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The Virus of Fear: The Political Impact of Ebola in the United States†

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We study how public anxiety over the threat of a disease outbreak can affect voter behavior by looking at the Ebola scare that hit the United States in 2014. Exploiting timing and locations of the four cases diagnosed in the country, we show that heightened concern about Ebola led to a lower Democratic vote share and lower turnout, despite no evidence of a general anti-incumbent effect (including 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, mediated by issues plausibly associated with the specific triggering factor. (*JEL* D72, D91, I12, J15)

Emotions are widely recognized, by both 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, and 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

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

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 United States 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 United States 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]

The Ebola episode is particularly interesting because it took place during campaign season in the weeks before the 2014 midterm elections, in which all US House seats were being chosen, along with a number of US 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 in lowering voter turnout. Moreover, we show that this did not happen because of a general anti-incumbent impact, whereby the perceived crisis may

[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/Democratic Republic of the Congo, Gabon, Uganda, and the 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 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 toward Republicans in places with more intense concerns about the disease (Beall, Hofer, and Schaller 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 toward immigrants (Adida, Dionne, and Platas 2018).

have, for instance, affected the perception of the 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 toward 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 US soil. First, a Liberian national visiting the United States was diagnosed in Dallas, Texas (September 30); then it was two nurses who had treated that patient, one of whom had then traveled to Akron, Ohio (October 14); and finally, an American doctor returning from Guinea was diagnosed in New York, New York (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 1 standard deviation increase in Ebola concerns, as expressed in tweets or searches, induced a lower Democratic vote share, by just over 4 percentage points in the House and by 3 and 4 percentage points in Senate and gubernatorial elections, respectively. This corresponds to just over one-seventh of the average margin of victory in House elections. Alternatively, 40 House races would have been swung by such a change—15 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 1 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 percent) since 1942, and the effect corresponds to about one-third of the drop relative to the preceding midterms in 2010 (40.8 percent) (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 suggest 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

[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.

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 toward 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 United States, 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 and is instead 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 toward 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, Redoano, and Proto 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

[8] This is consistent with the experimental findings in Adida, Dionne, and Platas (2018).

[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).

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 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, Pizarro, and Bloom 2008; Inbar et al. 2012b, a; Shook, Ford, and Boggs 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, Hofer, and Schaller 2016; Adida, Dionne, and Platas 2018; Maffioli 2021; Kostova et al. 2019; González-Torres and Esposito 2017; Flückiger, Ludwig, and Sina Önder 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 I outlines the context and background of the Ebola crisis and the 2014 midterm elections, and Sections II and III present the data and empirical strategy, respectively. Section IV discusses the results on voting, presidential approval ratings, and voter attitudes. Section V concludes.

I. Background

A. *Ebola Outbreak*

The 2014–2015 Ebola outbreak, the largest ever recorded for this virus, can be traced back to December 2013 when, in a village in rural Guinea, an 18-month-old 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 that 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 WHO declared the outbreak an international public health emergency (WHO 2014). The vast majority of the Ebola-related deaths recorded worldwide were in Guinea (2,543), Liberia (4,809), and Sierra Leone (3,956 deaths). Yet, over the following months, the virus spread to various other countries—including Italy, Mali, Nigeria, Senegal, Spain, and the United Kingdom—where, however, the death toll was much lower (i.e., between 3 and 20) (CDCP 2019).

The first case of Ebola in the United States 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

[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.

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 United States 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 United States 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 US 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 percent of Americans were worried or very worried that they or their family members might be exposed to the virus (SteelFisher, Blendon, and Lasala-Blanco 2015), and that a staggering 16 percent perceived the probability of contracting the virus within 6 months to be above 10 percent (Carman et al. 2015). Furthermore, when asked to identify the most urgent health problem affecting the nation, respondents would rank Ebola above other diseases such as obesity, cancer, and diabetes, which are three of the main causes of death in the United States (SteelFisher, Blendon, and Lasala-Blanco 2015). Fear of contagion was fueled by widespread misinformation about the way the disease spreads. Indeed, according to another poll, 85 percent of Americans believed that Ebola could be transmitted through sneezing or coughing, and 48 percent believed that asymptomatic carriers could be contagious (SteelFisher, Blendon, and Lasala-Blanco 2015), both claims with no scientific base.

B. *The 2014 US 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 3 special elections), and

[13] Seven additional people, mostly medical workers, became ill while in West Africa but were transported and cared for in the United States. 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] http://pewrsr.ch/1t4aEFI.

the governors of 36 states and 3 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 percent. This was about 5 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 2 seats, and 2 out of 3 in the territories.

The Ebola outbreak, and the way that 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 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).

II. Data

A. *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 (Google, n.d.). We collect data by media designated market area (DMA) and by week for the five-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 WHO declared Ebola an international health crisis but prior to the first case in the United States—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

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

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

[18] To create such a 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.

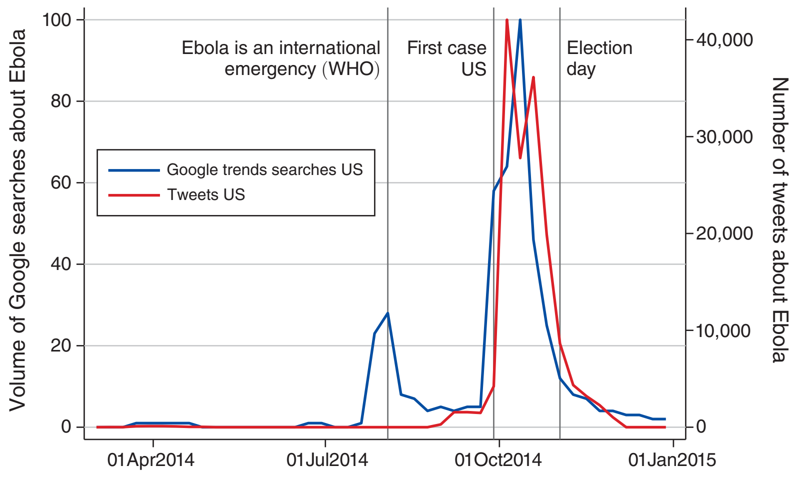

Figure 1. Google Searches and Ebola-Related Tweets

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 application programming interface. We focus on tweets that are geolocated, 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 the CDC announced the first Ebola case in the United States (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 a global peak right after the first case. Furthermore, Ebola-related online activity remained relatively high in the weeks before the elections, losing intensity immediately afterward.

B. *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 4, 2014—i.e., House, Senate, and governors—available from 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.

C. *Survey Data*

To further test the relationship between Ebola concerns and voters' attitudes, we use survey data from the 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 post-Ebola periods 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 of including 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).

D. *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 include 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 US Census Bureau (2010). DMA-level controls instead include 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] Online Appendix Table A.1 reports summary statistics for the complete set of variables exploited in the main analysis.

III. 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:

$$(1) \qquad Vote_{c,d}^{2014} = \alpha + \beta Ebola_d + \gamma Vote_{c,d}^{2010-06} + \lambda' \mathbf{X}_c + \theta' \mathbf{D}_d + \Lambda_r + \epsilon_{d,c},$$

where $Vote_{c,d}^{2014}$ is the Democratic vote share in county c located in DMA d. $Ebola_d$ is the proxy for Ebola concerns (Google searches or tweets per capita) in DMA d during the five weeks immediately before the 2014 election—that is, starting from the report of the first case diagnosed in the United States. The vector $Vote_{c,d}^{2010-06}$ includes the Democratic vote share in 2010 House (midterm) election and its change between the 2010 and 2006 elections. The vectors $\mathbf{X}_c$ and $\mathbf{D}_d$ 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 for 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 United States, as described in Section I: (i) Dallas, Texas; (ii) the Cleveland-Akron area in Ohio; and (iii) New York City, New York. 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 United States (CDC 2014).

It seems natural that people living closer to those key locations would display a heightened concern with the potential threat. Figure 2, depicting the geographic variation in Ebola searches and the locations 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 (online Appendix Table A.2).

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

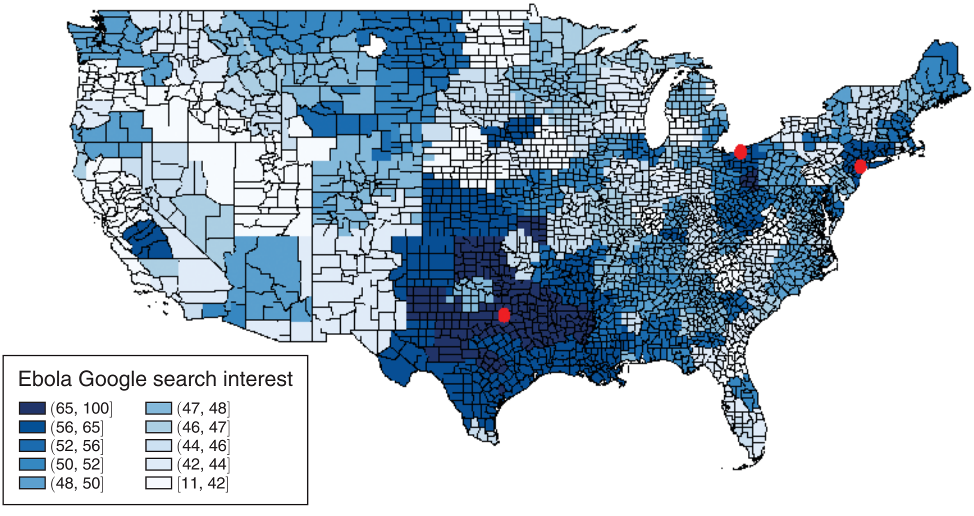

Figure 2. Geographic Distribution of Google Searches

Note: Red dots denote the three locations of Ebola cases (i.e., Dallas, Cleveland, and New York City).

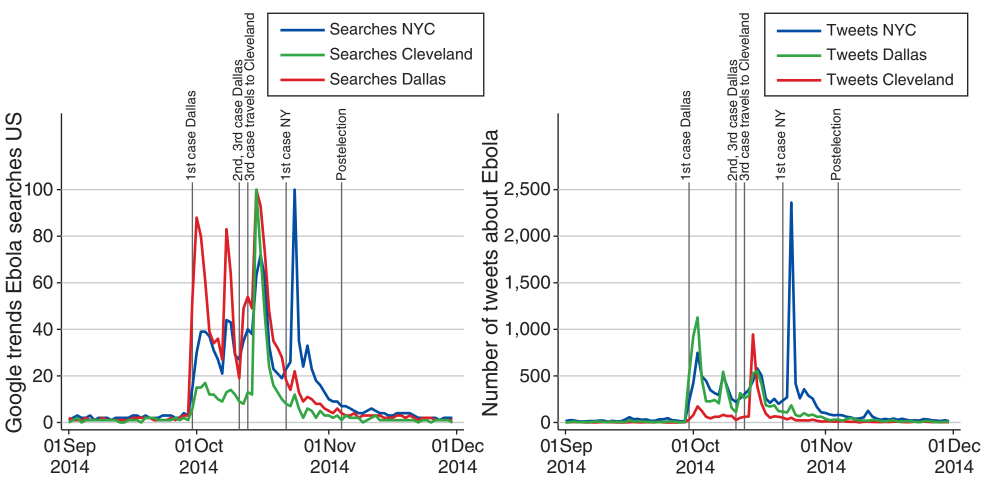

Figure 3. Timing of Ebola-Related Google Searches and Tweets

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 and 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:

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

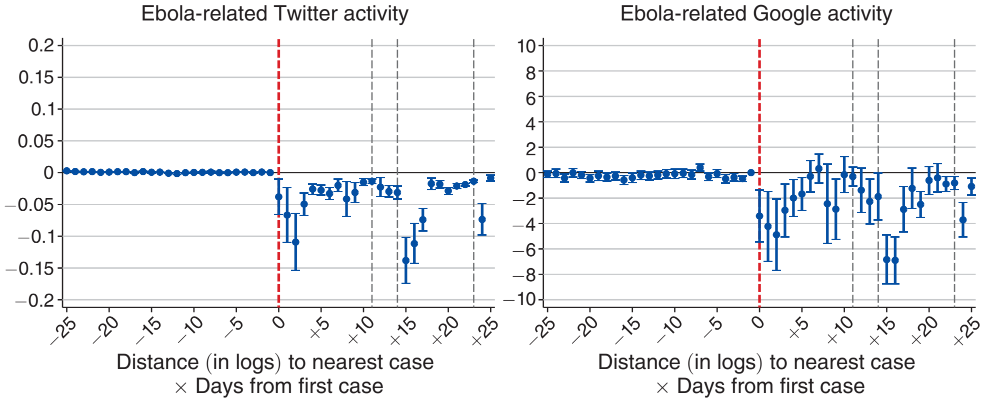

Figure 4. Event Study for Ebola-Related Google Searches and Tweets

Notes: These figures show point estimates and 95 percent confidence intervals of coefficients for relative time indicators (days) with respect to the first reported Ebola case (i.e., September 30, 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 search's time series is scaled by a DMA-specific weight based on the relative geographic distribution of Ebola searches between September 1 and November 30. The specifications include both DMA and day fixed effects. Standard errors are clustered at both the 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.

where $Ebola_{d,t}$ 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 the DMA and the 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] Online Appendix 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 seven days before and after the diagnosis of each case (i.e., Dallas, Cleveland, and New York City, 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 online Appendix, we alternatively estimate the following equation:

$$Ebola_{d,t(c)} = \gamma PostOnset_{t(c)} \times \ln\left(DistEbola_c\right)_d + \lambda_d + \theta_t + \Gamma_t \times \lambda_d + \epsilon_{d,t}, \tag{3}$$

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 (2.205)	−9.379 (1.953)	−8.824 (1.492)	−8.687 (1.475)	−7.389 (1.749)	−1.451 (0.285)	−1.418 (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	3,069	3,069	3,060	3,060	3,060	3,062	3,062
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 and each of the three Ebola locations. Heteroskedasticity-robust standard error estimates clustered at the DMA level are reported in parentheses. 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 United States, 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 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:

$$(4) \qquad Ebola_{c,d} = \pi_0 + \pi_1 \ln\big(DistanceNearestCase\big)_d + \pi_2 Vote_{c,d}^{2010-06} + \pi_3' \mathbf{X}_c + \pi_4' \mathbf{D}_d + \Lambda_r + \epsilon_{d,c}.$$

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 establishes the basic result using the search measure. Adding

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 $\ln(DistEbola_c)_d$ 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. Online Appendix 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.

[22] Online Appendix 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 online Appendix Figure A.5, showing the spatial distribution of the variable.

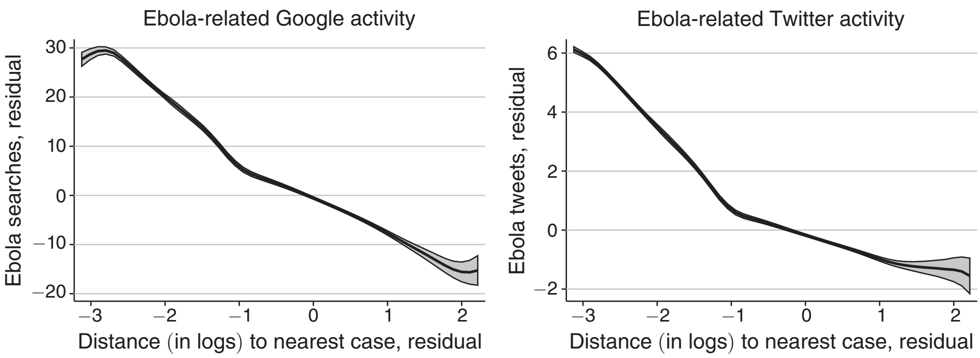

Figure 5. First-Stage Relationship (Nonparametric Estimation)

Notes: These figures nonparametrically 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 nonparametric 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.

the full set of county-level controls and regional dummies (column 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 of or very far from the key locations.[26]

We also want to ensure that we are picking up something specific to the location of Ebola cases—and not, say, about proximity to large urban centers. On that, it is reassuring that the distance to the nearest Ebola case is largely uncorrelated with observable variables, as can be seen in Table A.6 in the online Appendix. To further assuage concerns, we also conduct a placebo exercise: we randomly select 3 out of the top 100 cities in the United States by population (excluding the 3 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 1,000 random

[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's (2013) 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 percent confidence sets, which are robust to weak identification and are efficient in the just-identified case (Andrews, Stock, and Sun 2019).

[25] Online Appendix 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 100 km to 1,000 km.

[26] Online Appendix Figure A.6 depicts the nonparametric first-stage relationships for the unweighted cases.

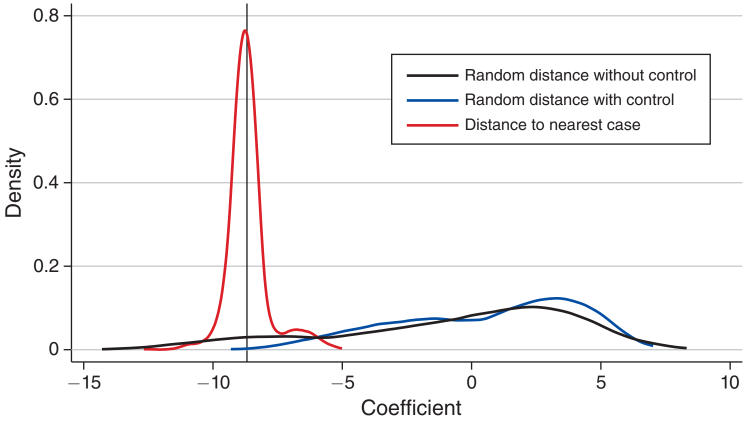

FIGURE 6. PLACEBO FIRST STAGE

Notes: The figure shows kernel density estimations for three pdfs of (i) 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) (1,000 random draws)—pdf labeled as random distance without control, (ii) coefficient of random minimum distance as before but controlling for the minimum distance to nearest Ebola case—pdf labeled as random distance with control, and (iii) 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).

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, online Appendix 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 the 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.

IV. The Political Impact of Ebola

A. *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 US 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

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

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 (0.211)	−0.333 (0.082)	−0.304 (0.066)	−0.163 (0.044)		
Ebola Tweets						−1.176 (0.408)	−0.767 (0.270)
SD Vote Share	20.61	20.61	20.61	20.61	20.61	20.61	20.61
SD Ebola (Searches or Tweets)	7.20	12.69	12.69	12.69	12.69	2.33	2.33
Effect of SD 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	0.02	0.50	0.55	0.74	0.54	0.73
Observations	3,061	3,063	3,063	3,054	3,054	3,056	3,056
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 five 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. 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 United States, and Google searches for the terms "anxiety" and "virus," both in 2013.

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 United States 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 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 1 standard deviation increase in Ebola searches is associated with a decrease in vote share of one-fifth of a standard deviation (about 4 percentage points).

Democrats thus did poorly in areas that display greater Ebola concerns. This, however, could be partly explained by selection: it could be that areas where Democrats had been doing poorly would also be disproportionately concerned about Ebola. Column 5 suggests that this is indeed the case: the coefficient of interest drops substantially once we control for the Democratic vote share in 2010 (the previous

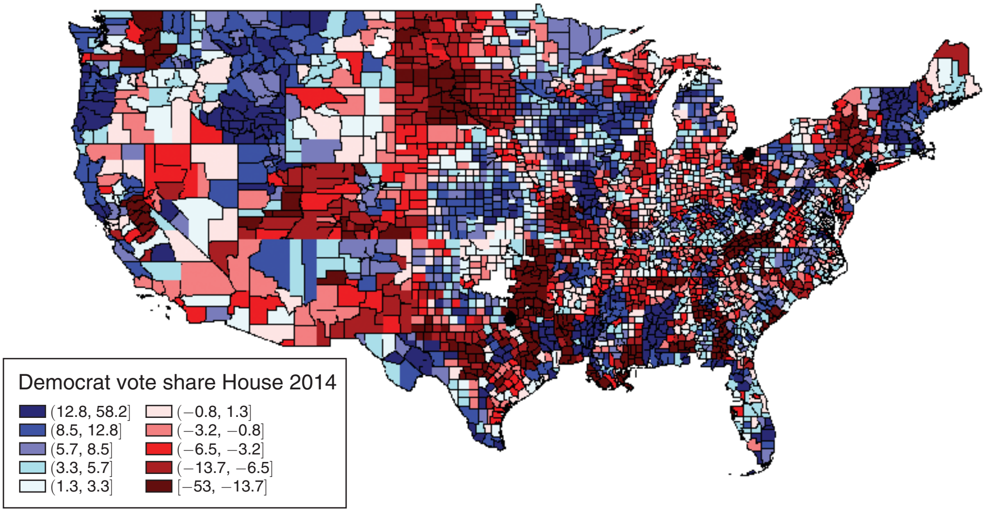

Figure 7. Democratic Vote Shares in House Elections

Notes: 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 locations of Dallas, Cleveland, and New York.

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 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 show that selection on preexisting 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.

B. *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 US 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.

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 nonparametric 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

[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.

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 (0.439)	2.569 (0.624)				
Ebola Searches			−0.339 (0.091)	−0.350 (0.111)		
Ebola Tweets					−2.014 (0.593)	−1.629 (0.506)
SD Vote Share	20.61	18.69	20.61	18.69	20.61	18.68
SD Ebola (Searches or Tweets)	1.34	0.82	12.69	10.73	2.33	1.82
Effect of SD 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	22.95
Anderson-Rubin CI	—	—	[−0.60, −0.21]	[−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	3,054	3,054	3,054	3,054	3,056	3,056
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 five 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 and 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. Anderson-Rubin CI reports the 95 percent confidence set, which is robust to weak identification and efficient in the just-identified case (Andrews, Stock, and Sun 2019). Effective *F*-statistic reports Olea and Pflueger (2013) robust weak instrument *F*-statistics. tF adjusted 95 percent CI reports Lee et al.'s (2022) 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 United States, 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.

of our instrument, *DistanceNearestCase*. This nonparametric 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]

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

[29] In online Appendix 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.

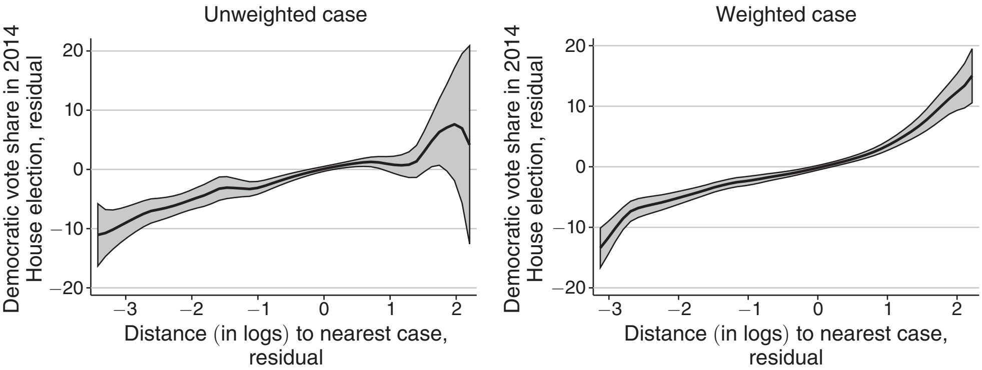

Figure 8. Reduced Form (Nonparametric Estimation)

Notes: These figures nonparametrically plot 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 nonparametric 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.

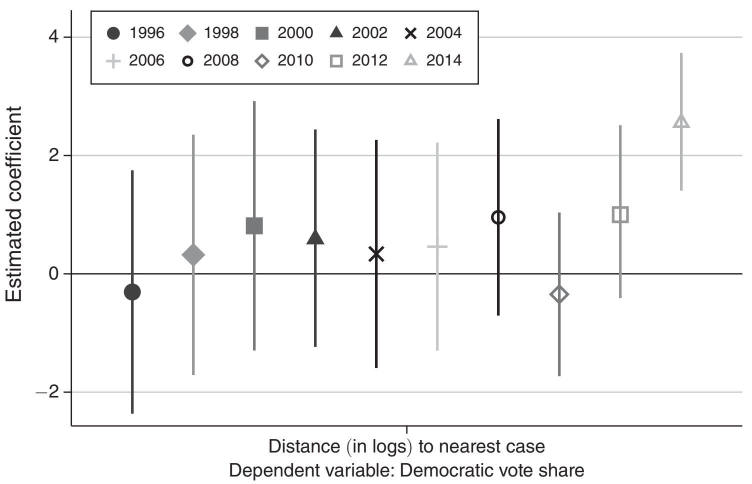

Figure 9. Distance to Nearest Case and Democratic Vote Shares in Previous Elections

Notes: This figure plots point estimates and 95 percent 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 taking 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.

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 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 US House elections.[30] Columns 3–6 show the population-weighted and population-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. Reassuringly, 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 1 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 9 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 (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 (online Appendix 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" 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 1 standard deviation increase in Ebola searches would have led to a drop of about

[30] Table A.10 in the online 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 online Appendix Table A.11.

[32] The magnitude of the standardized effects is also quite substantial for Senate and gubernatorial elections, as per Table A.10 in the online Appendix: a 1 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 6 percentage points. That the magnitude of the effect for House voting intentions is slightly smaller (about 2 p.p., as per online Appendix 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.

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)
SD Vote Share	10.50	10.50	7.84	7.84
SD Ebola (Searches or Tweets)	12.82	2.35	12.69	2.33
Effect of SD 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	25.85	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	3,092	3,094	3,053	3,055
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 five 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 and 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. Anderson-Rubin CI reports the 95 percent confidence set, which is robust to weak identification and efficient in the just-identified case (Andrews, Stock, and Sun 2019). Effective F-statistic reports Olea and Pflueger (2013) robust weak instrument F-statistics. tF adjusted 95 percent CI reports Lee et al.'s (2022) 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 United States, and Google searches for the terms "anxiety" and "virus," both in 2013.

1.6 percentage points. Interestingly, the 2014 midterm elections registered the lowest turnout (36.7 percent) since 1942, and the 1.6 percentage points correspond to about 40 percent of the drop relative to the preceding midterms in 2010 (40.8 percent) (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

[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 toward 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 online 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 in 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.

that is very much stable between elections. The magnitude of this decline is such that a 1 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 percent, 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: online Appendix 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.

C. *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 online Appendix, for the reduced-form and 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 online Appendix 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 online Appendix 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 3 cities out of the largest 100 cities (excluding Ebola locations), repeating the procedure 1,000 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 online 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 (online Appendix Table A.14), following Conley (1999). They also remain in place if we exclude the Dallas, Cleveland, and New York City DMAs or even the whole states of Texas, Ohio, and New York (online Appendix Tables A.15 and A.16), showing that they are not driven by unrelated factors in these regions. Additionally, online Appendix Figure A.11

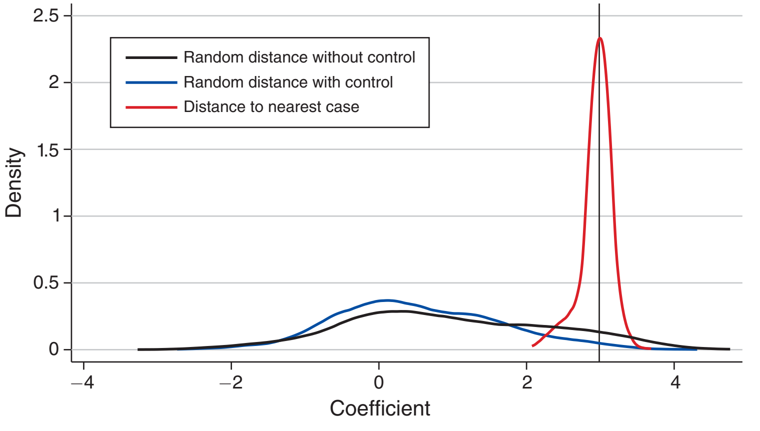

Figure 10. Placebo Reduced-Form 2014 Vote Share and Distance

Notes: The figure shows kernel density estimations for three pdf of (i) 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) (1,000 random draws)—pdf labeled as random distance without control, (ii) coefficient of random minimum distance as before but controlling for minimum distance to nearest Ebola case—pdf labeled as random distance with control, and (iii) 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).

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 (online Appendix Table A.17).

D. *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, at both the national and local levels, either rationally or through misattribution. After all, it is possible that voters could be making inferences about incumbent performance based on their perception of the government's response to the Ebola crisis, not to mention that there is substantial evidence that voters may punish or reward incumbents for outcomes over which they have little influence (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 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.

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		
SD Vote Share	15.64	15.91	16.21	14.19	13.04	15.12	15.73	13.28	10.80
SD Ebola Searches	13.40	9.58	14.34	9.18	13.94	9.32	14.24	16.72	15.39
Effect of SD 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	2,665	501	2,273	1,027	2,134	497	2,302	1,246	1,637
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 five 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 and each of the three Ebola locations. Heteroskedasticity-robust standard error estimates clustered at the DMA level are reported in parentheses. Anderson-Rubin CI reports the 95 percent confidence set, which is robust to weak identification and efficient in the just-identified case (Andrews, Stock, and Sun 2019). Effective F-statistic reports Olea and Pflueger (2013) robust weak instrument F-statistics. tF adjusted 95 percent CI reports Lee et al.'s (2022) 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 United States, and Google searches for the terms "anxiety" and "virus," both in 2013.

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

$$(5)\qquad Disapprove_{i,d,t} = \sum_{\substack{\tau=-25\\ \tau\neq-1}}^{25} \gamma_\tau \ln\big(DistanceNearestCase\big)_d \times \mathbf{1}\big\{\Upsilon_t = \tau\big\} + \delta'\mathbf{X}_i + \lambda_d + \theta_t + \epsilon_{d,t},$$

where $Disapprove_{i,d,t}$ 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 $\ln\big(DistanceNearestCase\big)_d$ is the (log) distance (in miles) of DMA d from the nearest

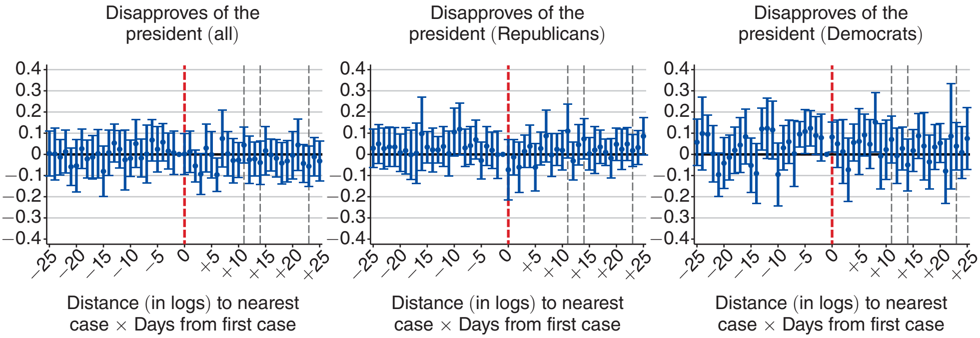

Figure 11. Event Study for President Obama's Approval Ratings (by Ideology)

Notes: These figures show point estimates and 95 percent confidence intervals of coefficients for relative time indicators (days) with respect to the first reported Ebola case (i.e., September 30, 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.

location of one of the Ebola cases, and Υ_t is a relative time indicator defined as days from the first case on September 30, 2014. The vector $\mathbf{X}_i$ 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) 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 from 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]

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

$$Disapprove_{i,d,t(c)} = \gamma PostCase_{t(c)} \times \ln\left(DistEbola_c\right)_d + \delta'\mathbf{X}_i + \lambda_d + \theta_t + \epsilon_{d,t}. \tag{6}$$

where $PostCase_{t(c)}$ is an indicator taking value 1 after the diagnosis of Ebola case c. The variable $\ln\left(DistEbola_c\right)_d$ is the distance (in logs) of DMA d from Ebola case c. The vector $\mathbf{X}_i$ 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 online Appendix 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.

E. *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.

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:

$$(7) \quad Y_{i,d,t} = \gamma PostOnset_t \times \ln\left(DistanceNearestCase\right)_d + \delta'\mathbf{X}_i + \lambda_d + \theta_t + \epsilon_{d,t},$$

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 $\mathbf{X}_i$ 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 case does not explain disagreement with gun control measures, beliefs regarding the importance of religion, opposition toward gay marriage, or self-reported conservatism. There is one dimension, however, that does seem to be impacted by Ebola: attitudes toward 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 United States. In fact, the working version of this paper (Campante, Depetris-Chauvin, and Durante 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 associations that can be more readily drawn by voters in regard to that threat.

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

Table 6—Proximity to Ebola Cases and Attitudes in CCES

	Anti-immigration (1)	Pro-gun (2)	Religious (3)	Anti–gay marriage (4)	Conservative (5)
Post-onset First Case × Distance (in logs) to Nearest Case	−0.019 (0.009)	−0.004 (0.013)	−0.007 (0.015)	−0.001 (0.004)	−0.002 (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	72,209	72,209	72,209	72,209	72,145
Number of clusters (DMA)	204	204	204	204	204

Notes: Sample includes all CCES's respondents for the 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) [the importance of religion]. The variable Anti–gay marriage takes the value of 1 if respondent is against gay marriage. The variable Conservative takes the value of 1 if respondent is conservative or very conservative, 0 otherwise (all related questions are described in the online 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-level controls 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., US$59,000). Heteroskedasticity-robust standard error estimates clustered at the county level are reported in parentheses.

V. Concluding Remarks

Our investigation of the political consequences of the 2014 Ebola episode in the United States 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 United States 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 United States, 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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