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The political economy of health epidemics

Evidence from the Ebola outbreak

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THE POLITICAL ECONOMY OF HEALTH EPIDEMICS: EVIDENCE FROM THE EBOLA OUTBREAK

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ABSTRACT. Health epidemics represent a unique test of governmental accountability. Compared to other disasters, the way the government responds is crucial to stop the contagion and limit the ultimate costs to citizens. However, political motives may distort the allocation of governmental resources. In this paper, I study the response of the Liberian government to the 2014 West Africa Ebola outbreak, and the subsequent effects on citizens' voting behavior and political perceptions. I combine proprietary data on Ebola cases, novel surveys, and publicly available data on the government's relief effort and post-outbreak Senatorial election. I first provide evidence of limited governmental response before the arrival of foreign aid, in contrast to improved assistance after aid was provided. I then build a spatio-temporal epidemiological model to estimate the ex-ante optimal allocation of relief effort. I find that the government misallocated resources towards swing villages affected by the contagion. Voters in turn reacted to the differential response: the incumbent party lost political support in areas hit in the first part of the epidemic, while it did not lose votes in areas hit in the second part and in swing villages. I conclude by discussing the costs to citizens of the political misallocation of resources. The findings provide novel evidence on the presence of strategic electoral motives in the allocation of resources in health epidemics.

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1. Introduction

Through the allocation of national resources, governments can improve economic development and have a direct impact on citizens' welfare. This is especially true in developing countries where the population is vulnerable and mostly relies on the state for basic services. However, political incentives may induce costly distortions at the expense of citizens' welfare. Although it is well documented that distortions exist in the provision of public goods and social welfare programs (Golden and Min, 2013), evidence on how governments allocate relief effort at the time of disasters is still scarce. Disasters, however, are a unique test of governmental accountability. On the one hand, governments have the opportunity to influence voters, signaling through their responsiveness to crises how well they can perform. On the other hand, citizens have a chance to learn about the incumbent government's capacity and thus ensure electoral accountability at the time of voting. Therefore, understanding the efficacy of and motives behind the response to disasters is of paramount policy relevance to provide the right incentives for governments to act appropriately in times of crisis.

There is evidence that political motives drive the allocation of relief effort in disasters such as earthquakes, floods, and hurricanes (Garrett and Sobel, 2003, Reeves, 2011, Gasper and Reeves, 2012). However, health epidemics have different implications for how governments allocate resources, and yet they have been largely unexplored. First, the presence of contagion effects might alter the ex-ante trade-offs politicians face to strategically allocate resources, as the government's response is a key determinant of the ultimate size of the disaster. Second, and related, compared to other disasters the dynamic nature and the duration of health epidemics imply that the costs to citizens may be potentially larger in presence of political misallocation of relief effort. This paper studies the political economy of a health epidemic, focusing on the 2014 West Africa Ebola (Ebola virus disease, EVD) outbreak in the country of Liberia.

The 2014 EVD epidemic was the largest and most devastating outbreak of the virus in recorded history. In just over one year, more than 28,000 cases were reported, almost half of which resulted in fatalities. The World Bank estimated that potentially catastrophic consequences may cost up to $25 billion (WBG, 2014a). By September 2014, an international "state of emergency" was declared and about $4 billion of foreign aid was channeled to the three countries most affected by the virus: Guinea, Liberia, and Sierra Leone. Schools and markets were closed; in Liberia, even elections were postponed due to increased fear over the epidemic.

This study examines how the Liberian government responded to the disaster, and whether political incentives distorted the allocation of resources, with a primary focus on the allocation of foreign aid. Then, it investigates whether the disaster shaped citizens' voting behavior and political perceptions. Learning about both how the government responded and how citizens reacted will shed light on ways to better align the government's political incentives with the improvement of citizens' welfare, especially in reaction to a next epidemic.

Theoretically, the impact of a health epidemic on political economy outcomes is ambiguous. A budget-constrained government, interested in maximizing its political support at the next election, has conflicting incentives in deciding where to respond. On the one hand, as in other settings, politicians might channel resources selectively by targeting specific voters, such as core or swing voters, or voters who share common characteristics (e.g. ethnicity) with politicians (Golden and Min, 2013). On the other hand, at the time of a health epidemic, the government might want to provide resources in a manner that minimizes the duration of the contagion and curb the spread of the disease.

It is also unclear how voters cast ballots in the wake of a health epidemic. On the one hand, citizens might solely respond to the direct allocation of resources to themselves. On the other hand, in health epidemics, voters might also value the final size of the contagion, and any action taken by the government to limit the ultimate costs. If voters were rational and had perfect information, they would trade-off these two interests to reward or punish the incumbent party at the time of voting (Healy and Malhotra, 2013). However, very high psychological or economic costs associated with the epidemic or imperfect information might reverse their judgment about the response. In terms of political participation, if the disaster highlights the role of the government in supporting (or not supporting) citizens in need, we might expect an increase in voter turnout (Fair et al., 2017). On the contrary, the disaster's displacement of resources might contribute to a decrease in turnout. The empirical analysis will test these predictions.[1]

In order to analyze the governmental response to the epidemic as well as its consequences for citizens, I created a comprehensive database on the EVD outbreak in Liberia. The database is at the smallest geographical unit of observation (a village) and it encompasses the entire set of 9,686 villages in 15 counties. I was granted access to a proprietary patient database from the Liberian Ministry of Health (MOH), which contained every person tested, as well as the timing when the test was done. Furthermore, I gathered data on relief effort measures, such as the construction of Ebola Treatment Units (ETUs) and Community Care Centers (CCCs), and the deployment of burial teams. I then collected publicly-available data regarding the 2011 and 2014 elections from the National Election Commission (NEC) and 2008 Census data from the Institute of Statistics and Geo-Information Services (LISGIS). Finally, I implemented a mobile phone survey of 2,265 respondents in about 600 villages, through which I gathered individual political perceptions about six months after the end of the epidemic.

Using this novel dataset, I compare the reaction of government and citizens in villages affected by EVD - primarily defined as villages where at least one suspected case of EVD was recorded - with villages in which no cases were registered, within the same county and controlling for a large set of observable pre-existing characteristics. However, one may be concerned that villages that were directly hit by EVD are different in terms of other unobserved characteristics in comparison

[1] See Section 5 and 6 for more discussion on the theoretical and empirical evidence.

to villages that were not hit. For example, the prior level of trust in the government might have affected how the government was able to effectively provide relief effort, and may thus also have influenced the recording of EVD cases. I then show the robustness of the results by using an alternative strategy that relies on an instrumental variable approach, based on the distance by road to the EVD place of origin. In the case data were available before the disaster, as in the case of voting behavior, I implement a difference-in-difference approach in order to minimize the influence of unobserved time-invariant determinants.

The first part of the paper studies the response of the government. After describing that the government provided more resources to villages affected by EVD compared to unaffected ones, I establish that in villages hit before September 2014, i.e., when foreign aid arrived, relief effort was provided on average 3 months after the recording of the first case. These villages were then affected 1.5 months longer, and took on average 2.6 months longer to fully recover compared to villages hit after the arrival of foreign aid. The finding suggests that the governmental response was limited at early stages of the epidemic due to the late arrival of foreign aid.

Next, I investigate whether the allocation of resources was distorted for political gains in anticipation of the December 2014 Senatorial election. Since not all affected villages might have equal political importance, I test whether the government provided more relief effort to affected villages with a higher share of swing voters, core voters, or voters who share the same ethnicity as the President of Liberia. I find evidence that more resources were allocated to swing villages. Following this, I constructed a spatio-temporal epidemiological model that identifies the villages that were ex-ante more likely to be affected by EVD. Computing misallocation as the difference between how much the government spent and how much it should have spent given the predicted number of EVD cases from the model, I examine whether more resources than needed were allocated towards swing villages. I find that the government misallocated on average \$42,600 in each swing village affected by the contagion, compared to affected non-swing ones. In total, 10% of the governmental expenses were misallocated. Specifically, more resources were targeted towards swing villages affected by EVD before the arrival of foreign aid - those villages which experienced an initially limited governmental response. The results suggest that also in a major contagious epidemic, politicians were able to channel part of the resources towards specific types of voters, in addition to allocating them to the victims.

After establishing that the government was indeed politically motivated in the allocation of disaster relief effort, the second part of the paper investigates the reaction of the citizens. I examine whether citizens' experience with EVD changed their voting behavior and political perceptions. In line with an improved government's performance over time due to the arrival of foreign aid, I find that citizens affected by EVD at earlier stages of the epidemic *punish* the incumbent party at the time of voting, making it lose 10 percentage points in vote share. By contrast, citizens affected by EVD at later stages did *not punish* the incumbent party at the time of voting. More specifically, the incumbent party lost political support (13.3 percentage points in vote share) from non-swing villages affected by EVD before the arrival of foreign aid. On the other hand, the incumbent party even gained vote share (15.3 percentage points) from citizens who received more resources than needed, due to the political misallocation, i.e., citizens in swing villages affected by EVD before the arrival of foreign aid. The results then indicate that citizens primarily responded to the resources they personally received. Finally, turnout was higher in the 2014 Senatorial election for citizens affected by EVD, compared to unaffected ones, suggesting that the experience with the disaster highlighted the role of the government in response to the crisis.

Exploring individual political perceptions by means of primary survey data, I show that all citizens affected by the disaster expressed lower trust in the government and perceived it to be more corrupt. Even though they did not attribute responsibility to the government itself, survey respondents affected by EVD before the arrival of foreign aid were more likely to report experiencing government's failures. This supports the interpretation that the delayed allocation of resources to villages hit by EVD before the arrival of foreign aid, is in fact the likely explanation why citizens, mainly in non-swing villages, punished the incumbent party. I exclude the explanation that differential economic or psychological costs associated with the epidemic contributed to the heterogeneous voting behavior. Lastly, I analyze complementary mechanisms such as more widespread knowledge and aggressive campaigning closer to the election.

Overall, the incumbent party successfully won four out of 15 seats in the 2014 Senatorial election, especially in those counties where more resources were misallocated. However, the governmental allocation of resources did not come without cost for citizens' welfare. In a cost-benefit analysis I estimate that an earlier, or non-political allocation of resources, might have reduced the number of deaths in the EVD outbreak. Specifically, 22% of lives could have been saved if the government had had resources available to intervene two months earlier than it did, and 9% of lives could have been saved if no resources had been misallocated for political gains.

This paper contributes to two strands of the literature. First, I build on the existing research studying the electoral incentives of politicians to allocate public funding (Brollo and Nannicini, 2012, Finan and Mazzocco, 2016), to manipulate social welfare programs (Brollo et al., 2015) and environmental policies (List and Sturm, 2006), and to request and spend resources after disasters in the USA (Garrett and Sobel, 2003, Reeves, 2011, Gasper and Reeves, 2012).[2] To the author's knowledge this is the first study that investigates whether a government behaves strategically in the case of a health epidemic. This setting is particularly important because it is ambiguous whether the government would politically allocate resources in a contagious disaster. Through the creation of a comprehensive database on the EVD outbreak in Liberia, this paper also adds to the disaster literature by exploring the governmental strategic behavior

[2]Previous studies find that politicians facing re-election behave opportunistically, asking for a disaster declaration (Garrett and Sobel, 2003, Reeves, 2011), requesting more federal funds than needed after a disaster declaration (Gasper and Reeves, 2012), and through higher disaster spending (Garrett and Sobel, 2003) in the USA. Cole et al., 2013 shows that the government of India spent more money in disaster relief in election years.

in a developing economy (Cole et al., 2013) and by directly measuring the political misallocation of resources and its costs for citizens' welfare.

Second, I contribute to a large body of literature exploring the impact of negative economic shocks on voting behavior. Part of these studies, mainly in the USA, show in a retrospective voting framework that voters are able to distinguish between events beyond the control of a politician (e.g., a disaster), and events in which politicians can take action (e.g., the response to it). They then punish or reward the incumbent government for the actions taken (Malhotra and Kuo, 2008, Healy and Malhotra, 2010, Gasper and Reeves, 2011, Healy and Malhotra, 2013 and Ashworth and Bueno de Mesquita, 2014).[3] This paper adds to this literature of rational voters[4] examining the effects on political perceptions, in addition to voting behavior (see also Fair et al., 2017 and Andrabi and Das, 2017) and by analyzing in depth the mechanisms of the impacts. The study finally explores the heterogeneous effects for citizens affected at different stages of the contagion, trying to understand how citizens responded to the direct allocation of resources due to the arrival of foreign aid.

The paper is structured as follows. In section 2, I provide background on the EVD outbreak and the context of politics in Liberia. Section 3 describes the data sources and descriptive statistics, and Section 4 elaborates on the empirical models. Consequently, Section 5 discusses the main results of the government's allocation of relief effort and its incentives, while Section 6 explores the citizens' reactions. I describe alternative mechanisms in Section 7, and provide a cost-benefit analysis in Section 8. Finally, Section 9 concludes.

2. Background

This section briefly provides an overview of the 2014 EVD outbreak in Liberia, including information on how the government and the international community responded over time to the contagion. I also provide some background on the politics in the country, focusing primarily on the Senatorial elections.

2.1. **The Ebola outbreak.**

[3]When the government takes appropriate actions, individuals do not blame politicians for the disaster (Healy and Malhotra, 2013). However, if citizens perceived the performance as inadequate, they do blame it (Malhotra and Kuo, 2008, Healy and Malhotra, 2010, Gasper and Reeves, 2011, Ashworth and Bueno de Mesquita, 2014). In this literature, voters are now thought to be fully rational, but able to commit mistakes of judgment (Huber et al., 2012), for example when irrelevant information influences individual decision-making (Healy et al., 2010, Cole et al., 2013), when they could be manipulated by rhetoric, framing, and marketing, or when they tend to give excessive weight to recent events (Healy and Lenz, 2014).

[4]Other studies provided evidence that voters are irrational and blame the government for events that are not directly under its control, such as bad weather (Gasper and Reeves, 2011, Cole et al., 2013), shark attacks, floods and flu (Achen and Bartles, 2004), and tornadoes (Healy and Malhotra, 2010). Caplan, 2007 suggests that citizens vote under the influence of false beliefs electing politicians who share their biases, and resulting in worse policies.

2.1.1. *Ebola in Liberia.* Identified for the first time in 1976 in two simultaneous outbreaks, in Sudan and in the Democratic Republic of Congo, the EVD involved only 1,716 cases in 24 different outbreaks in sub-Saharan Africa until the end of 2013. The West Africa EVD outbreak in 2014 was then the largest and most devastating outbreak of the virus in history, with a total of 28,646 reported confirmed, probable, and suspected EVD cases worldwide[5] and leading to the deaths of 11,323 individuals between December 2013 and early 2016.

EVD is a hemorrhagic fever, and is transmitted from wild animals, such as fruit bats and monkeys, to people through bodily fluids. EVD is then transmitted between humans through bodily fluids of infected people or through materials contaminated with these fluids. The movement of people because of work, trade, and even to attend burial ceremonies in home villages, in which mourners have contact with the deceased person's body, were all factors which contributed to how quickly the virus was transmitted in West Africa.

Liberia was among the West African countries most affected by EVD, along with Sierra Leone and Guinea. 10,675 cases, confirmed, probable or suspected were recorded in the country, where the cumulative number of deaths reached 4,809, the highest number of deaths in West Africa (WHO, 2016). The first EVD case was officially recorded in Lofa county at the border with Guinea on March 30th, 2014, though it is thought that patient zero of the outbreak was infected in December 2013 in the village of Meliandou in Guinea (Saez et al., 2015). Through mid-April, EVD cases were mainly confined to the area bordering Guinea, but by May 2014, other cases were being reported around Montserrado county, reaching in June the national capital, Monrovia, where more than 30% of the population lives. By the end of September 2014, almost all counties experienced at least one case. Using WHO public available data, Figure 1 shows that EVD reached the highest number of cases weekly recorded by the end of September 2014. By January 2015, there were fewer than 10 new cases weekly with the last case of EVD reported in mid-March 2015 and the country was declared EVD-free on May 9th, 2015. A small number of other cases were then seen in July and December of the same year, and Liberia was declared officially free on January 14th, 2016.

2.1.2. *The response.* From March 2014 onwards, the MOH, in collaboration with international partners, such as the World Health Organization, Center for Disease Control, and Medecins Sans Frontiers, and civil society organizations, tried to face the epidemic with available financial resources. In the first months of the outbreak, denial and suspicion about EVD were common, with people even suspecting that EVD was not a real disease. Communities started taking

[5]A "probable" case is a case evaluated by a clinician or any person who died from "suspected" EVD and had an epidemiological link to a confirmed case, but did not have laboratory confirmation of the disease. A "suspected" case is any person, alive or dead, who had sudden onset of high fever and had contact with a suspected, probable or confirmed EVD case, or a dead or sick animal OR any person with sudden onset of high fever and at least three of the following symptoms: headache, vomiting, anorexia/loss of appetite, diarrhea, lethargy, stomach pain, aching muscles or joints, difficulty swallowing, breathing difficulties, or hiccups; or any person with unexplained bleeding OR any sudden, unexplained death; a probable or suspected case is classified as "confirmed" when a sample was tested positive in the laboratory (WHO).

the contagion seriously after witnessing deaths and experiencing fear and panic. Only in July 2014, when the death toll accelerated, were international staff sent to Liberia to assess the situation. However, by the end of that month, the epidemic was already out of control. On July 28th, the government closed most border crossings, medical checkpoints were set up, and some international flights were suspended. On July 30th, Liberia shut down its schools in an attempt to prevent further spread of the disease.

On August 7th, 2014, the President of Liberia declared a 90-day "state of emergency", and an additional number of restrictions were implemented: public gatherings were banned, a curfew restricted travel from 9pm to 6am, agriculture markets were canceled, and major slums, such as West Point around the national capital, were quarantined (MercyCorps, 2014). Any interpersonal touching, such as handshaking, was discouraged. Information campaigns were launched to urge wide-scale behavior change, such as hand washing and safe burial practices. A hotline was also set-up to report EVD cases and call for help.

By early September, many organizations offered funding for the response, using their resources and staff to educate communities to prevent the transmission of EVD and to encourage people to seek medical care. On September 13th, Liberia formally appealed to the USA and the international community for help. A few days later, President Obama announced that he was sending a military command to help with the construction of ETUs. The first USA-funded ETU opened by the end of September in Monrovia, while most of the others were active only by November and December 2014.[6] Local communities started engaging in task-forces for education and information campaigns (MOH and UNICEF, 2015). In October and early November, additional resources were sent by WHO, the Gates' Foundation, and the United Nations. The Liberian President modified the state of emergency restrictions only on November 13th, reducing curfew hours, reopening most closed markets, and relaxing some domestic travel restrictions. All the restrictions were canceled, and borders and schools re-opened in February 2015, by which time the EVD rate of infection was already very low.

Given that the end of September 2014 coincided with the peak of the epidemic and the huge inflow of funding from the USA and international partners (Figure 1), for the purpose of the analysis, I use these events to split the EVD outbreak into two parts and to study the heterogeneous impacts of the disaster. I define the first part of the epidemic as between March and September 2014, and the second part as after September 2014.

2.2. **Elections in Liberia.** National elections in Liberia are regulated by the National Elections Commission of Liberia (NEC), and they involve the Presidency, the House of Representatives, and the Senate.[7] The main incumbent party, in power since 2005, is the Union

[6]Two ETUs (ELWA and JFK Hospital), run by Samaritan's Purse and MSF, opened in July in Monrovia, but they were temporarily shut down in August when their international staff was infected with EVD.

[7]The President of Liberia is elected every six years in a two-round system. A six-year term holds similarly for the House of Representatives, which has 73 members apportioned among the 15 counties on the basis of the national census, with each county receiving a minimum of two members.

Party (UP); the Congress for Democratic Change (CDC) represents the main opposition, with most of its support in Montserrado county, while the Liberty Party (LP) is the third national party (BTI, 2012). All citizens who are 18 years or older are allowed to register to vote in the elections. Voters can register only during the established registration period at a registration center, where they are provided with a card usable only in one pre-assigned precinct of the electoral district in which they registered (NEC, 2011).[8]

This paper focuses on Senatorial elections. Senators have the main responsibility to lobby for budgetary appropriations over the national budget to secure County and Social Development Funds for their county's projects, such as hospitals, schools, and roads, and they provide oversight of the use of resources in their county. The Senate has 30 members, two from each county, belonging to two classes of senators. 15 members are elected by plurality vote in multi-member constituencies to serve nine-year terms (First Category), while the other 15 are elected to serve six-year terms (Second Category). After the first democratic elections were held in 2005, the 15 senators with the highest number of votes were elected for a nine-year term, while the latter half for a six-year term. The Second Category was then re-elected in 2011 for a nine-year term, while the First was elected in 2014 for a six-year term. In the 2014 elections, everyone registered in 2011 could vote, as well as anyone who was registered by the NEC in the update of the Voter's Roll, implemented from January 13th 2014 to March 5th 2014.

A senatorial race was originally scheduled to be held on October 14th, 2014, as defined by the constitution. However, on October 9th, President Sirleaf, given her new authority under the state of emergency, suspended the national elections, citing the EVD outbreak as a major concern. The NEC then recommended the postponement through a consultative process of the National Legislature. Several petitions were filed with the Supreme Court to delay the elections until Liberia could be declared Ebola-free. Initially, the Supreme Court postponed the elections to December 16th and prohibited a number of election-related activities, including campaigning. Subsequently, on December 13th, the National Legislature agreed on December 20th as the new election date in order to allow candidates time to campaign through December 19th. A total of 139 candidates, 26 running as independents and the remaining nominated by 15 parties, ran for the 15 seats.

In this context, it is important to note that during the epidemic, foreign resources were channeled primarily through the MOH, which then allocated resources to the health teams at county level, i.e, the administrative level that Senators represent. Despite not directly managing the funding, Senators could lobby for more resources and work with the health teams in the decisions for their counties. Anecdotal evidence suggests that (runners-up) Senators were actively involved in the response. Since Senators are representatives of and financially supported by national political parties, voters could rationally attribute responsibility to their county representatives, for the actions taken by the main national political parties during the

[8]The NEC equally distributes all the registered voters at each electoral district among different precincts at a maximum of 500 people each, considering geographical boundaries and the population registered in each county.

outbreak. Thus, the performance of the President and the incumbent national party (UP) might affect down-ballot co-partisan Senators[9], who can be punished or rewarded by voters at the ballot box.

3. Data and Descriptive Statistics

I combined multiple data sources. First, the measures of EVD are constructed from the combination of records of the patients tested by the MOH and by the burial teams. I also collected data on some measures of relief effort, such as the construction of ETUs and CCCs and the deployment of burial teams, to investigate the government's response. Second, I gathered 2008 Census data and the location of villages from LISGIS to serve as controls in the analysis. Third, I collected publicly-available data on the 2011 and 2014 elections from the NEC to explore voting behavior. I manually coded and matched all data sources at the smallest geographical unit of observation for the entire set of 9,686 villages in the 15 counties of Liberia. Finally, I implemented a mobile phone survey (hereafter: survey sample) about six months after the end of the epidemic, covering 2,265 respondents in 571 villages to explore political perceptions (Appendix A, Table 1 to 4).

3.1. **Ebola cases.** Two data sources are used to construct measures of EVD for the analysis. First, I use the proprietary patient database from the MOH containing information on EVD (probable, confirmed, deaths) cases for more than 19,000 patients tested up to July 2015. As of today, it is widely considered the most comprehensive dataset, as the MOH coordinated the response and both local and international organizations taking part in the relief effort were required to report any EVD case to the MOH (MOH, 2017). Second, I use data from the Global Community (hereafter: GC), a global development organization that managed all the burials after July 2014; their database contains more than 4,000 buried individuals suspected with EVD, only half of whom were tested. Both databases record the village where the person resided when suspected to have contracted EVD, which allows me to match the data with the list of villages provided by LISGIS. I supplement MOH data with the cases recorded from GC.[10] I use the date when the blood for the test was taken to explore the heterogeneous impacts of the results.[11] See Appendix C for a comparison between data sources.

On the extensive margin, I construct an indicator of EVD as a dummy variable equal to 1 if at least one (probable, confirmed, or positive death) case was recorded in the village from the

[9]The analysis will be studying citizens' support for Senators from the main national incumbent party (UP).

[10]The recordings from the MOH are supplemented in 0.69% of the villages (See Table C1 in Appendix C), i.e., in the cases when the MOH does not report a case, but GC does. I used the date when the person died.

[11]While the MOH dataset collects the dates of symptoms, when the blood test was taken, and when the result was given for each patient, the GC dataset collects the times when the person died and was buried. From the MOH, I did not use the date on which the patient developed symptoms, because there are several missing values and very early dates compared to when the blood was taken. Also the date of testing is not used as the primary date because testing at the laboratory could take up to 2 weeks after the blood was taken. Similarly, I did not use the date of burial for GC because it is after the date of death.

two data sources. On the intensive margin, I construct the total number of cases per capita and the total number of months in which at least one case was recorded. Over the entire duration of the epidemic, about 7% of the villages experienced at least one EVD case (Map 1, Table A1, Panel A column 1). Almost all confirmed and positive-death cases were concentrated up to December 2014, while only 3.29% of the probable cases were tested before December 2014 (Panel A, column 2). In fact, in January 2015 the number of positive EVD cases dramatically waned, but still the government went ahead testing any probable case in the subsequent months. The percentage of villages affected is much higher in the 571 survey villages, with more than 17% of them affected at any time (Panel A, column 3). This is not surprising, considering that about 70% of respondents in the survey are from urban areas, which represent the worst hit parts of the country.[12] Since the majority of villages never recorded any EVD case, the averages of the intensive margin measures are very low (Table A1, Panel B): villages had, on average, 0.0018 people per capita affected at any time and they were hit for less than 1 month. In the sample of 677 villages hit by EVD, however, the average village experienced 0.027 cases per capita, and it was affected for 1.69 months (not shown). See Map 2 in Appendix C for a visual comparison between villages with EVD recorded from the administrative and survey data.

3.2. **Covariates.** I use the National Population and Housing 2008 Census to control for village characteristics before the epidemic. The data include information on the population, such as education, household size, working status, type of occupation, tribe and religion. They also include housing facilities and ownership of amenities, which I use as a proxy for village wealth. LISGIS also provided GPS coordinates of all villages and health facilities at the time of the census, and of ETUs and CCCs opened during the outbreak. I use ArcGIS to construct distances (by road) from each of the villages or electoral precincts to the EVD origin and the national capital, as well as for measures of elevation and slope.

As shown in Table A2 in Appendix A, the households from villages in the survey sample (column 2) appear to be statistically significantly different (at 5% level) from the average households in Liberia (column 1). They are slightly wealthier, more educated, with a higher number of members and less dependent on agriculture (Table A2, Panel A). This is not surprising since the majority of the respondents report having secondary or higher education and mostly live in urban areas (Table A4). The survey sample is, therefore, not representative of the national Liberian population, but it is more likely biased towards urban areas. Survey villages are also further from the capital city, closer to the EVD place of origin and health facilities, and at a higher elevation (Table A2, Panel B). The analysis is, however, robust to the re-weighting of

[12]I also collected measures of EVD from the survey data, where I asked respondents whether, in the past year, any of the people they knew personally in their community had suffered from or were suspected of having EVD. As reported by survey respondents, a higher percentage of villages had at least one EVD case: between 17% - if one-third of survey respondents in the village reported at least one case - and 30% - if at least one respondent in the village reported at least one case - not shown. Since respondents subjectively reported EVD cases, I do not use survey data as a measure for the analysis.

the sample based on village characteristics from the 2008 Census or individual characteristics taken from the 2013 Demographic Health Surveys (not shown).

3.3. **Senatorial election data.** Using publicly-available electoral data for the Senatorial elections from NEC, Table A3 in Appendix A shows that each of the 1,780 electoral precincts in Liberia has 2.5 polling stations, with less than 500 registered voters assigned to each. In the 2011 Senatorial election, turnout was 71%, with candidates from the incumbent party receiving 16% of votes. The shares of votes for the CDC and LP were similar (16% and 12%), while other parties and independent candidates added up to 32% and 24% respectively. Turnout was dramatically lower (27%) in 2014 elections, when the incumbent party received only about 10% of the votes, while the CDC increased its support at 27%, winning the most populous county, Montserrado. LP and independent candidates stood at 14% and 24% similar to their share in 2011. Other small parties reached a vote share of 25%.

3.4. **Survey data.** I collected data on 2,265 respondents across the entire Liberia, through mobile phone surveys. The initial list of phone numbers was selected through an online platform, using random dialing of phone numbers. The platform mimicked Liberian phone numbers, using the prefixes of the two main phone companies in the country. Once the phone number connects - it is an existing Liberian phone number, and a person picks up the call - an Interactive Voice Recognition (IVR) survey selects respondents based on their residence location at the beginning of the outbreak. During this screening process, I asked a small set of questions to identify the county and district where the respondent resided. The aim was to gather a sample of individuals, some with experience of EVD and some without, to be able to compare the two groups, and to limit respondents from Montserrado county, the most urbanized and populous county. This process resulted in the selection of enough respondents from all 15 counties of interest. Screened respondents were then called back by real enumerators of a local NGO to conduct a 30-45 minute interview (Appendix D for details).

The survey gathered (1) respondent and household socio-demographics; (2) political outcomes such as self-reported level of trust in governmental and non-governmental institutions and people, and perceived corruption towards similar institutions; and (3) EVD-related questions, such as self-reported EVD incidence in the community, the level of information received, the experience with the response, and perceptions about the government's performance. To avoid potential priming effects in the order of the questions between political outcomes and experience with EVD, I randomized half of the sample to receive the political outcomes section first, while the second half received the EVD-related questions first. No statistically significant differences were found in the data collected between the two samples (not shown).

Survey respondents are 65% male, on average 33 years old, and about 86% are Christian (Table A4). The sample mostly contains individuals who are educated (22% have some level of university, and 60% attended secondary school) and live in urban areas (69.5%). Since the survey screenings and interviews were both conducted through mobile phones, respondents needed to have access to a mobile phone at the time of the call: young people, males, and individuals from urban areas are more likely to own mobile phones (Demographic Health Surveys, 2013). As far as individual experiences with EVD are concerned, the majority of respondents felt that Liberia was badly hit by EVD, and about one-fourth also thought that their community was hit. Most of the respondents reported they had received information about EVD per se and about government actions. More than 90% said that someone visited their communities to hold hygiene meetings, to educate about EVD and safe burials, to bring prevention material or to pick up sick or dead people. However, the response was not without complaints. Respondents illustrated government's failures, such as delays in removing dead bodies, delays in sending ambulance services, and refusals of access to treatment in ETUs and CCCs. Overall, even though 57% of them believed that the government handled the outbreak well, the data suggests that the actions of the government in its handling of the crisis were not always adequate.

4. Empirical Strategy

To study the political economy of the EVD epidemic, I combine different statistical approaches. The analysis compares the reaction of government and citizens in villages hit and not hit by EVD, in a county fixed-effect model and controlling for a large set of pre-existing socio-demographic and geographical characteristics. The results are, however, robust to an instrumental variable approach which uses the distance (by road) to the EVD place of origin as quasi exogenous variation for the first EVD case appearing in the village. I implement a difference-in-difference empirical strategy when data before the disaster are available.

All empirical models control for three constant factors correlated both with EVD and political economy outcomes. First, I control for the distance to the national capital of Monrovia, because once EVD hit the city by June 2014, the likelihood of contracting EVD from the capital became much higher for individuals who lived closer to Montserrado county. Second, I add the elevation at the village level, as areas close to the border with Guinea, origin of EVD, are mountainous. Hence, a response to the crisis might have been more difficult to operationalize, contributing to a lower number of recorded cases. Third, I include the percentage of Muslims in each village; since Muslims mostly live around the border with Guinea and Sierra Leone and have different burial practices from Christians, their likelihood of contracting EVD was higher. Furthermore, political support towards the incumbent party might be correlated with each of these three factors: the national capital is historically pro the main opposition party (CDC); Lofa county, at the border with Guinea and at the highest elevation, is historically pro the third national party (LP); Muslims have also historically showed lower support towards the incumbent party.

Each specification (at the village, individual or precinct level) also includes an additional set of controls selected through the least absolute shrinkage and selection operator (Lasso) estimator (Belloni et al., 2014). This method selects the more predictive variables of outcomes and regressors of interest, penalizing the absolute size of the regression coefficients. It enhances the accuracy of the predictions, rendering it particularly useful when dealing with many highly correlated regressors.[13] In most of the specifications, I also control for voter turnout and vote share of the incumbent party in the 2011 elections.

4.1. **Governmental responsiveness.**

4.1.1. *Basic specification.* The basic empirical specification of the analysis is as follows:

$$Y_v = \alpha + \beta * T_v + \boldsymbol{\delta} * \boldsymbol{X}_v + \gamma_c + \epsilon_v \tag{4.1}$$

where v refers to a village in Liberia, and Y_v is the outcome variable of interest for the government's response, such as the distance to the closest CCCs or ETUs, whether any safe burial was made in the village, and the number of safe burials. T_v is a measure for whether a village was affected by EVD, either on the extensive margin (i.e., a dummy on whether at least one case was recorded) or on the intensive margin (i.e., number of cases per capita or number of months in which at least one case was recorded); $\boldsymbol{X}_v$ is a vector of village level controls which always includes the three variables described above (distance to Monrovia, elevation, and percentage of Muslims living in the village in 2008), and a subset of socio-demographic controls selected by the Lasso procedure, such as distance (by road) to EVD place of origin, population (log), the percentage of households from the main tribal groups in the country, and proxy measures for village wealth. $\boldsymbol{\gamma}_c$ is a vector of 15 dummies, each of them representing one of the counties in Liberia[14]. ϵ_v is the error term. The parameter of interest β estimates whether the government responded more in villages hit by EVD compared to unaffected villages, taking out differences across counties and any difference in the large set of controls. A similar empirical specification is used to analyze survey data at individual level when I explore the changes in political perceptions towards the government.

4.1.2. *Heterogeneous effects.* The analysis also studies whether the disaster had differential impacts depending on when each village experienced EVD. I define two indicators for part 1 and part 2 of the epidemic, i.e., before or after the arrival of foreign aid. The former takes a value of 1 if the village was hit by EVD a first time between March and September 2014, while the latter takes a value of 1 if the village was hit by EVD a first time between October 2014 and July 2015 (restricted to December 2014 for voting behavior) but it was never hit before. The specification is as follows:

$$Y_v = \alpha + \beta_1 * T1_v + \beta_2 * T2_v + \boldsymbol{\delta} * \boldsymbol{X}_v + \boldsymbol{\gamma}_c + \epsilon_v \tag{4.2}$$

[13]The initial full list of controls includes distance (by road) to the EVD place of origin, and to the closest health facility in 2008; population (log) and population density at district level; percentage of households with up to primary education, working in agriculture, owing a house, a 1-room house, TV, radio, phone, furniture, mattress, motorcycle, vehicle, and refrigerator; percentage of households with improved water source, toilet facility, roof material, floor material, wall material (as defined by the World Health Organization), with electricity for light, and with electricity as cooking fuel; percentage of households from each of the 16 tribes in Liberia; slope and whether the area is forest.

[14]Results are robust to the inclusion of 136 dummies, one for each administrative district.

where $T1_p$ is the dummy variable referring to the first part of the epidemic, and $T2_p$ is the dummy variable referring to the second part of the epidemic. All the other variables are defined as above. Similar regressions with indicators by timing of the first EVD case are also used to explore heterogeneous impacts at individual or precinct level.

4.1.3. *Alternative specification: Instrumental variable approach.* The alternative instrumental variable approach relies on two important points. First, the origin of the outbreak is thought to be quasi-random: there is no key reason why the first person carrying EVD was infected in Meliandou village (Guinea) rather than another location. The first EVD case was in fact attributed to an infected bat, which transmitted the virus to a child playing in a hollow tree. However, no other main determinants were found to explain the place of origin of the 2014 outbreak (Saez et al., 2015). The second key element is the way in which the virus was transmitted. After the first infection from animals to people, EVD spread in the population by human-to-human transmission through bodily fluids. Direct contact with people who were infected was the main determinant in how EVD spread. While many factors contributed to the contagion, such as the type of cultural burial practices, care of sick family members, low level of bio-security standards in health facilities, overpopulation, poverty, lack of information (Alexander et al., 2015, Fallah et al., 2015), the spread of human infections can be attributed primarily to the movement of people within Liberia and across borders (Shrivastava et al., 2016). For these two main reasons, I propose the shortest distance (by road) of a village to the EVD place of origin as a quasi-exogenous predictor of whether or not a village was hit by EVD.[15] Specifically, I use a non-linear (quadratic) relationship between the distance to the EVD place of origin and the indicator of EVD to allow for a more flexible functional form.[16] Controlling for a large set of observable characteristics, I expect similar villages to be less likely affected by EVD if they are further away from the place of EVD origin.

Note that, in this setting, the endogenous regressor is a binary variable. Hence, it is incorrect to assume linearity in the first stage of a two-stage least-squares (2SLS) estimation (the so called "forbidden regression" by Hausman, 1975). Moreover, a linear probability model is not a good fit because of the high percentage of zero extreme values in the regressor of interest. Thus, I follow the three-step procedure suggested by Wooldridge (2002).[17] First, I estimate a binary

[15]The instrumental variable is not predictive of measures of EVD on the intensive margin, and it does not strongly predict whether a village was affected at later stages of the epidemic. Thus, this specification is mainly used as a robustness check rather than as primary empirical approach.

[16]Results are robust to a linear function, but the relationship between the distance to the EVD place of origin and the indicator of EVD is less statistically significant.

[17]This procedure has important advantages compared to a 2SLS approach. First, it considers the binary nature of the endogenous variable, and this is particularly important when the variable has a high percentage of extreme values. Second, it does not require the first stage to be correctly specified (the probit does not have to be correct). Third, the standard errors generated by the instrument variable (step 2 and 3) are asymptotically valid. I bootstrapped standard errors.

response model (probit) of the determinants of the EVD indicator:

$$Pr(T_v = 1) = \Phi(\alpha_1 + \beta_1 * D_v + \gamma_1 * D_v^2 + \boldsymbol{\delta}_1 * \boldsymbol{X}_v + \epsilon_v) \tag{4.3}$$

where v refers to a village and T_v is a dummy variable equal to 1 if at least one EVD case was recorded in the village at any time during the outbreak. Φ is the cumulative distribution function of the regression expression in brackets, where α_1 is a constant, D_v is the shortest distance (by road) from the village to the EVD place of origin, $\boldsymbol{X}_v$ is a vector of village-level controls, and ϵ_v is the error term.

Second, I apply a 2SLS model using the predicted probabilities $\widehat{\Phi(.)}$ as an instrumental variable for the EVD indicator. The second and third steps of this procedure are as follows:

$$T_v = \alpha_2 + \beta_2 * \widehat{\Phi(.)} + \boldsymbol{\delta}_2 * \boldsymbol{X}_v + \epsilon_v \tag{4.4}$$

$$Y_v = \alpha_3 + \beta_3 * \widehat{\widehat{\Phi(.)}} + \boldsymbol{\delta}_3 * \boldsymbol{X}_v + \epsilon_v \tag{4.5}$$

where $\widehat{\Phi(.)}$ is the predicted probability of the first step and $\widehat{\widehat{\Phi(.)}}$ is the fitted value of the second step. Y_v is the outcome variable of interest. T_v, $\boldsymbol{X}_v$, and ϵ_v are defined as above. The parameter of interest β_3 in equation (4.5) estimates the impact of EVD on the governmental response. Standard errors are bootstrapped (500 replications) for the entire procedure.

Two conditions need to hold for the distance from the village to the EVD place of origin to be a valid instrument. First, the instrumental variable needs to be relevant: the distance from the village to the EVD place of origin has to be strongly correlated with the regressor of interest (T_v). Table 1 reports the χ^2 from the first step of the three-step procedure, testing the joint significance of the coefficients on D_v and D_v^2: the p-values associated with the χ^2 are always less than 1% in all three samples analyzed (χ^2 is greater than 10, Table 1 column 1, 3, and 5). Table 1, column 1, for example, shows that a 100 Km increase in the distance to EVD place of origin decreases the probability that a village was hit by EVD by about 20% over the mean of 6.99% of villages hit by EVD at any time. Second, the instrumental variable needs to be exogenous: the distance from the village to the EVD place of origin should be uncorrelated with the error term, i.e., it should influence the governmental response only through EVD. The most likely violation of the identification strategy is whether the distance to EVD place of origin is correlated with other variables that could directly explain the outcomes. One example could be the level of trust towards the government prior to EVD, which would influence how the government was able to provide relief effort (Blair et al., 2016). If specific geographical areas are correlated with the level of trust before EVD and I fail to control for this variable, the prior level of trust accounted for in the error term, could explain the relationship between the EVD indicator and the governmental response. Even though this assumption is not testable, I can use senatorial political outcomes pre-EVD (2011) as a proxy for the level of trust in the government before the epidemic, and explore the correlation with the instrumental variable. Table A5 in Appendix A shows that there is a lack of statistically significant correlation between the vote share of the incumbent party and turnout in the 2011 Senatorial election and distance to the place of EVD origin (column 4), controlling for a subset of selected covariates. Instead, I find other variables, such as elevation, distance to Monrovia and the closest health facility, percentage of Muslim population, and proxies for wealth, to be correlated with distance to the EVD place of origin. I control for these confounders in the analysis, as selected by the Lasso estimator.

An additional concern with this identification strategy is the potential measurement error in the regressor of interest. Places with ex-ante low trust in the government might have been harder to reach during the epidemic. The EVD indicator could record a lower number of cases in the villages with initial lower level of trust. Still, given the extensive response and preventive measures taken by government and international partners, this problem would have been limited to the initial months of the epidemic and should have been solved in the compilation of the MOH database at the end of the outbreak. Table 1 shows that the vote share of the incumbent party in 2011 does not consistently predict the measure of EVD used in the analysis[18], and Table C2 shows that it does not predict the under- or over-estimation of EVD from the MOH compared to other data sources, suggesting that this is not a major concern.

4.2. **Citizens' voting behavior.**

4.2.1. *Difference-in-difference approach.* To study citizens' voting behavior, I exploit EVD as a source of cross-sectional variation and the timing of the first EVD case recorded in a village as a source of time-series variation. Since the outcomes of interest, such as turnout, number of votes and vote share of different political parties, are at the electoral precinct level, I construct an indicator of EVD at the same level. I link each village to a precinct by the shortest distance, making the assumption that each voter goes to register at the closest precinct to her village and that the closest precinct is the one pre-assigned by the NEC. Through an iterative matching procedure[19], all 9,686 villages are matched to the closest precinct among the 1,780 in the country: each of them is matched on average with 13 villages at a distance of 3.6 km. The measure of EVD at the electoral precinct level sums up all EVD cases recorded in the villages matched to each precinct. The regressor of interest is a dummy variable equal to 1 if at least one EVD case is recorded in any of the villages around each electoral precinct, and equal to 0

[18]I also find that the vote share of the incumbent party in 2011 does not predict whether a village was affected by EVD at early or late stages of the epidemic, as well as the number of cases per capita recorded at any stage of the outbreak (not shown).

[19]The procedure entails two steps: (1) I match 1,780 electoral precincts to the closest village. When the same village is matched to multiple precincts, such as in populated areas, I pair that village only to the closest precinct and remove the unique pair from the sample. I then apply the same procedure to the remaining sample of villages and precincts until all of them are uniquely paired. The procedure takes 70 iterations to exhaust the sample. At the end of this first step, all 1,780 precincts are matched to an equal number of unique villages. (2) All other villages (9,686-1,780 already matched in step 1) are then matched to the closest precinct. Note that I cannot directly match all 9,686 villages to the closest precinct, because some precincts would not be matched to any village by closest distance.

otherwise. The main empirical specification is as follows:

$$Y_{pt} = \alpha + \beta * T_p + \gamma * Post_t + \delta * T_p * Post_t + \boldsymbol{\gamma} * \boldsymbol{X}_p + \boldsymbol{\gamma}_c + \epsilon_{pt} \tag{4.6}$$

where p refers to each electoral precinct, Y_{pt} is the outcome of interest, T_p is the dummy variable that indicates that at least one EVD case was recorded among all closest villages to each precinct, $Post_t$ takes value 0 for year 2011 and value 1 for the 2014 Senatorial election. $\boldsymbol{X}_p$ is a vector of controls, including elevation, distance (by road) to Monrovia, the percentage of Muslim population in the villages around each precinct, and a subset of socio-demographic controls selected by the Lasso procedure, including the distance (by road) to EVD place of origin, distance (by road) to the closest health facility in 2008, population (log), and the percentage of households from the main tribal groups in the country. $\boldsymbol{\gamma}_c$ is a vector of 15 county dummies, and ϵ_{pt} is the error term. Standard errors are clustered at the precinct level, and all specifications are weighted by the total number of registered voters in the electoral precinct in 2014 so that they roughly replicate the overall results of the election. The parameter of interest δ represents the impact of the EVD outbreak on voting behavior.

This identification strategy relies on the assumption that the trends in the outcomes of interest in electoral precincts which experienced or did not experience EVD (treatment and control, respectively) are similar in the absence of the treatment. Unfortunately, I cannot test the assumption directly, because I do not have election data from 2005 which is comparable to the data in 2011 and 2014. Since electoral precincts changed from 2005 to 2011, I am unable to match votes across years.[20] Nevertheless, several points support my identification assumption.

First, I control for the pre-existing characteristics that differ between treatment and control precincts, with the goal of removing any potential initial differences between the two groups. Second, there are no correlated shocks that could have had a different effect on treatment and control group. Most changes, such as restrictions on movements or school closure, were national policies. Moreover, even though other changes, such as quarantines or closure of markets, were targeted to areas affected by EVD, my intention is to capture them in the EVD indicator. The regressor of interest does not represent only the virus per se, but rather the whole experience that individuals had once their community was hit, including the governmental response. Instead, differential trends in governmental policies between treatment and control groups before the outbreak should be considered. For example, if the government had invested in public health provision at different rates in treatment and control groups before EVD, then those differential trends could bias the estimates. I explore this possibility by comparing the number of health facilities in 2008 and in 2014, excluding hospitals opened during the epidemic. I compute the difference between the distance from each village to the closest health facility in 2008 and 2014, and I find that there is no statistically significant difference between villages hit or not hit

[20] Liberia had 1,510 electoral precincts in 2005, and 1,780 both in 2011 and 2014. Of those 1,510, 1,176 matched between years, while 336 were only found in 2005, and 601 were only found in 2011 and 2014. Even for the ones that matched, the assignment of registered voters might have changed over time.

by EVD (p-value 0.6241). This suggests that, as far as health facilities are concerned, the government was not investing at different rates in the treatment and control groups.

Finally, a key concern is related to how differential mortality and migration due to EVD might have changed the composition of the two groups over time. As far as mortality is concerned, even though I lack data to directly measure whether those who died differ from those who survived the epidemic, the number of EVD deaths per village is very low (0.00011 deaths per capita at village level, Table A1, Panel B), suggesting that if any difference exists, estimates should not be too much biased. In addition, controlling for the number of EVD deaths in each location does not change the results (not shown). As far as migration is concerned, estimates could be biased if individuals were more likely to migrate from villages affected by EVD to less affected ones.[21] Still, these concerns are limited by the following facts: (i) There is no evidence of systematic migration from EVD highly-affected to less-affected areas during the epidemic (WBG, 2014b, WBG, 2015b). World Bank data collections in fact show that 18% of survey respondents migrated, but they mainly remained within their original county; (ii) similar patterns are confirmed from my survey data, where about 16.7% of the 2,265 respondents said they were living somewhere else at the beginning of the EVD outbreak. Among these individuals, 28.4% moved within the same county from late 2013 to early 2016. Among the remaining respondents who moved to a different county, 21% moved to Montserrado county, about 20% to the counties around it, and another 10% to the county close to the EVD place of origin, all counties heavily affected by EVD. This suggests that migration was not related to EVD per se; (iii) given that, by law, citizens had to vote in the electoral precincts where they registered, there is no concern that individuals voted in the places to which they migrated. The remaining concern is about those individuals who voted in their place of origin, but who lived somewhere else and had a different experience during the epidemic. In Appendix B, I show that results are robust to a sensitivity analysis following Dinkelman and Mariotti (2016) that bounds results for composition effects from internal migration.[22]

4.3. **Comparing areas with and without Ebola.** Before discussing the results, it is key to understand which have been the main predictors of the epidemic. Using a probit model on the three different samples used in the analysis (Table 1), I find that distances (by road) to the

[21]Consider, for example, that we are exploring the effects of EVD on vote share of the incumbent party. On the one hand, if citizens in places affected by EVD were more likely to reward the incumbent party than citizens in unaffected areas, and I fail to account for migration patterns from treatment to control group, then the positive coefficient would be biased upward. In the opposite scenario, in which citizens in places affected by EVD were more likely to punish the incumbent party than citizens in unaffected areas, failing to account for similar migration patterns would instead bias the estimates downward.

[22]Given the lack of data on net migration rate, I assume that half of the precinct has up to 17% of random net in-migration, while the other half has random net out-migration up to a similar magnitude as defined by survey data (16.7% have migrated among respondents). I re-estimate the main regression specifications for the adjusted outcome variables (lower and upper bound), and results are robust (Table B4, columns 9 to 12). As explained in Dinkelman and Mariotti (2016) these adjustments do not imply that the difference-in-differences regressions using the new outcome variables produce estimates containing the original estimates. I refer to the paper for more details.

EVD place of origin, to Monrovia, and to the closest health facility are negatively associated with the indicator of EVD. Furthermore, places with higher population, a higher percentage of Muslims, and at a higher elevation, are more likely to have experienced an EVD case. However, past political outcomes, such as turnout or vote share of the incumbent party in 2011 elections, do not consistently predict EVD across empirical specifications. All other characteristics are balanced between areas affected and not affected by EVD.

5. The Governmental Response to the Ebola outbreak

Imagine a government that needs to decide where to allocate resources at the time of a disaster, and assume that this government is strategic, i.e., it maximizes the probability of being re-elected. First, given the magnitude of the epidemic and the international attention focused on the country, I hypothesize that the government primarily tries to limit the contagion. I thus argue and test empirically in Table 2 and 3 whether the governmental responsiveness is higher in villages affected by EVD compared to those with no EVD cases recorded. In addition, Table 4 explores its performance in providing relief effort.

Second, I argue that the government might also have stronger political incentives (Burgess and Besley, 2002) and it might target resources to specific types of voters. Since the electoral data are defined at the electoral precinct level, I do not study voting behavior of individual citizens, but rather at village level, linking the village to the closest electoral precinct. Following the existing theoretical and empirical literature[23], I test in Table 5 whether the government provides more resources to swing villages, i.e., those undecided between political parties, and defined as those where the difference in the vote share between the winning and the first losing party in the 2011 Senatorial election was 10 percentage points or lower. Table A6 in Appendix A also explores an alternative strategic behavior towards core villages or villages who share the same ethnicity[24] as the President.[25]

5.1. **The performance of the government.** Table 2 establishes that the government was likely to open CCCs and build ETUs 2 km closer to places affected by EVD, compared to unaffected ones (Panel A, columns 1 and 2). Villages affected by the disaster were also 13

[23]I refer to the basic theoretical model of Dixit and Londregan (1996), which built on Cox and McCubbins (1986) and Lindbeck and Weibull (1987), as well as recent papers by Strokes (Strokes, 2005, Strokes et al., 2011) that study which types of voters (e.g. core or swing) politicians potentially target in the allocation of resources. Despite the empirical evidence (Ward and John, 1999, Dahlberg and Johansson, 2002, Arulampalam et al., 2009, Vaishnav and Sircar, 2010) favoring swing voters, the overall picture is not clear as the results often depend on the definitions of "swing" and "core" voters, as well as on the (individual or aggregate) levels of the data analyzed.

[24]Recent empirical studies find that African politicians allocate more resources to coethnic groups, resulting in them having better health and educational outcomes (Franck and Rainer, 2012), higher economic development as measured by nightlights (Hodler and Raschky, 2014), better road infrastructure (Burgess et al., 2015), and higher access to foreign aid (Jablonski, 2014 and Briggs, 2014).

[25]I define "core villages" as those which supported the incumbent party (UP) in the 2011 Senatorial election, and villages with a percentage of people who share characteristics with the incumbent party higher than the median, in this case defined by having the same ethnicity as the President (Gola and Kru tribes).

percentage points more likely to have experienced any instances of safe burials (Panel A, column 3), and had on average 2 more persons safely buried (Panel A, column 3). Results are robust to the alternative instrumental variable approach.[26] Additionally, the government provided consistent relief effort to those villages which experienced EVD prior to and after the arrival of foreign aid in September 2014 (Table 2, Panel B). However, the allocation of resources was slightly higher in villages affected at earlier stages, since these locations were more in need of relief effort to stop the epidemic from spreading further.[27] Table 3 examines the intensive margin of the epidemic and confirms a higher response towards the victims of the disaster. The government was indeed more responsive in villages with a higher number of cases per capita (Table 3, Panel A) as well as in those villages hit for more months (Table 3, Panel B).

Even though the government provided more resources to villages hit by the disaster, foreign aid only arrived in the middle of the contagion, allowing the incumbent party to build ETUs, CCCs, and send burial teams, mainly in the second part of the epidemic. Using administrative data on the relief effort provided, Table 4 explores the performance of the government for villages hit by the disaster at different points in time. Despite the government providing more relief effort by the end of the epidemic, to places affected at earlier stages (Panel B, column 1, 0.443 standard deviation increase in an index of response[28], for villages hit in the first part compared to 0.260 for those hit in the second part), villages hit by EVD before September 2014 were affected on average for 2.8 months, compared to 1.3 months for villages hit after the arrival of foreign aid (Panel B, column 2). Similarly, villages hit at earlier stages took on average of 2.6 months longer to recover compared to villages hit later on (Panel B, column 3), suggesting that the response of the government was limited at early stages of the epidemic. Columns 4 and 5 describe in fact how the governmental relief effort was delayed in those villages hit by EVD in the first part. Exploring how much time the government took to build ETUs, while villages affected in the first part had an ETU built on average 3.2 months *after* they were hit by EVD (Panel B, column 4), villages affected at later stages had an ETU built close by 2.1 months

[26]Even though the magnitude of the OLS and IV coefficients are different, recall that the two specifications estimate different coefficients. While the OLS specification estimates an Average Treatment Effect (ATE, on the full population), the IV specification estimates a Local Average Treatment Effect (LATE, on the compliers). The compliers are those moved by the instrument, i.e. those who are more likely to be affected by the outbreak because they live closer to the EVD place of origin. For example, the compliers might be those who are more connected, either through road networks or with higher access to information. To check that this is true, I re-estimate the IV coefficients on the sub-sample of more isolated villages (25 km or more further away from the main city, at the median value) as well as on the sub-sample of villages with lower access to radio or phone (at the median values). I do find that the IV coefficients are much closer in magnitude to the OLS estimates (not shown), suggesting the compliers might be very different than the full population and this might explain why the magnitude of the OLS and IV coefficients are different.

[27]Results are robust to a variety of additional empirical checks reported in Table B1 in Appendix B, as the use of: additional controls (columns 1 to 4), an alternative definition of EVD (columns 5 to 8), spatial standard errors (columns 9 to 12), and a definition of EVD at a higher geographical level, i.e., clan (columns 13 to 16).

[28]The index of government response at the village level is constructed as an indicator equal to 1 if a burial team was sent to the village or if the closest ETU or CCC was within a 10 km radius.

before being hit by EVD.[29] Safe burial teams, instead, were sent to nearly every village prior to the recording of their first EVD case. The coefficients in column 5 are, in fact, negative, but highlight a difference of 7.7 months between villages affected in the first and second parts of the epidemic. Overall, the results show that the governmental response was delayed in villages hit by EVD before the arrival of foreign aid, compared to those villages affected after September 2014. This is why villages which experienced EVD at early stages were affected for longer time, despite having received more foreign resources by the end of the epidemic.

5.2. **The strategic behavior of the government.** Table 5 explores whether the incumbent party had any political incentives in the allocation of relief effort, focusing on swing villages.[30] Linking each respondent's village to the closest electoral precinct, I define a measure of competitiveness as a dummy variable indicating a margin of 10 percentage points or lower between the vote share of the winning and first losing political party in the 2011 Senatorial election.[31] Estimates in Table 5, Panel A, show that, among the villages affected by the epidemic, the government opened CCCs about 3 km closer (column 1) and built ETUs about 2 km closer (column 2) to swing villages. The results are consistent with anecdotal evidence indicating that the decisions on the location of CCCs and ETUs were made by the MOH, sometimes jointly with the international partners, and by local leaders and staff at the county level. Despite the coefficients not being statistically significant on other measures of relief (Table 5, columns 3 and 4), they are in the right direction. In particular, swing villages affected by the disaster before the arrival of foreign aid received a higher response in terms of burial teams, while the government constructed CCCs even closer to villages affected by EVD at later stages (Table 5, Panel B) compared to non-swing villages hit at each stage of the epidemic.

Overall, the evidence suggests that the government might indeed have had incentives to gain political support in anticipation of the Senatorial election, in swing villages affected by the disaster. The government did not respond more in places with core voters or where the population had the same ethnicity as the President (Table A6).[32]

5.3. **The misallocation of resources.** Since more relief effort was provided towards swing villages affected by the contagion, I next examine whether governmental resources were misallocated for political motives. To assess this, I construct a spatio-temporal epidemiological model

[29]I assign 0 for the time to the first ETU (burial) for villages never hit by EVD. Results are robust to the exclusion of control villages, and comparing only villages affected by EVD at early and late stages.

[30]There is no statistically significant correlation (correlation coefficient 0.0055) between the measures of EVD and the measure of political competitiveness, controlling or not controlling for the set of covariates in the models.

[31]Results are robust also to a margin of votes of 5 percentage points or lower or to a measure of EVD on the intensive margin, as reported in Table 2 in Appendix B, Panel A and B, respectively.

[32]I constructed an indicator of "incumbent support", which takes a value 1 if the vote share of the incumbent party in the 2011 Senatorial election was higher than 50% (at the 90th percentile of the distribution), as well as an indicator of "tribe", which takes value 1 if the percentage of households from either Kru or Gola tribes is higher than the median. The President of Liberia is, in fact, ethnically a mix of Kru and Gola Liberian tribes, and also has German ancestors.

where the number of EVD cases in each month is a function of an endemic and an epidemic component of the outbreak. Specifically, the endemic component only captures the number of cases in March 2014, based on basic socio-demographics and taking into account the size of the population. The epidemic component is modeled as the sum of an autoregressive effect, i.e., the reproduction of the disease depends on the counts in the same village the month before, and a neighborhood effect, i.e., the disease depends on the counts transmitted from neighborhood villages (Appendix E for details). Using the observed EVD counts, I fit the model until September 2014, the time when foreign aid started flowing into the country, and then I predict the number of EVD counts from October to the end of the epidemic, under the assumption that the government would not have taken any action. Thus, I use the predicted counts in the second part of the epidemic as a proxy for places where the epidemic had the potential to spread further and where the government should have allocated foreign resources. I standardize the total number of observed and predicted counts of EVD per each village to have a proxy of observed and predicted probabilities from 0 to 100%.[33]

First, I assign a proxy of observed costs at the village level based on the USAID budgeted costs for the three types of relief effort I observed in the data, i.e., the management of ETUs and CCCs, and the deployment of burial teams. Specifically, I assign a cost per buried person in the village and costs for the opening an ETU and a CCC, inversely proportional to the distance from the village.[34] Second, keeping constant the total observed costs to provide relief effort in Liberia ($61.5 million), I re-assign how much the government should have spent in each village based on the predicted probability of getting EVD estimated from the epidemiological model. Finally, I construct a measure of misallocation at village level indicating the difference between how much the government spent (observed costs) and how much it should have spent given the predicted counts of EVD (predicted costs). The government over-spent in about 52% of the villages, while it under-spent in the remainder. On average, it over-spent $6,500 in villages hit by EVD, while it under-spent $489 in villages which never recorded a case.

Table 5, Panel A, column 5 shows that the government targeted on average $42,632 more in swing villages hit by the epidemic, for a total of $6.3 million (about 10% of the total observed costs). The increased misallocation per swing village affected by EVD derives both from an increase in over-spending (Table 5, Panel A, column 6) and a decrease in under-spending (Table 5, Panel A, column 7), even though the estimates are not statistically significant at 10% level. Table 5, Panel B also illustrates that the government misallocated resources mainly towards

[33] I construct village-specific probabilities as the share of EVD counts in Liberia, i.e., as the total number of EVD counts in each village divided by the total number of counts in the country.

[34] From the costs in Table F1, I estimate a cost per buried person of $15,646, i.e., the cost of 56 burial teams divided by the average 42 safe burials that each team provided at village level. I assigned the total cost of an ETU ($28,615,789) and of a CCC ($5,317,500) if the village has an ETU/CCC within a 1 km radius. If further away, I assign the cost divided by the distance. Results are robust to alternative definitions of costs, such as computed in number of units or using a cost of burial teams at the village level rather than per buried person (not shown). Note that each village is assigned to a positive cost based on its distance to the closest ETU/CCC.

swing villages affected at early stages of the epidemic (about $229,140). Column 8, however, suggests that the additional resources spent in villages where fewer resources were needed, did not help these villages to recover faster from the contagion, suggesting that the misallocation could have come with a cost for citizens' welfare. I also do not find instances of misallocation in villages with core voters or with an ethnicity similar to that of the President (Table A6, column 5). Results on misallocation are robust to the exclusion of the most affected city, i.e., the national capital (Table B3, column 1), to the exclusion of two main counties which historically favored the two main opposition parties (CDC and LP, Table B3, column 2) as well as to the removal of big outliers (Table B3, column 5) or the inclusion of district fixed effects (Table B3, column 6). The estimates are even bigger in magnitude when I narrow down the definition of swing locations to villages in which the incumbent party slightly won or lost (Table B3, column 3), when I define a measure of swing locations at the clan level, considering only locations where more than 20% of the villages (at the 75th percentile of the distribution) are swing (Table B3, column 4), as well as when I examine the effects using a measure of EVD on the intensive margin (Table B3, Panel B).

6. The Citizens' Reaction to the Ebola outbreak

The different performance of the government in providing relief effort, and its political incentives in allocating resources, suggest that citizens who experienced EVD at different stages might have had different political reactions to the actions of the incumbent party. Tables 6 and 7 examine, in a difference-in-difference framework at the electoral precinct level, how the disaster affected voting behavior in the 2014 Senatorial election, while Tables 8 and 9 explore changes in political perceptions, such as trust and perceived corruption, towards governmental institutions as well as individual opinions on government's failures.

6.1. **Voting behavior.** Starting from voter turnout, the existing literature details conflicting predictions. On the one hand, political science research argues that economic shocks such as natural disasters negatively impact social and economic resources (e.g. job opportunities, income and family relationships). The displacement of these resources, critical for civic engagement, might then reduce people's participation in politics and voluntary organizations (Verba et al., 1995). On the other hand, research from sociology and psychology argues that individual exposure to the disaster might highlight the value of the actions of the government in mitigating the economic costs of the crisis and lead individuals to be more involved in politics (Jackman, 1987, Hajnal and Lewis., 2003, Pacek et al., 2009, Myatt, 2015).

In line with the latter channel, Table 6, Panel A, shows an increase of 2.7 percentage points in turnout in precincts affected by EVD compared to those which never experienced it (column 1). In fact, 83 more people went to vote in precincts hit by EVD compared to unaffected ones (column 4). In particular, both groups of individuals hit before or after the arrival of foreign aid, were more likely to turn out to vote (6.5 and 1.9 percentage points respectively, Panel

B, column 1). However, in absolute terms, only precincts hit by EVD at later stages had on average 116 more citizens who turned out to vote. These patterns suggest that the disaster highlighted the governmental capacity to help the victims, especially after the influx of foreign aid in September 2014, when the incumbent party provided an improved relief effort.

Turning to political support for the incumbent party, I follow the retrospective voting behavior literature (Key, 1966 and Fiorina, 1981). Supported by the facts that citizens affected by the disaster do not attribute any responsibility to the government (Table A9) and that more than 90% of them reported having information about the outbreak (Table A4), I argue that voters can be considered to have enough information to (rationally) judge the actions of their representatives. They observe the events in the world (e.g., disaster), its outcomes (e.g., income, deaths), and the actions taken by politicians, and then they evaluate the performance of elected officials and attribute responsibilities at the time of voting. A priori, it is ambiguous whether political support for the incumbent party in 2014 should increase or decrease in comparison to 2011 elections, when comparing those affected by the disaster with citizens who never experienced it. This might depend on how much citizens value the direct governmental allocation of resources to themselves or how much they value the actions taken by the government to limit the overall size and duration of the contagion. In the latter case, voters' judgment might also depend on the level of information they had about which would be the most efficient allocation of relief effort to limit the spread of the contagion.

Overall, I do not find statistically significant differences in vote share of the incumbent party at 10% level (Panel A, column 3), despite the coefficient being negative (-0.021, SE=0.017). Still, in absolute terms, the incumbent party lost 63 votes in each electoral precinct affected by EVD (Panel A, column 4) and its margin of votes decreased by 4 percentage points (Panel A, column 5). However, consistent with a delayed and limited performance of the government at early stages of the epidemic, individuals hit by EVD in the first part were less likely to vote for the incumbent (10.1 percentage points in vote share and 173 votes, Panel B, columns 3 and 4). In contrast, the availability of foreign resources allowed the incumbent party to show an improved relief effort and not to lose votes from those affected in the second part (Panel B, columns 3 to 5). Estimates are robust to other empirical specifications (Table B4).[35]

Even though the incumbent party lost political support in villages where the first EVD case was recorded before the arrival of foreign aid, I also find evidence that more resources were misallocated towards swing villages hit by the contagion ($42,632 on average), and specifically towards villages hit in the first part ($229,140). The next obvious question to ask is whether the incumbent party lost or gain support in these villages, depending on whether citizens were able to punish for the unnecessary relief effort provided in their villages or whether they

[35]Table B4 shows robustness of the estimates on turnout and vote share of the incumbent party to: (i) an un-weighted specification (columns 1 and 2), (ii) the addition of other control variables (columns 3 and 4), (iii) the use of different definitions of the EVD indicator (columns 5 and 6), (iv) the use of spatial standard errors (columns 7 and 8), and (v) matching difference-in-difference (columns 13 and 14).

primarily care about the direct allocation of resources to themselves. I find that in villages where misallocation was higher, i.e. swing villages hit by EVD at early stages, the incumbent party gained 15.3 percentage points in vote share (Table 7, column 3, Panel B). This completely overcomes the loss in vote share in non-swing villages affected by the disaster in the first part (13.3 percentage points in vote share), suggesting that the misallocation of resources helped the government to maintain its political support. Results appear then to be in line with the latter channel. However, they can also be consistent with a lack of perfect information about which other villages would need resources more, to limit further the spread of the disease. I also find that, among villages hit by the epidemic, turnout was 4.9 percentage points higher in swing villages compared to non-swing ones (column 1, Panel A).

Finally, given the high participation of several political parties in the elections, I also investigate whether other parties lost or gained votes after the contagion (Table A7 in Appendix A).[36] I find some substitution between vote shares of the main opposition party (CDC) and other small parties over the entire epidemic; CDC lost 5 percentage points (column 1), while other political parties gained votes by a higher magnitude (7.3 percentage points, column 4). While the disaster decreased the vote share of the CDC, and increased the vote share of the third national party (LP) and other parties for those affected in the first part of the epidemic, it mainly increased the vote share of other parties in the second part. Overall, both the incumbent and the main opposition party lost politically support specifically in villages affected at early stages which experienced a limited response. This is in line with the fact that both political parties were primarily and locally involved during the response, and they both had enough political power in the legislature to find ways to provide a better relief effort early on.

6.2. **Political perceptions towards the government.**

6.2.1. *Trust and perceived corruption.* Using survey data on 2,265 individuals in Liberia, Table 8 studies whether the disaster affected self-reported levels of trust and perceived corruption towards governmental institutions. I collected data on level of trust (on a scale from 0 to 10) and perceived corruption (on a 5-step scale, from "strongly disagree" to "strongly agree") on the President, the government, the legislature, the NEC, the revenue department, local authorities, national police, and the main opposition party (CDC). Following Kling et al. (2007), I constructed indexes grouping governmental institutions (column 1 and 4), with the exception of the opposition party (columns 2 and 5). I also separately analyzed perceptions towards the MOH and health workers due to the important role they played during the response (columns 3 and 6). The indexes are constructed from dummy variables equal to 1 when the respondent had a high level of trust (equal to or more than the median) or agreed or strongly agreed with

[36]Following previous studies in Liberia (Mvukiyehe and Samii, 2015), I categorize other political parties as follows: the main national opposition party (CDC) and the third national party (LP), based on the percentage of national votes received in 2011; I also group the independent candidates (i.e., individuals who claim no affiliation to any existing party) into one category and other smaller political parties in a separate category.

the statement that a certain institution was corrupt. Overall, individuals affected by EVD are less likely to trust the government in general (Panel A, column 1, 0.12 standard deviation in the index of trust), and this is consistent among individuals hit at different stages of the epidemic (Panel B, column 1). Individuals hit by EVD are also more likely to believe that both the government and the opposition are corrupt (Panel A, columns 4 and 5, 0.142 and 0.254 standard deviation in the index of corruption). In fact, there were serious scandals in the news entailing unaccounted foreign aid provided to the government.[37] I do not find differential effects by respondents in swing or non-swing villages (not shown).

Exploring the relationship between exposure to EVD and trust in non-governmental institutions[38] (Table A8, Appendix A), I also find that citizens in EVD affected areas were less likely to trust people in general, but they did not change their perceptions towards other non-governmental actors.

6.2.2. *Government's performance.* Despite citizens who experienced EVD not attributing different responsibility[39] (Table A9, column 1) or having different perceptions on how the government handled the epidemic (Table A9, column 5), compared to unaffected citizens, survey respondents reported different experiences with the relief effort received depending on the timing when the first EVD case was recorded in their village. In line with results in Table 4, Table 9 Panel B suggests, in fact, a subpar government performance in those villages hit in the first part, and an improved government performance in the villages hit at later stages. Citizens affected at earlier stages were 12.1 percentage points more likely to report that sick people or dead bodies were brought for treatment to the closest available health facility or to the morgue late (after four hours[40]) by NGOs or governmental health workers. Instead, individuals affected by the disaster in the second part were 5.7 percentage points less likely to report a late arrival of the ambulance (after four hours since the call) and 2.4 percentage points less likely to say that someone they knew had to wait for treatment outside ETUs/CCCs. The difference in the estimates between the different stages of the contagion is statistically significant (at 5% level). Overall, the individual experience with a delayed response and government's failures for citizens

[37]The General Auditing Commission (GAC) in Liberia audited part of the funding (about $15 million) spent by the National Ebola Trust Fund (NETF) for the period of August to October 2014, and found that about $800,000 was unaccounted for, due primarily to financial irregularities and material control deficiencies.

[38]I created similar indexes grouping institutions in three categories for the self-reported level of trust (Table A8, columns 1 to 3): (1) "people", which includes those within or outside the community, family, neighbors or friends; (2) "leaders", which includes traditional and religious leaders; and (3) "NGOs", which includes local and international NGOs. Similar categories to (2) and (3) (columns 4 and 5) were constructed for perceived corruption. I did not ask about corruption levels of people in general.

[39]I grouped institutions into: (1) "people", including the main tribes in Liberia, people from Guinea and from Sierra Leone, and traders; (2) "foreign", including white people, UNMIL, and foreign NGOs; (3) "god", given the several stories heard at the beginning of the outbreak about EVD not being a real disease, but rather a punishment from God. About 27% of respondents answered that they did not know who was responsible: these cases were coded as 0 in the estimates in Table A9, but they are robust to coding them as missing.

[40]Four hours is the median value in the distribution of number of hours that NGOs or governmental health workers took to bring suspected EVD patients to health facilities or to the morgue.

affected before the arrival of foreign aid in September 2014 corroborates a lower support for the incumbent party at the time of voting by this group of citizens.

7. Alternative Mechanisms

Aside from the improved performance of the government due to the arrival of foreign aid in September 2014, other factors might explain the heterogeneous voting behavior by part of the contagion. First, individuals hit by the disaster at different stages could have been economically or psychologically affected in a different way. In fact, even though the EVD outbreak overall was considered a major economic shock (WBG, 2015c) which affected the whole of Liberia, travel restrictions and quarantines were imposed mainly in the first part and most of the unexplained deaths were concentrated in the earlier stages. Table A10 describes to what extent respondents perceived that their community or family was badly hit (as a proxy of psychological cost) and whether their working income was lower at the time of the interview compared to the end of 2013 (as a proxy of economic cost). There is no statistically significant evidence that individuals affected by EVD experienced worse psychological or economic costs compared to unaffected ones. Everyone was, indeed, equally likely to feel badly hit (20%) and earn less income at the time of the interview than in 2013 (41%). Lack of differential effects, specifically on income, is not surprising and confirms other studies' findings (Bowles et al., 2016) that the economic effects of EVD on production, employment, and trade were at the national level, and did not affect villages which experienced EVD more than unaffected ones. I also do not find any difference in costs for citizens affected at different stages, suggesting that this channel is not an important explanation of the heterogeneous voting behavior.

Another potential mechanism which might explain the differential voting behavior among citizens affected by EVD before or after the arrival of foreign aid, is the level of information which both citizens (and government) were in possession of at different stages of the outbreak. Given the unexpected nature of the epidemic, the knowledge about EVD was very low in the first months, and everyone over time learned appropriate ways to fight the contagion. Citizens affected at early stages had to learn without much help from the government how to tackle EVD, whereas villages affected at later stages were more informed from the outset and knew what to do. Unfortunately, I lack data on how knowledge changed over time to understand how much this channel contributed to the differential voting behavior, in addition to a limited governmental response before the arrival of foreign aid. However, I asked survey respondents retrospectively about the information they received during the epidemic. I can then test whether citizens affected at different stages of the epidemic reported access to different levels of information about EVD and the actions taken by the government. Table A11 in Appendix A suggests that knowledge might have been slightly higher at later stages. However, estimates should be interpreted cautiously because more than 90% of the respondents received some information during the epidemic, and the coefficients by part of the epidemic are small in magnitude and not statistically different from each other.

I also explore heterogeneous effects in villages with ex-ante high or low access to media outlets, as defined by a dummy variable equal to 1 if the percentage of households owning a phone or radio in 2008 was higher than the median. Assuming that, in villages with a higher initial level of information, learning about EVD could have been potentially lower, the impacts on voting behavior should be muted in villages affected by EVD and with higher ex-ante access to media outlets. In Table A12, however, I find that there are no consistent differential impacts on voting behavior by initial access to information, with the exception of the incumbent margin of vote share, suggesting that this channel might not play a primary role.

Finally, it is worth mentioning that political campaigning could have been more aggressive after the Senatorial election was postponed and closer to the actual voting day, as this would correspond precisely to the second part of the epidemic. As described in Section 3, due to fear over the contagion, political campaigning was not officially allowed until five days before the day of the election in December 2014. However, I cannot exclude the possibility that politicians campaigned informally before this, despite the warnings, and more vigorous campaigning closer to the election day could have contributed to why the incumbent party did not lose votes from citizens affected by the disaster in the second part.

8. Cost-Benefit Analysis

8.1. **Saving lives with an earlier response.** I conduct a cost-benefit exercise to estimate how many lives could have been saved if the government had dedicated resources to promptly respond to the epidemic. I start from 2015 USAID budget costs for the epidemic in Liberia (Table F1) to compute single costs for the relief effort analyzed in this paper: the management of 31 ETUs and 78 CCCs, and the deployment of 74 burial teams which performed on average 42 burials per village. Table F1, Panel B shows that the total budgeted costs were approximately \$1.35 billion. I started from these estimated budgeted costs to assign observed costs at village level (see Section 5 for details), which accumulated to a total of \$61.5 million, and an average \$6,345 for each village (Table F1, Panel C). In line with the estimates in Table 4, column 1, which shows a higher relief effort provided to places hit by EVD in the first part, these calculations confirm that the government spent on average \$106,834 for each village hit at early stages of the epidemic, while it spent only \$28,493 for each village hit at later stages, and even less (\$3,602) in villages never affected. In the data, I observe that, while the response to the epidemic[41] in the second part was almost immediate (0.25 months), villages hit in the first part received relief effort on average 3.18 months later. Hence, I calculate that the government spent an additional \$78,340 in each village hit at early stages compared to each village affected later

[41]I consider the construction of ETUs as the main example and I exclude prevention activities.

on. Since \$78,340 represents the additional cost of three months' delayed response, I assume that the cost of one month of delay corresponds to one third of that value, i.e., \$26,113.

Suppose now that the international community or the government had been able to allocate resources to villages hit between March and September 2014, on average one month earlier, delaying the response by two months rather than by three. How many lives could have been saved? In this scenario, the government would have spent an additional \$52,226 (two thirds of \$78,340) for each village hit at early stages of the epidemic. Considering that, when the government spent \$106,834, the average village took 4.26 months to fully recover, the additional spending of \$52,226 would correspond to a recovery time of 2.08 months (Table F2, Panel B, column 4). This implies that a village hit at the early stages would have taken to recover an initial 1.60 months - the baseline level estimated for villages hit at later stages, which received an almost immediate response - plus an additional 2.08 months, estimated from the two-month delayed response rather than three months. As a result, these villages would have taken only 3.68 months (Panel B, column 5) to recover with a two-month delayed response rather than the estimated 4.26 months with a three-month delayed response. Given the mean number of EVD cases (suspected deaths or confirmed cases) in villages hit at early stages of the epidemic, providing relief effort one month earlier would have saved about 391 lives and avoided 202 infections (Panel B, column 8). With similar calculations, providing relief effort two months earlier could have saved 1,090 lives and avoided 564 infections (Panel B, column 13).[42] The last estimates correspond to about 22% and 24%, respectively, of the total number of deaths and confirmed cases in the dataset.

8.2. **Saving lives without misallocation of resources.** I conduct a simple cost-benefit exercise to estimate how many lives the government could have saved if there had been no misallocation of resources towards swing villages, but if, instead, the incumbent party had allocated these extra resources towards the victims of the disaster.

First, I estimate in Table F3 the total number of lives saved during the outbreak. Considering only the three types of response analyzed in this paper, I assume that 55% of the patients treated at ETUs or CCCs could have been saved.[43] I also assume that, for each person safely buried, the main care giver could have been prevented from getting infected and dying. Given these assumptions, a total of 4,604 lives could have been saved through the management of ETUs and CCCs, and the deployment of burial teams.[44] Second, I estimate an approximate cost (in\$) per life saved, using the computed costs in the analysis at village level. Since a total of \$61,455,152 were spent for the three types of relief effort in the analysis (column 1), and

[42]Table F2 also provides estimates based on the average number of cases for villages affected in the second part of the epidemic and over the entire outbreak as a reference.

[43]The overall fatality rate of the epidemic is in fact 45% (CDC, Ebola updated).

[44]It is reassuring that this number is lower than the total number of lives saved during the entire epidemic in Liberia. In fact, about 5,860 lives were saved - the difference between 10,666 infections and 4,806 deaths - taking into account a wider range of relief effort provided with respect to the one considered in this analysis (CDC, Ebola updates).

I estimate that 4,604 lives were saved through the spending of these resources (column 2), I calculate an approximate cost per life saved of $13,348 (column 3). Next, we turn to the finding that $42,632 were misallocated (Table 5, column 5) towards each swing village affected by EVD. This corresponds to a total of $6,309,536 for the 148 villages in this category. As a result, if these resources had been spent towards other victims, 473 lives could have been saved (column 6), corresponding to about 9% of the total number of deaths in the dataset.

Both exercises are, however, not without limitations. First, the initial data used to calculate costs at village level are not real expenditures during the EVD response, but rather the budgeted amounts taken from the US Government and USAID for the year 2015. Second, for the purposes of the analysis, I consider only the three main types of relief effort for which I have data and that I used in the analysis (ETUs, CCCs, burial teams). The cost-benefit analysis does not take into account other costs, such as information campaigns, contact tracing, and training of other health workers. In addition, the exercise only includes the costs associated to the management of an ETU/CCC, but it excludes the costs of constructing an ETU/CCC because of the lack of information in the US Government and USAID 2015 budget. Third, the exercises assume a linear relationship between costs and number of lives saved. Finally, the number of cases, in particular the deaths, might be underestimated because an earlier response could have avoided potential infections and thus avoided additional deaths at later stages of the epidemic. Overall, these calculations might then under-estimate the number of lives which could have been saved during the contagion. Despite these limitations, these exercises are important because they highlight the fact that the human costs of the outbreak could have been reduced with a more targeted response to the epidemic.

8.3. **Winning seats in the Senate.** Section 8.2 shows that the governmental misallocation of resources towards swing villages, among those affected by EVD, came at a cost for citizens' welfare. However, how beneficial was this misallocation for the incumbent party's victory in the 2014 Senatorial election? Given the low number of seats in the Senate - only 15, one per county - it is hard to formally draw conclusions. However, Table F5 shows descriptively the results of the 2014 elections. Specifically, I computed how many votes the incumbent party needed to win a seat as the absolute difference in the vote share between the losing incumbent party and the winning political party multiplied by the total number of votes in each electoral precinct. Then, I assigned a unit cost per vote as the constant budget constraint of the government (the total observed costs of $61.5 million) divided by the total number of voters in the 2014 Senatorial election. The table shows that the incumbent party (UP) won four out of 15 seats in the election (Table F5, column 5). These four seats were among the cheapest to win (Table F5, column 2) and they corresponded to the counties where the incumbent party misallocated more resources (Table F5, column 4). Interestingly, the incumbent party under-spent in the most expensive counties to win, which were also exactly those historically supporting other political parties. The descriptive statistics seem to suggest that higher misallocation towards the politically cheapest counties might have helped the incumbent government to be the political party winning most of the seats in the election.[45]

9. Conclusion

This paper makes use of the unique setting given by the evolution of the 2014 West Africa Ebola outbreak, combined with the timing of Senatorial elections in Liberia, to show that governments are politically motivated in the allocation of resources, even during a major health epidemic. The analysis shows that the availability of foreign aid allowed the incumbent government to mitigate the political consequences of the disaster. Due to limited performance at early stages of the contagion, the incumbent government lost votes from those citizens affected by EVD before the arrival of foreign aid. However, it was able to maintain its political support by providing an improved response in those villages affected after the arrival of foreign aid, and by disproportionately targeting swing villages.

Several policy lessons can be drawn from these findings. First, citizens are very well able to punish politicians at the time of voting, if they do not see a good performance. This punishment should in principle create the right incentives for governments to perform better in future crises. Nonetheless, it is foreign resources that appear to have played the major role in the fight to end the epidemic. It is unquestionable that governments need to become better-prepared to face the next disaster. Extreme events, such as highly infectious diseases or weather disasters are expected to remain a worldwide threat (UNISDR, 2015). Even though they might be unpredictable, the number of deaths and the amount of damage can be mitigated through appropriate governmental actions. Feeling compelled to support the victims when disasters are happening, simply for the recognition given to good politics, is not enough. Helping poor countries to mobilize resources in preparation for future disasters is critical, and it is particularly important to stop health epidemics at early stages.[46] This would drastically limit costly economic and political consequences for the citizens.

Furthermore, in the studied setting, I show that even when more resources were available - for example due to the arrival of foreign aid - the government's incentives did not appear to be aligned with citizens' welfare: rather, the political distortion of resources was costly in term of human lives. The findings that the individual level of trust and suspicion of corruption towards the government deteriorated suggest that citizens also suspected foul play of the foreign aid received for political gains. However, citizens were not able to fully hold politicians accountable.

[45]At the county level, the correlation between the cost to win a seat and misallocation is negative at -0.34, but not statistically significant. However, analysis at the village level shows that the villages affected by EVD and cheaper to win (defined as below the median cost) have statistically significant higher misallocation compared to villages affected by EVD and more politically expensive (not shown).

[46]In line with this, for example The World Bank had just set up the Pandemic Emergency Financing Facility (PEF) in July 2017. See http://www.worldbank.org/en/topic/pandemics/brief/pandemic-emergency-financing-facility; see http://blogs.worldbank.org/health/disease-outbreaks-are-still-certainty-no-longer-uninsured for more discussion.

They did not punish their representatives at the time of voting for the additional misallocated resources they received, suggesting that also during health epidemics they primarily valued the allocation of resources to themselves. Therefore, another important policy lesson is the evident need for higher transparency and accountability standards to ensure that resources are used for the purposes they are allocated for. A better coordination between international partners and governments, including local officials, seems critical to efficiently track how and where aid is spent. This would improve the management of the resources allocated to combat the impact of future health epidemics.

Overall, this study has demonstrated that politics play a considerable part in how governments face and overcome crises. The results investigated from the Ebola outbreak in Liberia are a good example of how political incentives drove the allocation of resources even at the time of a health epidemic. Understanding how costly to citizens are the political distortions of relief effort in other health epidemics should be the object of future studies.

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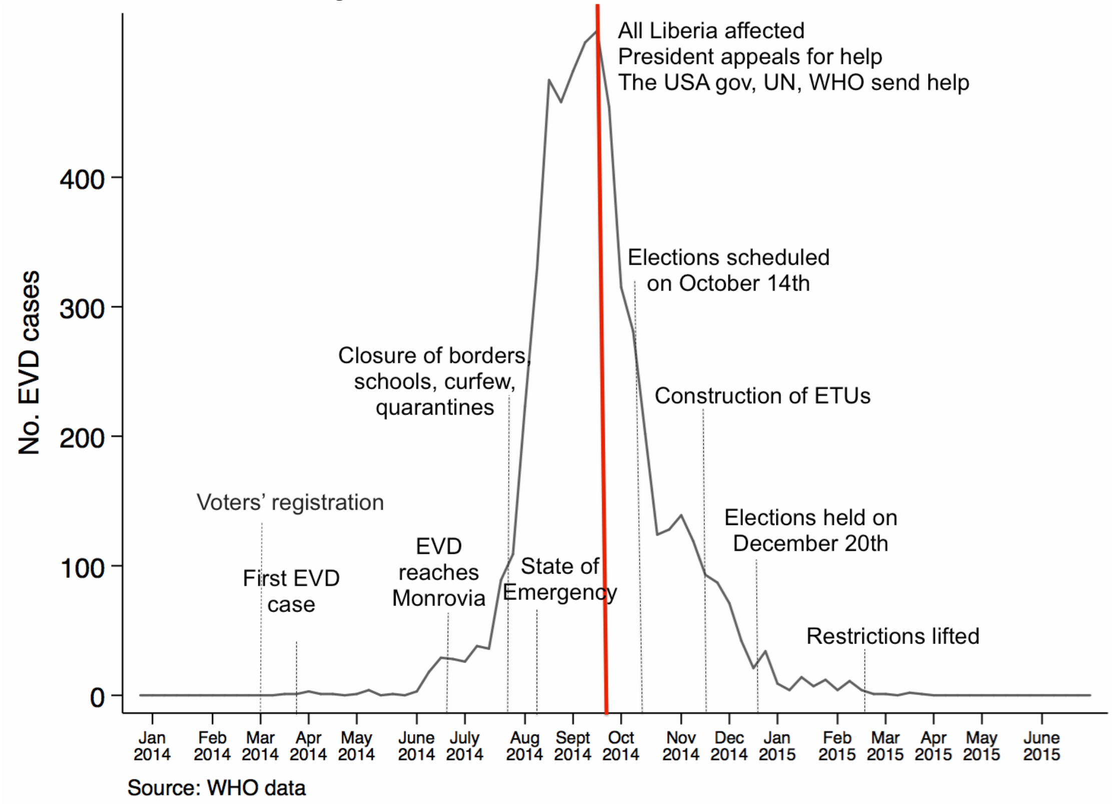
Main Figures and Tables.

Figure 1: Timeline of EVD in Liberia



Map 1: EVD epidemic in Liberia

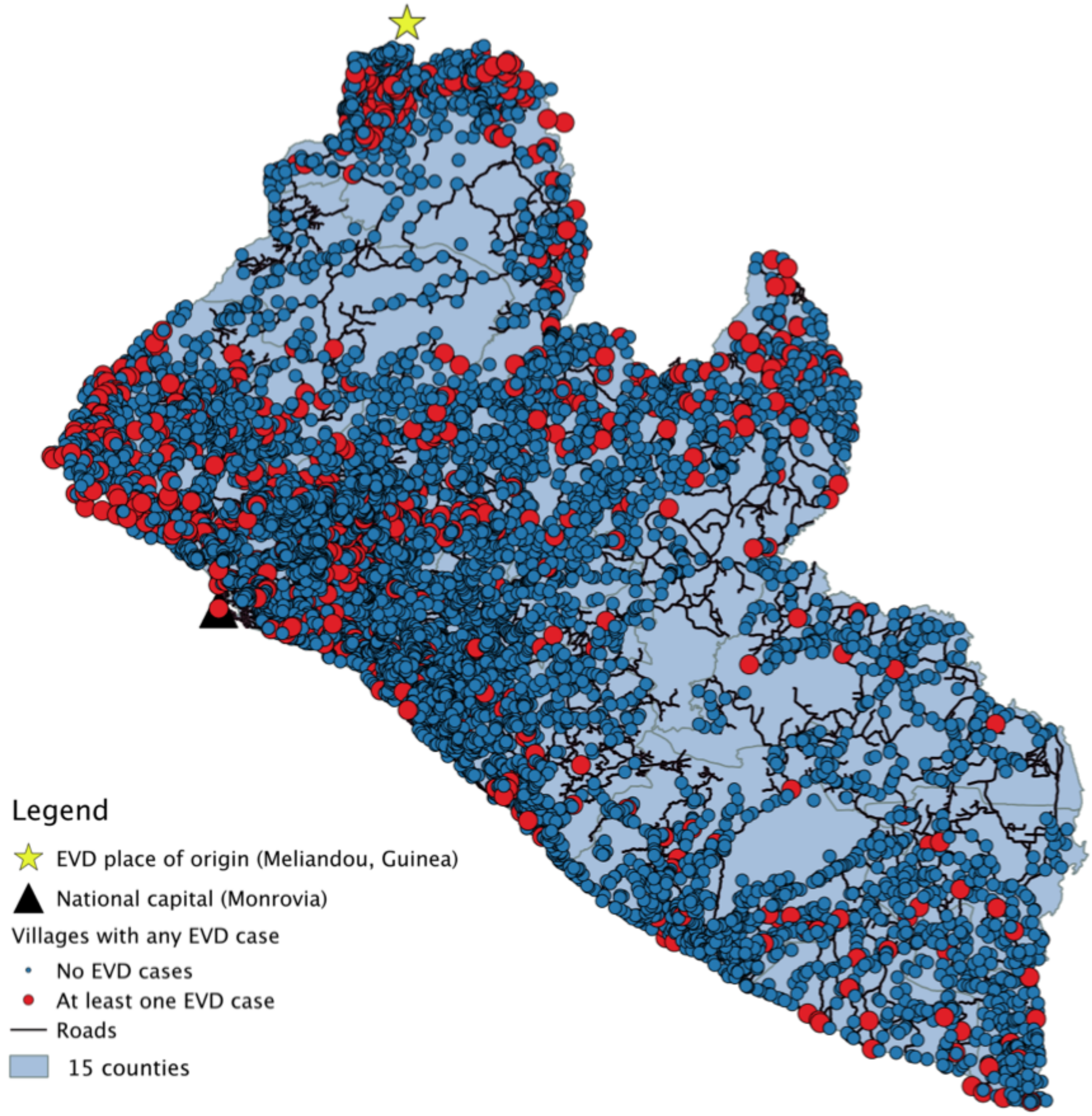


Table 1: The predictors of EVD

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	Any EVD case					
Sample	Village		Individual		Electoral precinct	
Dist EVD origin (100km)	-0.0197*	-0.0249	-0.00211*	-0.000433	-0.00169***	-0.00366***
	(0.00804)	(0.0145)	(0.00103)	(0.00155)	(0.000426)	(0.000780)
Dist EVD origin sq (100km)	0.00574***	0.00697*	0.000631**	0.000492	0.000259***	0.000569***
	(0.00160)	(0.00272)	(0.000201)	(0.000323)	(0.0000641)	(0.000113)
Dist Monrovia (100km)	-0.0355***	-0.0366***	-0.00250***	-0.00297**	-0.00115***	-0.00214***
	(0.00612)	(0.00887)	(0.000642)	(0.00110)	(0.000261)	(0.000421)
Dist health facility 2008 (100km)	-0.265***	-0.250***	-0.0122	-0.0125	-0.000749**	-0.000702**
	(0.0540)	(0.0533)	(0.00688)	(0.00721)	(0.000233)	(0.000234)
Elevation (100km)	0.0145***	0.0159***	0.147***	0.157***	0.0296*	0.0455**
	(0.00419)	(0.00431)	(0.0409)	(0.0466)	(0.0151)	(0.0154)
Population (log)	0.0325***	0.0318***	0.162***	0.173***	0.163***	0.152***
	(0.00160)	(0.00159)	(0.0238)	(0.0252)	(0.00874)	(0.00897)
Muslim pop	0.0422***	0.0274*	0.273	0.307	0.0452	0.0399
	(0.0112)	(0.0121)	(0.180)	(0.185)	(0.0596)	(0.0639)
Educ up to primary	0.00388	0.00598	0.0418	0.0826	-0.111	-0.0871
	(0.0143)	(0.0142)	(0.205)	(0.222)	(0.0952)	(0.101)
Working in agriculture	-0.00652	-0.00666	0.139	0.117	-0.0226	-0.0279
	(0.00853)	(0.00832)	(0.124)	(0.131)	(0.0530)	(0.0549)
Improved roof material	0.0106	0.00770	-0.0413	0.0190	0.0434	0.0163
	(0.00761)	(0.00771)	(0.0985)	(0.105)	(0.0530)	(0.0563)
Improved wall material	-0.00467	-0.00147	-0.0425	-0.0170	-0.0154	-0.0179
	(0.0120)	(0.0117)	(0.110)	(0.125)	(0.0820)	(0.0821)
Own radio	0.00528	0.00282	-0.0808	-0.0510	0.0738	0.0913
	(0.0105)	(0.0102)	(0.177)	(0.181)	(0.0701)	(0.0727)
Own phone	0.00169	0.00319	0.319	0.242	-0.124	-0.0740
	(0.0166)	(0.0161)	(0.212)	(0.259)	(0.122)	(0.125)
Turnout (2011)	0.00936	-0.00459	-0.333	-0.470	-0.109	-0.114
	(0.0253)	(0.0264)	(0.286)	(0.302)	(0.122)	(0.134)
Vote share incumbent (2011)	0.0229*	-0.00867	0.00503	0.0838	0.0775	-0.0809
	(0.00929)	(0.0109)	(0.0907)	(0.136)	(0.0520)	(0.0667)
Tribes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	No	Yes	No	Yes	No	Yes
Mean Dep Var	0.0699	0.0699	0.643	0.643	0.275	0.275
No. Obs	9686	9686	2265	2265	1780	1780
Joint sign test IV (Chi square)	13.99	7.47	20.47	7.6	15.61	25.44
P-value	0.0009	0.0239	0.0000	0.0224	0.0004	0.0000

Notes: This table illustrates the main geographical and socio-demographic predictors of the EVD outbreak. "Any EVD case" is constructed as a dummy equal to 1 if at least one (probable, confirmed, death) EVD case was recorded in the village (columns 1 and 2), in the village where the respondent resides (columns 3 and 4), in at least one of the villages matched to the closest electoral precincts (columns 5 and 6). The records are constructed from the MOH patient database and Global Communities safe burials. Socio-demographic controls are constructed from 2008 Population and Demographic Census. Turnout and vote share of the incumbent party are constructed from the closest electoral precinct in Senatorial Elections in 2011. Tribes include dummies for the main tribes in Liberia (Bassa, Gola, Kpelle, Mano, Vai). County fixed effects include a total of 15 indicators. The estimates are marginal effects from a Probit model, evaluated at the mean values. Standard errors are clustered at village level for columns 1 to 4, and at the precinct level for columns 5 and 6. The table reports the chi square value and the corresponding p-value for the joint significance test on the coefficients on distance to EVD place of origin and distance to EVD place of origin squared (the instrumental variable used in the analysis). *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 2: The response to EVD - extensive margin

Dependent Variable	(1) Distance to CCCs	(2) Distance to ETUs	(3) Any safe burial	(4) No. safe burials
Panel A: Entire epidemic				
Specification: OLS + county FE				
Any EVD case	-1.751***	-1.917***	0.131***	1.929***
	(0.340)	(0.505)	(0.016)	(0.240)
Specification: IV				
Any EVD case	-15.507***	-5.617	0.083*	12.102***
	(2.185)	(5.432)	(0.049)	(3.843)
Panel B: Heterogeneity by timing of first EVD case				
Specification: OLS + county FE				
First EVD case in part 1	-4.076***	-4.416***	0.054*	5.831***
	(0.858)	(1.160)	(0.030)	(1.749)
First EVD case in part 2	-1.248***	-1.376**	0.147***	1.084***
	(0.359)	(0.547)	(0.018)	(0.189)
Mean Control	16.55	29.16	0.04	0.08
No. Obs	9686	9686	9686	9686
Pv p1=p2	0.062	0.19	0.052	0.012

This table illustrates the government's response to the extensive margin of the EVD outbreak. "Any EVD case" is constructed as a dummy equal to 1 if at least one (probable, confirmed, death) EVD case was recorded in the village. "First EVD case recorded in p1 (p2)" is constructed as a dummy equal to 1 if at least one (probable, confirmed, death) EVD case was recorded in the village before or in (after) September 2014. The records are constructed from the MOH patient database and Global Communities safe burials. The dependent variables are constructed as distance (by road, in km) from the village to the closest Community Care Center (column 1) or Ebola Treatment Unit (column 2), whether a burial team was sent to the village (column 3) and number of safe burials done (column 4). Controls not shown include elevation, distance (by road) to Monrovia, the percentage of Muslim population, and turnout and vote share of the incumbent party at the closest electoral precinct in 2011. Additional controls, chosen by the Lasso procedure (Belloni et al. 2014), include distance (by road) to EVD place of origin (only for OLS specification), population (log), the average percentage of households with improved roof and floor material and with improved water, and the average percentage of households from the main tribes in Liberia (Bassa, Gola, Kpelle, Mano, Vai). Socio-demographic controls are constructed from 2008 Population and Demographic Census. In the OLS specification standard errors are clustered at village level. County fixed effects include a total of 15 indicators. The IV specification follows procedure 18.1 in Wooldridge 2002 and uses a quadratic function of distance (by road) from the village to the EVD place of origin as instrumental variable for "Any EVD case". Standard errors are bootstrapped (500 replications). *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 3: The response to EVD - intensive margin

	(1)	(2)	(3)	(4)
Dependent Variable	Distance to CCCs	Distance to ETUs	Any safe burial	No. safe burials
Specification: OLS + county FE				
Panel A: No. cases per capita				
No. EVD cases per capita	-5.920***	1.406	0.325**	5.962***
	(2.106)	(3.487)	(0.146)	(1.755)
Panel B: No. months with at least one case				
No. months with EVD	-1.001***	-1.128***	0.025***	0.688***
	(0.154)	(0.237)	(0.006)	(0.142)
Mean Control	16.55	29.16	0.01	0.02
No. Obs	9686	9686	9686	9686

Notes: This table illustrates the government's response to the intensive margin of the EVD outbreak. "No. EVD cases per capita" is constructed as the number of (probable, confirmed, death) EVD cases recorded in the village divided by the total population. "No. months with EVD" is constructed as the total number of months over the epidemic for which at least one (probable, confirmed, death) EVD case was recorded in the village. The records are constructed from the MOH patient database and Global Communities safe burials. The dependent variables are constructed as distance (by road, in km) from the village to the closest Community Care Center (column 1) or Ebola Treatment Unit (column 2), whether a burial team was sent to the village (column 3) and number of safe burials done (column 4). Controls not shown include elevation, distance (by road) to Monrovia, the percentage of Muslim population, and turnout and vote share of the incumbent party at the closest electoral precinct in 2011. Additional controls, chosen by the Lasso procedure (Belloni et al. 2014), include distance (by road) to EVD place of origin, population (log), the average percentage of households with improved roof and floor material and with improved water, and the average percentage of households from the main tribes in Liberia (Bassa, Gola, Kpelle, Mano, Vai). Socio-demographic controls are constructed from 2008 Population and Demographic Census. Standard errors are clustered at village level. County fixed effects include a total of 15 indicators. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: The government's performance in response to EVD

Dependent Variable	(1) Index Response	(2) No. months hit	(3) No. months recover	(4) Time to first ETU [months]	(5) Time to first burial [months]
Panel A: Entire epidemic					
Specification: OLS + county FE					
Any EVD case	0.272***	1.615***	2.073***	-1.171***	-11.581***
	(0.018)	(0.049)	(0.082)	(0.120)	(0.196)
Specification: IV					
Any EVD case	0.945***	3.849***	5.051***	-0.772**	-9.454***
	(0.101)	(0.359)	(0.426)	(0.327)	(0.543)
Panel B: Heterogeneity by timing of first EVD case					
Specification: OLS + county FE					
First EVD case in part 1	0.441***	2.854***	4.253***	3.172***	-5.267***
	(0.035)	(0.225)	(0.338)	(0.141)	(0.357)
First EVD case in part 2	0.255***	1.347***	1.602***	-2.106***	-12.959***
	(0.021)	(0.037)	(0.059)	(0.107)	(0.175)
Mean Control	0.38	0.00	0.00	0.00	0.00
No. Obs	9686	9686	9686	9686	9686
Pv p1=p2	0.00	0.00	0.00	0.00	0.00

Notes: This table illustrates the government's performance in the response to the EVD outbreak, using as proxies the total resources, how long villages were affected, and the timing of the response after the first EVD case. "Any EVD case" is constructed as a dummy equal to 1 if at least one (probable, confirmed, death) EVD case was recorded in the village. "First EVD case recorded in p1 (p2)" is constructed as a dummy equal to 1 if at least one (probable, confirmed, death) EVD case was recorded in the village before or in (after) September 2014. The records are constructed from the MOH patient database and Global Communities safe burials. The "index response" is a dummy equal to 1 if the village had a ETU or a CCC within 10km radius or whether a burial team was sent. "No. months hit" is the total number of months in which an EVD cases was recorded. "No. months to recover" is the total number of months from when the first to the last case of EVD was recorded. "Time to first ETU (burial)" is constructed as the difference between the month, from 1 to 18 (January 2014 to June 2015), when the village had the closest ETU built (the first burial team was sent) and the first EVD case was recorded in the village. I assign 0 for the time to the first ETU (burial) for villages never hit by EVD. Controls not shown include elevation, distance (by road) to Monrovia, the percentage of Muslim population, and turnout and vote share of the incumbent party at the closest electoral precinct in 2011. Additional controls, chosen by the Lasso procedure (Belloni et al. 2014), include distance (by road) to EVD place of origin, population (log), the average percentage of households with improved roof and floor material and with improved water, and the average percentage of households from the main tribes in Liberia (Bassa, Gola, Kpelle, Mano, Vai). Socio-demographic controls are constructed from 2008 Population and Demographic Census. In the OLS specification standard errors are clustered at village level. County fixed effects include a total of 15 indicators. The IV specification follows procedure 18.1 in Wooldridge 2002 and uses a quadratic function of distance (by road) from the village to the EVD place of origin as instrumental variable for "Any EVD case". Standard errors are bootstrapped (500 replications). *** p<0.01, ** p<0.05, * p<0.1.

Table 5: The strategic response to EVD

Dependent Variable	(1) Distance to CCCs	(2) Distance to ETUs	(3) Any safe burial	(4) No. safe burials	(5) Misallocation ($1000)	(6) Over spending	(7) Under spending	(8) No. months to recover
Panel A: Any EVD case								
Specification: OLS + county FE								
Any EVD case X swing	-2.812***	-2.198*	0.035	0.511	42.632**	23.119	-90.741	-0.060
	(0.861)	(1.212)	(0.038)	(0.828)	(21.656)	(15.693)	(56.992)	(0.208)
Swing	0.846***	1.455***	0.010**	0.025	0.929	1.441**	0.511	-0.002
	(0.243)	(0.343)	(0.005)	(0.019)	(1.265)	(0.674)	(2.637)	(0.005)
Any EVD case	-1.127***	-1.340**	0.123***	1.814***	1.633	26.330***	82.949*	2.086***
	(0.367)	(0.561)	(0.018)	(0.301)	(12.452)	(3.067)	(49.901)	(0.096)
Specification: IV								
Any EVD case X swing	-9.931***	-14.702***	0.053	2.570	278.296*	85.103	-569.347	0.464
	(3.416)	(4.214)	(0.081)	(4.739)	(156.345)	(53.698)	(752.061)	(0.695)
Swing	2.757***	3.424***	0.006	-0.168	-15.318	-6.409	17.457	-0.053
	(0.358)	(0.454)	(0.007)	(0.287)	(9.565)	(4.724)	(27.283)	(0.043)
Any EVD case	-12.142***	-2.206	0.070	11.500**	-206.684	107.611***	1189.608	4.945***
	(1.802)	(2.877)	(0.045)	(4.936)	(226.763)	(15.168)	(813.199)	(0.475)
Panel B: Heterogeneity by timing of first EVD case								
Specification: OLS + county FE								
First EVD case in part 1 X swing	-1.744	-3.354	0.174**	2.710	229.140**	101.116	-439.845	-0.539
	(2.313)	(2.842)	(0.089)	(3.964)	(113.242)	(67.838)	(273.213)	(0.780)
First EVD case in part 2 X swing	-3.036***	-1.904	0.003	-0.039	0.361	2.958	7.010	0.028
	(0.897)	(1.311)	(0.042)	(0.358)	(6.685)	(8.373)	(7.545)	(0.149)
Swing	0.843***	1.453***	0.010*	0.029	0.742	1.452**	0.336	0.001
	(0.243)	(0.343)	(0.005)	(0.019)	(1.286)	(0.665)	(2.560)	(0.004)
First EVD case in part 1	-3.547***	-3.602***	0.015	5.204**	-121.225	45.226***	458.388*	4.379***
	(0.909)	(1.266)	(0.027)	(2.086)	(95.123)	(8.100)	(272.698)	(0.392)
First EVD case in part 2	-0.606	-0.858	0.147***	1.092***	28.380***	22.566***	-14.513	1.593***
	(0.388)	(0.610)	(0.020)	(0.203)	(6.719)	(3.201)	(10.108)	(0.067)
Mean Dep.Var.	16.55	29.16	0.04	0.08	-0.49	4.25	5.23	0
No. Obs	9,686	9,686	9,686	9,686	9,686	4,989	4,697	9,686
Pv p1Xswing=p2Xswing	0.60	0.64	0.08	0.49	0.04	0.15	0.11	0.48

Notes: This table illustrates the politically motivated government's response to the EVD outbreak in swing villages. "Any EVD case" is constructed as a dummy equal to 1 if at least one (probable, confirmed, death) EVD case was recorded in the village. "First EVD case recorded in p1 (p2)" is constructed as a dummy equal to 1 if at least one (probable, confirmed, death) EVD case was recorded in the village before or in (after) September 2014. The records are constructed from the MOH patient database and Global Communities safe burials. "Swing" is defined as a dummy equal to 1 if the difference in vote share between the winning and the first losing party in the Senatorial election in 2011, to the closest electoral precinct, was equal or less than 10 percentage points. The dependent variables are constructed as distance (by road, in km) from the village to the closest Community Care Center (column 1) or Ebola Treatment Unit (column 2); whether a burial team was sent to the village (column 3) and number of safe burials done (column 4); "Misallocation" (in $1000) is defined as difference between the observed costs and the predicted ones calculated based on the predicted counts of EVD estimated by the spatio-temporal epidemiological model (column 5); "Over (under) spending" (in $1000) refers to positive (negative) misallocation (columns 6 and 7); "No. months to recover" is the total number of months from when the first to the last case of EVD was recorded (column 8). Controls not shown include elevation, distance (by road) to Monrovia, the percentage of Muslim population, and turnout at the closest electoral precinct in 2011. Additional controls, chosen by the Lasso procedure (Belloni et al. 2014), include distance (by road) to EVD place of origin, population (log), the average percentage of households with improved roof and floor material and with improved water, and the average percentage of households from the main tribes in Liberia (Bassa, Gola, Kpelle, Mano, Vai). Socio-demographic controls are constructed from 2008 Population and Demographic Census. In the OLS specification standard errors are clustered at village level. County fixed effects include a total of 15 indicators. The IV specification follows procedure 18.1 in Wooldridge 2002 and uses a quadratic function of distance (by road) from the village to the EVD place of origin as instrumental variable for "Any EVD case". Standard errors are bootstrapped (500 replications). *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 6: The effect of EVD on voting behavior

Dependent Variable	(1) Turnout	(2) Votes total	(3) Vote share Incumbent	(4) Votes Incumbent	(5) Margin Incumbent
Specification: Diff-in-diff					
Panel A: Entire epidemic until Dec 2014					
Any EVD case X post	0.027***	83.713***	-0.021	-63.098***	-0.040**
	(0.008)	(27.678)	(0.017)	(18.891)	(0.018)
Post	-0.466***	-635.704***	-0.065***	-84.611***	0.183***
	(0.004)	(15.498)	(0.006)	(6.369)	(0.006)
Any EVD case	-0.024***	45.004	0.024*	58.851***	0.004
	(0.007)	(39.266)	(0.013)	(17.363)	(0.014)
Panel B: Heterogeneity by timing of first EVD case until Dec 2014					
First case in part 1 X post	0.065***	56.980	-0.101***	-172.529***	-0.031
	(0.013)	(41.401)	(0.029)	(41.728)	(0.030)
First case in part 2 X post	0.019**	115.974***	0.032	-26.204	-0.036
	(0.010)	(34.286)	(0.025)	(21.717)	(0.027)
First case in part 1	-0.053***	58.148	0.086***	151.810***	-0.008
	(0.009)	(51.824)	(0.023)	(36.855)	(0.022)
First case in part 2	-0.020**	6.312	-0.020	26.080	0.001
	(0.008)	(53.653)	(0.016)	(17.938)	(0.018)
Post	-0.469***	-636.566***	-0.064***	-79.861***	0.182***
	(0.004)	(15.728)	(0.006)	(6.303)	(0.007)
Mean Control 2011	0.72	977.99	0.13	104.49	0.45
Mean Treat 2011	0.69	966.62	0.24	246.03	0.38
No. Obs	3560	3560	3560	3560	3560
Pv p1Xpost=p2Xpost	0.00	0.23	0.00	0.00	0.89

Notes: This table illustrates the effects of the EVD outbreak on the citizens' voting behavior. "Any EVD case" is constructed as a dummy equal to 1 if at least one (probable, confirmed, death) EVD case was recorded in any of the villages matched to each electoral precinct. The records are constructed from the MOH patient database and Global Communities safe burials. "First EVD case recorded in p1 (p2)" is constructed as a dummy equal to 1 if at least one (probable, confirmed, death) EVD case was recorded in the village before or in (after) September 2014. "Turnout" is constructed as total number of votes divided by total number of registered voters (column 1). "Vote share incumbent" is constructed as total number of (valid) votes for the incumbent party divided by total number of votes (column 3). "Margin incumbent" is constructed as the absolute difference between the vote share of the incumbent party and the highest vote share among other political parties (column 5). Controls not shown include elevation, distance (by road) to Monrovia, and the percentage of Muslim population. Additional controls, selected through the Lasso procedure (Belloni et al. 2014), include the distance (by road) to EVD place of origin, distance (by road) to the closest health facility in 2008, population (log), and the average percentage of households from the main tribes in Liberia (Bassa, Gola, Kpelle, Mano, Vai). Socio-demographic controls are constructed from 2008 Population and Demographic Census. Standard errors are clustered at precinct level. All specifications include county fixed effects for a total of 15 indicators. Regressions (and means) are weighted by the number of registered voters in 2014 election. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: The effect of EVD on voting behavior in swing villages

Dependent Variable	(1) Turnout	(2) Votes total	(3) Vote share Incumbent	(4) Votes Incumbent	(5) Margin Incumbent
Specification: Diff-in-diff					
Panel A: Entire epidemic until Dec 2014					
Any EVD case X swing X post	0.049***	-0.715	0.060	2.254	0.017**
	(0.018)	(68.301)	(0.047)	(42.348)	(0.008)
Any EVD case X post	0.017*	79.437***	-0.032*	-63.762***	-0.015*
	(0.009)	(30.796)	(0.018)	(20.973)	(0.008)
Swing X post	-0.007	-28.560	-0.046***	-41.097***	-0.004***
	(0.010)	(37.507)	(0.013)	(14.572)	(0.001)
Any EVD case X swing	-0.026*	103.568	-0.034	13.117	-0.076***
	(0.014)	(92.148)	(0.026)	(34.788)	(0.018)
Post	-0.465***	-628.840***	-0.056***	-75.729***	0.003**
	(0.004)	(17.614)	(0.007)	(7.301)	(0.001)
Any EVD case	-0.019***	21.861	0.030**	55.841***	0.027*
	(0.007)	(37.863)	(0.015)	(19.773)	(0.015)
Swing	-0.007	37.069	0.016**	17.979	-0.197***
	(0.007)	(40.372)	(0.008)	(11.174)	(0.009)
Panel B: Heterogeneity by timing of first EVD case until Dec 2014					
First EVD case in part 1 X swing X post	0.035	67.055	0.153**	165.131**	-0.000
	(0.030)	(105.267)	(0.065)	(81.906)	(0.002)
First EVD case in part 2 X swing X post	0.037*	-79.992	-0.000	-66.060	0.002
	(0.021)	(81.803)	(0.066)	(48.101)	(0.002)
First EVD case in part 1 X post	0.058***	42.768	-0.133***	-207.505***	0.001
	(0.015)	(46.064)	(0.032)	(49.095)	(0.001)
First EVD case in part 2 X post	0.011	136.352***	0.034	-8.446	-0.000
	(0.012)	(38.049)	(0.027)	(24.065)	(0.001)
Swing X post	-0.005	-26.479	-0.048***	-46.883***	-0.001**
	(0.010)	(37.696)	(0.013)	(14.521)	(0.001)
First EVD case in part 1 X swing	0.023	27.852	-0.104**	-99.220	-0.060**
	(0.017)	(130.255)	(0.041)	(70.109)	(0.030)
First EVD case in part 2 X swing	-0.039*	189.862	0.009	45.011	-0.058**
	(0.021)	(130.164)	(0.035)	(37.826)	(0.023)
Post	-0.468***	-630.922***	-0.054***	-69.889***	0.000
	(0.004)	(17.935)	(0.007)	(7.195)	(0.000)
First EVD case in part 1	-0.058***	50.851	0.108***	172.912***	0.005
	(0.011)	(55.687)	(0.028)	(44.723)	(0.022)
First EVD case in part	-0.010	-40.446	-0.024	13.929	0.002
	(0.008)	(54.488)	(0.018)	(20.246)	(0.017)
Swing	-0.009	34.898	0.018**	24.029**	-0.199***
	(0.007)	(40.677)	(0.008)	(11.184)	(0.009)
Mean Control 2011	0.72	977.99	0.13	104.49	0.45
Mean Treat 2011	0.69	966.62	0.24	246.03	0.38
No. Obs	3560	3560	3560	3560	3560
Pv p1XswingXpost=p1Xpost	0.56	0.85	0.00	0.00	0.74
Pv p2XswingXpost=p2Xpost	0.37	0.04	0.67	0.37	0.34

Notes: This table illustrates the effects of the EVD outbreak on the citizens' voting behavior in swing villages. "Any EVD case" is constructed as a dummy equal to 1 if at least one (probable, confirmed, death) EVD case was recorded in any of the villages matched to each electoral precinct. "First EVD case recorded in p1 (p2)" is constructed as a dummy equal to 1 if at least one (probable, confirmed, death) EVD case was recorded in the village before or in (after) September 2014. The records are constructed from the MOH patient database and Global Communities safe burials. "Swing" is defined as a dummy equal to 1 if the difference in vote share between the winning and the first losing party in the Senatorial election in 2011, to the closest electoral precinct, was equal or less than 10 percentage points. "Turnout" is constructed as total number of votes divided by total number of registered voters (column 1). "Vote share incumbent" is constructed as total number of (valid) votes for the incumbent party divided by total number of votes (column 3). "Margin incumbent" is constructed as the absolute difference between the vote share of the incumbent party and the highest vote share among other political parties (column 5). Controls not shown include elevation, distance (by road) to Monrovia, and the percentage of Muslim population. Additional controls, selected through the Lasso procedure (Belloni et al. 2014), include the distance (by road) to EVD place of origin, distance (by road) to the closest health facility in 2008, population (log), and the average percentage of households from the main tribes in Liberia (Bassa, Gola, Kpelle, Mano, Vai). Socio-demographic controls are constructed from 2008 Population and Demographic Census. Standard errors are clustered at precinct level. All specifications include county fixed effects for a total of 15 indicators. Regressions (and means) are weighted by the number of registered voters in 2014 election. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 8: Political perceptions toward governmental institutions

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	Index of trust			Index of corruption		
	Government	Opposition	MOH	Government	Opposition	MOH
Specification: OLS + county FE						
Panel A: Entire epidemic						
Any EVD case	-0.120**	-0.015	0.003	0.142**	0.254***	0.001
	(0.055)	(0.075)	(0.076)	(0.056)	(0.073)	(0.065)
Panel B: Heterogeneity by timing of first EVD case						
First EVD case in part 1	-0.161**	-0.028	0.064	0.176**	0.174*	-0.017
	(0.070)	(0.102)	(0.098)	(0.072)	(0.091)	(0.086)
First EVD case in part 2	-0.107*	-0.011	-0.015	0.131**	0.278***	0.006
	(0.056)	(0.075)	(0.077)	(0.056)	(0.074)	(0.066)
Mean Control	-0.03	0.02	-0.04	0.07	0.08	0.07
No. Obs	2265	2265	2265	2011	2077	2182
Pv p1=p2	0.69	0.87	0.10	0.73	0.46	0.15

Notes: This table illustrates the effects of the EVD outbreak on the citizens' political perceptions towards governmental institutions. "Any EVD case" is constructed as a dummy equal to 1 if at least one (probable, confirmed, death) EVD case was recorded in the village. "First EVD case recorded in p1 (p2)" is constructed as a dummy equal to 1 if at least one (probable, confirmed, death) EVD case was recorded in the village before or in (after) September 2014. The records are constructed from the MOH patient database and Global Communities safe burials. The indexes of trust and corruption are constructed from dummies for whether the respondent had a level of trust equal to or more than the median (columns 1 to 3) or agreed or strongly agreed with the statement that a certain institution was corrupt (columns 4 to 6), following Kling et al. 2007. Controls not shown include elevation, distance (by road) to Monrovia, the percentage of Muslim population, and turnout and vote share of the incumbent party at the closest electoral precinct in 2011. Additional controls, chosen by the Lasso procedure (Belloni et al. 2014), include distance (by road) to EVD place of origin, population (log), whether the house has only one room, whether the household owns a mobile phone, a dummy for urban village, a dummy for the round of interview, and the average percentage of households from the main tribes in Liberia (Bassa, Gola, Kpelle, Mano, Vai). Socio-demographic controls are constructed from 2008 Population and Demographic Census. Standard errors are clustered at village level. County fixed effects include a total of 15 indicators. *** p<0.01, ** p<0.05, * p<0.1.

Table 9: Government's failures

Dependent Variable	(1) Bodies removed late	(2) Ambulance late	(3) Waiting at ETUs/CCCs
Specification: OLS + county FE			
Panel A: Entire epidemic			
Any EVD case	0.031	-0.045**	-0.018
	(0.026)	(0.019)	(0.013)
Panel B: Heterogeneity by timing of first EVD case			
First EVD case in part 1	0.121***	-0.005	0.001
	(0.033)	(0.029)	(0.016)
First EVD case in part 2	0.004	-0.057***	-0.024*
	(0.025)	(0.017)	(0.013)
Mean Control	0.10	0.07	0.04
No. Obs	2265	2265	2265
Pv p1=p2	0.00	0.00	0.04

Notes: This table illustrates government's failures in the response to the EVD outbreak at early stages of the epidemic. "Any EVD case" is constructed as a dummy equal to 1 if at least one (probable, confirmed, death) EVD case was recorded in the village. "First EVD case recorded in p1 (p2)" is constructed as a dummy equal to 1 if at least one (probable, confirmed, death) EVD case was recorded in the village before or in (after) September 2014. The records are constructed from the MOH patient database and Global Communities safe burials. The dependent variables are constructed as dummies equal to 1 whether the survey respondents reported that sick or dead bodies were removed (column 1) or the ambulance arrived (column 2) more than 4hrs after the call, and whether the survey respondents knew someone who waited at the gate of ETU/CCC for treatment (column 3). Controls not shown include elevation, distance (by road) to Monrovia, the percentage of Muslim population, and turnout and vote share of the incumbent party at the closest electoral precinct in 2011. Additional controls, chosen by the Lasso procedure (Belloni et al. 2014), include distance (by road) to EVD place of origin, population (log), whether the house has only one room, whether the household owns a mobile phone, a dummy for urban village, a dummy for the round of interview, and the average percentage of households from the main tribes in Liberia (Bassa, Gola, Kpelle, Mano, Vai). Socio-demographic controls are constructed from 2008 Population and Demographic Census. Standard errors are clustered at village level. County fixed effects include a total of 15 indicators. *** p<0.01, ** p<0.05, * p<0.1.

Appendix A: Additional figures and tables.

Table A1: Descriptives of EVD measures

	(1)	(2)	(3)	(4)
Sample	All villages		Survey villages	
	Jan2014-July2015	Jan2014-Dec2014	Jan2014-July2015	Jan2014-Dec2014
Panel A: Extensive margin				
Any EVD probable case	6.99%	3.29%	17.1%	15.5%
1. Part 1	1.28%	1.28%	8.14%	8.14%
2. Part 2	5.71%	2.01%	8.91%	7.36%
Any EVD confirmed case	1.49%	1.48%	9.50%	9.50%
1. Part 1	0.92%	0.92%	7.56%	7.56%
2. Part 2	0.57%	0.56%	1.94%	1.94%
Any EVD positive death case	0.81%	0.79%	5.23%	5.23%
1. Part 1	0.54%	0.54%	3.88%	3.88%
2. Part 2	0.27%	0.26%	1.36%	1.36%
Panel B: Intensive margin				
EVD probable cases				
No. cases per capita (x100)	0.18 (2.49) [0-100]	0.098 (1.94) [0-100]	0.19 (1.31) [0-21.4]	0.14 (0.93) [0-17.4]
No. months hit	0.12 (0.59) [0-11]	0.049 (0.33) [0-8]	0.60 (1.77) [0-11]	0.32 (0.98) [0-8]
EVD confirmed cases				
No. cases per capita (x100)	0.047 (1.39) [0-100]	0.046 (1.39) [0-100]	0.078 (0.60) [0-9.94]	0.077 (0.60) [0-9.94]
No. months hit	0.024 (0.24) [0-9]	0.023 (0.22) [0-6]	0.21 (0.84) [0-9]	0.20 (0.74) [0-6]
EVD positive death cases				
No. cases per capita (x100)	0.011 (0.45) [0-40]	0.011 (0.45) [0-40]	0.0073 [0.060] [0-1.14]	0.0070 [0.059] [0-1.14]
No. months hit	0.011 (0.15) [0-8]	0.010 (0.13) [0-5]	0.091 (0.51) [0-8]	0.081 [0.41] [0-5]
No. Obs	9686	9686	571	571
Data sources	MOH and GC	MOH and GC	MOH and GC	MOH and GC

Notes: This table reports summary statistics on the extensive and intensive margin of the EVD outbreak. In Panel A, "Any (probable, confirmed, death) EVD case" is constructed as a dummy equal to 1 if at least one (probable, confirmed, death) EVD case was recorded in the village. In Panel B, "No. EVD cases per capita" is constructed as the number of (probable, confirmed, death) EVD cases recorded in the village divided by the total population (multiplied by 100). "No. months hit" is constructed as the total number of months for which at least one (probable, confirmed, death) EVD case was recorded in the village. The records are constructed from the MOH patient database and Global Communities safe burials. Panel B also reports the standard deviation in parentheses and the minimum and maximum values in square brackets.

Table A2. Characteristics of villages in sample

	(1)	(2)
Sample	All villages	Survey sample
Panel A: Socio-demographic characteristics		
Pop (log)	4.319	5.694
Household size	4.952	5.125
Muslim (%)	0.103	0.126
Married (%)	0.378	0.354
Up to primary educ (%)	0.260	0.318
Literate pop (%)	0.340	0.428
Working in agriculture (%)	0.391	0.326
Working (%)	0.518	0.455
Own house (%)	0.855	0.801
Improved water (%)	0.239	0.479
Improved toilet (%)	0.102	0.213
Improved roof (%)	0.332	0.500
Improved wall (%)	0.0677	0.139
Improved floor (%)	0.0958	0.196
Own furniture (%)	0.157	0.179
Own tv (%)	0.00989	0.0195
Own radio (%)	0.294	0.328
Own phone (%)	0.373	0.427
Own matress (%)	0.00310	0.00641
Own refrigerator (%)	0.0104	0.0188
Own motorcycle (%)	0.00400	0.00729
Own vehicle (%)	0.0866	0.140
Panel B: Geographical characteristics		
Distance to Monrovia (Km)	149.1	162.4
Distance to EVD origin (Km)	251.9	226.1
Distance to health facility (Km)	6.553	5.315
Elevation (Km)	157.1	206.2
Slope (percent)	0.846	0.853
No. Obs	9686	571

Notes: This table reports the socio-demographic and geographical characteristics at the village level. Socio-demographic characteristics (Panel A) are constructed from 2008 Population and Demographic Census. Geographical characteristics (Panel B) are constructed through ArcGIS from the villages' GPS coordinates from the Institute of Statistics and Geo-Information Services (LISGIS). "All villages" (column 1) include all 9,686 villages in Liberia, while "survey sample" (column 2) includes only 571 villages of the survey respondents.

Table A3. Political outcomes (Senatorial election 2011)

	Mean	SD	Min	Max
No. registered voters	1010.6	677.6	38	3680
No. polling stations	2.5	1.41	1	8
Turnout (total votes/registered)	0.71	0.089	0.15	1.05
Share Valid Votes - Incumbent Party	0.16	0.2	0	0.96
Share Valid Votes - Main Opposition Party	0.16	0.24	0	0.92
Share Valid Votes - Third National Party	0.12	0.15	0	0.98
Share Valid Votes - Other parties	0.32	0.27	0.0045	1
Share Valid Votes - Independent candidates	0.24	0.23	0	0.94
No. Obs	1780			

Notes: This table reports the political outcomes of the 2011 Senatorial election for the 1,780 electoral precinct in Liberia. The variables are constructed from the National Election Commission (NEC) data.

Table A4: Sample characteristics

	Mean	SD	No. Obs
Panel A: Individuals' characteristics			
Resp male	0.651	0.477	2265
Resp age	32.65	10.63	2265
Resp hh size	6.876	3.527	2265
Resp main lang English	0.0583	0.234	2265
Resp lives urban area	0.695	0.460	2265
Resp is catholic	0.684	0.465	2265
Resp is protestant	0.181	0.385	2265
Resp is muslim	0.0927	0.290	2265
Resp educ primary	0.0804	0.272	2265
Resp educ secondary	0.604	0.489	2265
Resp educ university	0.224	0.417	2265
Resp self-emp	0.426	0.495	2265
Resp work for wage	0.183	0.387	2265
Resp professional	0.0287	0.167	2265
Resp not working	0.249	0.433	2265
Resp migrated since Ebola	0.167	0.373	2265
Wealth: Lower 40th percentile	0.494	0.500	2265
Income last month (USD)	109.7	387.5	2263
Panel B: Self-reported experience with EVD			
Perceptions on EVD experience			
Family hit badly	0.0706	0.256	2265
Community hit badly	0.215	0.411	2265
Liberia hit badly	0.985	0.122	2265
Information on EVD and government's actions			
Info EVD, daily	0.929	0.256	2265
Info EVD - trust health workers	0.764	0.425	2265
Info EVD - trust radio/tv	0.762	0.426	2265
Info EVD - trust family/friend/neighb	0.225	0.417	2265
Info actions, daily	0.993	0.0811	2265
Info actions - trust health workers	0.588	0.492	2265
Info actions - trust radio/tv	0.571	0.495	2265
Info actions - trust family/friend/neighbors	0.0781	0.268	2265
Response			
Someone came	0.916	0.278	2254
Govnt health workers came	0.544	0.498	2254
NGO health workers came	0.608	0.488	2254
INGO health workers came	0.340	0.474	2254
Community taskforce came	0.230	0.421	2254
Any resistance in community	0.0406	0.197	2265
Government's failures			
Dead bodies removed	0.328	0.469	2259
Dead bodies removed late (4hrs)	0.1301	0.3365	2259
Any burial change in community	0.891	0.312	2245
Ambulance came late (4hrs)	0.0704	0.2559	2258
Refused treatment at ETUs or CCCs	0.0377	0.190	2256
Lost job or work less than in 2013	0.437	0.496	2265
Perceptions on government handling problems			
Gov handle well EVD	0.569	0.495	1917
Gov handle well health issues	0.372	0.483	1892
Gov handle well other issues	0.175	0.380	1907

Notes: This table reports summary statistics for the individual characteristics and self-reported experienced with EVD of the 2,265 survey respondents.

Table A5: Correlation between distance to EVD place of origin and ex-ante support for incumbent party

	(1)	(2)	(3)	(4)
Dependent Variable		Dist to EVD origin (km)		
Added controls	Political Vars	Geography	Socio-Demog	Lasso
Turnout (2011)	-111.815***	-6.781	45.060***	-0.146
	(16.095)	(8.299)	(9.625)	(6.117)
Vote share incumbent (2011)	-130.866***	-32.237***	-7.813*	3.380
	(7.660)	(3.446)	(4.061)	(2.527)
Dist Monrovia (km)		0.808***		0.668***
		(0.005)		(0.012)
Dist health facility (km)		1.769***		
		(0.129)		
Elevation (km)		-0.784***		-0.665***
		(0.006)		(0.009)
Muslim pop			-230.888***	-119.667***
			(7.698)	(4.094)
Population (log)			-1.719***	-0.602*
			(0.532)	(0.340)
Improved roof material			-39.375***	-11.072***
			(3.330)	(1.925)
Improved floor material			33.879***	12.646***
			(5.259)	(2.809)
Improved water			-11.482***	-12.434***
			(2.310)	(1.367)
Own tv			14.340	
			(14.733)	
Own radio			6.755**	
			(2.846)	
Own phone			7.784	
			(4.867)	
Improved wall material			11.388**	
			(5.460)	
Electricity			-13.544	
			(17.801)	
Controls for tribes	No	No	Yes	Yes
Constant	404.195***	297.882***	405.258***	344.937***
	(11.452)	(5.989)	(7.879)	(5.727)
Observations	9,686	9,686	9,686	9,686
R-squared	0.051	0.755	0.714	0.885
Mean Dep.Var.	301.9	301.9	301.9	301.9

Notes: This table illustrates the correlation between the distance to the EVD place of origin and political outcomes in 2011 Senatorial election. The dependent variable is the distance (by road) from the village to the EVD place of origin (in km). The political variables in column 1 are constructed as follows: Turnout is constructed as total number of votes divided by total number of registered voters; Vote share incumbent is constructed as total number of (valid) votes for the incumbent party divided by total number of votes. The geographical controls in column 2 are constructed through ArcGIS from the villages' gps coordinates from the Institute of Statistics and Geo-Information Services (LISGIS). The socio-demographic controls in column 3 are constructed from 2008 Population and Demographic Census. The Lasso controls in column 4 are chosen by the Lasso procedure (Belloni et al. 2014). Controls for tribes include the average percentage of households from the main tribes in Liberia (Bassa, Gola, Kpelle, Mano, Vai). Standard errors are clustered at village level.

Table A6: The (strategic) response to EVD - core villages or tribal groups

Dependent Variable	(1) Distance to CCCs	(2) Distance to ETUs	(3) Any safe burial	(4) No. safe burials	(5) Misallocation ($1000)	(6) Over spending	(7) Under spending	(8) No. months to recover
Specification: OLS + county FE								
Panel A: Any EVD case, Incumbent support								
Any EVD case X incumbent support	0.600	-0.523	-0.036	-0.902*	7.190	-13.281**	-14.165	-0.051
	(0.760)	(1.168)	(0.040)	(0.475)	(17.757)	(6.659)	(57.052)	(0.261)
Incumbent support	-1.016***	-2.759***	-0.010	-0.085**	1.386	-0.956	-1.532	-0.037***
	(0.278)	(0.468)	(0.007)	(0.037)	(2.245)	(1.011)	(7.812)	(0.010)
Any EVD case	-1.837***	-1.764***	0.136***	2.055***	10.107	33.302***	61.249	2.080***
	(0.378)	(0.557)	(0.017)	(0.290)	(10.686)	(3.953)	(39.392)	(0.088)
Panel B: Any EVD case, Tribe								
Any EVD case X tribe	0.288	1.678*	0.081*	1.929	-67.672	-0.877	417.770	0.249
	(0.720)	(0.970)	(0.042)	(1.576)	(71.928)	(7.576)	(363.293)	(0.222)
Tribe	0.159	0.308	-0.010	-0.085	-9.422**	-2.646**	13.744	-0.027
	(0.322)	(0.507)	(0.010)	(0.079)	(4.595)	(1.326)	(11.030)	(0.022)
Any EVD case	-1.801***	-2.154***	0.114***	1.534***	24.871***	31.333***	6.547	2.022***
	(0.392)	(0.592)	(0.017)	(0.257)	(7.855)	(4.219)	(14.183)	(0.093)
Mean Control	16.55	29.16	0.04	0.08	-0.49	4.25	5.23	0.00
No. Obs	9686	9686	9686	9686	9686	4989	4697	9686

Notes: This table illustrates the (non) politically motivated government's response to the EVD outbreak in core villages or villages with similar tribal groups as the President of Liberia. "Any EVD case" is constructed as a dummy equal to 1 if at least one (probable, confirmed, death) EVD case was recorded in the village. "First EVD case recorded in p1 (p2)" is constructed as a dummy equal to 1 if at least one (probable, confirmed, death) EVD case was recorded in the village before or in (after) September 2014. The records are constructed from the MOH patient database and Global Communities safe burials. In Panel A "Incumbent support" is defined as a dummy equal to 1 if the vote share of the incumbent party in the Senatorial election in 2011 is higher than 50% (at the 90th percentile of the distribution). In Panel B 'Tribe" is defined as a dummy equal to 1 if the percentage of households from Kru or Gola tribes is above the median value (Census, 2008): the President of Liberia is a mix of these two Liberian tribes. The dependent variables are constructed as distance (by road, in km) from the village to the closest Community Care Center (column 1) or Ebola Treatment Unit (column 2); whether a burial team was sent to the village (column 3) and number of safe burials done (column 4); "Misallocation" (in $1000) is defined as difference between the observed costs and the predicted ones calculated based on the predicted counts of EVD estimated by the spatio-temporal epidemiological model (column 5); "Over (under) spending" (in $1000) refers to positive (negative) misallocation (columns 6 and 7); "No. months to recover" is the total number of months from when the first to the last case of EVD was recorded (column 8). Controls not shown include elevation, distance (by road) to Monrovia, the percentage of Muslim population, and turnout at the closest electoral precinct in 2011. Additional controls, chosen by the Lasso procedure (Belloni et al. 2014), include distance (by road) to EVD place of origin, population (log), the average percentage of households with improved roof and floor material and with improved water, and the average percentage of households from the main tribes in Liberia (Bassa, Gola, Kpelle, Mano, Vai). Socio-demographic controls are constructed from 2008 Population and Demographic Census. Standard errors are clustered at village level. County fixed effects include a total of 15 indicators. *** p<0.01, ** p<0.05, * p<0.1.

Table A7: The effect of EVD on voting behavior (other parties)

Dependent Variable	(1) Vote share Opposition	(2) Vote share Third party	(3) Vote share Independent	(4) Vote share Other
Specification: Diff-in-diff				
Panel A: Entire epidemic until Dec 2014				
Any EVD case X post	-0.050***	0.023	-0.018	0.073***
	(0.015)	(0.017)	(0.024)	(0.024)
Post	0.144***	0.005	-0.017**	-0.068***
	(0.006)	(0.006)	(0.009)	(0.008)
Any EVD case	0.026***	-0.031***	0.009	-0.030**
	(0.007)	(0.011)	(0.014)	(0.015)
Panel B: Heterogeneity by timing of first case until Dec 2014				
First EVD case in part 1 X post	-0.070***	0.080***	0.026	0.064**
	(0.018)	(0.028)	(0.032)	(0.032)
First EVD case in part 2 X post	-0.034	-0.024	-0.055	0.081**
	(0.022)	(0.015)	(0.034)	(0.034)
First EVD case in part 1	0.026***	-0.070***	-0.017	-0.025
	(0.009)	(0.017)	(0.017)	(0.022)
First EVD case in part 2	0.025***	-0.000	0.030	-0.035*
	(0.008)	(0.012)	(0.021)	(0.018)
Post	0.144***	0.005	-0.017**	-0.068***
	(0.006)	(0.006)	(0.009)	(0.008)
Mean Control 2011	0.23	0.11	0.26	0.27
Mean Treat 2011	0.09	0.10	0.22	0.24
No. Obs	3560	3560	3560	3560
Pv p1Xpost=p2Xpost	0.19	0.00	0.07	0.71

Notes: This table illustrates the effects of the EVD outbreak on the citizens' voting behavior for other political parties. "Any EVD case" is constructed as a dummy equal to 1 if at least one (probable, confirmed, death) EVD case was recorded in any of the villages matched to each electoral precinct. "First EVD case recorded in p1 (p2)" is constructed as a dummy equal to 1 if at least one (probable, confirmed, death) EVD case was recorded in the village before or in (after) September 2014. The records are constructed from the MOH patient database and Global Communities safe burials. Vote share of each party is constructed as total number of (valid) votes for the party divided by total number of votes. Controls not shown include elevation, distance (by road) to Monrovia, and the percentage of Muslim population. Additional controls, selected through the Lasso procedure (Belloni et al. 2014), include the distance (by road) to EVD place of origin, distance (by road) to the closest health facility in 2008, population (log), and the average percentage of households from the main tribes in Liberia (Bassa, Gola, Kpelle, Mano, Vai). Socio-demographic controls are constructed from 2008 Population and Demographic Census. Standard errors are clustered at precinct level. All specifications include county fixed effects for a total of 15 indicators. Regressions (and means) are weighted by the number of registered voters in 2014 election. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A8: Political perceptions toward non-governmental institutions

	(1)	(2)	(3)	(4)	(5)
Dependent Variable	Index of trust			Index of corruption	
	People	Leaders	NGOs	Leaders	NGOs
Specification: OLS + county FE					
Entire epidemic					
Any EVD case	-0.122**	-0.094	-0.007	0.055	0.095
	(0.059)	(0.059)	(0.065)	(0.058)	(0.064)
Panel B: Heterogeneity by timing of first EVD case					
First EVD case in part	-0.126*	-0.083	-0.062	0.086	0.104
	(0.076)	(0.074)	(0.082)	(0.071)	(0.082)
First EVD case in part 2	-0.121**	-0.097	0.009	0.045	0.093
	(0.061)	(0.060)	(0.068)	(0.060)	(0.066)
Mean Control	-0.07	-0.06	-0.06	0.02	0.08
No. Obs	2265	2265	2265	2106	2136
Pv p1=p2	0.94	0.79	0.26	0.48	0.86

Notes: This table illustrates the effects of the EVD outbreak on the citizens' political perceptions towards non-governmental institutions. "Any EVD case" is constructed as a dummy equal to 1 if at least one (probable, confirmed, death) EVD case was recorded in the village. "First EVD case recorded in p1 (p2)" is constructed as a dummy equal to 1 if at least one (probable, confirmed, death) EVD case was recorded in the village before or in (after) September 2014. The records are constructed from the MOH patient database and Global Communities safe burials. The indexes of trust and corruption are constructed from dummies for whether the respondent had a level of trust equal to or more than the median (columns 1 to 3) or agreed or strongly agreed with the statement that a certain institution was corrupt (columns 4 and 5), following Kling et al. 2007. Controls not shown include elevation, distance (by road) to Monrovia, the percentage of Muslim population, and turnout and vote share of the incumbent party at the closest electoral precinct in 2011. Additional controls, chosen by the Lasso procedure (Belloni et al. 2014), include distance (by road) to EVD place of origin, population (log), whether the house has only one room, whether the household owns a mobile phone, a dummy for urban village, a dummy for the round of interview, and the average percentage of households from the main tribes in Liberia (Bassa, Gola, Kpelle, Mano, Vai). Socio-demographic controls are constructed from 2008 Population and Demographic Census. Standard errors are clustered at village level. County fixed effects include a total of 15 indicators. *** p<0.01, ** p<0.05, * p<0.1.

Table A9: Other political perceptions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable	Attributed responsibility				Badly	Com participation	
	Government	Foreign	People	God	handle EVD	monthly	no. groups
Specification: OLS + county FE							
Panel A: Entire epidemic							
Any EVD case	-0.023	0.028**	0.034	-0.006	0.007	0.016	0.145*
	(0.027)	(0.013)	(0.036)	(0.017)	(0.031)	(0.037)	(0.085)
Panel B: Heterogeneity by timing of first EVD case							
First EVD case in part 1	-0.016	0.033*	0.080*	-0.008	0.019	-0.034	0.065
	(0.036)	(0.017)	(0.044)	(0.022)	(0.037)	(0.043)	(0.113)
First EVD case in part 2	-0.025	0.026*	0.020	-0.005	0.003	0.031	0.170**
	(0.028)	(0.014)	(0.037)	(0.017)	(0.032)	(0.037)	(0.083)
Mean Control	0.20	0.02	0.46	0.05	0.16	0.36	1.18
No. Obs	2265	2265	2265	2265	2248	2265	2265
Pv p1=p2	0.76	0.61	0.08	0.82	0.58	0.05	0.17

Notes: This table illustrates the effects of the EVD outbreak on the citizens' perceptions about the responsibility of the epidemic and about the government's performance in handling EVD, and on community participation. "Any EVD case" is constructed as a dummy equal to 1 if at least one (probable, confirmed, death) EVD case was recorded in the village. "First EVD case recorded in p1 (p2)" is constructed as a dummy equal to 1 if at least one (probable, confirmed, death) EVD case was recorded in the village before or in (after) September 2014. The records are constructed from the MOH patient database and Global Communities safe burials. The dependent variables are constructed as dummies equal to 1 if the survey respondents attributed any responsibility of the disaster to a different group of institutions (governmental, foreign, people in general or god, columns 1 to 4), if the survey respondents reported that the incumbent government handled Ebola badly or very badly (column 5), if the survey respondents participated in any community group at the time of the interview at least monthly (column 6) and the total number of community groups they participated in (column 7). Controls not shown include elevation, distance (by road) to Monrovia, the percentage of Muslim population, and turnout and vote share of the incumbent party at the closest electoral precinct in 2011. Additional controls, chosen by the Lasso procedure (Belloni et al. 2014), include distance (by road) to EVD place of origin, population (log), whether the house has only one room, whether the household owns a mobile phone, a dummy for urban village, a dummy for the round of interview, and the average percentage of households from the main tribes in Liberia (Bassa, Gola, Kpelle, Mano, Vai). Socio-demographic controls are constructed from 2008 Population and Demographic Census. Standard errors are clustered at village level. County fixed effects include a total of 15 indicators. *** p<0.01, ** p<0.05, * p<0.1.

Table A10: Costs of the epidemic

Dependent Variable	(1) Badly hit Community	(2) Less Income since 2013
Specification: OLS + county FE		
Panel A: Entire epidemic		
Any EVD case	0.004	-0.016
	(0.034)	(0.040)
Panel B: Heterogeneity by timing of first EVD case		
First EVD case in part 1	0.017	-0.062
	(0.048)	(0.052)
First EVD case in part 2	0.001	-0.003
	(0.035)	(0.041)
Mean Control	0.20	0.41
No. Obs	2265	2265
Pv p1=p2	0.70	0.11

Notes: This table illustrates the effects of the EVD outbreak on the citizens' psychological and economic costs. "Any EVD case" is constructed as a dummy equal to 1 if at least one (probable, confirmed, death) EVD case was recorded in the village. "First EVD case recorded in p1 (p2)" is constructed as a dummy equal to 1 if at least one (probable, confirmed, death) EVD case was recorded in the village before or in (after) September 2014. The records are constructed from the MOH patient database and Global Communities safe burials. The dependent variables are constructed as dummies equal to 1 if the survey respondents reported their community and/or family was badly hit by EVD (column 1) or if their reported monthly work income at the time of the interview was less than the one reported at the end of 2013 (column 2). Controls not shown include elevation, distance (by road) to Monrovia, the percentage of Muslim population, and turnout and vote share of the incumbent party at the closest electoral precinct in 2011. Additional controls, chosen by the Lasso procedure (Belloni et al. 2014), include distance (by road) to EVD place of origin, population (log), whether the house has only one room, whether the household owns a mobile phone, a dummy for urban village, a dummy for the round of interview, and the average percentage of households from the main tribes in Liberia (Bassa, Gola, Kpelle, Mano, Vai). Socio-demographic controls are constructed from 2008 Population and Demographic Census. Standard errors are clustered at village level. County fixed effects include a total of 15 indicators. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A11: Information during the epidemic

	(1)	(2)
Dependent Variable	Received daily information	
	Virus	Gov actions
Specification: OLS + county FE		
Panel A: Entire epidemic		
Any EVD case	0.019	0.009*
	(0.018)	(0.005)
Panel B: Heterogeneity by timing of first EVD case		
First EVD case in part 1	0.035	0.004
	(0.024)	(0.008)
First EVD case in part 2	0.014	0.010**
	(0.018)	(0.005)
Mean Control	0.93	0.99
No. Obs	2265	2265
Pv p1=p2	0.26	0.20

Notes: This table illustrates the effects of the EVD outbreak on the citizens receiving daily information about the EVD virus and the actions taken by the government during the epidemic. "Any EVD case" is constructed as a dummy equal to 1 if at least one (probable, confirmed, death) EVD case was recorded in the village. "First EVD case recorded in p1 (p2)" is constructed as a dummy equal to 1 if at least one (probable, confirmed, death) EVD case was recorded in the village before or in (after) September 2014. The records are constructed from the MOH patient database and Global Communities safe burials. The dependent variables are constructed as dummies equal to 1 if the survey respondents reported having received daily information on the EVD virus per se (column 1) or on the actions the government took during the outbreak (column 2). Controls not shown include elevation, distance (by road) to Monrovia, the percentage of Muslim population, and turnout and vote share of the incumbent party at the closest electoral precinct in 2011. Additional controls, chosen by the Lasso procedure (Belloni et al. 2014), include distance (by road) to EVD place of origin, population (log), whether the house has only one room, whether the household owns a mobile phone, a dummy for urban village, a dummy for the round of interview, and the average percentage of households from the main tribes in Liberia (Bassa, Gola, Kpelle, Mano, Vai). Socio-demographic controls are constructed from 2008 Population and Demographic Census. Standard errors are clustered at village level. County fixed effects include a total of 15 indicators. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A12: Voting behavior, by access to information

Dependent Variable	(1) Turnout	(2) Votes total	(3) Vote share. Incumbent	(4) Votes Incumbent	(5) Margin Incumbent
Specification: Diff-in-diff					
Panel A: Entire epidemic until Dec 2014					
Any EVD case X post X info	-0.031	-37.052	0.069	75.924	0.086*
	(0.019)	(68.401)	(0.047)	(61.679)	(0.050))
Any EVD case X post	0.066***	126.771**	-0.081**	-152.402***	-0.101**
	(0.016)	(59.759)	(0.041)	(55.747)	(0.044)
Any EVD case X info	0.003	104.944	-0.082**	-76.724	-0.084**
	(0.013)	(75.520)	(0.039)	(59.541)	(0.033)
Post X info	-0.016**	-87.376***	-0.013	-2.835	-0.004
	(0.008)	(31.977)	(0.012)	(13.778)	(0.014)
Post	-0.458***	-576.038***	-0.055***	-77.896***	0.185***
	(0.006)	(25.051)	(0.010)	(11.577)	(0.011)
Info	0.003	84.942**	-0.003	-0.258	-0.011
	(0.005)	(33.006)	(0.009)	(11.665)	(0.010)
Any EVD case	-0.038***	-59.624	0.092***	142.513***	0.064**
	(0.012)	(60.337)	(0.035)	(53.666)	(0.030)
Panel B: Heterogeneity by timing of first EVD case until Dec 2014					
First EVD case in part 1 X post X info	-0.038	35.217	0.067	112.295	0.139**
	(0.028)	(100.661)	(0.066)	(97.414)	(0.069)
First EVD case in part 2 X post X info	-0.014	-139.208**	0.041	2.470	0.031
	(0.022)	(56.032)	(0.054)	(41.042)	(0.066)
First EVD case in part 1 X post	0.094***	30.162	-0.150***	-257.788***	-0.135**
	(0.023)	(89.564)	(0.057)	(85.496)	(0.061)
First EVD case in part 2 X post	0.033*	243.489***	0.000	-27.565	-0.062
	(0.018)	(39.724)	(0.045)	(32.164)	(0.059)
First EVD case in part 1 X info	0.020	-49.960	-0.092	-129.353	-0.111**
	(0.018)	(112.662)	(0.064)	(102.900)	(0.048)
First EVD case in part 2 X info	-0.019	199.175**	-0.071*	-33.498	-0.055
	(0.015)	(97.494)	(0.038)	(49.314)	(0.042)
Post X info	-0.016**	-85.962***	-0.013	-2.397	-0.004
	(0.008)	(32.022)	(0.012)	(13.763)	(0.014)
Post	-0.458***	-576.219***	-0.055***	-78.068***	0.184***
	(0.006)	(25.038)	(0.010)	(11.571)	(0.011)
Info	0.000	96.145***	0.000	3.730	-0.017*
	(0.005)	(35.676)	(0.008)	(11.704)	(0.010)
First EVD case in part 1	-0.070***	79.874	0.164***	260.838***	0.094**
	(0.016)	(93.266)	(0.058)	(92.318)	(0.044)
First EVD case in part 2	-0.004	-210.775***	0.034	45.212	0.061
	(0.013)	(69.724)	(0.033)	(43.896)	(0.038)
Mean Control 2011	0.72	977.99	0.13	104.49	0.45
Mean Treat 2011	0.69	966.62	0.24	246.03	0.38
No. Obs	3560	3560	3560	3560	3560
Pv p1XpostXinfo=p1Xpost	0.01	0.98	0.07	0.04	0.03
Pv p2XpostXinfo=p2Xpost	0.22	0.00	0.66	0.66	0.44

Notes: This table illustrates the effects of the EVD outbreak on the citizens' voting behavior, by access to media outlets before the epidemic. "Any EVD case" is constructed as a dummy equal to 1 if at least one (probable, confirmed, death) EVD case was recorded in any of the villages matched to each electoral precinct. The records are constructed from the MOH patient database and Global Communities safe burials. "First EVD case recorded in p1 (p2)" is constructed as a dummy equal to 1 if at least one (probable, confirmed, death) EVD case was recorded in the village before or in (after) September 2014. "Info" is defined as a dummy equal to 1 if the percentage of households with radio or mobile phone is above the median value (Census, 2008). "Turnout" is constructed as total number of votes divided by total number of registered voters (column 1). "Vote share incumbent" is constructed as total number of (valid) votes for the incumbent party divided by total number of votes (column 3). "Margin incumbent" is constructed as the absolute difference between the vote share of the incumbent party and the highest vote share among other political parties (column 5). Controls not shown include elevation, distance (by road) to Monrovia, and the percentage of Muslim population. Additional controls, selected through the Lasso procedure (Belloni et al. 2014), include the distance (by road) to EVD place of origin, distance (by road) to the closest health facility in 2008, population (log), and the average percentage of households from the main tribes in Liberia (Bassa, Gola, Kpelle, Mano, Vai). Socio-demographic controls are constructed from 2008 Population and Demographic Census. Standard errors are clustered at precinct level. All specifications include county fixed effects for a total of 15 indicators. Regressions (and means) are weighted by the number of registered voters in 2014 election. *** p<0.01, ** p<0.05, * p<0.1.

Appendix B: Robustness checks.

Table B1: The response to EVD, robustness checks

Robustness checks	Additional controls				Any confirmed case				Spatial SE				Higher geographical level (Clan)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Dependent Variables	Distance to CCCs	Distance to ETUs	Any safe burial	No. safe burials	Distance to CCCs	Distance to ETUs	Any safe burial	No. safe burials	Distance to CCCs	Distance to ETUs	Any safe burial	No. safe burials	Distance to CCCs	Distance to ETUs	Any safe burial	No. safe burials
Panel A: Entire epidemic																
Any EVD case	-1.675***	-1.784***	0.130***	1.912***	-4.111***	-3.091***	-0.001	5.640***	-1.752***	-1.920***	0.131***	1.929***	-1.736**	-3.268**	0.185***	3.372***
	(0.337)	(0.499)	(0.016)	(0.234)	(0.695)	(1.072)	(0.025)	(1.473)	(0.345)	(0.510)	(0.016)	(0.239)	(0.772)	(1.327)	(0.044)	(0.687)
Panel B: Heterogeneity by timing of first EVD case																
First EVD case in part 1	-4.118***	-4.205***	0.054*	5.796***	-5.195***	-4.803***	0.001	7.408***	-4.078***	-4.420***	0.054*	5.831***	-4.002***	-4.428**	0.119*	11.203***
	(0.851)	(1.135)	(0.030)	(1.728)	(0.940)	(1.380)	(0.031)	(2.426)	(0.876)	(1.171)	(0.029)	(1.750)	(1.276)	(1.805)	(0.061)	(2.763)
First EVD case in part 2	-1.146***	-1.259**	0.147***	1.069***	-2.390**	-0.372	-0.003	2.833***	-1.249***	-1.378**	0.147***	1.084***	-1.314*	-2.692**	0.202***	1.679**
	(0.355)	(0.543)	(0.018)	(0.189)	(0.937)	(1.615)	(0.041)	(0.813)	(0.371)	(0.553)	(0.018)	(0.188)	(0.759)	(1.288)	(0.043)	(0.758)
Mean Control	16.55	29.16	0.0354	0.0778	16.48	28.98	0.0457	0.151	16.55	29.16	0.0354	0.0778	15.84	37.02	0.0440	0.108
No. Obs	9,686	9,686	9,686	9,686	9,686	9,686	9,686	9,686	9,686	9,686	9,686	9,686	626	626	626	626
Pv p1=p2	0.00	0.02	0.01	0.01	0.03	0.03	0.93	0.09	0.00	0.02	0.01	0.01	0.06	0.42	0.26	0.00

Notes: This table illustrates robustness checks for the government's response to the extensive margin of the EVD outbreak. "Any EVD case" is constructed as a dummy equal to 1 if at least one (probable, confirmed, death) EVD case was recorded in any of the villages matched to each electoral precinct. The records are constructed from the MOH patient database and Global Communities records of safe burials. "First EVD case recorded in p1 (p2)" is constructed as a dummy equal to 1 if at least one (probable, confirmed, death) EVD case was recorded in the village before or in (after) September 2014. The dependent variables are constructed as distance (by road, in km) form the village to the closest Community Care Center (column 1,5,9,13) or Ebola Treatment Unit (columns 2,6,10,14), whether a burial team was sent to the village (column 3,7,11,15) and number of safe burials done (columns 4,8,12,16). Controls not shown include elevation, distance (by road) to Monrovia, the percentage of Muslim population, and turnout and vote share of the incumbent party at the closest electoral precinct in 2011. Additional controls, chosen by the Lasso procedure (Belloni et al. 2014), include distance (by road) to EVD place of origin (only for OLS specification), population (log), the average percentage of households with improved roof and floor material and with improved water, and the average percentage of households from the main tribes in Liberia (Bassa, Gola, Kpelle, Mano, Vai). Socio-demographic controls are constructed from 2008 Population and Demographic Census. Standard errors are clustered at village level. Columns 1 to 4 include additional controls such as average household size, average percentage of households with improved wall and floor material, with improved toilet facility, owning a phone, a radio, a tv, owning a house, and whether the house has only one room; columns 5 to 8 use as regressor "Any confirmed EVD case" constructed as dummy equal to 1 if at least one confirmed positive EVD case was recorded in the village; columns 9 to 12 uses Conley (2008) spatial standard errors with 2 km cutoff. Columns 13 to 16 show estimates at a higher geographical level than village, i.e. clan for a total of 626 clans. Standard errors are clustered at clan level. All specifications in columns 1 to 16 include county fixed effects for a total of 15 indicators. *** p<0.01, ** p<0.05, * p<0.1.

Table B2: The (strategic) response to EVD, robustness checks

Dependent Variable	(1) Distance to CCCs	(2) Distance to ETUs	(3) Any safe burial	(4) No. safe burials	(5) Misallocation ($1000)	(6) Over spending	(7) Under spending	(8) No. months to recover
Specification: OLS + county FE								
Panel A: Any EVD case, swing (5pp)								
Any EVD case X swing (5pp)	-1.649	-3.155*	0.050	-0.026	30.886*	19.827	-76.908	-0.093
	(1.189)	(1.736)	(0.052)	(0.676)	(17.740)	(14.799)	(47.832)	(0.265)
Swing (5pp)	1.016***	2.268***	0.003	0.002	2.175*	1.223	-1.365	-0.005
	(0.309)	(0.412)	(0.006)	(0.020)	(1.178)	(1.011)	(2.400)	(0.005)
Any EVD case	-1.563***	-1.555***	0.125***	1.932***	7.743	29.218***	70.822*	2.082***
	(0.355)	(0.529)	(0.017)	(0.274)	(10.138)	(3.561)	(42.379)	(0.088)
Panel B: No. months with at least one case, swing (10pp)								
No. months with EVD X swing (10pp)	-1.023***	-0.880	0.003	0.763	82.421**	25.238	-115.078	-0.112
	(0.336)	(0.567)	(0.013)	(1.159)	(41.869)	(15.369)	(74.236)	(0.069)
Swing (10pp)	0.875***	1.406***	0.012**	-0.049	-5.864	-1.837	5.282	0.004
	(0.240)	(0.337)	(0.005)	(0.097)	(3.845)	(2.022)	(4.786)	(0.005)
No. months with EVD	-0.766***	-0.932***	0.018***	1.933**	-47.091	20.890***	119.613*	1.358***
	(0.177)	(0.266)	(0.006)	(0.821)	(38.579)	(2.802)	(72.187)	(0.038)
Mean Control	16.55	29.16	0.04	0.08	-0.49	4.25	5.23	0.00
No. Obs	9686	9686	9686	9686	9686	4989	4697	9686

Notes: This table illustrates robustness checks for the politically motivated government's response to the EVD outbreak in swing villages. "Any EVD case" is constructed as a dummy equal to 1 if at least one (probable, confirmed, death) EVD case was recorded in the village. "No. months with EVD" is constructed as the total number of months over the epidemic for which at least one (probable, confirmed, death) EVD case was recorded in the village. The records are constructed from the MOH patient database and Global Communities records of safe burials. "Swing (10 (5) pp)" is defined as a dummy equal to 1 if the difference in vote share between the winning and the first losing party in the Senatorial election in 2011, to the closest electoral precinct, was equal or less than 10 (5) percentage points. The dependent variables are constructed as distance (by road, in km) from the village to the closest Community Care Center (column 1) or Ebola Treatment Unit (column 2); whether a burial team was sent to the village (column 3) and number of safe burials done (column 4); "Misallocation" (in $1000) is defined as difference between the observed costs and the predicted costs calculated from the predicted counts of EVD estimated by the spatio-temporal epidemiological model (column 5); "Over (under) spending" (in $1000) refers to positive (negative) misallocation (columns 6 and 7); "No. months to recover" is the total number of months from when the first to the last case of EVD was recorded (column 8). Controls not shown include elevation, distance (by road) to Monrovia, the percentage of Muslim population, and turnout at the closest electoral precinct in 2011. Additional controls, chosen by the Lasso procedure (Belloni et al. 2014), include distance (by road) to EVD place of origin, population (log), the average percentage of households with improved roof and floor material and with improved water, and the average percentage of households from the main tribes in Liberia (Bassa, Gola, Kpelle, Mano, Vai). Socio-demographic controls are constructed from 2008 Population and Demographic Census. Standard errors are clustered at village level. County fixed effects include a total of 15 indicators. *** p<0.01, ** p<0.05, * p<0.1.

Table B3: Misallocation, additional analysis

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	Misallocation ($1000)					
Sample	Exclude Monrovia	Keep swing counties	Swing [Incumbent]	Clan Level	Drop outliers	District FE
Specification: OLS + county FE						
Panel A: Any EVD case						
Any EVD case X swing	24.830**	23.433*	45.576*	152.687**	26.121**	24.750**
	(12.196)	(14.073)	(25.085)	(75.146)	(12.111)	(12.541)
Swing	1.135	3.193**	2.910*	-6.021	0.286	1.447
	(1.234)	(1.577)	(1.500)	(29.409)	(0.895)	(1.311)
Any EVD case	13.282***	15.664***	5.223	-16.744	12.056***	12.519***
	(4.577)	(4.131)	(10.686)	(37.261)	(4.391)	(4.668)
Panel B: No. months with at least one case						
No. months with EVD X swing	41.802**	38.647**	82.437**	130.876*	42.262***	41.933**
	(16.431)	(17.649)	(41.819)	(75.197)	(16.389)	(16.582)
Swing	-2.200	-0.857	-5.936	-80.183	-3.013*	-1.986
	(1.757)	(2.364)	(3.953)	(78.135)	(1.556)	(1.777)
No. months with EVD	-7.264	-1.868	-47.143	-63.925	-7.640	-7.750
	(8.147)	(7.497)	(38.581)	(60.055)	(8.095)	(8.180)
Mean Control	-0.489	-0.137	-0.489	-1.683	0.0735	-0.489
No. Obs	9,685	6,973	9,686	626	9,684	9,686

Notes: This table illustrates robustness checks for the politically motivated government's response to the EVD outbreak in swing villages, focusing on the measure of misallocation. "Any EVD case" is constructed as a dummy equal to 1 if at least one (probable, confirmed, death) EVD case was recorded in the village. "No. months with EVD" is constructed as the total number of months over the epidemic for which at least one (probable, confirmed, death) EVD case was recorded in the village. The records are constructed from the MOH patient database and Global Communities records of safe burials. "Swing" is defined as a dummy equal to 1 if the difference in vote share between the winning and the first losing party in the Senatorial election in 2011, to the closest electoral precinct, was equal or less than 10 percentage points. "Misallocation" (in $1000) is defined as difference between the observed costs and the predicted costs calculated from the predicted counts of EVD estimated by the spatio-temporal epidemiological model. Column 1 excludes the most populous county the national capital, Monrovia; column 2 excludes two counties which historically favor the two main opposition parties, CDC and LP (Montserrado and Grand Bassa); column 3 defines "Swing" as a dummy equal to 1 if the difference in vote share between the winning and the first losing party (and either the former or the latter is the incumbent party) in the Senatorial election in 2011, to the closest electoral precinct, was equal or less than 10 percentage points; column 4 defines "Swing" at the clan level, as a dummy equal to 1 if 20% or more of the villages (at the 75th percentile of the distribution) within the clan is swing; column 5 excludes observations with misallocation bigger than $3 million or smaller than -$3 million; column 6 controls for district fixed effects (136 districts). Controls not shown include elevation, distance (by road) to Monrovia, the percentage of Muslim population, and turnout at the closest electoral precinct in 2011. Additional controls, chosen by the Lasso procedure (Belloni et al. 2014), include distance (by road) to EVD place of origin, population (log), the average percentage of households with improved roof and floor material and with improved water, and the average percentage of households from the main tribes in Liberia (Bassa, Gola, Kpelle, Mano, Vai). Socio-demographic controls are constructed from 2008 Population and Demographic Census. Standard errors are clustered at village level. County fixed effects include a total of 15 indicators. *** p<0.01, ** p<0.05, * p<0.1.

Table B4: The effects of EVD on voting behavior, robustness checks

Robustness checks:	Unweighted		Additional controls		Any confirmed case		Spatial SE		Migration - lower bound		Migration - upper bound		Matching [coarsened]	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Dependent Variable	Turnout	Vote share Incumbent	Turnout	Vote share Incumbent	Turnout	Vote share Incumbent	Turnout	Vote share Incumbent	Turnout	Vote share Incumbent	Turnout	Vote share Incumbent	Turnout	Vote share Incumbent
Panel A: Entire epidemic until Dec 2014														
Any EVD case X post	0.015*	-0.020	0.040***	-0.028	0.060***	-0.024	0.011	-0.022	0.071***	-0.026	0.072***	-0.025	0.033***	-0.022
	(0.008)	(0.020)	(0.009)	(0.020)	(0.011)	(0.031)	(0.010)	(0.017)	(0.014)	(0.020)	(0.011)	(0.019)	(0.010)	(0.021)
Any EVD case	-0.020***	0.016	-0.028***	0.017	-0.037***	0.034	-0.025***	0.012	-0.059***	0.019	-0.054***	0.024*	-0.028***	0.023
	(0.006)	(0.013)	(0.007)	(0.013)	(0.008)	(0.022)	(0.007)	(0.014)	(0.011)	(0.015)	(0.008)	(0.013)	(0.007)	(0.014)
Post	-0.444***	-0.054***	-0.469***	-0.064***	-0.467***	-0.066***	-0.440***	-0.052***	-0.488***	-0.057***	-0.490***	-0.059***	-0.461***	-0.068***
	(0.003)	(0.007)	(0.004)	(0.006)	(0.004)	(0.006)	(0.006)	(0.008)	(0.006)	(0.006)	(0.005)	(0.006)	(0.005)	(0.007)
Panel B: Heterogeneity by timing of the first EVD case until Dec 2014														
First EVD case in part 1 X post	0.043***	-0.084***	0.065***	-0.100***	0.062***	-0.089**	0.039***	-0.086***	0.117***	-0.079***	0.107***	-0.090***	0.057***	-0.096***
	(0.012)	(0.028)	(0.013)	(0.029)	(0.014)	(0.036)	(0.014)	(0.027)	(0.020)	(0.029)	(0.016)	(0.027)	(0.014)	(0.030)
First EVD case in part 2 X post	-0.004	0.025	0.019*	0.032	0.058***	0.100*	-0.008	0.023	0.032*	0.018	0.044***	0.029	0.013	0.040
	(0.010)	(0.025)	(0.010)	(0.025)	(0.019)	(0.051)	(0.012)	(0.021)	(0.018)	(0.026)	(0.013)	(0.024)	(0.011)	(0.026)
First EVD case in part 1	-0.039***	0.064***	-0.042***	0.071***	-0.046***	0.059**	-0.033***	0.064***	-0.091***	0.064***	-0.079***	0.076***	-0.045***	0.079***
	(0.009)	(0.020)	(0.009)	(0.020)	(0.010)	(0.027)	(0.010)	(0.022)	(0.015)	(0.023)	(0.011)	(0.021)	(0.010)	(0.022)
First EVD case in part 2	-0.007	-0.017	-0.016**	-0.025	-0.021*	-0.015	-0.018**	-0.023	-0.033**	-0.017	-0.035***	-0.018	-0.015*	-0.021
	(0.007)	(0.016)	(0.008)	(0.016)	(0.012)	(0.032)	(0.008)	(0.016)	(0.014)	(0.017)	(0.010)	(0.015)	(0.008)	(0.016)
Post	-0.444***	-0.054***	-0.469***	-0.064***	-0.467***	-0.066***	-0.440***	-0.052***	-0.488***	-0.057***	-0.490***	-0.059***	-0.461***	-0.068***
	(0.003)	(0.007)	(0.004)	(0.006)	(0.004)	(0.006)	(0.006)	(0.008)	(0.006)	(0.006)	(0.005)	(0.006)	(0.005)	(0.007)
Mean Control 2011	0.71	0.14	0.72	0.13	0.72	0.13	0.72	0.13	0.72	0.13	0.72	0.13	0.72	0.13
Mean Treat 2011	0.70	0.24	0.69	0.24	0.69	0.24	0.69	0.24	0.69	0.24	0.69	0.24	0.69	0.24
No. Obs	3,560	3,560	3,560	3,560	3,560	3,560	3,560	3,560	3,560	3,560	3,560	3,560	2,452	2,452
Pv p1Xpost=p2Xpost	0.00	0.00	0.00	0.00	0.62	0.05	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00

Notes: This table illustrates robustness checks for the effects of the EVD outbreak on the citizens' voting behavior. "Any EVD case" is constructed as a dummy equal to 1 if at least one (probable, confirmed, death) EVD case was recorded in any of the villages matched to each electoral precinct. The records are constructed from the MOH patient database and Global Communities safe burials. "First EVD case recorded in p1 (p2)" is constructed as a dummy equal to 1 if at least one (probable, confirmed, death) EVD case was recorded in the village before or in (after) September 2014. Turnout is constructed as total number of votes divided by total number of registered voters. Vote share of the incumbent party is constructed as total number of (valid) votes for the incumbent party divided by total number of votes. Controls not shown include elevation, distance (by road) to Monrovia, and the percentage of Muslim population. Additional controls, selected through the Lasso procedure (Belloni et al. 2014), include the distance (by road) to EVD place of origin, distance (by road) to the closest health facility in 2008, population (log), and the average percentage of households from the main tribes in Liberia (Bassa, Gola, Kpelle, Mano, Vai). Socio-demographic controls are constructed from 2008 Population and Demographic Census. Standard errors are clustered at precinct level. Columns 1 and 2 show estimates (and means) not weighted by the number of registered voters in 2014 election; columns 3 and 4 include additional controls such as average household size, average percentage of households with improved roof, wall and floor material, with improved water source, with improved toilet facility, owning a phone, a radio, a tv, owning a house, and whether the house has only one room; columns 5 and 6 use as regressor "Any confirmed EVD case" constructed as dummy equal to 1 if at least one confirmed positive EVD case was recorded in any of the villages matched to each electoral precinct; columns 7 and 8 uses Conley (2008) spatial standard errors with 2km cutoff; column 9 to 12 construct estimates bounds to migration, following Dinkelman et al. 2016; columns 13 and 14 show estimates using a difference-in-difference matching estimator. A coarsened matching is implemented using population (log), distance (by road) to Monrovia, elevation, average percentage of Muslim households, distance (by road) to EVD place of origin, distance (by road) to the closest health facility, average percentage of households with improved floor material and average household size, above and below the median. The analysis is conducted on the matched sample. The specifications also control for 86 strata indicators from the matching procedure. All specifications in columns 1 to 16 include county fixed effects for a total of 15 indicators. *** p<0.01, ** p<0.05, * p<0.1.

Appendix C: EVD data sources' comparison.

This section compares the records of EVD at village level between the patient database from MOH and (i) all buried individuals by Global Community (GC) for the entire set of 9,686 villages in the country, and (ii) the self-reported EVD incidence from survey respondents for the 571 villages in the sample. Table C1 shows that MOH and GC data sources do not match in 6.57% of the cases, and in the majority of the villages the MOH reports an EVD case in the village while GC does not. This is not surprising since the MOH patient database should incorporate records from all NGOs who participated in the response. In addition, the MOH and survey data do not match in 33.8% of the villages in the sample. Specifically, in 13.84% of the cases the MOH reports an EVD case, while the survey respondents claim to not know anyone with confirmed or suspected with EVD. For the remaining 20% of the cases, the MOH does not report any EVD case, while the survey respondents claim to know someone with confirmed or suspected EVD. I did not have any prior knowledge about how likely these two data sources were to match. In the latter case, for example, it is possible that the survey indicator captures suspicion about cases that the MOH never officially recorded. Correlations among the MOH database, and GC or survey data, are statistically significant at 1% level at 0.135.

Table C2 provides basic analysis of the main factors which predict mismatching between data sources at village level, testing whether the MOH database overestimates or underestimates the other two data sources. I am mainly worried that in villages more difficult to reach, i.e., with low initial level of trust towards the government, the recording of the EVD cases by the MOH could be underestimated. Overall, I find that the mismatching between the data sources, and specifically the overestimation of EVD cases by the MOH, is more likely in places with higher population and a higher percentage of Muslims. However, the vote share of the incumbent party in 2011 (proxy for initial trust in the government) does not predict any mismatch between data sources. Other factors, such as distances to EVD place of origin, Monrovia and closest health facility, and elevation also matter, but they mainly explain the mismatch between the MOH and GC data sources.

Table C1: Comparing MOH data with burials data (9,686 village) and with survey data (571 villages)

Any EVD case	Burials			Survey data		
MOH	Yes	No	Tot	Yes	No	Tot
Yes	0.41%	5.88%	6.30%	9.46%	13.84%	23.29%
No	0.69%	93.01%	93.70%	19.96%	56.74%	76.71%
Tot	1.10%	98.90%	100.00%	29.42%	70.58%	100.00%

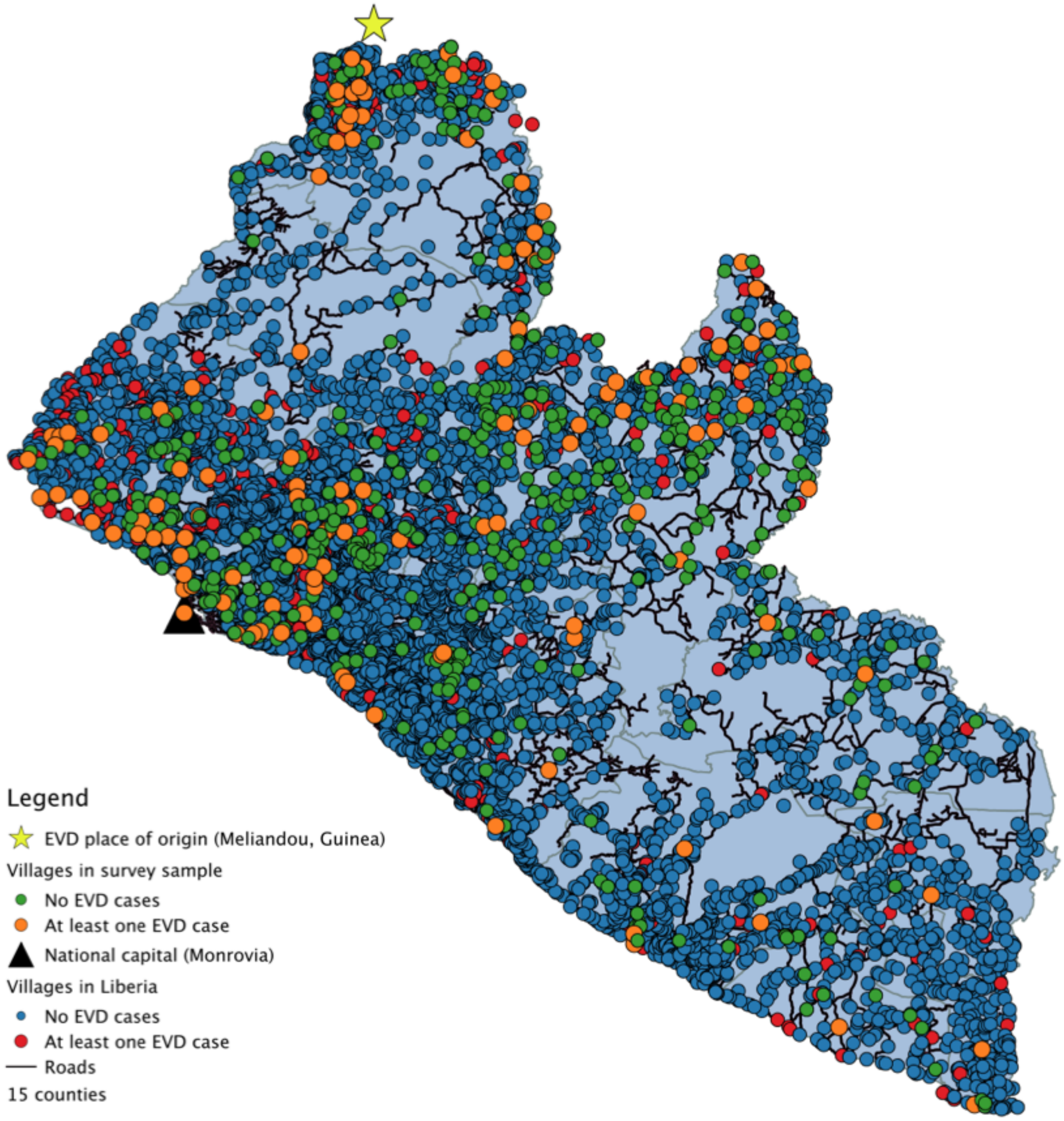
Note: This table illustrates the comparison between different EVD data sources. The correlation between MOH and burials is 0.135***; the coefficient of MOH on burials is 0.314***, while the coefficient of burials on MOH is 0.058***. The correlation between MOH and survey data is 0.135***; the coefficient of MOH on survey data is 0.125***, while the coefficient of survey data on MOH is 0.146***.

Table C2: Factors predicting mismatching between EVD data sources

	(1)	(2)	(3)	(4)	(5)	(6)
	Mismatch between MOH and burials			Mismatch between MOH and survey		
	Any mismatch	MOH underestimate	MOH overestimate	Any mismatch	MOH underestimate	MOH overestimate
Distance to EVD origin (100km)	0.00006	0.00005**	0.00001	-0.00014	-0.00019	0.00006
	(0.00006)	(0.00002)	(0.00005)	(0.00038)	(0.00031)	(0.00027)
Distance to Monrovia (100km)	-0.00015***	-0.00008***	-0.00007	-0.00010	0.00009	-0.00019
	(0.00005)	(0.00002)	(0.00005)	(0.00039)	(0.00032)	(0.00028)
Distance to health facility (100km)	-0.00374***	-0.00023	-0.00351***	-0.00661	0.00005	-0.00667*
	(0.00053)	(0.00021)	(0.00049)	(0.00475)	(0.00390)	(0.00355)
Population (log)	0.04067***	0.00306***	0.03760***	0.02893**	-0.01549	0.04441***
	(0.00233)	(0.00072)	(0.00226)	(0.01345)	(0.01113)	(0.00929)
Household size	-0.00566***	0.00022	-0.00588***	-0.00302	-0.00469	0.00167
	(0.00154)	(0.00051)	(0.00146)	(0.00574)	(0.00476)	(0.00448)
Muslim pop	0.09779***	-0.00019	0.09798***	0.19253**	0.01631	0.17622**
	(0.01615)	(0.00437)	(0.01574)	(0.09563)	(0.08078)	(0.07567)
Elevation (100km)	0.011**	0.003	0.008*	0.012	0.007	0.005
	(0.005)	(0.002)	(0.005)	(0.032)	(0.026)	(0.024)
Educ up to primary	0.01636	0.00654	0.00981	-0.01086	-0.10919	0.09833
	(0.01342)	(0.00501)	(0.01258)	(0.14206)	(0.12570)	(0.08859)
Working in agriculture	-0.00552	0.00283	-0.00835	0.14669*	0.13768*	0.00901
	(0.00828)	(0.00292)	(0.00780)	(0.08549)	(0.07820)	(0.05443)
Improved roof material	0.01296*	0.00155	0.01140	-0.05197	-0.05809	0.00612
	(0.00779)	(0.00257)	(0.00740)	(0.07135)	(0.05930)	(0.04946)
Improved wall material	0.01246	0.01107	0.00140	0.04011	0.06997	-0.02987
	(0.01647)	(0.00759)	(0.01507)	(0.11289)	(0.10306)	(0.07192)
Own radio	0.00463	-0.00287	0.00750	0.01609	0.08045	-0.06436
	(0.00828)	(0.00288)	(0.00781)	(0.10166)	(0.09152)	(0.06225)
Own phone	0.02158	0.00760	0.01398	0.24524	0.24223	0.00302
	(0.01573)	(0.00669)	(0.01454)	(0.17367)	(0.15536)	(0.11168)
Own 1-room house	-0.00779	-0.00160	-0.00618	-0.05200	0.00474	-0.05674
	(0.00813)	(0.00319)	(0.00754)	(0.08926)	(0.08359)	(0.05172)
Turnout (2011)	-0.01148	-0.01019	-0.00128	0.10968	0.23704	-0.12736
	(0.02838)	(0.00909)	(0.02711)	(0.23110)	(0.19373)	(0.16549)
Vote share incumbent (2011)	0.01789	-0.00021	0.01810	-0.02864	0.03745	-0.06608
	(0.01399)	(0.00463)	(0.01341)	(0.10676)	(0.09289)	(0.07452)
Observations	9,686	9,686	9,686	571	571	571
Adj. R-squared	0.0777	0.00590	0.0779	0.0168	0.00487	0.0626
Mean Dep.Var.	0.0658	0.00692	0.0588	0.338	0.200	0.138

Notes: This table illustrates the factors predicting mismatch between EVD data sources. Socio-demographic covariates are constructed from 2008 Population and Demographic Census, geographic covariates are constructed in ArcGIS, while political outcomes in 2011 are from the closest precinct linked to each village. Standard errors are clustered at village level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Map 2: Comparing survey sample with villages in Liberia



Appendix D: Sample selection procedure.

This section provides more details on how the survey sample has been selected and potential concerns.

Procedure for sample selection. Due to the lack of a representative sample in the period pre-EVD, I selected more than 2,000 respondents for the data collection using an online platform called VotoMobile[47], through random dialing of phone numbers. Given the known structure of the mobile phone numbers in Liberia, a list of randomly generated phone numbers that fits that structure is created. The platform selected phone numbers from two main companies, LonestarCell/MTN ahead with a share of 49.55% and Cellcom, which follows second as a strong competitor with a share of 40.36%[48]. These companies have a similar phone structure, but different phone-prefixes[49], which were exploited in the algorithm used for the random selection. The platform was set up to randomly select half of the numbers from LonestarCell/MTN and half from Cellcom (LTA, 2012).

The platform presented two main advantages. First, since it has been shown that people are less likely to answer calls from international numbers (WBG, 2014b), the calls launched from the online platform mimicked an original Liberian phone number. Similarly, phone-surveys for the main data collection were performed by a local Liberian NGO[50]. This attempted to limit a potential low response rate. Second, the platform could be used to screen respondents based on their location. I implemented a very short Interactive Voice Recognition survey (IVR) to screen respondents based on where they were living at the beginning of the EVD outbreak.

The platform went through all the randomly generated phone numbers, implementing more than 200,000 calls (Table D1). When the call connected and a real individual picked up, the audio recording informed the respondent that she was selected for an interview. The IVR message asked the respondent three questions to locate her: whether she lived in Montserrado county at the beginning of the EVD outbreak; if not, in which other county she lived, and in which district. If the respondent answered all the three questions, then she would also be informed that someone would call back from the local NGO, and that, upon completion of the live-call interview, she would receive 1$ free airtime for her phone as a sign of appreciation for the time spent on the survey.

For each phone number that VotoMobile called, the platform recorded different codes to distinguish whether the number was a real or fake phone number, and to provide information on the completion of the IVR message: (1) In the case the phone connected, an individual picked up the call, and the IVR message started, three codes recorded whether the respondent

[47] https://www.votomobile.org/.

[48] Other companies are Comium and LiberCell that follow third and fourth with market shares of 8.34% and 1.29% respectively, and Libtelco, the designated national operator which has the least share of 0.46%.

[49] Both companies' phone numbers are 10 digit numbers: LonestarCell/MTN starts with 0880, 0886, 0888, while Cellcom has prefixes 0770, 0775, 0776, 0777.

[50] I worked with a local NGO called Parley, based in Gbarnga, Bomi County, which had past experience with phone surveys, also during the EVD outbreak.

completed the survey, whether she started it but she did not complete it, or whether she did not even start it; (2) If the call connected, but individuals did not pick up the call, the platform registered tones up to 12 seconds as in case of voice mail; (3) The platform registered another code if the call was not picked-up and tones were not registered. The phone number could be a non-existing number, there could have been network problems or platform errors. From VotoMobile past experiences, however, when a call is recorded in this category, the majority of phone numbers are fake numbers. The platform attempted up to 4 calls to the same phone numbers: the second call after 5 minutes, while the third and the fourth after 8 hours each.

Final sample. The main data collection by the local NGO proceeded in two rounds because of budget constraints. The initial sample started from the existing Liberian phone numbers for which the calls were picked up, including both completed responses (d1. 2,733 phone numbers) and not completed IVR surveys (d2. 1,276 phone numbers). The enumerators were instructed to call the full list of phone numbers multiple times to reach the respondents. The field team had also the flexibility to re-contact the respondent at her most preferred time and to call her back when the survey was interrupted for any reason.

As shown in Table D2, in round 1, the local NGO called back 2,319 respondents from the initial list of 2,733 who completed the IVR survey, while in round 2 it called back the remaining numbers and some of the 1,276 incomplete responses. Even though in round 1 all respondents finished the IVR survey and completed their location at the beginning at the EVD outbreak, when enumerators called back, 17% of the respondents reported that they were living in a different location from the one they had answered in the IVR survey (the majority in Montserrado county). Qualitatively, this sub-group reported that they had input the wrong answers at the time of IVR. Thus, I considered correct the respondent's response during the live call with the field team and I interviewed everyone who responded to the IVR message. As result, a total of 2,319 individuals consented and were surveyed in round 1. In round 2, for the majority of respondents, the location from the IVR survey was not completed. The team from the local NGO went through a similar screening process to the one in the IVR survey. As expected from the habit of Liberians frequently changing phone numbers, the NGO found that 43% of the numbers were permanently switched off and 28% were not ringing. Among the initial list provided for the second round, the NGO stopped at 313 individuals interviewed. The final sample for the analysis includes 2,265 individuals.

Potential concerns. The first concern with this novel sample approach is sample selection. In fact, I cannot escape the fact that only people who have a mobile phone were targeted in the survey and this group is not representative of the Liberian population (see Table D3 for a description of the population and survey respondents by county, and Table A2 for village characteristics). The second main concern is attrition: starting from the initial list of phone numbers generated by the online platform, the number of individuals the local NGO was not able to interview. World Bank researchers who performed phone surveys during the outbreak in

Liberia reported that, from their initial sample of respondents with phone numbers, only 30% completed the survey (16% of the original sample WBG, 2014b). In Sierra Leone, the response rate was also lower than expected, given the nature of the survey and the difficult conditions under which it was conducted: about 69% of the sample with phone numbers completed the survey (45% of the original sample, WBG, 2015a). In the former case, different reasons were conjectured about why the response rate was so low: one was related to the use of unknown foreign numbers, while a second reason was thought to be the lack of resources to pay for phone charging in a period of crisis. Other surveys, performed through face-to-face interviews in Montserrado county, reached 95% of the respondents (Blair et al., 2016). Follow-up phone surveys reached about 80% of the original sample, but the initial in-person interaction between the field team and respondents during the baseline survey seemed to have been the main factor determining the lower attrition rate. In my project, none of the reasons for low response rate in the World Bank surveys were a concern because the data collection happened in late 2015, when the EVD outbreak was completely over and life was back to normal. Moreover, the online platform masked the international phone numbers as original Liberian numbers, and live-voice surveys were performed by Liberian enumerators in Liberian English. I also provided 1$ of airtime incentive to finish the survey. Overall attrition, counted as refusals or phone ringing but individuals not picking up, was very low at about 5% (Table D2, in italics).

Table D1: Sample selection

Total calls placed	214,823	
[Average no. attempts 3.55 out of 4]		
a1) Not picked up	170,825	80%
a2) Picked-up	43,998	20%
Among who picked-up		
b1) Did not answer any question	30,021	68%
b2) Started survey	13,977	32%
Among the 32% started survey:		
c1) Montserrado county	9,968	71%
c2) Other county of interest	4,009	29%
Among the 29% from 12 counties		
d1) Completed responses (county and district)	2,733	68%
d2) Not completed (only county, county/district other)	1,276	32%

Notes: This table illustrates summary statistics for the sample selection through VoteMobile platform.

Table D2: Final Sample

	No. phone numbers	Respondents (%)
ROUND 1 (Dec 2015 - Feb 2016)		
Interviewed	1,957	84.39%
Refused to participate	79	3.41%
Phone ringing, no pick up	25	1.08%
Previously Interviewed	15	0.65%
Not eligible (Less than 18 yrs old)	49	2.11%
Phone not ringing	194	8.37%
Total	2,319	100%
Sample analysis	1,952	
ROUND 2 (June 2016)		
Interviewed	314	22.0%
Refused to participate	34	2.3%
Phone ringing, no pickup	69	4.7%
Not eligible (Less than 18 yrs old)	1	0.3%
Phone not ringing	408	27.7%
Switch off	634	43.0%
Total	1475	100%
Sample analysis	313	
Total sample analysis	2,265	

Notes: This table illustrates summary statistics about the final sample of respondents called and interviewed by the local Liberian NGO in two rounds of data collection. In italics the reasons for no-interview counted towards attrition.

Table D3: Description of survey sample by county

	Pop (2014)	Pop (%) (2014)	Pop density (pop/sq mile) (2014)	Rural (%) (2012)	Phone coverage (2012)	No. resp (2015)	No. resp (%) (2015)
Bomi	94,418	2.4%	127	79.9%	91.4%	75	3.3%
Bong	401,500	10.2%	119	70.3%	86.2%	431	19.0%
Gbarpolu	93,598	2.4%	24	88.7%	40.0%	20	0.9%
Grand Bassa	251,938	6.4%	84	74.1%	55.9%	169	7.5%
Grand Cape Mount	142,304	3.6%	77	92.0%	72.3%	59	2.6%
Grand Gedeh	140,594	3.6%	34	61.8%	58.1%	60	2.7%
Grand Kru	65,004	1.7%	43	93.3%	18.0%	15	0.7%
Lofa	300,747	7.7%	78	70.7%	84.1%	235	10.4%
Margibi	235,625	6.0%	227	60.5%	90.7%	316	14.0%
Maryland	152,582	3.9%	172	60.3%	69.9%	13	0.57%
Montserrado	1,255,152	32.0%	1729	8.1%	89.9%	314	13.86 %
Nimba	522,155	13.3%	117	76.1%	78.7%	499	22.0%
River Gee	74,966	1.9%	34	74.0%	53.6%	7	0.31%
Rivercess	80,264	2.0%	41	96.5%	47.2%	14	0.6%
Sinoe	114,927	2.9%	30	83.6%	32.1%	38	1.7%
Total	3,925,773	100.0%	105	51.2%	64.5%	2,265	

Notes: This table illustrates summary statistics by county in comparison with the survey sample.

Contribution to literature. This novel data collection approach contributes to a small growing literature about methodologies for data collection in developing countries. First, I build on a similar sample selection approach - through "random-dialing" of phone numbers - used by Leo et al. (2015), where the authors randomly select the sample through VotoMobile platform and they use an Interactive Voice Recognition (IVR) survey for the main data collection. The authors analyzed whether mobile phone-based surveys are a feasible and cost-effective approach to collect data in four low-income countries, focusing mainly on whether this method can reach a nationally representative sample (through quotas) and how to improve its survey completion (through monetary compensation).

Second, the project is also related to few existing studies that rely on voice-based phone surveys to collect (high frequency) data. Croke et al. (2012) provide examples of phone surveys at high frequency in Tanzania and South Sudan through a call center. A similar approach is used by Dillon (2012) to elicit farmers' expectations, production, and income levels over time. Demombynes et al. (2013) also worked on a similar study in South Sudan, where the authors randomize the level of incentives along with the type of phone provided to participants, to increase their response rate.

Because of the difficulty and the high costs of implementing face-to-face interviews in a widespread geographical area, the setting of the EVD outbreak allowed the opportunity to build on the current literature and test the combination of (i) sample selection through "random-dialing" of phone numbers; (ii) Interactive Voice Recognition (IVR) survey to screen respondents, rather than fixed quotas; (iii) a full-length (30-45 minutes) live-voice phone survey to gather data. Despite the concerns discussed above, the data collection method used in this project provides an additional test of the feasibility of this methodology in another developing country.

Appendix E: Endemic-Epidemic Modeling of Ebola.

This section explains in details the spatio-temporal epidemiological model I build on to construct the measure of misallocation used in the empirical analysis. Since the 2014 West Africa EVD outbreak was the first epidemic of this size in the recorded history of the virus, it is unclear what is the best modeling approach. For my purposes, I follow the epidemiological literature (Meyer and Held, 2017) to estimate a spatio-temporal model of the count time series of EVD *confirmed* cases[51] at the village level. I rely on simplifying, but realistic assumptions that allow me to estimate the model using the observed counts of EVD for the first part of the epidemic, and predict how the contagion would have evolved at later stages, in each village.

Specifically, the spatio-temporal data gathered from the MOH allow me to follow the estimation of the so called "hhh4" model proposed by Held et al., 2005 and extended by Paul et al., 2008, Paul and Held, 2011, Meyer and Held, 2014 that assumes that, conditional on past observations, Y_{it} has a negative binomial distribution with mean:

$$\mu_{it} = e_i \nu_t + \lambda Y_{i,t-1} + \phi \sum_{j \neq i} w_{ji} Y_{j,t-1} \tag{9.1}$$

and overdispersion parameter $\psi_i > 0$ such that the conditional variance of Y_{it} is $\mu_{it}(1+\psi_i\mu_{it})$[52]. i refers to the 9,686 villages in Liberia, t refers to a month, from March 2014 to March 2015 for a total of 13 months, while j refers to neighboring villages.

The model decomposes the mean in two parts: (i) an endemic component ($e_i\nu_t$) that is modeled proportional to an offset of expected counts (e_i), assumed to be the population living in village i; (ii) an epidemic component ($\lambda Y_{i,t-1} + \phi \sum_{j\neq i} w_{ji} Y_{j,t-1}$) decomposed in an autoregressive effect ($\lambda Y_{i,t-1}$), i.e. the reproduction of the disease depends on the counts in the same village the month before, and a neighborhood effect ($\phi \sum_{j\neq i} w_{ji} Y_{j,t-1}$), i.e. the disease depends on the counts transmitted from other villages j. w_{ji} are in fact weights which reflect the flow of infections from village j to village i. As in Meyer and Held, 2014, I assume a power-law distance decay $w_{ij} = o_{ij}^{-d}$ where o_{ij} is the adjacency order in the neighborhood graphs of the villages in Liberia based on the distance d between village i and j. I consider village i and j as neighbors if they are within 2 km of each other. I normalize the transmission weights such that $\sum_i w_{ji} = 1$. I also assume for simplicity that $w_{ji} = 1(j \sim i) = 1(o_{ji} = 1)$, i.e., all villages have the same ability ϕ to import cases from neighboring villages[53].

I assume a log-linear prediction in all the three components ($\nu_t = exp(\alpha^{(\nu)})$; $\lambda = exp(\alpha^{(\lambda)})$; $\phi = exp(\alpha^{\phi})$. In fact, I adjust the endemic component to exclude the seasonality part and

[51] I use the R package surveillance that analyzes area-level time series of counts using the endemic-epidemic multivariate time-series model "hhh4".

[52] I assume a negative binomial distribution. An alternative would be a Poisson distribution, but this assumes that $\psi_i = 0$, which is not the case in this context.

[53] The model can be extended to a "gravity" model, where the infection probability from neighboring villages is scaled by the population, $\phi * e_i^{\beta_{pop}}$. I compare the two models and the Akaike Information Criterion (Akaike, 1974), however, is very similar across models (AIC=2254.532 in the former case and AIC=2256.422 scaling by population).

a time trend - given the short duration of EVD - and allowing only for covariates to explain the first cases of EVD recorded in March 2014.[54]. For simplicity I assume that the intercepts are identical across villages ($\alpha^{(\nu)}$, $\alpha^{(\lambda)}$, $\alpha^{(\phi)}$), rather than village specific, to avoid forcing the model to exclude villages without any reported case of EVD[55]. The basic model is fitted via (penalized) maximum likelihood, through quasi-Newton algorithm, using only the first part of the epidemic from March 2014 to September 2014 (Table E1).

Table E1: Estimates (Basic Model)

First part (March-September 2014)		
	Coefficient	SE
exp(ar.1)	1.196	4.394
exp(ne.1)	0.03312	0.08534
exp(end.1)	0.005923	0.0007939
overdisp	871.6	107.2
Log-likelihood:	-1123.27	
AIC:	2254.53	
BIC:	2290.41	
No. village	9686	
No. months	6	

Notes: This table illustrates estimates from the estimation of the spatio-temporal epidemiological model on the first part of the epidemic. The model is estimated starting from March 2014 when the first case of EVD was recorded in Liberia to September 2014 (7 data points). Since March 2014 is used as input for the auto-regressive component, the model is estimated on a total of 6 data points. The package "surveillance" is used for the implementation.

Only the initial endemic component model is statistically significant, as well as the overdispersion parameter, suggesting that a Negative Binomial distribution should be preferred to a Poisson. In fact, re-estimating the model while fitting a Poisson distribution, the AIC criteria are much higher compared to the Negative Binomial case (AIC (Poisson) = 7417.391, AIC (Neg Binomial=2254.532).

I then use the fitted estimates from the model in September 2014 to simulate the epidemic in the next months per each village in the country. I rely on the fact that resources started flowing

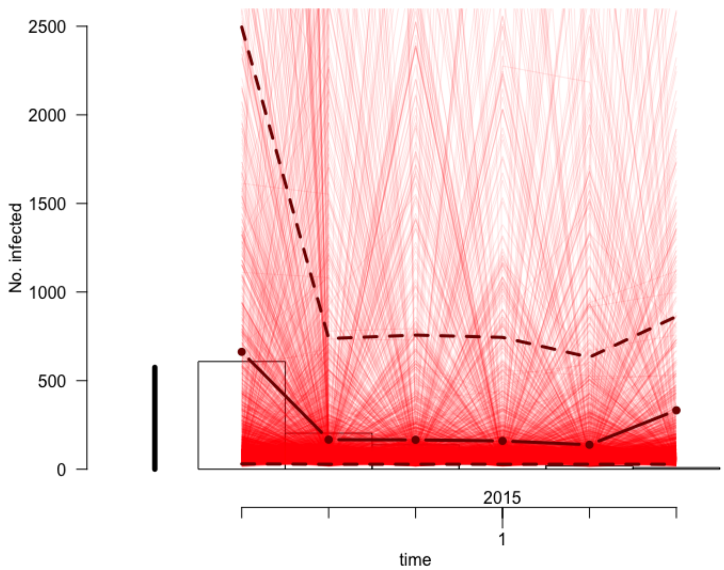
[54]Covariates are household size, percentage of female population, percentage of households from the main tribes in Liberia, with at least primary education, working in agriculture, owning a 1-room house, having an improved source of water, having an improved toilet or a house with improved roof or floor material, owning tv, radio and phone, Christian, and 2011 turnout and vote share of the incumbent party. The population fraction e_i is included as a multiplicative offset.

[55]The model could be extended to random effects to account for unobserved heterogeneity of the villages, for example, in the case of unobserved measurement error in the counts. However, given the high number of villages, a random effect model does not converge. Still, most of the villages have a similar trend over time, with a pick of cases around August-October.

into the country by September, and that, at that point in time, the government needed to decide where to put foreign relief effort. I argue that the government should have put resources in places in which the number of counts was expected to be higher in the following months.

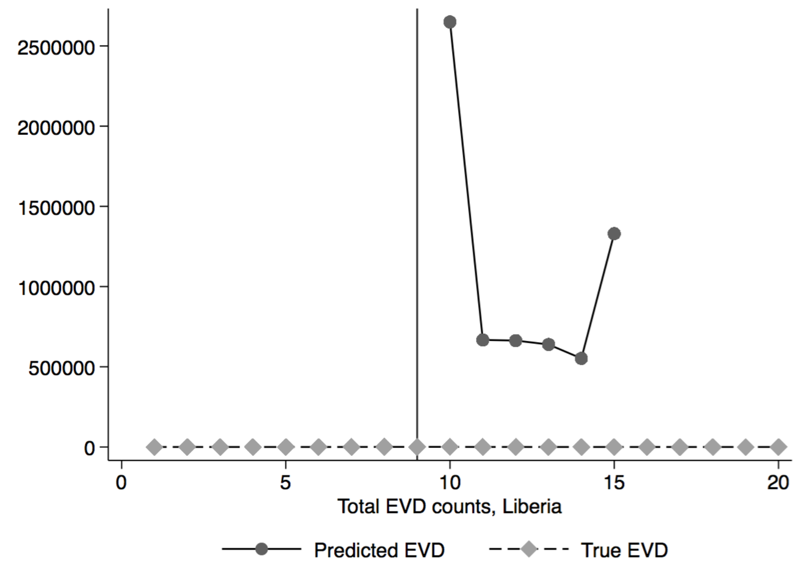
Figure E1 shows the results from the simulation-based long-term forecast starting from September 2014 for the rest of the epidemic. The monthly mean of the simulations is represented by dots and the dashed lines correspond to the point-wise 2.5% and 97.5% quantiles; the actually observed counts are shown in the background. Figure E2 shows the comparison between the total predicted and the true (total) counts of EVD for the whole country of Liberia.

Figure E1: Simulated model for second part of EVD outbreak (4000 simulations)



For the empirical analysis, I use the sum of the predicted counts from this exercise, per each village, between October 2014 and March 2015, as proxy for places where the potential of disease infection could have been higher and where the government should have allocated more resources. I then standardized the predicted counts to get a measure of ex-ante probability of getting EVD between 0 and 100% at village level (as number of counts per village divided by total number of counts in Liberia). I use this measure of predicted probability to compute how many resources the government should have allocated in each villages (predicted costs). I refer to Section 6 for details on the construction of the observed costs, predicted costs, and thus the measure of misallocation.

Figure E2: Comparison between predicted and true (total) counts of EVD, Liberia



As last, to support the choice of the basic model to conduct this exercise, Figure E3 presents the in-sample fit of the model, suggesting that the model is a good fit for the entire epidemic. In addition, Table E2 describes the results from one-step-ahead forecasts from three competitive models by proper score rules suggested by Czado et al., 2009. These scores from the out-of-sample predictive model assessment (on the second part of the epidemic) measure the discrepancy between the predictive distribution from the fitted and the observed counts. The basic model (Model 1) is chosen for the final exercise because it corresponds to better predictions.

Figure E3: In-sample fit of the basic model

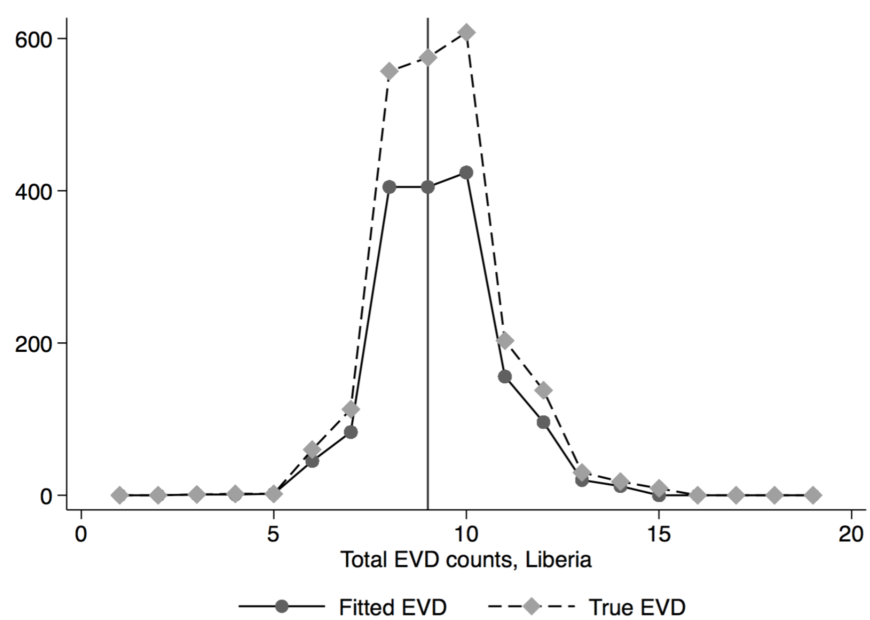


Table E2: Results from out-of-sample predictive model assessment

Models	Logs	Rps	Dss	Ses
Model 1 (Negative Binomial)	0.02261479	0.02394556	2.118023	2.962059
Model 2 (Poisson)	0.07417876	0.02504813	25.370932	3.031943
Model 3 (Gravity Model)	0.02261359	0.02394992	2.123785	3.033383

Notes: The table illustrates out-of-sample predictive model assessment on three different model variations: (1) assuming a Negative Binomial distribution; (2) assuming a Poisson distribution; (3) gravity model, where the infection probability from neighboring villages is scaled by the population. Proper scoring rules for count data are used to measure the discrepancy between the predictive distribution from the fitted and the observed counts (Czado et al. 2009). "Logs" refers to the logarithmic score, "Rps" to ranked probability score, "Dss" refers to Dawid-Sebastiani score, "Ses" refers to the squared error score. Lower scores correspond to better predictions. Model 1 is the preferred model (basic model).

Appendix F: Cost-Benefit Analysis.

Table F1: Assumed and calculated costs for EVD response

Panel A: Budgeted costs for response to EVD (USAID)				
Item	$Budgeted	No. units	Unit	$Cost/Unit
Contract Tracing	$ 25,000,000	15 teams	Team	$ 1,666,667
Health workers	$ 32,000,000	2510 trained staff	Health worker	$ 12,749
ETUs*	$ 543,700,000	19 ETUs	ETU	$ 28,615,789
CCCs*	$ 212,700,000	40 CCCs	CCCs (25bed)	$ 5,317,500
Burial Teams*	$ 36,800,000	56 burial teams	Team	$ 657,143
Control infections	$ 28,100,000	Training staff health facilities	N/A	N/A
Community outreach	$ 66,900,000	4 million people	N/A	N/A
Logistics and Supplies	$ 269,100,000	17 ETUs/4m - 3 ETUs/12m	PPP (ETUs)/12m	N/A

Panel B: Calculated costs per unit/item			
Item	Tot units	$Cost/Unit	$Tot cost
ETUs	31	$ 28,615,789	$ 887,089,474
CCCs	78	$ 5,317,500	$ 414,765,000
Burial teams	74	$ 657,143	$ 48,628,571
Total			$ 1,350,483,045

Panel C: Calculated costs/village	
Item	$Cost/village
ETUs	$ 3,812
CCCs	$ 1,725
Safe burials	$ 808
Average cost per village	$ 6,345
Tot cost for all villages	$ 61,455,152

Notes: This table illustrates the costs of the EVD response. Panel A describes the budgeted costs from the Emergency Request Justification, Department of State, Foreign Operations, and Related Programs, United States of America, Fiscal Year 2015. Panel B describes calculated costs per each unit for the three relief effort considered in the analysis (*construction of ETUs and CCCs and deployment of burial teams). I consider 74 teams as reported in Global Communities' data. Panel C describes the calculated costs per village. From the budgeted costs in Panel A, I assigned to each village the total costs of an ETU ($28,615,789) and of a CCC ($5,317,500) if the village has an ETU/CCC within a 1 km radius. If further away, I assign the cost divided by the distance. I estimate a cost per buried person of $15,646, as the cost of 74 burial teams ($657,143) divided by the average 42 safe burials that each of the teams provided at village level from the Global Communities data.

Table F2: Cost-benefit analysis - number of lives saved with earlier response

A) COSTS

Village type	(1) No. villages	(2) Calculated cost per village	(3) No. months recovery*	(4) No. months taken to respond	(5) Add resources spent per delayed month
Hit by EVD in part 1	124	$ 106,834.51	**4.26**	3	$ 26,113.59
Hit by EVD in part 2	553	$ 28,493.75	**1.60**	0	
Never affected	9,009	$ 3,602.03	0	0	

B) BENEFITS

				2 months-delayed response					1 month-delayed response				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Village type	No. villages	Average no. EVD cases per village	Average no. EVD cases per village [each month]	Additional recovery* [months]	Total months recovery [1.60+(4)]	Saved time [4.26-(5)]	Avoided EVD cases per village [(3)X(6)]	Avoided EVD cases total [(1)X(7)]	Additional recovery* [months]	Total months recovery [1.60+(9)]	Saved time [4.26-(10)]	Avoided EVD cases per village [(3)X(11)]	Avoided EVD cases total [(1)X(12)]
B.1 Suspected deaths													
Hit by EVD in part 1	124	32.58	5.43	2.08	3.68	0.58	3.15	391	1.04	2.64	1.62	8.79	1,090
Hit by EVD in part 2	553	2.60	0.37	2.08	3.68	0.58	0.22	119	1.04	2.64	1.62	0.60	332
Hit at any time	667	6.36	0.49	2.08	3.68	0.58	0.28	189	1.04	2.64	1.62	0.79	528
B.2 Confirmed cases													
Hit by EVD in part 1	124	16.87	2.81	2.08	3.68	0.58	1.63	202	1.04	2.64	1.62	4.55	564
Hit by EVD in part 2	553	0.37	0.05	2.08	3.68	0.58	0.03	17	1.04	2.64	1.62	0.09	47
Hit at any time	667	3.39	0.26	2.08	3.68	0.58	0.15	101	1.04	2.64	1.62	0.42	282

Notes: This table illustrates a cost-benefit analysis exercise computing the number of lives which could have been saved with an earlier response. No. months of recovery* is estimated in the empirical analysis Table 4, column 3. Additional recovery* is estimated from the proportion $106,834.51 (column 2, Panel A) : 4.26 months recovery (column 2, Panel A) = $26,113.59 (x1 or x2): X. To anticipate the response of 1 month (2 month-delayed response) the proportion uses $26,113.59 X 2 months of response, while to anticipate the response of 2 month (1 month-delayed response) the proportion uses $26,113.59 X 1 month of response. $26,113.59 represents the additional resources the government spent for villages affected in part 1 compared to part 2 ($106,834.51 - $28,493.75) per each of the 3 months of delayed response.

Table F3: Estimation of total number of lives saved

Item	Expected lifes saved [Best scenario]	Expected lifes saved [Realistic scenario]	No. lives saved	No. item units	Total no. lives saved
ETUs	50 beds	50 beds x survival rate*	27.5	31	852.5
CCCs	15 beds	15 beds X survival rate*	8.25	78	643.5
Burial teams	42 burials X hh size	42 burials X 1 care giver	42	74	3,108
					4,604

Notes: This table illustrates the estimated number of lives saved given the three types of relief effort used in the analysis (ETUs, CCCs, and burial teams). * Survival rate is assumed to be 55%. Over the epidemic, 4,806 people died over the 10,666 infections. This corresponds to an average fatality rate of 45% (CDC, Ebola updates).

Table F4: Cost benefit analysis - number of lives saved in the absence of misallocation

(A) COSTS					(B) BENEFITS
(1)	(2)	(3)	(4)	(5)	(6)
Total cost per village [Table F1, Panel C]	Total lives saved [Table F3]	Cost per life saved [(1)/(2)]	Misallocated per village [Table 5, column 5]	Misallocated total [(4)X148]	Tot no. lives saved [(5)/(3)]
$ 61,455,152	4,604	$ 13,348	$ 42,632	$ 6,309,536	473

Notes: This table illustrates a cost-benefit analysis exercise computing the number of lives which could have been saved without misallocation for political gains.

Table F5: Descriptive results of the 2014 Senatorial election, by county

	(1) Calculated no. votes to win a seat	(2) Calculated cost to win a seat (1000$)	(3) Total observed costs (1000$)	(4) Total misallocation (1000$)	(5) Party winning Senate seat
Grand Cape Mount	1,075	$ 137.60	$ 36,750.20	$ 1,888.02	UP
Bomi	2,370	$ 303.33	$ 22,246.78	$ 3,203.16	UP
River Cess	2,758	$ 353.02	$ 25,073.72	$ (24.70)	NDC
Sinoe	3,658	$ 468.22	$ 41,973.89	$ 949.81	UP
River Gee	3,732	$ 477.70	$ 11,553.58	$ 1,350.27	UP
Gbarpolu	4,653	$ 595.58	$ 22,799.88	$ 1,105.38	ANC
Grand Kru	7,489	$ 958.59	$ 9,648.47	$ 730.96	IND
Maryland	9,830	$ 1,258.24	$ 12,967.04	$ 1,303.37	IND
Grand Gedeh	11,009	$ 1,409.15	$ 15,363.80	$ 804.90	CDC
Margibi	11,295	$ 1,445.76	$ 63,790.49	$ 2,016.34	PUP
Bong [NPP]	17,145	$ 2,194.56	$ 73,992.05	$ 790.85	NPP
Grand Bassa [LP]	19,606	$ 2,509.57	$ 45,353.93	$ (1,966.53)	LP
Lofa [LP]	29,111	$ 3,726.21	$ 45,353.93	$ (2,912.99)	LP
Nimba [NUDP]	44,294	$ 5,669.63	$ 47,013.22	$ 1,694.45	IND
Montserrado [CDC]	100,953	$ 12,921.98	$ 46,767.40	$ (10,933.28)	CDC

Notes: This table illustrates the results of the 2014 Senatorial election, by each of the 15 seats in the Senate. The counties are order by the cheapest seat to win. The political party that historically had more political support in the county is reported. Column (1) reports the calculated number of votes needed to win each seat, constructed as the absolute difference in the vote share between the (losing) incumbent party and the winning political party multiplied by the total number of voters; column (2) reports the total costs (in $1000) needed to win each seat, calculated as the unit cost per vote multiplied by the total number of votes needed to win each seat. The unit cost per vote is computed as the limited government's observed costs ($61.5 million) divided by the total number of votes in 2014 elections; column (3) reports the total observed costs (in $1000) per each seat; column (4) reports the total misallocation (in $1000) per each seat; column (5) reports the party that won the seat in the 2014 Senatorial election (UP is the incumbent party).

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