearest Large City		Top 100	Top 50	More than 500k	More than 1 million
Std Dev Vote Share	12.80	12.80	12.80	12.80	12.80
Std Dev Distance Nearest Case	1.34	1.34	1.34	1.34	1.34
Effect of Std Dev Δ in Distance	-11.65	-11.61	-11.60	-11.77	-12.10
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	0.70	0.70	0.71	0.70	0.71
Observations	3059	3059	3059	3059	3059
Number of Clusters (DMA)	200	200	200	200	200

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

	Ebola Tweets				
	(1)	(2)	(3)	(4)	(5)
Distance (in logs) to Nearest Case	-1.451***	-1.448***	-1.462***	-1.410***	-1.437***
	(0.285)	(0.284)	(0.245)	(0.290)	(0.300)
Distance (in logs) to Nearest Non-Ebola Large City		-0.029	-0.370***	-0.162	-0.073
		(0.131)	(0.134)	(0.132)	(0.148)
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	2.35	2.35	2.35	2.35	2.35
Std Dev Distance Nearest Case	1.34	1.34	1.34	1.34	1.34
Effect of Std Dev Δ in Distance	-1.94	-1.94	-1.96	-1.89	-1.93
Adjusted-R^2	0.76	0.76	0.78	0.76	0.76
Observations	3061	3061	3061	3061	3061
Number of Clusters (DMA)	201	201	201	201	201

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.10: Democratic Vote Share in Other Races (IV)

	Democratic Vote Share			
	Senatorial		Gubernatorial	
	(1)	(2)	(3)	(4)
Ebola Searches	-0.206**		-0.304***	
	(0.085)		(0.114)	
Ebola Tweets		-1.372**		-1.892***
		(0.592)		(0.708)
Std Dev Vote Share	17.68	17.68	15.68	15.67
Std Dev Ebola (Searches or Tweets)	14.34	2.60	13.94	2.54
Effect of Std Dev Δ in Searches/Tweets	-2.96	-3.57	-4.24	-4.81
County-Level Controls	Yes	Yes	Yes	Yes
DMA-Level Controls	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Previous Election Controls	Yes	Yes	Yes	Yes
Effective F Statistic	61.23	32.03	90.00	55.60
Anderson-Rubin CI	[-0.38, -0.05]	[-2.80, -0.36]	[-0.58, -0.12]	[-3.65, -0.80]
tF adjusted 95% CI	[-0.38, -0.03]	[-2.74, -0.00]	[-0.53, -0.08]	[-3.38, -0.40]
Adjusted-R^2	0.76	0.75	0.79	0.78
Observations	2273	2275	2134	2136
Number of Clusters (DMA)	152	153	170	171

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. Anderson-Rubin CI reports the 95% confidence set which is robust to weak identification and efficient in the just-identified case (Andrews et al., 2019). Effective F Statistic reports Olea and Pflueger (2013) 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.

Table A.11: Ebola and Intentions to Vote for Democrats

	Intention to Vote for Democrats in 2014 House Reps. Election					
	(1)	(2)	(3)	(4)	(5)	(6)
Distance (in logs) to Nearest Case	0.013**	0.012**				
	(0.005)	(0.005)				
Ebola Searches			-0.002**	-0.002**		
			(0.001)	(0.001)		
Ebola Tweets					-0.008**	-0.008**
					(0.004)	(0.004)
County-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
DMA-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual Controls	No	Yes	No	Yes	No	Yes
Effective F Statistic			28.66	28.71	24.12	24.17
Adjusted-R^2	0.06	0.09	0.06	0.09	0.06	0.09
Observations	53304	53304	53304	53304	53314	53314
Number of Clusters (DMA)	202	202	202	202	203	203

Notes: Sample includes all CCES's respondents in October 2014. 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 use sample weights. 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. Anderson-Rubin CI reports the 95% confidence set which is robust to weak identification and efficient in the just-identified case (Andrews et al., 2019). Effective F Statistic reports Olea and Pflueger (2013) 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.

Table A.12: Ebola Concerns, Democratic Vote Share and Extended Set of Previous Election Controls

	Democratic Vote Share in 2014 House Reps. Election					
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Controlling for All House Elections in 2012-2006					
Distance (in logs) to Nearest Case	2.650***	2.132***				
	(0.424)	(0.621)				
Ebola Searches			-0.311***	-0.297***		
			(0.086)	(0.104)		
Ebola Tweets					-1.779***	-1.279***
					(0.505)	(0.419)
Adjusted-R^2	0.79	0.72	0.77	0.69	0.77	0.70
Observations	2998	2998	2998	2998	3000	3000
Number of Clusters (DMA)	200	200	200	200	201	201
	Panel B: Controlling for 2012 and 2008 Presidential Elections					
Distance (in logs) to Nearest Case	2.566***	2.658***				
	(0.560)	(0.633)				
Ebola Searches			-0.301***	-0.364***		
			(0.093)	(0.134)		
Ebola Tweets					-1.478***	-1.467***
					(0.508)	(0.478)
Adjusted-R^2	0.73	0.67	0.71	0.63	0.72	0.65
Observations	3053	3053	3053	3053	3055	3055
Number of Clusters (DMA)	200	200	200	200	201	201
	Panel C: Controlling for Elections in Panel A and B					
Distance (in logs) to Nearest Case	2.537***	2.121***				
	(0.481)	(0.590)				
Ebola Searches			-0.299***	-0.291***		
			(0.090)	(0.102)		
Ebola Tweets					-1.624***	-1.214***
					(0.506)	(0.388)
Adjusted-R^2	0.80	0.74	0.77	0.71	0.78	0.72
Observations	2998	2998	2998	2998	3000	3000
Number of Clusters (DMA)	200	200	200	200	201	201
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

Notes: The different panels show that main results are unaffected by the inclusion of democratic vote share in previous house and presidential elections. 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 in odd columns 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: Democratic Vote Share and Distances to Large Cities

	Democratic Vote Share in 2014 House Reps. Election				
	(1)	(2)	(3)	(4)	(5)
Distance (in logs) to Nearest Case	2.928***	2.913***	2.920***	2.909***	2.652***
	(0.439)	(0.453)	(0.460)	(0.481)	(0.387)
Distance (in logs) to Nearest Non-Ebola Large City		0.116	0.312	0.067	1.294***
		(0.429)	(0.437)	(0.428)	(0.458)
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	1.34	1.34	1.34	1.34	1.34
Effect of Std Dev Δ in Distance	3.92	3.90	3.90	3.89	3.55
Adjusted-R^2	0.74	0.74	0.74	0.74	0.75
Observations	3053	3053	3053	3053	3053
Number of Clusters (DMA)	200	200	200	200	200

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.14: Ebola Searches/Tweets and Democratic Vote Share (IV - Standard Errors Adjustment for Spatial Autocorrelation)

	Democratic Vote Share in 2014 House Reps. Election					
	(1)	(2)	(3)	(4)	(5)	(6)
Distance (in logs) to Nearest Case	2.928***	2.569***				
100km	(0.569)	(0.667)				
200km	(0.551)	(0.739)				
500km	(0.385)	(0.852)				
1000km	(.)	(0.779)				
Ebola Searches			-0.339***	-0.350***		
100km			(0.080)	(0.098)		
200km			(0.092)	(0.109)		
500km			(0.085)	(0.075)		
1000km			(0.063)	(.)		
Ebola Tweets					-2.014***	-1.629***
100km					(0.504)	(0.502)
200km					(0.603)	(0.553)
500km					(0.632)	(0.472)
1000km					(0.459)	(0.143)
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	3053	3053	3053	3053	3055	3055

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.15: Ebola Concerns and Democratic Vote Share. Excluding DMAs for Dallas, NYC, and Cleveland

	Democratic Vote Share in 2014 House Reps. Election					
	(1)	(2)	(3)	(4)	(5)	(6)
Distance (in logs) to Nearest Case	3.199***	2.253**				
	(0.990)	(1.113)				
Ebola Searches			-0.721**	-0.485*		
			(0.310)	(0.278)		
Ebola Tweets					-2.733***	-1.680
					(0.927)	(1.131)
Std Dev Vote Share	19.51	18.49	19.51	18.49	19.51	18.49
Std Dev Distance Nearest Case	0.70	0.64	8.49	9.51	1.57	1.49
Effect of Std Dev Δ in Distance	2.24	1.43	-6.12	-4.61	-4.28	-2.50
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	-	-	13.07	11.59	37.73	28.41
Adjusted-R^2	0.69	0.62	0.63	0.59	0.66	0.60
Observations	2977	2977	2977	2977	2979	2979
Number of Clusters (DMA)	197	197	197	197	198	198

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 Olea and Pflueger (2013) 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.

Table A.16: Ebola Concerns and Democratic Vote Share.Excluding Texas, Ohio, and New York

	Democratic Vote Share in 2014 House Reps. Election					
	(1)	(2)	(3)	(4)	(5)	(6)
Distance (in logs) to Nearest Case	3.401***	2.246*				
	(0.981)	(1.258)				
Ebola Searches			-0.729***	-0.547		
			(0.282)	(0.356)		
Ebola Tweets					-6.711*	-2.679
					(3.460)	(2.184)
Std Dev Vote Share	19.28	18.01	19.28	18.01	19.28	18.01
Std Dev Distance Nearest Case	1.03	0.64	8.40	8.89	1.54	1.37
Effect of Std Dev Δ in Distance	3.52	1.45	-6.12	-4.86	-10.36	-3.67
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	-	-	19.44	7.15	8.56	12.9
Adjusted-R^2	0.71	0.61	0.64	0.56	0.56	0.56
Observations	2651	2651	2651	2651	2653	2653
Number of Clusters (DMA)	177	177	177	177	178	178

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 Olea and Pflueger (2013) 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.

Table A.17: Ebola Concerns and Democratic Vote Share using Linear Instrument

	Democratic Vote Share in 2014 House Reps. Election					
	(1)	(2)	(3)	(4)	(5)	(6)
Distance to Nearest Case (in '000 miles')	9.181***	5.201**				
	(2.069)	(2.482)				
Ebola Searches			-0.475***	-0.464*		
			(0.136)	(0.241)		
Ebola Tweets					-2.687***	-1.860*
					(0.758)	(1.098)
Std Dev Vote Share	20.61	18.69	20.61	18.69	20.61	18.69
Std Dev Ebola (Searches or Tweets)	0.39	0.34	12.69	10.73	2.33	1.82
Effect of Std Dev Δ in Searches/Tweets	3.58	1.77	-6.03	-4.98	-6.27	-3.39
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	-	-	8.62	7.6	8.4	13.1
Adjusted-R^2	0.74	0.63	0.71	0.60	0.71	0.61
Observations	3053	3053	3053	3053	3055	3055
Number of Clusters (DMA)	200	200	200	200	201	201

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 Olea and Pflueger (2013) 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.

Table A.18: 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	-0.022			0.011		
	(0.022)			(0.012)		
Post-Onset Cleveland x Distance (in logs) to Cleveland		-0.017		-0.003		
		(0.019)		(0.008)		
Post-Onset NYC x Distance (in logs) to NYC			0.013	-0.012		
			(0.010)	(0.007)		
Post-Onset First-Case x Distance (in logs) to Nearest Case					-0.013	0.004
					(0.010)	(0.004)
Mean Value Dep. Var.	0.56	0.58	0.58	0.56	0.56	0.56
Survey	Gallup	Gallup	Gallup	Gallup	Gallup	CCES
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
DMA FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted-R^2	0.16	0.17	0.18	0.17	0.17	0.13
Observations	7999	7936	7555	30947	30947	72209
Number of Clusters (DMA)	178	179	178	179	179	204

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. *** 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)

Table A.19: Attitudes in CCES and Proximity to Ebola Cases

	Anti-Immigration	Pro-Gun	Religious	Anti-gay Marriage	Conservative
	(1)	(2)	(3)	(4)	(5)
Post-Onset Dallas x Distance (in logs) to Dallas	-0.028**	-0.013	-0.018	-0.004	-0.009*
	(0.013)	(0.014)	(0.014)	(0.005)	(0.005)
Post-Onset Cleveland x Distance (in logs) to Cleveland	-0.042**	-0.008	0.021	-0.007	-0.008
	(0.018)	(0.022)	(0.018)	(0.005)	(0.006)
Post-Onset NYC x Distance (in logs) to NYC	-0.001	0.017	0.034*	0.009	0.008
	(0.030)	(0.029)	(0.017)	(0.007)	(0.009)
Mean Value Dep. Var.	0.06	0.12	0.07	0.44	0.37
DMA 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	0.13	0.11	0.11	0.10	0.08
Observations	72209	72209	72209	72209	72145
Number of Clusters (DMA)	204	204	204	204	204

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 4 (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 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.