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Better Containment but Less Health Access

How past exposure to health crises affects the Covid-19 response

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Better Containment but Less Health Access: How Past Exposure to Health Crises Affects the Covid-19 Response

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Abstract

In this paper I provide micro evidence for one mechanism behind the dramatically different political responses to the Covid-19 pandemic, namely how an increase in the perceived risk of Covid-19 among individuals stemming from past exposure to similar health crises generates citizen demand for containment measures. Exploiting exogenous variation in exposure to the 2014 Ebola outbreak across villages in Sierra Leone, I find that past exposure leads to significant increases in risk perception regarding Covid-19 and trust in health professionals among households. I then show that this also translates into Ebola-affected villages being significantly more likely to have organized the public distribution of face masks. However, the increased caution comes at the cost of reduced health access as households in Ebola-affected villages are more likely to avoid health clinics during the pandemic out of fear of contracting Covid-19.

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1 Introduction

Why did Liberia declare a national health emergency and close down most public places within 6 days of recording the first Covid-19 case in the country whereas in the United States life continued mostly uninterrupted for weeks after the first Covid-19 case was recorded? Why did South Korea manage to contain the spread of Covid-19 very well early in the pandemic whereas some regions in Italy lost control of the outbreak and were unable to admit patients to already overcrowded hospitals? While there likely is a plethora of reasons for these differential responses, I argue in this paper that one part of the story relates to past exposure to similar health crises, e.g. the 2002 SARS outbreak which affected South Korea or the 2014 Ebola outbreak which affected Liberia, which has raised individuals' perceived risk of Covid-19 and has led to a higher demand for containment measures. However, I also find that the increased caution of individuals comes at the cost of reduced health access stemming from a fear of contracting Covid-19 at health facilities.

In this paper I investigate how the 2014-16 outbreak of the Ebola Virus Disease (EVD) in West Africa, which mainly affected Guinea, Liberia, and Sierra Leone, affects households and villages in Sierra Leone in terms of risk perception of Covid-19 as well as trust in health professionals and how these subsequently affect containment measures and health access. The Sierra Leonean context is especially suitable because the 2014-16 EVD epidemic, which was the largest in recorded history and led to 14,124 cases and 3,956 deaths in Sierra Leone alone, directly affected only a subset of villages in the country. Thus, instead of comparing countries like Liberia and the United States which are very different from each other in many dimensions, I look at Covid-19-related outcomes in similar villages in Sierra Leone, some of which were directly affected by the 2014-16 EVD epidemic and some which were not. After that, I go one step further and try to estimate the causal effect of EVD exposure by taking an instrumental variable approach and instrument EVD exposure by the village distance to the EVD index case in Guinea, which I treat as an exogenous event.

In my empirical exercise I use primary data collected for this study from phone surveys with household respondents and health workers from 535 villages in Sierra Leone during the Covid-19 pandemic in October and November 2020. First, I create a binary EVD indicator for each village which cross-validates responses from households and health workers in the same village. I then compare outcomes related to risk perception, trust in health professionals, Covid-19 prevention, and health access between households in villages directly affected by EVD and those not directly affected by EVD controlling for geographic village characteristics and demographic household characteristics. As EVD-affected and non-affected villages might still differ in other unobserved dimensions, I then use the village road distance to the place of the EVD index case as an instrumental variable for EVD exposure controlling for a set of geographic characteristics. The idea is that geographically comparable villages that are closer to the index case were more likely to be affected by EVD than villages further away. My data confirms that available demographic characteristics of households do not predict EVD exposure.

I estimate that household respondents in EVD-affected villages are 50 pp. more likely to believe they can contract Covid-19 and 32 pp. more likely to know that it is possible for asymptomatic individuals to infect others with Covid-19. Furthermore, households in EVD-affected villages are 44 pp. more likely to say that they trust health professionals when it comes to information about Covid-19. This translates into stronger containment measures in EVD-affected villages which are 44 pp. more likely to have organized the public distribution of face masks. However, households in EVD-affected villages were also 43 pp. more likely to have avoided going to the local health clinic out of fear of contracting Covid-19. These results highlight how past exposure to a health crisis persistently affects individuals' risk perceptions and leads to a higher demand for prevention and containment measures. At the same time, the increase in the perceived risk of Covid-19 reduces health access for households.

This paper contributes to two strands of the literature. First, this study adds to the literature on the political determinants of preventing and containing the spread of Covid-19. A number of studies suggests that countries affected by the 2002 SARS outbreak, the 2012 MERS outbreak, or the 2014 Ebola outbreak were better prepared for the current

Covid-19 pandemic and adopted decisive measures early on (Fotiou and Lagerborg, 2021; Chua et al., 2021), which in turn has been linked with better containment of and a faster recovery from the Covid-19 pandemic (Caselli et al., 2021). The potential reasons mentioned for this link between past exposure to health crises and better containment include the training of primary health care providers, centralized data-driven surveillance systems, widespread testing and contact tracing, and increased citizen demand. While these studies rely on cross-country comparisons or evidence from case studies, I provide micro evidence for a specific mechanism linking past exposure to a higher demand for containment measures: I show that past exposure to the 2014-16 Ebola epidemic on the village-level increases households' perceived risk of Covid-19, increases their trust in health professionals, and increases the likelihood of adopting preventive measures.

Second, this study adds to the literature on the trade-off between fewer Covid-19 cases and higher socio-economic costs resulting from containment measures.[1] In particular, I add to the literature on the consequences of Covid-19 on health care access. Overall, there is evidence for a great reduction of health care access due to Covid-19 (World Health Organization, 2021). On the supply side, there is evidence for an increase in the morbidity and mortality of health workers which has negatively affected health care access (Bandyopadhyay et al., 2020; Gholami et al., 2021). Furthermore, many health workers and health care facilities were utilized in the Covid-19 response and therefore unavailable for non-Covid-related services (Abelson, 2021). On the demand side, there is evidence that mobility restrictions and lockdowns prevented people from accessing health care services (Cantor et al., 2020). I add to this literature by highlighting another channel limiting health access for individuals, namely decreased demand due to a fear of contracting Covid-19 at the health facility. Furthermore, I show that this effect is stronger for households in villages previously affected by EVD, probably because they perceive Covid-19 to be riskier than households in non-affected villages. There already is some evidence for a deterioration of non-Covid-related health outcomes during the pandemic (Jain and Dupas, 2021) and the predicted negative impact of the current decrease

[1] Miguel and Mobarak (2021) provide a great review of the empirical literature on the economic and non-economic consequences of the Covid-19 pandemic, with a focus on low- and middle-income countries.

in health access on future health outcomes is substantial (McQuaid et al., 2020; Glaziou, 2020; Sherrard-Smith et al., 2020). Thus, understanding individual beliefs and risk perceptions around health care services is crucial in order to improve health access during the Covid-19 pandemic.

The rest of the paper is structured as follows: Section 2 provides some background about the 2014-16 Ebola epidemic and the Covid-19 pandemic in Sierra Leone. Section 3 describes the data and variables used in this paper. Section 4 lays out the empirical strategy. Section 5 discusses the results. Section 6 concludes.

2 Background

2.1 The 2014-16 Ebola Epidemic

Together with Guinea and Liberia, Sierra Leone was one of the three countries that experienced widespread transmission of EVD following the 2014 EVD outbreak in West Africa. Over the course of the 2014-16 West African EVD epidemic, 28,616 cases and 11,310 deaths were recorded in the three countries, making it the deadliest EVD outbreak in history. Out of these, Sierra Leone accounted for 14,124 cases and 3,956 deaths. Different from other viral diseases, including Covid-19, EVD does not spread through airborne transmission but through people getting in contact with body fluids of an infected person. The index case of the 2014-16 EVD outbreak occurred when a 18-month old toddler came into contact with an infected fruit bat in the town of Meliandou, Guinea, close to Sierra Leone's eastern border.[2] As Fang et al. (2016) show, the subsequent spread of EVD in Sierra Leone closely followed the country's road network starting from the eastern border with a second transmission corridor originating from Freetown, the country's capital city, emerging in the later stages of the outbreak. There are a number of aspects of the 2014-16 EVD outbreak that might have affected the way people react to future disease outbreaks: First, with an average case fatality rate of around 50% EVD is much more deadly than most other common diseases. Second, while EVD transmission hap-

[2] A brief summary about the 2014-16 West African EVD outbreak is available from the Centers for Disease Control and Prevention.

pens through body fluids and is not airborne, the set of effective containment measures is very similar to that for other viral diseases. The key to halt the spread of EVD is to limit human-to-human interaction, to identify, trace, and isolate infected people, and to take accompanying measures that raise awareness and generate buy-in from the population.[3] In Sierra Leone some of these EVD containment measures created tensions as they interfered with deeply rooted burial traditions or because the bodies of the deceased were taken away from villages by health workers in hazmat suits who were unknown to the local population.[4] Third, a disproportionate share of people who became infected with EVD were health workers (Evans et al., 2015). Among other potential negative consequences on the provision of health services, this might have affected people's risk perceptions about interacting with health workers or visiting health care facilities during a disease outbreak.

2.2 Covid-19 in Sierra Leone

As of November 2021, Sierra Leone has recorded just under 6,400 Covid-19 cases, a remarkably low number given its population of around 8 million, although part of the reason this number is so low is likely the lack of testing capacities as in many African countries.[5] Compared to most Western governments, the government of Sierra Leone took strong measures to halt the spread of Covid-19 very early relative to the local spread of the pandemic: Even before the first Covid-19 case was recorded in the country on March 31, 2020, the government closed its border for international air traffic and mandated the closure of places of worship as well as schools and universities. Upon recording the first case, the government imposed a 3-day country-wide lockdown at the start of April and after that announced a some additional containment measures including the ban of

[3] A chronology of previous EVD outbreaks, their case fatality rates, and current recommendations regarding disease control for EVD is available from the World Health Organization.

[4] A great ground report on the issues around burial practices from the time of the 2014-16 EVD outbreak in Sierra Leone is available from the National Geographic.

[5] Cumulative case numbers are regularly updated by the World Health Organization. A lack of testing capacities in many African countries has been reported by several media such as the BBC and Scientific American.

inter-district travel and a nighttime curfew.[6] Not only did the government react quickly and in a determined way, but also people's compliance with and support for government measures has been quite high: Ndubuisi-Obi et al. (2021) find that human movement indeed decreased dramatically during the government-mandated lockdowns and Solís Arce et al. (2020) show that (self-reported) compliance with wearing face masks and hygienic protocols was high among Sierra Leoneans in June 2020.

3 Data and Measurement

3.1 Data

This study leverages a number of different data sources:

Household Survey

In October and November 2020 enumerators conducted a phone survey with 879 primary care givers from households in 535 villages across 6 districts in Sierra Leone. The survey covered attitudes and beliefs about Covid-19, compliance with containment measures, utilization of health services, and basic demographic information. In addition to that, households were asked whether there had been an Ebola case in their village during the 2014-16 Ebola epidemic.

Village-Level Survey

In the same time period, enumerators conducted a survey with the local health worker responsible for each village. The goal of this survey was to get village-level information both about Covid-19 containment measures that were taken in the village and whether there had been Ebola cases in the village during the 2014-16 Ebola epidemic.

Geographic Data

Village-level geographic data used in this study include GPS coordinates and altitude collected for a previous study by Deserranno et al. (2021). In addition, the study utilizes a shapefile of Sierra Leone's road network from World Bank Group (2009) in order to calculate the Euclidean distance between each village and the nearest main road.

[6] A graphical illustration of the timeline of government containment measures for Covid-19 in Sierra Leone is available from Reuters.

3.2 Measuring Ebola Exposure

Based on the household survey and the village-level survey, I construct a measure of Ebola exposure in the following way: For every village, the binary EVD indicator is equal to 1 if the health worker and at least one household in the village say that there had been an Ebola case in the village during the 2014-16 Ebola epidemic. It is equal to 0 if neither the health worker nor any household say that there had been an Ebola case in the village during the 2014-16 Ebola epidemic. Villages are removed from the sample if neither of these two conditions hold. Figure 1 shows the distribution of villages with and without Ebola cases across Sierra Leone. In total, 10 % of the villages in my sample were directly exposed to EVD according to my measure. An alternative measure of Ebola incidence would be official cases recorded at the time of the epidemic. However, the number of official cases is not available on the village level. In addition to that, Christensen et al. (2021) show that the official number of cases depends on sick people reporting to health facilities which conditional on being sick is a function of several factors such as trust in the health system and cultural beliefs. To alleviate similar concerns for my measure of Ebola incidence I will use an instrumental variable approach that deals with both endogeneity concerns and potential measurement error.

3.3 Outcome Variables

Risk Perception and Knowledge Related to Covid-19

My main measure of household risk perception is the household respondents' answer to the question whether or not they think it is possible for them to contract Covid-19. Perceiving a risk of contracting Covid-19 clearly seems a pre-requisite for households to adopt appropriate preventive measures. As Table 1 shows, only 37.3% of respondents say that they believe they can contract Covid-19. A substantially larger share of households in villages affected by Ebola believe they can contract Covid-19 (54.9%) compared to households in villages not affected by Ebola (33.8%).

I also asked households whether or not they know about the possibility of an asymptomatic person to transmit Covid-19 to others. This measure captures both the perceived risk of contracting Covid-19, which should be higher for those who believe they can contract the virus from asymptomatic people, and knowledge about Covid-19. Overall, 59.3% of households say they know about the possibility of asymptomatic transmissions of Covid-19. Again, this number is substantially higher in villages affected by Ebola (72.8%) compared to villages not affected by Ebola (56.6%).

Trust in Health Professionals

I asked households whether they trust health professionals when it comes to information about Covid-19. During the Ebola epidemic, difficulties in slowing down the spread of Ebola have been partially attributed to the lack of locally trusted health workers providing information. At the same time, local health workers are involved in the fight against Covid-19 in Sierra Leone at the community level. Thus, the level of trust households have in health workers is an important factor for their perception and knowledge about Covid-19. In the whole sample, 42.1% of households say that they trust health professionals, with 63.1% in villages affected by Ebola and 37.9% in villages not affected by Ebola.

Covid-19 Prevention

My first measure of Covid-19 prevention is the willingness to pay for a Covid-19 vaccination. Given that the survey took place prior to the approval of the first Covid-19 vaccine, the question did not specify any of the currently used vaccines. Since the distribution of this variable is right-skewed with a large share of zero values, I use as my outcome variable the inverse hyperbolic since transformation of the willingness to pay. As Table 1 shows, the willingness to pay for a vaccination is slightly higher in villages affected by Ebola compared to villages not affected by Ebola.

The second measure of Covid-19 prevention is the answer of household respondents to the question what percentage of other adults in their village regularly wear a face mask at the local market. The reason for asking about the behavior of others rather than the respondents themselves is that when piloting this question there seemed to be a strong experimenter demand effect driving almost all respondents to say they comply wearing face masks. With 85.5% in the whole sample the share of people wearing a face mask at the local market is still quite high. There are slightly more people wearing a face mask at the local market in villages affected by Ebola (90.5%) compared to villages not affected by Ebola (84.5%).

Finally, I use a measure from the village-level survey, namely whether or not there had been a public distribution of face masks in the village between the start of the Covid-19 measures in Sierra Leone in March/April 2020 and the time of the interview. In 44.2% of villages face masks were publicly distributed, but there is a stark difference between villages affected by Ebola (67.5%) and villages not affected by Ebola (41.6%).

Utilization of Health Services

My measure of health service utilization is whether or not households state that they have actively avoided visiting the local health clinic because they are afraid of contracting Covid-19. Given that health workers were disproportionately affected by Ebola during the 2014-16 Ebola epidemic and there is evidence for households avoiding health services during the Ebola epidemic, it is important to understand the determinants of health care utilization during the Covid-19 pandemic. 29.7% of households say that they did avoid their local health clinic out of fear of contracting Covid-19. This share is substantially higher in villages affected by Ebola (41.7%) than in villages not affected by Ebola (27.2%). Delaying or avoiding necessary health services is a potentially important indirect cost of the Covid-19 pandemic that might be exacerbated by higher risk perceptions related to previous exposure to a health crisis as in Sierra Leone.

4 Empirical Estimation

In the empirical estimation I always control for a set of geographic village characteristics which are correlated with the EVD indicator and could potentially affect outcome variables. The reason for including these geographic controls is that the transmission dynamics of EVD closely followed human travel routes (Fang et al., 2016). Thus, the probability of an EVD case in a village is expected to be lower in less accessible villages. This is captured by the three variables I use as controls: First, I control for a measure of a village's network centrality. I follow Aggarwal et al. (2021) and measure network centrality of each village by the sum of population-weighted distances to the 25 largest towns in the country.[7] Formally, I measure the remoteness of village v as

$$remoteness_v = \sum_t distance_{vt} * weight_t \tag{1}$$

where $distance_{vt}$ is the road distance between village v and town t and $weight_t$ is the relative population of town t (compared to the rest of the 25 largest towns). My data confirms the negative relationship of this control variable with the probability of having an EVD case as the correlation between the EVD indicator and remoteness is -0.36 (significant at the 1% level). Second, I control for a village's distance to the nearest main road. Again the data confirms the relevance of this control variable as the correlation between the EVD indicator and the distance to the nearest main road is -0.20 (significant at the 1% level). Third, I control for a village's altitude. Higher altitude places should be less accessible on average and therefore are expected to be less likely to have EVD cases. This is also confirmed in the data as the correlation between the EVD indicator and altitude is -0.10 (significant at the 1% level).

4.1 Ordinary Least Squares (OLS) and Probit

The OLS specification for my continuous outcome variables is

$$Y_{v,i} = \alpha + \beta * T_v + \delta * X_v + \zeta * \Psi_{v,i} + \epsilon_{v,i} \tag{2}$$

where i denotes a household and v denotes a village, $Y_{v,i}$ is the continuous outcome variable of interest, T_v is the EVD indicator, X_v is a vector of village-level controls including the geographic village characteristics mentioned above, $\Psi_{v,i}$ is a vector of household-level controls, and $\epsilon_{v,i}$ is the error term. Standard errors are clustered at the village-level. The main coefficient of interest β estimates the effect of village exposure to EVD on the outcome variable $Y_{v,i}$ conditional on controls.

[7] I use town populations from the 2004 Census as weights.

The Probit specification for my binary outcome variables is

$$Pr(Y_{v,i} = 1) = \Theta(\alpha + \beta * T_v + \delta * X_v + \zeta * \Psi_{v,i} + \epsilon_{v,i}) \quad (3)$$

where i denotes a household and v denotes a village, $Y_{v,i}$ is the binary outcome variable of interest, T_v is the EVD indicator, X_v is a vector of village-level controls including the geographic village characteristics mentioned above, $\Psi_{v,i}$ is a vector of household-level controls, and $\epsilon_{v,i}$ is the error term. Standard errors are clustered at the village-level. Throughout the paper I report the marginal effect of the Ebola indicator on $Y_{v,i}$ derived from the Probit model evaluated at the means of the covariates.

4.2 Instrumental Variables (IV) and Recursive Bivariate Probit

Villages affected by EVD could still differ from villages not affected by EVD in terms of unobserved characteristics such as burial practices, access to information, or trust in health professionals. Therefore, I follow Gonzalez-Torres and Esposito (2020) and Maffioli (2021) and use a village's road distance to the EVD index case as an instrumental variable for the EVD indicator. As Marí Saéz et al. (2015) argue, the index case of the 2014-16 EVD epidemic most likely occurred when a 18 months old toddler came into contact with an infected fruit bat in the town of Meliandou, Guinea, close to Sierra Leone's eastern border. Thus, the location of the index case is plausibly unrelated to the outcome variables considered in this paper. While villages closer to the Guinean border might still differ from villages further away, I argue that my instrumental variable satisfies the exclusion restriction conditional on geographic village characteristics. As Fang et al. (2016) show, the transmission of EVD in Sierra Leone mainly followed human travel routes. Therefore, a village's road distance should have predictive power for the EVD indicator. In particular, I use a quadratic function of distance to the Ebola index case as an instrument for my Ebola indicator because a quadratic functional form results in a stronger first stage in this context. Overall, my IV strategy captures the idea that between two villages which are similar in terms of remoteness, distance to the nearest main road, and altitude, the one that is closer to the index case was more likely to be exposed to EVD in 2014-16 but was otherwise comparable to the one that is further away.

A complication arises from my endogenous regressor, the EVD indicator, being a binary variable and my instrumental variable, the village road distance to the index case, being a continuous variable and the fact that my endogenous regressor has a high share of zero values. For my continuous outcome variables, I therefore use the 3-step estimation method suggested in Wooldridge (2010) which has been used also in Maffioli (2021): First, I estimate the following Probit model for the EVD indicator

$$Pr(T_v = 1) = \Theta(\alpha_1 + \beta_1 * D_v + \gamma_1 * D_v^2 + \delta_1 * X_v + \epsilon_v) \tag{4}$$

where v denotes a village and T_v is the EVD indicator. Θ is the cumulative distribution function of the estimation function in which D_v is the distance of village v to the Ebola index case, X_v is a vector of village-level controls, and ϵ_v is the error term.

Second, I use the predicted values from step 1 as the instrumental variable in the first stage of a conventional 2SLS regression

$$T_v = \alpha_2 + \beta_2 * \hat{T}_v + \delta_2 * X_v + \epsilon_v \tag{5}$$

where v denotes a village, T_v is the EVD indicator, $\hat{T}_v$ is the predicted value from the first step, X_v is a vector of village-level controls, and ϵ_v is the error term.

Third, I estimate the second stage of the 2SLS regression using the predicted values from the second step

$$Y_{v,i} = \alpha_3 + \beta_3 * \hat{\hat{T}}_v + \delta_3 * X_v + \zeta_3 * \Psi_{v,i} + \epsilon_{v,i} \tag{6}$$

where i denotes a household and v denotes a village, $Y_{v,i}$ is the continuous outcome variable of interest, $\hat{\hat{T}}_v$ is the predicted value from the second step, X_v is a vector of village-level controls, $\Psi_{v,i}$ is a vector of household-level controls, and $\epsilon_{v,i}$ is the error term. The main coefficient of interest β_3 estimates the causal effect of village exposure to EVD on the continuous outcome variable $Y_{v,i}$. In order to account for both the estimation uncertainty from all three steps and the fact that the level of observation is the village in steps one and two whereas it is the household in step 3, I bootstrap the standard errors with resampling clustered at the village-level (200 replications).

For my binary outcome variables, I estimate a recursive bivariate probit model that captures the same idea as the IV for my continuous outcome variables. The first equation models the binary outcome variable as a function of the EVD indicator and village-level controls and the second equation models the EVD indicator as a quadratic function of a village's road distance to the EVD index case and the same village-level controls as in the first equation. As the Ebola indicator in the second equation only varies at the village-level I also aggregate the outcome variables in the first equation at the village-level. Formally, I estimate

$$Pr(Y_v = 1; T_v = 1) = \Phi(f_v^Y; f_v^T; \rho_v) \tag{7}$$

where v denotes a village, Y_v is the binary outcome variable of interest, T_v is the EVD indicator, and Φ is the cumulative distribution function of the bivariate standard normal distribution with

$$f_v^Y = (2 * Y_v - 1) * (\alpha_1 + \beta_1 * T_v + \delta_1 * X_v + \epsilon_v) \tag{8}$$

and

$$f_v^T = (2 * T_v - 1) * (\alpha_2 + \beta_2 * D_v + \gamma_2 * D_v^2 + \delta_2 * X_v + \epsilon_v) \tag{9}$$

and

$$\rho_v = (2 * Y_v - 1) * (2 * T_v - 1) * \rho \tag{10}$$

where X_v is a vector of village-level controls, D_v is the distance of village v to the EVD index case, ϵ_v is the error term, and ρ is the correlation coefficient of the bivariate standard normal distribution. I then proceed to estimate the average treatment effect of EVD exposure on the binary outcome variable as

$$ATE = E[\Theta(\alpha_1 + \beta_1 + \delta_1 * X_v) - \Theta(\alpha_1 + \delta_1 * X_v)] \quad (11)$$

where Θ is the cumulative standard normal distribution. I bootstrap the standard errors for the average treatment effect (200 replications).

In order to shed light on the relevance of the instrumental variable, Table 2 shows the results from estimating equation 4, i.e., the first step of the 3-step generated IV estimation procedure. The χ^2 statistic of the test of joint significance of the coefficients on D_v and D_v^2 is 13.21 (p-value < 0.01). Table 3 looks at predictors of the EVD indicator and the results are consistent with the exclusion restriction laid out in this section: The geographic variables have the expected sign and the remoteness measure significantly predicts the EVD indicator while the available household controls do not significantly predict the EVD indicator. As with any instrumental variable approach, I can of course not rule out that the Ebola indicator conditional on the instrumental variables and further controls can be predicted by unobserved household or village characteristics.

5 Results

Risk Perception and Knowledge Related to Covid-19

Table 4 shows the OLS/Probit results. The share of household respondents that believe they can contract Covid-19 is 13.5 pp. higher in villages that were affected by Ebola (significant at the 10% level). Table 5 shows the results from the recursive bivariate probit and IV models aimed at getting causal effects of Ebola exposure. The ATE of the Ebola indicator on whether household respondents believe they can contract Covid-19 is 0.50 (significant at the 1% level), quite a bit higher than the estimate of the marginal effect from the Probit model. This suggests that either there is measurement error in the Ebola indicator leading to attenuation bias in the Probit model or the Ebola indicator is indeed endogenous. As a robustness check, Table 6 shows the IV estimates also for the binary outcome variables. For the effect of the Ebola indicator on whether household respondents believe they can contract Covid-19, with 0.41 (significant at the 5% level) the IV estimate is similar to the estimate from the recursive bivariate probit model.

For household respondents' knowledge about the possibility of asymptomatic transmissions, the marginal effect from the Probit model is 0.12 (significant at the 10% level). The estimate from the recursive bivariate probit model in column 2 of Table 5 is somewhat larger at 0.32 (significant at the 5% level). The IV estimate in column 2 of Table 6 is qualitatively similar to that, although less precise.

Overall, these results suggest that people living in villages directly affected by Ebola perceive Covid-19 to be significantly riskier than those living in non-affected villages: They are more likely to believe that they can contract Covid-19 and more likely to know about the possibility of asymptomatic transmissions of Covid-19. While both of these measures likely capture differences in religious and spiritual beliefs, education, and media consumption habits, I show that risk perception and knowledge about Covid-19 are affected by exposure to previous (health) crises such as the 2014-16 Ebola epidemic.

Trust in Health Professionals

The Probit marginal effect of the Ebola indicator on respondents' trust in health professionals when it comes to information about Covid-19 in column 3 of Table 4 is 0.18 (significant at the 5% level). Again the estimate from the recursive bivariate probit model in column 3 of Table 5 is larger with 0.44 (significant at the 1% level) and the IV estimate is qualitatively similar to the other two estimates, but less precise. This resembles the finding in Flückiger et al. (2019) that Ebola-affected areas in Sierra Leone exhibit greater trust in government authorities. The authors argue that the mechanism behind this finding is that affected areas value state control more highly. Similarly, it seems plausible that having been affected by a traumatic health-related crisis like the 2014-16 Ebola epidemic increases one's valuation of health care services and providers.

Covid-19 Prevention

Having established that exposure to Ebola increased the perceived risk of Covid-19 and the trust in health professionals for household respondents in affected villages, I now turn to the question whether this had an impact on two policy-relevant margins. Attitudes and behaviors related to the prevention of the spread of Covid-19 are crucial in the fight against Covid-19 and understanding their determinants is important for policy makers during the current pandemic and potential future health crises.

My first outcome related to the prevention of Covid-19 is the percentage of adults wearing a face mask at the local market as reported by household respondents. The OLS estimate in column 4 of Table 4 suggests that the share of adults wearing a face mask at the local market is 6 pp. higher in villages affected by Ebola compared to non-affected villages (significant at the 5% level). However, with the IV this becomes an imprecisely estimated zero (column 4, Table 5), suggesting a lack of power to detect a not-so-large effect.

My second outcome is (the inverse hyperbolic sine transformation of) the willingness to pay for a vaccination against Covid-19. The OLS (column 5, Table 4) and the IV (column 5, Table 5) coefficients confirm the unconditional result of no differences between affected and non-affected villages in Table 1, but the zero coefficient is very imprecisely estimated both in the OLS and IV specifications.

Finally, I look at whether face masks were publicly distributed in a village. The probit marginal effect is 0.21 (significant at the 5% level) as shown in column 6 of Table 4. The estimate from the recursive bivariate probit model in column 6 of Table 5 is 0.44 (significant at the 1% level). The IV estimate in column 6 of Table 6 is 0.55 (significant at the 5% level). This constitutes strong evidence for Ebola-affected villages taking Covid-19 more serious and making sure that face masks are available for households. In addition to a higher risk perception of Covid-19 and higher trust in health professionals, a similar mechanism as in Flückiger et al. (2019) mentioned above might be at play here: People living in villages directly affected by the 2014-16 Ebola epidemic might value public goods more highly and therefore managed to take collective action to prevent the Covid-19 pandemic to have a similarly negative impact.

Utilization of Health Services

The last outcome I consider is a measure of health service utilization, namely whether or not households actively avoided visiting their local health clinic out of fear of contracting Covid-19. The probit marginal effect estimate for the EVD indicator on whether respondents say they did avoid visiting their local health clinic is 0.18 (significant at the 5% level) as shown in column 7 of Table 4. The estimate from the recursive bivariate probit model in column 7 of Table 5 is 0.43 (significant at the 1% level). The IV estimate is qualitatively similar but less precisely estimated (column 7, Table 6). These results point towards the avoidance of health services being an important indirect cost of increased caution in the light of Covid-19 induced by previous EVD exposure. While I am not able to assess whether avoiding health clinic visits is consistent with rational expectations of patients, i.e., whether there is a sufficiently high risk of contracting Covid-19 at health clinics that outweighs the risk from not receiving health services, it is clear that increased caution due to the Covid-19 pandemic does come at the cost of reducing health access. This has potentially important implications for the debate on whether to adopt stricter containment measures such as lockdowns (which lead to fewer Covid-19 infections) or more lenient containment measures (which are less disruptive to the economic lives of people but also their health-seeking behavior).

6 Conclusion

Using novel survey data from Sierra Leonean villages I show that households in villages affected by the 2014-16 EVD epidemic perceive Covid-19 to be riskier and trust health professionals more than households in non-affected villages. This in turn translates into EVD-affected villages to be more likely to adopt a key containment measure, namely the public distribution of face masks. This highlights on the micro level how past exposure to a health crisis affects the response to Covid-19 and could partially explain why countries with recent experience of major disease outbreaks like SARS, MERS, or Ebola appear to have reacted more swiftly and decisively at the onset of the Covid-19 pandemic than other countries. However, the increased caution of households in EVD-affected villages comes at the cost of reduced health access due to households avoiding the local health clinic out of fear of contracting Covid-19.

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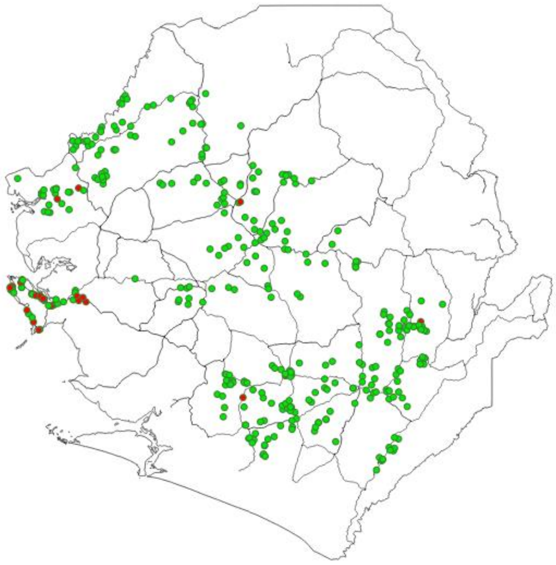
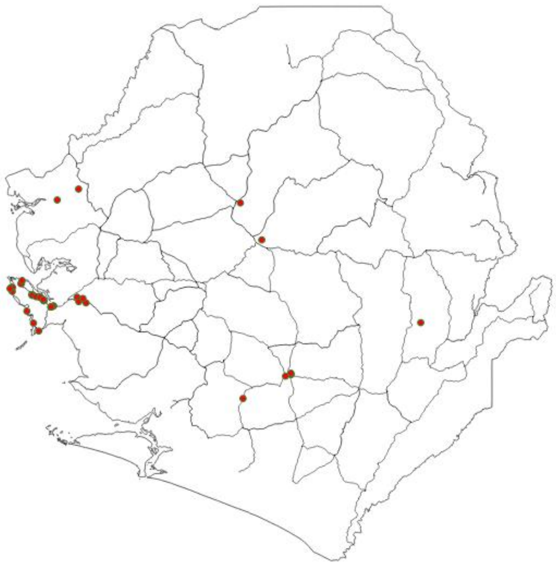
Appendix A Figures and Tables



(a) All Villages



(b) Villages Affected by Ebola

Figure 1: Green dot: Non-Ebola Village Red dot: Ebola Village

Table 1: Outcome Variables

	(1) Obs.	(2) Mean	(3) Mean EVD = 0	(4) Mean EVD = 1	(5) (4) - (3)
Outcome Variable					
Can Contract Covid?	614	0.373	0.338	0.549	0.211***
Knows Asymp. Transm.	617	0.593	0.566	0.728	0.162***
Trust Health Prof.	617	0.421	0.379	0.631	0.252***
WTP Vaccination	612	4.222	4.283	3.909	−0.374
Perc. Wearing Face Mask	614	85.487	84.483	90.486	6.002***
Face Mask Distribution	391	0.442	0.416	0.675	0.259***
Avoided Health Clinic	617	0.297	0.272	0.417	0.145***

* $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table 2: First Stage

	(1) EVD Indicator = 1
Distance Meliandou	-0.271^{***}
	(0.101)
Distance Meliandou Sq.	0.042^{***}
	(0.014)
Remoteness	-0.001^{***}
	(0.000)
Distance Mainroad	-0.004
	(0.003)
Altitude	-0.005
	(0.005)
Observations	392
Mean EVD Indicator	0.102
Chi2 statistic	13.208
P-value	0.001

Standard errors are in parentheses.

* p<0.1, ** p<0.05, *** p<0.01.

Table 3: Predictors of Ebola Case in Village

	(1) EVD Indicator = 1
Distance Meliandou	-0.305^{***}
	(0.099)
Distance Meliandou Sq.	0.045^{***}
	(0.014)
Remoteness	-0.001^{***}
	(0.000)
Distance Mainroad	-0.003
	(0.003)
Altitude	-0.005
	(0.005)
Age	-0.001
	(0.001)
Muslim	0.013
	(0.025)
Mende Ethnicity	-0.038
	(0.028)
Temne Ethnicity	-0.018
	(0.025)
Observations	392
Mean EVD Indicator	0.102

Standard errors are in parentheses.

* p<0.1, ** p<0.05, *** p<0.01.

Table 4: Probit/OLS

	(1) Can Contract Covid?	(2) Knows Asymp. Transm.	(3) Trust Health Prof.	(4) Perc. Wearing Face Mask	(5) WTP Vaccination	(6) Face Mask Distribution	(7) Avoided Health Clinic
EVD Indicator = 1	0.135*	0.120*	0.176**	6.046**	−0.070	0.212**	0.181**
	(0.070)	(0.062)	(0.072)	(2.506)	(0.704)	(0.088)	(0.084)
Observations	614	617	617	616	612	391	617
Mean Dep. Var	0.373	0.593	0.421	85.487	4.223	0.442	0.297
Estimation	Probit	Probit	Probit	OLS	OLS	Probit	Probit
Individual Controls	Yes	Yes	Yes	Yes	Yes	No	Yes
Geographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors are in parentheses. Individual controls include age, religion, and ethnicity. Geographic controls include remoteness, distance to the main road, and altitude.

* $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table 5: Biprobit/IV

	(1) Can Contract Covid?	(2) Knows Asymp. Transm.	(3) Trust Health Prof.	(4) Perc. Wearing Face Mask	(5) WTP Vaccination	(6) Face Mask Distribution	(7) Avoided Health Clinic
Treatment Effect	0.504***	0.320**	0.440***	−1.570	0.013	0.440***	0.430***
	(0.115)	(0.155)	(0.110)	(7.498)	(1.639)	(0.121)	(0.147)
Observations	390	392	392	616	612	391	392
Mean Dep. Var	0.330	0.569	0.416	85.487	4.223	0.442	0.263
Estimation	Biprobit	Biprobit	Biprobit	IV	IV	Biprobit	Biprobit
Effect	ATE	ATE	ATE	LATE	LATE	ATE	ATE
Individual Controls	No	No	No	Yes	Yes	No	No
Geographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Bootstrapped standard errors (200 replications) are in parentheses. Individual controls include age, religion, and ethnicity. Geographic controls include remoteness, distance to the main road, and altitude.

* $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table 6: Only IV

	(1) Can Contract Covid?	(2) Knows Asymp. Transm.	(3) Trust Health Prof.	(4) Perc. Wearing Face Mask	(5) WTP Vaccination	(6) Face Mask Distribution	(7) Avoided Health Clinic
Treatment Effect	0.414**	0.205	0.165	−1.570	0.013	0.546**	0.256
	(0.186)	(0.181)	(0.157)	(7.498)	(1.639)	(0.216)	(0.193)
Observations	614	617	617	616	612	616	617
Estimation	IV	IV	IV	IV	IV	IV	IV
Effect	LATE	LATE	LATE	LATE	LATE	LATE	LATE
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean Dep. Var	0.373	0.593	0.421	85.487	4.223	0.472	0.297

Bootstrapped standard errors (200 replications) are in parentheses. Individual controls include age, religion, and ethnicity. Geographic controls include remoteness, distance to the main road, and altitude.

* $p<0.1$, ** $p<0.05$, *** $p<0.01$.