The Impact of Quarantining on School Enrollment: Evidence from the Ebola Epidemic in Sierra Leone*

Ulrike Malmendier†
UC Berkeley, NBER, CEPR, CESifo

David Willigrod‡
UC Los Angeles

June 2022

Abstract

Common response measures to viral epidemics include school closures and quarantining. We provide evidence on the long-term consequences of these measures for school-aged children from the Ebola epidemic in Sierra Leone. Quarantining in combination with nationwide school closures reduced school enrollment by 4.7% in the three years after school re-opened, corresponding to a 29% reduction in enrollment gains. Our results hold instrumenting for the incidence of quarantines with the date of the first confirmed case of Ebola in a chiefdom. We estimate that about one third of these children never enroll, with significant consequences for their lifetime earnings. The effect is strongest in areas of lower educational attainment, and it disrupts the upward trend in regions with the steepest gains in enrollment pre-epidemic. Contrary to common perceptions, the adverse effects were strongest for the non-enrollment of newly school-aged children rather drop-out rates of older children. Additional results point to the unravelling of social fabric, including stigmatization, as explanations. The experience of quarantine predicts less social integration, e. g., at weddings, but no increase in financial hardship.

*Thanks to Elizabeth Mary Foster for providing assistance with the data. We have benefited from discussions with Abou Bakarr Kamara, Supret Kaur, Niccolo Meriggi, Edward Miguel, Rachel Glennester, Nikhil Chacko, and Yuen Ho, as well as research assistance of Charles Gong, Leon Chen, and Isaak Heller.

†Department of Economics and Haas School of Business, University of California, 501 Evans Hall, Berkeley, CA 94720-3880; ulrike@berkeley.edu.

‡Department of Economics, UCLA, Bunche Hall 8283, 315 Portola Plaza, Los Angeles, CA 90095; david-willigrod@g.ucla.edu

1 Introduction

Lockdown and quarantine measures are a common response to viral epidemics. For example, in 2019-2021, many governments across the globe issued stay-at-home orders and other movement restrictions in order to prevent the spread of the coronavirus during the COVID-19 pandemic. Workplaces and schools were shut down for extended time spells, relegating adults and children alike to working and learning from home. Infected people, or even those who had traveled, had to quarantine for days and weeks.

Much of the academic and policy discussion of the economic and social consequences of such crises and of the response measures revolves around the short- and medium-term effects on outcomes such as unemployment, education, and health. But one might wonder whether the experience of an epidemic and living under these restrictions alter individuals' behavior and life paths in the longer run. For example, in the COVID-19 pandemic, teachers in the US and other countries reported that certain student populations, in particular from disadvantaged households and racial minorities, did not return to school at the rates expected when schools reopened (Goldstein 2021),[1] raising concerns about these groups educational attainment, job opportunities, and future earnings. As a result, high-school students and their drop-out rates were at the center of the debate.

In this paper, we study the longer-term consequences of the quarantine and restricted-movement measures aimed at combating the spread of the Ebola virus on school-aged children in Sierra Leone. We document that children from households that were affected by quarantine are significantly less likely to be enrolled in school after schools reopened. That is, controling for the regional severity of the crisis and given (nationwide) school closures, individual-level variation in mandated household-level isolation predicts significant differences in schooling outcomes. These results hold instrumenting for the incidence of quarantines with the date of the first confirmed case of Ebola in a chiefdom. Chiefdoms were Ebola arrived early, prior

[1]Cf. reports such as "Missing in School Reopening Plans: Black Families' Trust", The New York Times (02/01/2021) or "The racial divide in returning to the classroom", Axios (02/06/2021).

to closures of public places of gathering and the deployment of troops to enforce quarantine measures, tended to witness a higher overall outbreak and ultimately higher quarantining.

These adverse effects persist for several years. They are strongest in educationally weak areas where school enrollment was already low pre-epidemic, and they disrupt the improvements in districts where school enrollment had been on an upward trend in recent years. Contrary to common perceptions, and findings for some earlier epidemics,[2] however, the adverse effects were strongest for the non-enrollment of newly school-aged children. We do not detect a significant increase in drop-out rates of older school-aged children. Instead, the drop in enrollment rates is driven by families who are withholding the enrollment of their younger children.

Additional findings point to the underlying channel of adverse educational outcomes. First, we document that the experience of quarantine predicts less social integration, e. g., at weddings, even though we find no significant increase in financial hardship. Second, newly school-aged children from families that had already been "integrated" in the school community prior to the epidemic (due to older siblings) are more likely to be enrolled as soon as schools reopened. These findings are consistent with the reduction in social interaction and in the cohesion of local communities playing a role in the adverse longer-term outcomes. The point to lingering effects of the experience of social isolation, including post-quarantine stigma, as plausible factors contributing to the drop in enrollment. We find little evidence that increased financial constraints among those experiencing quarantine can explain our findings.

The 2014-16 Ebola epidemic led to major loss of life and socio-economic disruptions in West Africa. Sierra Leone was one of the countries most affected with 14,124 cases and 3,956 deaths before being declared Ebola-free by the World Health Organization (WHO) on March 17, 2016 (Kaner and Schaack 2016).[3] During the outbreak, all schools were closed for

[2]Meyers and Thomasson (2017) attribute the reduced educational attainment after short-term school closures during the US 1916 polio epidemic to older students refusing to return to school.

[3] Guinea and Liberia were also heavily affected by the outbreak, with 3,814 and 10,678 cases respectively.

approximately nine months across the country, from June 2014 to April 2015. In addition, various districts and chiefdoms implemented isolation and quarantine measures in order to slow the spread of the Ebola virus. Some of these measures limited movement in and out of entire regions to delivery and essential service workers for months at a time. Other measures were household-specific: if a household member had been exposed to Ebola, the home was quarantined for 21 days with the aid of military personnel so that nobody left or entered. Such quarantines were often poorly implemented without sufficient support for households to obtain food, water, and other basic supplies (Wahome 2014). There is little evidence that the assignment of households to quarantine were politically motivated.

We analyze the longer-lasting consequences of living through the epidemic and experiencing household-level quarantine on school-aged children. Our focus is school enrollment post epidemic. Improvements in the enrollment of school-aged children and in their school attendance have been a major policy goal in Sierra Leone for decades. Since its independence in 1961, the country has made major progress, with enrollment rates climbing from around 10% (Wang 2007) to 85% in 2018. After the severe disruptions during the civil war in 1991-2002, at the end of which the vast majority of school-aged children were out of school, Sierra Leone successfully managed to return to previous enrollment rates, and continued the positive upward trend. Twelve years later, during the Ebola crisis, schools were closed again for nine months, and many children faced social isolation and further challenges.

Our analysis utilizes the Sierra Leone Integrated Household Survey (SLIHS), which was conducted jointly by Statistics Sierra Leone, The World Bank, and the Government of Sierra Leone from January to December 2018 (de la Fuente and Foster 2018). The survey records school enrollment over five school years, from the last one before the Ebola crisis (2013-14) to the fourth school years after the reopening in April 2015. Respondents also report whether they were subject to quarantine measures. The key survey question is: "During the Ebola outbreak, did you experience quarantine or time when they didn't let people go where they wanted?" Thus, this data allows us to analyze how quarantine affected enrollment on an individual level, rather than on a more aggregate level as has been done in prior literature. In addition to the SLIHS 2018, we also utilize data from the SLIHS 2011 in order to analyze regional enrollment trends. The SLIHS 2011 ... [details: reports data collected from a representative household sample throughout (???) 2010???/2011??]. The sample is different in that ... Th questions are similar/different? Compared to the SLIHS 2018 ...].

We also use data from Fang et al. (2016) on confirmed and suspected cases of Ebola from May 2014 to September 2015 in Sierra Leone. This data ... (how collected, how cleaned by previous research teams/for previous papers) ... The data not allows us to control for severity of the outbreak in different regions. It also provides us with data on early Ebola was detected in a chiefdom, which is the basis of our instrument.

We analyze the enrollment rates of school-aged children in each of the post-epidemic school years, relative to their pre-epidemic enrollment rates, comparing children that were versus were not affected by quarantine. We further distinguish between the effects of quarantine on the first-time enrollment of school-aged children and on the drop-out rates among previously enrolled children.

Estimates from the difference-in-differences analysis reveal that children who were placed under quarantine orders had between 3.0% and 5.6% lower enrollment in each of the four school years following the Ebola epidemic. The estimates are robust to controlling for potential violations of the parallel trends assumption by first instrumenting for quarantine with whether an individual lived in a chiefdom in which an individual tested positive for EVD prior to August 2014. We use this as an instrument because July 30, 2014 is when troops were deployed to deploy quarantines in EVD hotspots. Beyond instrumenting for quarantine, we also add explanatory variables that may affect enrollment trends, such as gender, age, family structure, education of the father, socio-economic status, region (urban versus rural), severity of the Ebola outbreak (measured by cases in a chiefdom), and timeliness of school opening, both in terms of level and in terms of trend. The estimated effects are driven by reduced first-time enrollment, while drop-out rates remain very low. Based on the data from four school years after the crisis, we predict that 5.6% of school-aged children who were not attending school prior to Ebola will never be enrolled as a result of quarantining measures.

Next, we analyze whether the estimated effects result from household-level isolation or from wider, regional lockdown and curfew measures. We find that hospital closures, market closures, and workplace closures do not robustly predict lower school enrollment, whether we substitute the *Quarantine* measure with one of these closure indicators or whether we include the closure measures in addition in the estimation. Similarly, when we identify districts that underwent two-week lockdown periods, in which only deliveries and essential services were allowed to exit or enter the districts, we find that the district-wide restrictions did not significantly affect post-epidemic school enrollment. In other words, our baseline results do not appear to reflect more general effects of regional lock-downs, whether in terms of closures or wider restricted-movement measures. Instead, children facing a home quarantine due to someone in their household having been exposed to or exhibiting symptoms of Ebola suffer adverse consequences in terms of educational attainment.

Next, we turn to exploring the mechanisms that could explain the effect of quarantine during the Ebola crisis. We consider both standard economic explanations, in particular financial constraints, and psychological and social factors, which reflect the impact of quarantine measures on the social fabric of communities. Financial constraints could explain the drop in school enrollment if families need their children to enter the workforce and to provide supplementary income for their household after experiencing an Ebola infection or even Ebola-related deaths in their household. Relatedly, higher medical bills and debt might make it harder to pay the cost of schooling; however, we don't find evidence that quarantine induced these burdens.

Sociopsychological factors include the role of stigma and social isolation. The role of stigma has been much-discussed in Sierra Leone after the Ebola crisis,[4] and it might link the reduced enrollment of children to the ostracizing of families affected by Ebola follow-

[4] Cf. Davtyan, Brown, and Folayan (2014), Yadav and Rawal (2015) James, Wardle, Steel, and Adams (2020).

ing quarantine. These papers compare the stigma of EVD with that of HIV/AIDS, citing misinformation leading to widespread stigmatization and psychological distress. Recently Davidson et al. (2022) found that being quarantined was significantly correlated with perceived community stigma. Beyond the blatant, more pointed stigma, the broader role of disrupted social interactions and social isolation have been less discussed. In our context, less exposure to social norms (or even social pressure) to enroll children at school might play a role in explaining the drop in school enrollment. School enrollment had been a hard-fought policy issue in Sierra Leone for years. Despite significant improvements it had remained difficult for policy makers and educators to bring all families on board and induce them to send their children to school. The isolation and quarantining during the epidemic might have worsened those tendencies.

We start from building on our finding that the reduced enrollment largely reflects a drop in first-time enrollments rather than an increase in drop-outs. This finding is, in and of itself, not easy to reconcile with the cost interpretation, given the higher cost of sending multiple children and the higher ability of older children to generate earnings. To probe the role of social interaction further, we test whether the outcomes in terms of *first-time* enrollment are different for newly school-aged children who do and those who do not have older siblings attending school prior to the Ebola-induced school closures. We hypothesize that other siblings attending school pre-Ebola likely implies integration in the school community, both of the children and of the parents.

We find that individuals whose older sibling attended school in 2013 did not face the negative effect of quarantining on enrollment. Instead, children who do not have an older sibling or whose older sibling did not attend school in 2013 display between 5.5% and 8.3% lower enrollment if they quarantined. This evidence supports the view that social integration plays a role in overcoming the adverse effects of social isolation. Families with older children at school likely were integrated in the school community, and have already been convinced of the value of education. They are less likely to fall off post-pandemic. It is also possible, though maybe less plausible that, having an older child integrated in the school community diminished the stigmatization of quarantine for such families. The results further challenge the cost explanation as increased financial constraints would make it harder, not easier to send more than one child to school.

To further probe the notion that social disintegration played a role in families failing to send their children to school, we check the SLIHS 2018 survey for data on expenditures related to social occasions. Specifically, we retrieve the data on household expenditures for weddings in the past 12 months. These expenditures reflect whether a household attended or held any weddings in the past year (and spent money on gift purchases or holding the event), and thus serves as a proxy for social integration.

We find that quarantined households were 3.7 pp less likely to have spent money on a wedding in the past 12 months. Considering that only 8.3% of those who did not quarantine spent money on weddings in the past 12 months, having quarantined resulted in an over 44% reduction in the likelihood that a household spent money on a wedding in the past year.

At the same time, the reduction in spending does not appear to reflect a lower ability to spend money. The SLIHS data shows that households that quarantined faced fewer medical costs and had similar amounts of debt outstanding. We further explore whether quarantining increased the financial burdens of households in unobserved ways in that children were driven to the labor force in order to provide supplementary income to their households. The data reveals that this is not the case.

The only piece of evidence in support of financial constraints that we are able to extract from the data comes from a question eliciting the reasons for why families do not send their children (back) to school. Here, concerns about the cost of schooling and the need to work play a somewhat larger role in families who experienced quarantine than among those who did not. Based on this suggestive evidence, we go one step further and test whether the effect of quarantine on school enrollment is stronger for families who face higher school costs. We estimate that, for every 10,000 Sierra Leonean Leones of school costs (approximately 1 USD), the impact of quarantine increases by between 4.8% and 8.7%.

In other words, while the evidence on reduced first-time enrollment and the amelioration coming from older siblings point to social disintegration, and not cost as the main drivers of the longer-term effects of quarantine, the cost of schooling does appear to exacerbate the effect of quarantine experience.

This is consistent with the notion of financial constraints, for example, the need of children to enter the workforce in order to provide supplementary income for their household after experiencing Ebola infection or even Ebola related deaths in their household. We note, however, since Sierra Leone faced less than 4,000 deaths related to Ebola, it is unlikely this led to a substantive impact on enrollment.

***

We now turn to investigating whether more vulnerable regions were hit hardest by quarantine. We find that the effect of quarantine is strongest in areas where school attendance was lowest pre-epidemic: The impact of being isolated in one's home is three to four times as large, between -8.7% and -12.6%, in regions (at the section level) that were in the bottom quartile with respect to school enrollment rates prior to the epidemic. Hence, quarantine measures widened the enrollment gap between different regions in Sierra Leone.

Restricted-movements measures also caused a severe disruption in regions where enrollment rates had been improving in recent years. The better the upward trend was pre-Ebola, the larger was the quarantine- and isolation induced decrease, with every additional 10% increase in enrollment during the pre-epidemic years (from 2011-2013) predicting an additional negative effect of 1.2-1.7% resulting from the restrictions during the epidemic. This provides evidence that quarantine halted the progress that was being made on school enrollment in educationally weaker regions.

Finally, we provide some back-of-the envelope calculation of the loss in spending ability resulting from the quarantine-induced reduction in educational attainment. We estimate a significant reduction in total consumption spending around 18% during prime working age (between 36 and 55) due to the lack of education. Our results indicate the large extent of the harm caused by quarantine measures during viral epidemics, such as the current COVID-19 crisis, which go beyond.

Related Literature. Before the onset of COVID-19, there was little research on the effects of viral epidemics on schooling decisions. Much of the research surrounding the Ebola epidemic in West Africa focuses on the short-term impact of the epidemic on households and firms. For instance, Bowles, Hjort, Melvin, and Werker (2016) document job losses and reduced economic activity during the Ebola outbreak in Liberia. Gonzalez-Torres and Esposito (2017) provide evidence of increased civil violence across Western Africa during the duration of the Ebola outbreak.[5] Other work surrounding the Ebola epidemic includes investigations of the impact of the outbreak on public attitude. For example, Flückiger, Ludwig, and Sina Önder (2019) document greater trust in government authorities in the regions affected the most by Ebola. These works often exploit the quasi-random nature of the severity of the Ebola outbreak across regions, similar to our methodology exploiting the quasi-random assignment of Ebola-induced quarantine.

There have also been works exploring the short-term consequences of the Ebola outbreak on schooling. Himelein, Testaverde, Turay, and Turay (2015) find that 13 percent of primary school-age children in Sierra Leone did not return to school in the short-term following school closures; however, only between 1 and 2 percent of respondents claimed it was over fears of the virus. Selbervik (2020) finds that enrollment rates in Sierra Leone, Guinea, and Liberia were back to pre-Ebola levels or higher by the 2016/2017 school year. Overall, these works find that school enrollment recovered quickly following the Ebola outbreak. More recently, Smith (2021) conducted a country-level difference-in-differences estimation of the impact of the school closures in Sierra Leone and Guinea using Côte d'Ivoire as a control group. This study found that the poorest youth in Sierra Leone and Guinea faced larger rates of dropping out in secondary school. It is difficult to discern whether this result is due to the

[5] Other work providing similar evidence on employment, economic activity, and public unrest during the Ebola crisis include (Adegun 2014, Himelein et al. 2015, Huber et al. 2018, and Kostova et al. 2019).

Ebola outbreak or other institutional factors, and if Côte d'Ivoire is an appropriate control group as it faced higher enrollment growth relative to other countries in the region (Yao et al. 2021).

Concerning education outcomes in the long run, Yao, Memon, Amaro, Rigole, and Abdou (2021) uses an interrupted time series (ITS) design at the district-level in Sierra Leone, Guinea, and Liberia to identify how the 2013-2016 outbreak affected school enrollment in 2018-2020. The study used cross-sectional data from 9 different Demographic and Health Surveys (DHS) and 4 different Multiple Indicator Cluster Surveys (MICS) across the 3 countries. This study found that enrollment returned to long-term trends regardless of how prevalent Ebola was in a district. It also found that those of a more vulnerable background were equally effected as the rest of the population.

Less work has been done investigating the long-run economic consequences of the Ebola outbreak at the individual and household level, especially in regard to education. A notable exception is Bandiera, Buehren, Goldstein, Rasul, and Smurra (2018), who conducted a series of surveys among 4,700 women ages 12-25 in Sierra Leone across 200 villages. The surveys were conducted from 2014, just as the first cases of Ebola were being reported, to 2016, six months after new cases of Ebola were reportedly at or near 0. These surveys focused on the impact of an Empowerment and Livelihood for Adolescents (ELA) program, which was implemented in randomly selected 150 of 200 villages. Bandiera et al. found that villages with greater disruptions as a result of Ebola had a 16% drop in school enrollment among women, but that this adverse effect was almost entirely mitigated by ELA programs.

A follow-up paper by Bandiera, Buehren, Goldstein, Rasul, and Smurra (2020) argues that school closures in Sierra Leone led to women spending more time socializing with men, higher rates of pregnancy, and 17% lower rates of enrollment among young women (Bandiera, Buehren, Goldstein, Rasul, and Smurra 2020). In addition to the emphasis on education, the paper also relate to our analysis here by establishing longer-lasting effects. Differently from their paper, however, we use household-level variation in quarantine, rather than village aggregates of disruptions caused by Ebola. Our data also includes a larger sample of both male and female respondents from across Sierra Leone as opposed to the female respondents across the 50 control villages from the above study. Consistent with our study, the 2019 report of the organizations that conducted the 2018 SLIHS (Statistics Sierra Leone, The World Bank, the Sierra Leone Government) point out that enrollment rates increases after the nine-month school closures for both male and female respondents. Our analysis reveals that this conclusion embeds, though a 29% reduction in upward trend among those placed under quarantine.

Regarding the longer-term consequences of children not enrolling in school, Filmer, Langthaler, Stehrer, and Vogel (2018) estimate that, in Sub-Saharan Africa, for each additional year of schooling wages increase by more than 14% for women, and by more than 10% for men. They also find that education leads to a higher probability of employment, greater productivity, higher earnings, and reduced poverty. Later in the paper, we attempt to estimate the returns to ever having enrolled in school in regard to aggregate consumption.

The remainder of the paper is organized as follows. Section 2 provides historical and institutional background information on the Ebola virus disease, the timeline of the 2014-16 outbreak, and the institutional and cultural environment in Sierra Leone at the time. In Section 3, we introduce the main source of data and discuss enrollment patterns in the raw data. Section 4 introduces the empirical estimation strategy, and Section 5 presents the results. We discuss possible causes and longterm consequences of the effect on enrollment in Section 6. Section 7 concludes.

2 Institutional Background

In this section, we provide some background about the Ebola epidemic, including a timeline of its outbreak in Sierra Leone and the cultural practices that affected its spread. We also discuss Sierra Leone's government and education system.

Ebola Virus Disease (EVD). People infected with the Ebola virus tend to display influenza-like symptoms of fatigue and muscle ache two days after contracting the virus, before progressing to headache and nausea, which is then followed by severe vomiting and diarrhea lasting up to 21 days after exposure. Out of the 28,616 people reported to have contracted Ebola during the 2014-16 outbreak, 11,310 died, amounting to a case-fatality rate of 40% (Wappes 2018).

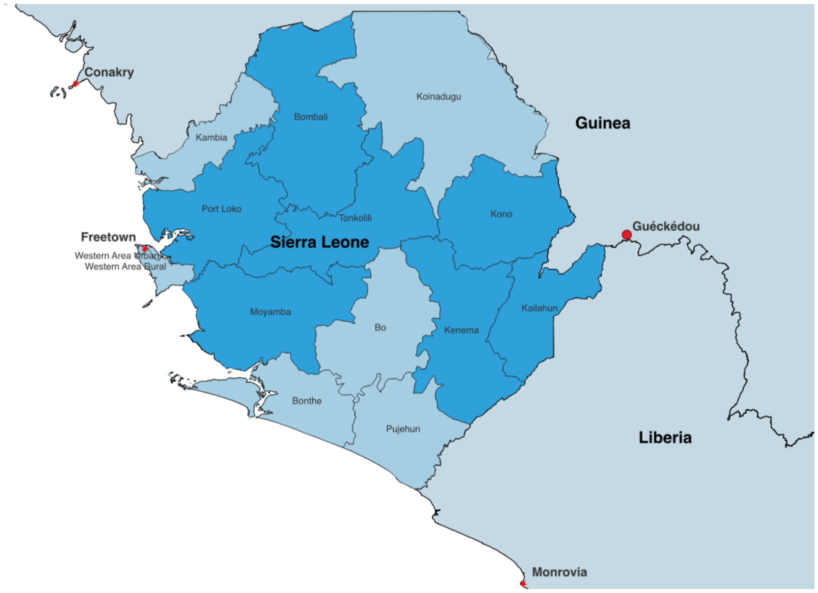
The virus is transmitted through direct contact with blood or other bodily fluids of a symptomatic person, or contact with the body of a person who has died of Ebola (Osterholm et al. 2015). The high contagiousness of those who had died from Ebola played a major part in the spread of the virus due to funeral traditions often consisting of contact with the deceased. Another factor was that spread through sexual contact became understood only later during the Ebola crisis.

Timeline of the Ebola epidemic. Ebola is believed to have originated in bats, with the first case being an 18-month-old boy from a small village in Guinea in December 2013 (see map in Figure 1). Soon, the virus spread to Canakry, the capital of Guinea, where health officials issued an alert for an unidentified illness (Kaner and Schaack 2016). Following confirmation that the cause of these illnesses was Zaire ebolavirus, the WHO declared an EVD outbreak on March 23, 2014. Weak tracking mechanisms and poor health systems allowed the virus to enter Liberia and Sierra Leone (Bell 2016).

The virus most likely entered Sierra Leone in late May 2014, when a group of 14 people returned from Guinea where they had attended the funeral of a traditional healer who had been treating those with Ebola (Gire et al. 2014). The first person to have been reported as infected in Sierra Leone was a tribal healer who passed on the disease when her body was washed at her funeral.

On June 11, 2014, Sierra Leone's government closed the borders to Guinea and Liberia. One day later, the district of Kailahun in Sierra Leone declared a state of emergency and closed schools as a result of Ebola. By July 11, Ebola had made its way to Freetown,

Figure 1: Ebola Virus Outbreak 2014-2016



Notes. The map shows the key locations of the 2014-2016 Ebola virus outbreak in Western Africa. Red dots identify (i) the location of the first case in Guinea in December 2013, Gueckedou, (ii) the capital of Guinea, Conakry, to which EVD spread in early 2014, (iii) the capitals of Sierra Leone, Freetown, and (iv) of Liberia, Monrovia, to both of which EVD had spread by July 2014. The map delineates the districts of Sierra Leone (14 at the time, 16 districts since 2017), with darker blue indicating districts that imposed at least two weeks of district-wide restricted-movement orders.

Sierra Leone's capital and most populous city. On July 30, 750 troops were deployed to quarantine Ebola hot spots and homes of those who had contracted the virus (Nossiter 2014b). Quarantine later was found to increase one's perceived stigma community stigma (Davidson et al. 2022), indicating that if one was quarantined, they believed the community was aware of their situation. This serves as evidence towards stigma reducing enrollment. The government attempted to raise awareness of the threat of Ebola through radio and loudspeaker messages as well as imposed a law subjecting anyone who was hiding someone they believed to be infected to two years in jail.

In September, the virus had begun to rapidly spread, with the number of cases seemingly doubling every 20 days (Coy 2014). In an attempt to slow the spread, Sierra Leone was placed under a nation-wide curfew from September 19 to September 21, under which residents were not allowed to leave their homes. During this time 28,500 volunteers went door to door to provide information about how to prevent the spread of Ebola. Although this curfew was put in place for the entire Sierra Leone population, many failed to comply, and as we will find later, even claim to have never been under a lockdown. By late September, five out of the fourteen districts in Sierra Leone (more than two million people out of the seven-million population) were placed under "isolation" in which "only people delivering essential services [were allowed] to enter and circulate within these areas," (Bindra 2014). In Freetown and other parts of Sierra Leone, security forces would be sent to enforce quarantines in homes where there had been a case of Ebola. More lockdowns were instituted through the end of 2014 and into early 2015 including another three-day curfew, under which over 2.5 million people were not allowed to leave their homes. These restricted-movement mandates worsened the population's food insecurities and economic woes, and many individuals were reported to have broken quarantine to obtain food (DiLorenzo 2014). Other instances of resistance against the lockdowns included rioting in the town of Koidu.

Cases declined throughout 2015, and the WHO first declared Sierra Leone Ebola free on November 7, 2015. After two more fatalities linked to Ebola in January 2016, the WHO made the final declaration that Sierra Leone was Ebola free on March 17, 2016.

Institutions. The governance of Sierra Leone is highly decentralized, with many extremely rural areas where the central government has limited reach. There are 190 chiefdoms (149 up until 2017) with a ruling chief that has the power over taxation, the judicial system, and the allocation of land, the latter being "the most important resource in rural areas" (Acemoglu, Reed, and Robinson 2014). These chiefdoms and their corresponding chiefs were established in 1896 by the British Colonial Administration with ruling power being passed down through the ruling chief's family.

One step above chiefdoms are the 16 districts (14 districts at the time of the survey). Each district is governed by a district council that has various responsibilities at the local level (Renner-Thomas 2010).

The central government was headed by president Ernest Bai Koroma at the time of the crisis. It has been heavily criticized for its handling of the crisis. The combination of weak state-capacity, corruption, and heavy reliance on external health assistance appears to have amplified the harm of this virus (Anderson and Beresford 2016). There were also notable instances of intransigence regarding reception of foreign aide. For example on August 9, a shipping container full of $140,000 worth of medical supplies and mattresses donated from the United States were left sitting on the dock in Freetown through October 5 (Nossiter 2014a).

Rather responding to the increasing criticism, the central government's response was to heavily punish any critics. David Tam-Baryoh, a prominent journalist and radio host, was held for 11 days in prison for criticizing President Koroma, who subsequently filed an executive order for his arrest (Mackey 2014).

Cultural practices. Funeral traditions played a major role in the spread of Ebola across Sierra Leone. These traditions include having bodies buried near homes, rubbing corpses with oil, and having attendees of funerals hug and kiss the dead (McConnell 2014). These practices amplified the spread the virus as those who have died from Ebola are highly contagious soon after death (Prescott et al. 2015). Moreover, the elderly, who were more likely to care for those sick with Ebola, were also the most likely to have heavily involved funerals with many attendees, further exacerbating the spread.

Other cultural factors contributing to the outbreak included a distrust of health workers. Part of the population in Sierra Leone believed that health workers deliberately spread the virus, especially seeing the spread of Ebola in healthcare facilities and the poor conditions in many of the Ebola holding facilities (Richards et al. 2020).[6] Early on in the outbreak, parts of the population did not believe the disease existed, or thought that the disease was caused by supernatural means. By the time of answering the Sierra Leone Integrated Household Survey (SLIHS) in 2018, however, only 553 out of the 40,680 respondents claimed Ebola was caused by supernatural means or did not exist. The reliance on traditional healers who would often contract and spread the virus also played a major role.

[6]The work of Christensen et al. (2021) towards mitigating this distrust of health workers shows that community monitoring and nonfinancial awards increase the perceived quality of care.

The ultimate shift in understanding of the causes of infection and factors contributing to its wide spread occurred at the local level within chiefdoms. For example, one chiefdom put together an epidemiological task force in order to perform contact tracing and slow the spread of the virus (Richards 2016). The weak response of the central government necessitated the role of chiefdoms in slowing the spread, especially before international aid arrived.

Schooling. School attendance and educational attainment has been a major policy goal in Sierra Leone over the past decades. Enrollment rates have climbed from 5-15% at the time Sierra Leone declared independence in 1961 to 84.8% for children aged 6-14 in 2018 (calculated from the SLIHS).

Sierra Leone's education system is divided into six years of primary school (ages 6-12), three years of junior secondary school (JSS, ages 12-15), and three years senior secondary school (SSS, ages 15-18), after which students can enter university. The six years of primary school and three years of JSS are mandatory since the 2007 Child Act. The lack of 100% compliance has been attributed to (1) parents failing to see the value in schooling, often believing that the child would be better off working, but also to (2) shortages of schools and teachers (Mackintosh et al. 2020). Historically, the 1991-2002 Civil War has been a major disruption of the progress in education since Sierra Leone's independence in 1961.

Children who are enrolled drop out for a variety of reasons, including failure to pass the examinations at the end of each stage of schooling, but also because of the financial burden of school fees. In 2004, Sierra Leone abolished fees for primary school as well as for girls in JSS in the northern and eastern region. Since August 2018, the government's Free Quality School Education (FQSE) initiative covers further school fees and teaching materials from primary school to SSS at approved schools.

Most schools are run by the central government. However, local governments, communities, religious organizations, and private organizations also control many of the schools in Sierra Leone (Sankoh 2019).

School years typically last nine months from September to July; however, the two school years following the school closures ran from April 2015 to December 2015 and January 2016 to July 2016 before returning to the standard schedule with the 2016-2017 school year.

3 Data

The vast majority of the data used for this analysis comes from the Sierra Leone Integrated Household Survey (SLIHS) 2018. This survey was conducted in-person by trained interviewers from January to December 2018. It includes 40,680 individuals across all 14 districts, 149 chiefdoms, and 513 sections. There were 6,840 households surveyed, with 10 households in each of the 684 enumeration areas (EAs) used to cluster the survey respondents. The sample was selected from the 2015 Population and Housing Census (PHC) which had 12,856 EAs and 1,248,218 households. A two-stage stratification strategy was used to select the sample by first dividing the sample-space by the 14 districts and then dividing each district by rural and urban localities. Probability Proportional to Size (PPS) was used to select the 684 EAs used as clusters for the survey. Due to the wide variation in the living conditions of urban localities, the urban population is overrepresented in the survey with 340/684 (49.7%) of the EAs being urban despite making up 37% of the population. We control for this when running our tests.

One of the key questions of interest is the question about quarantine and restricted movement. It asks: "During the Ebola outbreak, did you experience quarantine or time when they didn't let people go where they wanted?" We construct an indicator variable *Quarantine*, which assigns the value of one if an individual lives in a household where the head of house answered yes, and zero otherwise. We treat the act of quarantining as a time when individuals in a household were not allowed to leave their home rather than a time when individuals faced broader region-level restricted-movement measures. We are confident that this is how the household head viewed the survey question as individuals in regions facing more broad movement restrictions that restricted movement between districts did not answer this question at a much higher rate than individuals in regions that did not face such restrictions as seen in Table A.3.

Another key variable of interest uses the answer to the question "What class did you attend during the following school years?", which is asked for one school year before the Ebola crisis (September 2013 to July 2014), and for four more school years post-crisis (April 2015 to December 2015, January 2016 to July 2016, September 2016 to July 2017, and September 2017 to July 2018).

We construct an indicator variable *Enrolled*, which is equal to one if the respondent indicated any class, and zero otherwise.

Finally, our last key variable of interest is *Early Ebola* which we use to instrument for quarantine. This variable is a dummy equal to 1 if a respondent lives in a chiefdom in which the first positive Ebola test came prior to the deployment of troops to enforce quarantine in July 30, 2014. The dates of the positive tests were obtained through (Fang et al. 2016).

All survey questions of interest can be found in Appendix-Table A.2. The summary statistics for all the variables used in this paper are in Table 1.

Although the survey was collected at a single point in time, we have the equivalent of panel data that we will use to look at enrollment over time. Poor memory should not significantly impact the results of this enrollment data since an individuals' enrollment decision for a school year is a significant life event that is very likely remembered within 5 years. Further, the enrollment rate of respondents aged 6-14 in the first schooling period in 2013 is closely aligned with that of the SLIHS 2011 survey for the 2011 schooling period (68.4% in 2011 and 67.9% in 2013).

All of the data was obtained from the SLIHS 2018 except for *Early Ebola* and *EVD Per 1000* which was collected from Fang et al. (2016). This paper made available all of the confirmed and expected EVD cases by chiefdom in Sierra Leone, as well as the corresponding dates in which these cases were expected or confirmed by a positive EVD test. *Early Ebola* is a dummy equal to 1 if an individual lives in an area were the first case of Ebola took

Table 1: Summary Statistics

Variable	Mean	Median	St. Dev.
Quarantine	0.294	0	0.455
Early Ebola	0.469	0	0.499
Hospital Closure	0.127	0	0.333
Job Closure	0.209	0	0.407
Buy Market Closure	0.241	0	0.428
Sell Market Closure	0.259	0	0.438
EVD Per 1000	2.177	1.482	2.772
Age	9.682	9	2.574
Female	0.496	0	0.500
urban	0.477	0	0.500
Has Father	0.544	1	0.498
Father Educ	2.122	1	1.573
Late Region	0.120	0	0.325
Log Consumption	8.186	8.132	0.537
No Oldest Att 2013	0.640	1	0.480
HH Head Age	44.854	43	14.257
School Expenses	331.400	135	609.670
Iso	0.498	0	0.500
Enr Rate	0.650	0.727	0.254
Any Wedding Expenditure	0.071	0	0.258
Medical Expenditure	155.192	68	314.486
Outstanding Debt	1.626	2	0.483

place prior to August 2014. This instrument allows us to mitigate the risk that the random assignment criterion does not hold. For *EVD Per 1000*, we use the sum of confirmed and expected cases to find the total EVD cases per 1000 people in each chiefdom. We also use this data to produce our instrument of whether an individual lived in a chiefdom where the first positive EVD test took place before August 2014[7].

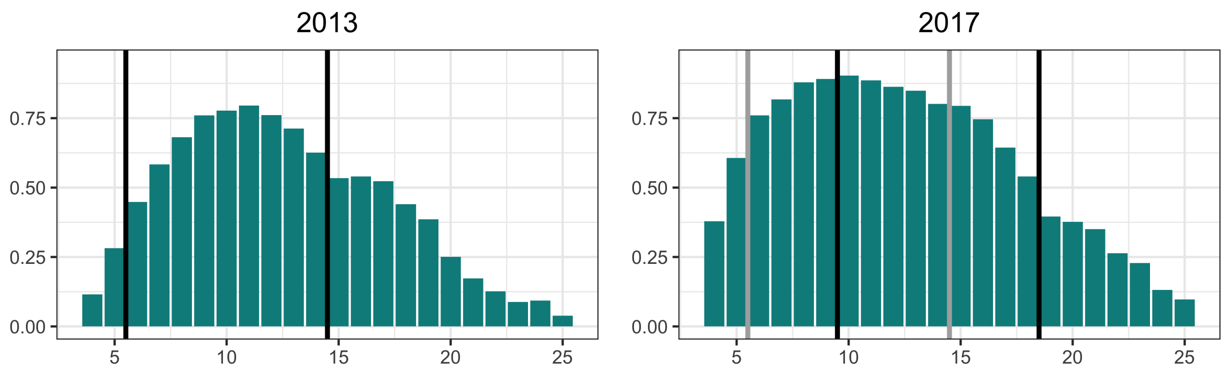
In order to verify the validity of the quarantine variable, we check whether those who answered affirmatively to having quarantined were in regions that faced the higher incidence of EVD. Controlling for the 27 Urban $\times$ rural regions designated in the SLIHS, we find that households that were in chiefdoms with higher incidence of Ebola were significantly more

[7] We analyzed the Demography and Health Survey (DHS) from years 2013 and 2019, but the data mainly includes health data unrelated to Ebola that would not aide in our analysis.

likely to quarantine as per Table A.1.

Turning to enrollment, the age which students enroll for the first time as well as graduate or dropout widely varies as shown by Figure 2. We subset the data to include the 7821 individuals aged 6-14 at the start of the 2013 school year (before the Ebola outbreak) as this is the age range that the WHO identifies as "school-age."

Figure 2: Enrollment rate by Age (Cohort Bounded by Vertical Lines)



In both of these graphs, the vertical axis represents school enrollment rates, and the horizontal axis represents age. The black vertical bars on the left borders the enrollment rates of our starting sample of kids aged 6-14 in 2013, the first year in which we have data. On the right, the same black bars border the same cohort 4 years later, while the gray vertical bars border our other specification of kids aged 6-14 in 2017. Throughout the paper, we verify that our results hold for both specifications: the same cohort of those aged 6-14 in 2013 represented by the black bars, and children aged 6-14 in each school year represented by the grey bars.

There are two ways that one may be interested in tracking the enrollment of students: track the 7821 individuals aged 6-14 at the start of the 2013 school year (labeled black in both panels of Figure 2), and track the individuals aged 6-14 in each schooling period, dropping those who age out of the window and appending those who age into the window (labeled grey in the right panel of Figure 2). Going forward we will primarily focus on the fixed-age window sample as to restrict our sample to school-age children as defined by the WHO; however, we will also include results for the cohort specification in the Appendix.

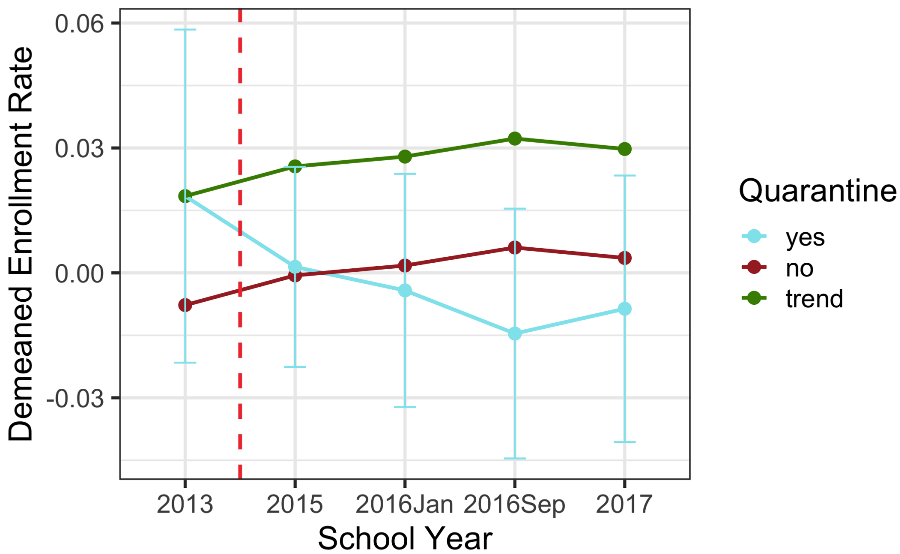
Other benefits of this 6-14 age specification are that age 6 is when close to 50% of the population had enrolled and individuals aged 14 are unlikely to have graduated by 14 with the fixed-age range specification and 18 with the cohort specification. This is because a student would not be able to complete SSS by age 18 if he or she started school at age 6 and enrolled in every subsequent year. Thus, the changes in enrollment over time will be mostly comprised of late first-time enrollment and dropouts, two outcomes that have significant implications on long-term outcomes.

Other questions regarding the experiences of households during the Ebola epidemic were asked to the heads of each household. Specifically, four other questions were asked regarding health care facility closures, job closures, and market closures. This data is important as it allows us to control for more regional virus containment efforts to verify that the impact of quarantine is not capturing these other impacts. Therefore, we can isolate the impact of quarantine independent of the overall effect of the Ebola epidemic on a household. These variables and their corresponding questions are listed in Table A.2.

The initial analysis of the enrollment over time by quarantine or control groupings in Figure 3 indicates that enrollment rates for those who did not experience quarantine were lower than for those who experienced quarantine initially; however, two schooling periods later, those who did not quarantine experienced higher rates of enrollment than those who did quarantine. Thus, we see that those who did quarantine had lower enrollment growth over this period than those who did not experience quarantine. This supports our hypothesis that facing quarantine measures negatively impacted enrollment rates in subsequent years. Similar results are found with the cohort specification as indicated in figure A.2 in the Appendix.

We performed the same analysis as the quarantine grouping for the four Ebola closure dummy variables in Figure A.1 in the Appendix. The differences in enrollment rates over time are much less pronounced. For health care facility closures, the gap widens in 2015 but returns to pre-Ebola levels for the January 2016 School year. For job closures, the gap widens for 2015 through September 2016 school years but at a lower rate than quarantine and a diminishing rate for the 2016 school years. We include this figure for the cohort specification in Figure A.3 of the Appendix. The overall trends of enrollment are similar for this specification.

Figure 3: Enrollment Over Time by Quarantine



The light blue line represents the enrollment of those who indicated that they faced quarantine measures as a result of Ebola, and the dark brown line represents the enrollment of those who did not. The dark green line represents what the enrollment rate would have been for the quarantine group had it followed the trends of of the group not quarantined. This figure captures between 7,821 and 9,022 kids aged 6-14 in the school years from 2013 to 2017. The red, dashed line represents the start of the Ebola crisis. The question of enrollment was asked to each kid, while the question of quarantine was asked to the head of each household.

4 Empirical Strategy

In this section, we will describe our strategy to isolate the effect of being quarantined on enrollment trends over time. We first do so through a simple difference-in-differences approach before verifying that the necessary assumptions of this approach hold.

We perform a difference-in-differences analysis as it allows us to isolate the effect of the one-time shock of the Ebola crisis on enrollment trends from the pre-Ebola schooling period to the post-Ebola schooling period. For the cohort specification, this method accounts for fixed effects of those forced to quarantine and the overall time trend effect of our cohort in aggregate (this includes time trends involved in the aging of the cohort as well as overall trends in enrollment in Sierra Leone during this time). For the fixed-age specification, many of the fixed effects of the students will be accounted for as most of the sample overlap, while the overall enrollment trends in Sierra Leone can also be accounted for.

We estimate the shock of Ebola was greatest from the end of the school year in 2013 to the beginning of the school year in 2015, but that the crisis continued to weigh on enrollment for all subsequent school years observed. We see from Figure 3 that this difference in enrollment trends widens across the first three schooling periods following the epidemic before narrowing closer to its original 2013 level in 2017. Therefore, we expect strengthening results for the first 3 periods before a weakened result for the final 2017 period.

We use the following model:

$$Y_{it} = \alpha + \gamma(Q_i) + \lambda(POST_t) + \beta(Q_i \times POST_t) + u_{it}$$

Where Y_{it} indicates whether an individual i was enrolled at time period t, α is the fixed effects shared by all subjects, γ is the additional fixed effects of those in the quarantine group, Q_i is a dummy which is 1 if an individual is in the quarantine group, λ is the time variant effect shared all subjects, $POST_t$ is a dummy which is 1 if the time period is after the treatment, β is the main effect of interest as it is the effect of Ebola induced quarantine on enrollment over time from 2013 school year to the post-Ebola school year, and u_{it} is the residual term. We cluster standard errors at the level of randomization: the SLIHS clusters which consist of 10 households each (684 total).

This model isolates the effect that the Ebola epidemic and subsequent quarantining has on school enrollment by comparing enrollment rates over time of those who quarantined and those who did not. The data has 1 pre-Ebola school period beginning in September 2013 and 4 post-Ebola school periods beginning April 2015, January 2016, September 2016, and September 2017. The September 2016 school year is the first schooling period with the same start and end dates as the pre-Ebola schooling period following the outbreak and it is the first schooling period following the WHO declaration that Sierra Leone was Ebola free.

This model's assumption that the assignment of individuals to the quarantine (treatment) group and non-quarantine (control) group is close to random with respect to enrollment trends seems reasonable. Although we do not have enough data to analyze enrollment trends pre-Ebola, our model controls for the fixed effects of enrollment between these two groups (fully for the cohort specification and partially for the fixed-age window specification) and it is reasonable to assume that enrollment trends are close to parallel for this quasi-random assignment. To support the assumption that the assignment of quarantine does not lead to different enrollment trends independent of the quarantine, we will now instrument an individual's quarantine assignment with whether the individual lived in a chiefdom which had a positive EVD test prior to August 2014. Further, we add controls for other factors that may impact trends of enrollment over time.

We use whether the individual lived in a chiefdom which had a positive EVD test prior to August 2014 as our instrument as troops were sent to quarantine at the very end of July, August was the month when the national awareness campaign began, and it became illegal to hide people who potentially had Ebola. Further, it is when approximately 50% of our sample lived in chiefdoms where there was a positive test. It also stands to reason (and is verified in our first stage) that chiefdom's which faced incidence of Ebola first were more likely to implement quarantine on those exposed to Ebola.

Our instrument is *Early Ebola* and we control for the following variables: *EVD Per 1000*, *Age*, *Female*, *Urban*, *Has Father*, *Father Education*, *Log Consumption*, *Late Region*, and *District*. *Early Ebola* is a dummy variable which is equal to 1 when an individual lives in a chiefdom in which the first positive test occurred prior to July 30, 2014. *EVD Per 1000* is defined as the number of cases of Ebola confirmed or suspected per 1000 people in one's chiefdom. *Father Education* is defined as (1) no father, (2) has a father who never attended school, (3) highest educational achievement of father was primary school, (4) highest educational achievement of father was JSS or SSS, and (5) highest educational achievement of father was higher education. We use the father's education instead of the mother's education as it was especially difficult for female children to receive education in Sierra Leone in the past, when current school-age children's parents would have been school-age. It is of note that we don't control for the trend effects of *Father Education* as they are insignificant, while we leave in the level effects to control for the *Father Education* of students entering and leaving sample window. Although the educational level of one's father may impact if they go to school, we find it doesn't impact when they enter school.

Consumption is defined as the aggregate consumption after controlling for purchasing power. It is broken up into five main components: food, health and education services, non-food items, durable goods, and housing. *Consumption* was then adjusted based on regional cost-of-living and household composition. This is used over income because income is particularly difficult to measure due to much of the economic activity in Sierra Leone occurring in the informal economy, which is very difficult to track. Further, aggregate consumption is likely a more reliable indicator of long-term living standards than income (Deaton and Zaidi 2002) (Haughton and Khandker 2009).

The consumption data on food is based on a diary that households kept over a twenty-day period including over 200 food item codes. Health expenses include consultation fees, payments for prescribed medications purchased within or outside of the health care provider, and fees for tests and medical supplies over the past 4 weeks while education expenses include spending on school fees and purchase of uniforms, school supplies, school books etc. and also Quranic education. Non-food item consumption was collected every 5 days along with the food diary and included items purchased frequently by the household. Durable good consumption includes 31 durable goods with the following information for each good: number owned, purchase price, age and current value; which was then used to determine the annual use value. For housing consumption, the value of a dwelling is computed using a hedonic rental regression is estimated using actual rents as the dependent variable, and models log rent as function of the number of rooms, various region-urban/rural dummies, characteristics of water source, cooking fuel and lighting sources, and building materials of the dwelling. For a more in-depth description of how *Consumption* was formulated, see (de la Fuente and Foster 2018).

Late Region is defined as a one for students living in a section that had over 50% of students claim that their schools did not open on time during the 2015 school year following the worst of the Ebola epidemic and a zero otherwise. This question was only answered by those who attended school, hence the section aggregate. District is a collection of 14 dummies that are one if an individual lives in that district.

Table A.2 in the Appendix outlines the specific survey questions asked regarding the controls except for consumption as consumption was aggregated using hundreds of survey questions. We lose 94-101 observations due to a lack of responses to these survey questions.

In the following IV model, we shift from using a respondent's enrollment (either 0 or 1) to using the respondent's change in enrollment from the year being analyzed to 2013 (-1, 0, or 1) in order to unify the *POST : Quarantine* interaction into a single estimated variable for our second stage.

We estimate the following IV model, with the first-stage estimation

$$Q_i = \alpha + \gamma(EE_i) + \sum_{k=1}^{21} \delta_k(control_{k,i}) + u_i, \tag{1}$$

and the second-stage estimation

$$Y_{it} = \alpha + \beta(\hat{Q}_i) + \sum_{k=1}^{21} \delta_k(control_{k,it}) + u_{it}. \tag{2}$$

Where δ_k is the effect on enrollment of the control variable $control_k$, Y_{it} is individual i's change in enrollment from year t to 2013 (either 1, 0, or -1), and $\hat{Q}_i$ is our estimate from quarantine in the first stage.

Finally, we run the simple difference-in-differences analysis with the same controls as in the above model. Here is the specification of the difference-in-difference with controls:

$$Y_{it} = \alpha + \gamma(Q_i) + \sum_{k=1}^{21} \delta_k(control_{k,i}) + \lambda(POST_t) + \beta(Q_i \times POST_t) + \sum_{k=1}^{20} \eta_k(control_{k,i} \times POST_t) + u_{it}$$

Where η_k is the effect on the time trend of enrollment of $control_k$. This model is the result of adding in the desired controls to the previous model. Here, we cluster standard errors at the SLIHS clusters as well.

5 Results

This section goes over the results of the difference-in-differences estimation of the effect of being heavily impacted by Ebola and quarantining on enrollment trends over time. We first assume parallel trend assumptions hold. We then include level effects and trend effects to control for biased assignment into the quarantine (treatment) grouping. Next, we verify that it is quarantine that leads to lower enrollment rather than regional lockdowns caused by the Ebola epidemic. Finally, we determine whether dropouts or lower first-time enrollment are driving the results.

5.1 Main Results

First, we will turn to the simple difference-in-differences result where we assume parallel trends would have occurred if not for the quarantine measures. Table 2 shows the estimate of the impact of being forced to quarantine on enrollment. There are statistically significant results at the 5% level for quarantine reducing enrollment trends from the pre-Ebola school year to the first two and final post-Ebola school year and at the 1% level for the third school year. Thus, there is statistically significant evidence that quarantine led to lower enrollment rates across all schooling periods.

Other results of note are that those who were in the quarantine grouping had 2.6% higher enrollment in 2013 (value repeats in the table as it represents this higher enrollment in 2013). Overall enrollment increased from the 2013 school year to the 2017 school year by 18% for the control group: a very vast increase that is consistent with the findings of the SLIHS 2018 report. We leave in the Constant so that enrollment rates can be constructed for both groups in each schooling period. Similar estimates are obtained for the cohort specification in Table A.4 in the Appendix.

Table 2: Quarantine on Enrollment, No Controls

	Dependent variable:			
	Enrolled			
	2015	2016Jan	2016Sep	2017
	(1)	(2)	(3)	(4)
Quarantine	0.026	0.026	0.026	0.026
	(0.020)	(0.020)	(0.020)	(0.020)
POST	0.021**	0.068***	0.163***	0.180***
	(0.008)	(0.009)	(0.010)	(0.010)
POST : Quarantine	−0.024**	−0.032**	−0.047***	−0.038**
	(0.012)	(0.014)	(0.015)	(0.016)
Constant	0.672***	0.672***	0.672***	0.672***
	(0.012)	(0.012)	(0.012)	(0.012)
Observations	16,149	16,656	16,656	17,043
R^2	0.001	0.004	0.031	0.041
Note:				*p<0.1; **p<0.05; ***p<0.01

We employ following model: $Y_{it} = \alpha + \gamma(Q_i) + \lambda(POST_t) + \beta(Q_i \times POST_t) + u_{it}$ where Y_{it} is *Enrolled*, Q_i is *Quarantine*, and α is *Constant* as defined in *Empirical Methodology.* Observations include the 7,821 individuals age 6-14 in 2013 summed with the number of kids age 6-14 in the corresponding school year. *Quarantine* and *Constant* values are repeated as they represent the effects on enrollment in 2013 (the λ and α of the above model) which is obviously the same across the four tests. Standard errors are clustered on the SLIHS cluster level.

From the pre-Ebola school year beginning in 2013 to the post-Ebola school year beginning in September 2016, the control group had increased enrollment by 16.3%. We find that during this same time period, Ebola-induced quarantine led to 4.7% less enrollment than the control group. Thus, quarantining led to an almost 29% smaller increase in enrollment then would have occurred in the absence of the epidemic-induced quarantine.

For a greater appreciation of scale, the SLIHS 2018 report estimates that approximately 1,846,904 were in the school-age range of 6-14 in 2016. We estimate that 29.6% or 546,684 of these school-age children were affected by quarantine. Therefore, we estimate that 25,694 school-age children in Sierra Leone did not enroll in school due to quarantine measures $(546,684 \times 0.047)$.

We undergo the same analysis for the other Ebola exposure dummy variables in place of *Quarantine* using the cohort specification in tables A.8-A.11 the Appendix (similar results hold for the fixed-age window specification but they are cut for brevity). They indicate that there is no significant depressed enrollment caused by the closure of a primary health facility, place of work, market for buying, and market for selling produce as a result of Ebola. This suggests that quarantining is the primary cause of this depressed enrollment. We will further verify that this is the case in later.

Now, we will investigate our model with controls to check for omitted variable bias. This test will control for the possibility that the assignments to the quarantine group were not random and that the grouping would have experienced lower enrollment trends independently of quarantine. We control for the level effects of *Father Educ*, as well as the level effects and enrollment trends of *EVD Per 1000*, *Age*, *Female*, *Urban*, *Has Father*, *Log Consumption*, *Late Region*, and *District*. Further, we use whether the individual lived in a chiefdom which had a positive EVD test prior to August 2014 as an instrument for whether a respondent quarantined to further mitigate concerns against the random assignment assumption. As a reminder, we shift from using a respondent's enrollment to using the respondent's change in enrollment from the year listed in the column to 2013 in order to unify the $POST : Quarantine$ interaction into a single estimated variable for our second stage.

We find in Table 3 that we get statistically significant results at the 5% level in the first, third, and fourth time periods and at the 10% level in the second time period. Our first stage is strong with those living in chiefdoms where there was a positive EVD test prior to August were 6.7% more likely to quarantine. Our results strengthen when restricting our sample to those aged 6-14 in 2013.

We also verify that this result holds without instrumenting for quarantine. Table 4 indicates that we get statistically significant results for all 4 time periods. Thus, the assignment of the subjects with varying *EVD Per 1000*, *Age*, *Female*, *Urban*, *Has Father*, *Father Educ*, *Log Consumption*, *Late Region*, and *District* to the control and treatment groups does not

Table 3: IV Quarantine on Enrollment, Early Ebola Instrument

	Dependent variable:				
	Quarantine	Delta Enrollment			
	First Stage	*Second Stage*			
	2015	2015	2016Jan	2016Sep	2017
	(1)	(2)	(3)	(4)	(5)
Early Ebola	0.067***				
	(0.013)				
Quarantine		−0.288**	−0.287*	−0.449**	−0.291**
		(0.141)	(0.155)	(0.178)	(0.128)
EVD Per 1000	0.004**	−0.002	−0.001	−0.002	−0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Female	−0.012	−0.004	−0.003	−0.012	−0.003
	(0.009)	(0.007)	(0.008)	(0.009)	(0.008)
Urban	−0.012	−0.023***	−0.031***	−0.037***	−0.034***
	(0.012)	(0.008)	(0.009)	(0.011)	(0.010)
Has Father	−0.006	−0.012*	−0.003	−0.001	0.004
	(0.009)	(0.007)	(0.007)	(0.008)	(0.008)
Father Educ	0.007**	0.002	−0.001	−0.001	−0.003
	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)
Age	0.002	−0.0003	0.011***	0.011***	0.022***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
Log Welfare	0.013	−0.010	−0.016*	−0.019*	−0.012
	(0.010)	(0.008)	(0.009)	(0.010)	(0.009)
Late Region	−0.062***	−0.035***	−0.025*	−0.040**	−0.031**
	(0.013)	(0.013)	(0.014)	(0.017)	(0.014)
District FE	Y	Y	Y	Y	Y
Observations	8,273	8,273	8,775	8,775	9,160
Note:					*p<0.1; **p<0.05; ***p<0.01

This table represents the IV estimates from model (1) and (2), where is *Delta Enrolled* is the change in enrollment for individual i from period t to 2013, and *Quarantine* as defined in Section 3. The controls include district fixed effects. Column 1 shows the first stage of the 2015 analysis. The other first stages are omitted for brevity as the analyses are time-invariant and share approximately 90% of the sample. The samples include all individuals aged 6-14 in the year indicated by the column.

Table 4: Quarantining on Enrollment, with Controls

	Dependent variable:			
	Enrolled			
	2015	2016Jan	2016Sep	2017
	(1)	(2)	(3)	(4)
Quarantine	0.019	0.019	0.019	0.019
	(0.016)	(0.016)	(0.016)	(0.016)
POST	−0.118	−0.003	0.416***	0.643***
	(0.108)	(0.121)	(0.120)	(0.127)
POST : Quarantine	−0.023**	−0.031**	−0.044***	−0.031**
	(0.012)	(0.014)	(0.014)	(0.016)
POST : EVD Per 1000	−0.003*	−0.003	−0.005**	−0.009***
	(0.002)	(0.002)	(0.002)	(0.002)
POST : Female	0.024**	0.027**	0.025**	0.035***
	(0.010)	(0.011)	(0.011)	(0.011)
POST : Urban	−0.056***	−0.066***	−0.085***	−0.102***
	(0.013)	(0.015)	(0.016)	(0.016)
POST : Has Father	−0.046***	−0.036***	−0.030**	−0.038***
	(0.010)	(0.012)	(0.012)	(0.012)
POST : Age	0.033***	0.027***	−0.008***	−0.018***
	(0.003)	(0.003)	(0.003)	(0.003)
POST : Log Consumption	−0.019	−0.018	−0.012	−0.026*
	(0.013)	(0.014)	(0.014)	(0.014)
POST : Late Region	−0.029*	0.008	0.013	0.017
	(0.017)	(0.021)	(0.021)	(0.023)
POST : District	Y	Y	Y	Y
Observations	16,055	16,558	16,558	16,942
R^2	0.158	0.153	0.145	0.145
Note:				*p<0.1; **p<0.05; ***p<0.01

The estimation includes all level effects, and the table shows only *Quarantine* level effects, *POST* and *POST* interactions based on the following model: $Y_{it} = \alpha + \gamma(Q_i) + \sum_{k=1}^{21} \delta_k(control_{k,i}) + \lambda(POST_t) + \beta(Q_i \times POST_t) + \sum_{k=1}^{20} \eta_k(control_{k,i} \times POST_t) + u_{it}$ where Y_{it} is *Enrolled* and Q_i is *Quarantine* as defined in *Empirical Methodology*. The 21 controls include the controls in this table as well as the district level controls. Observations include the 7,821 individuals age 6-14 in 2013 summed with the number of kids age 6-14 in the corresponding school year. Standard errors are clustered on the SLIHS cluster level.

explain our main results. We also note that the level effect of quarantine (the difference between enrollment rates in 2013 between those that later quarantined) fell to 1.9% from the prior model. This level effect is well overtaken by the trend effects of quarantine in all four years.

One may worry that quarantine may lead to lower consumption in 2018 at the time of the survey, however, we find nearly identical results removing the *Log Consumption* variable from the model. We also test for robustness to other specifications of the model in the next table, which will include the effect of quarantining on other socioeconomic factors that may influence enrollment.

We also note that *Female*, *Urban*, *Has Father*, *Age*, and *District* (omitted from table) controls are the only controls with statistically significant impacts on enrollment trends for all 4 time periods. Over this time period, female enrollment increased relative to male enrollment, likely due to a recent push for female education in Sierra Leone. Rural regions and children without fathers also experienced enrollment gains likely due to increased access to schooling for rural children as well as policies aimed at targeting regions struggling with school attendance. Despite this, our result supports that the assignment of quarantining to certain regions or ages does not significantly impact our main results. *EVD Per 1000* also has a statistically significant negative impact on the enrollment in the final two school years observed. This follows from the intuition that regions struck hardest by the epidemic faced lower enrollment following the epidemic. We obtain similar results for the cohort specification in Table A.6 in the Appendix.

We also verify that the results hold for alternate specifications of the model. We verify that our results are robust to controlling for just the level effects of all of the controls, as well as the level effects of all of the controls and the trend effects of *EVD Per 1000*, *Urban*, and *District*. In order to display these alternate specifications on a single table, we restrict our focus to the "2016Sep" school year as it is the first year following the WHO's declaration that Sierra Leone was Ebola-free, as well as it was the first school year that followed the typical start and end dates. Table 5 indicate that our results hold steady for these alternate specifications. Additionally, the results remain robust for the final school year in our sample, the 2017 school year, as shown in Table A.7 in the Appendix.

Table 5: Robustness to Alternate Specifications

	Dependent variable:			
	Enrolled			
	Simple	Level Controls	FE Controls	All Controls
	(1)	(2)	(3)	(4)
POST	0.163***	0.176***	0.231***	0.416***
	(0.010)	(0.010)	(0.033)	(0.120)
POST : Quarantine	−0.047***	−0.052***	−0.045***	−0.044***
	(0.015)	(0.014)	(0.014)	(0.014)
POST : EVD Per 1000			−0.005**	−0.005**
			(0.002)	(0.002)
POST : Urban			−0.088***	−0.085***
			(0.015)	(0.016)
POST : Female				0.025**
				(0.011)
POST : Has Father				−0.030**
				(0.012)
POST : Age				−0.008***
				(0.003)
POST : Log Consumption				−0.012
				(0.014)
POST : Late Region				0.013
				(0.021)
POST : District	N	N	Y	Y
Observations	16,656	16,558	16,558	16,558
R^2	0.031	0.141	0.144	0.143
Note:				*p<0.1; **p<0.05; ***p<0.01

The table shows only *POST* and *POST* interactions for the four alternate specifications of our model for the *POST* year of 2016Sep. The "Simple" model is as follows: $Y_{it} = \alpha+\gamma(Q_i)+\lambda(POST_t)+\beta(Q_i \times POST_t)+u_{it}$. The "Level Controls" model is as follows: $Y_{it} = \alpha + \gamma(Q_i) + \sum_{k=1}^{21} \delta_k(control_{k,i}) + \lambda(POST_t) + \beta(Q_i \times POST_t) + u_{it}$. The "FE Trend Controls" model is as follows: $Y_{it} = \alpha + \gamma(Q_i) + \sum_{k=1}^{21} \delta_k(control_{k,i}) + \lambda(POST_t) + \beta(Q_i \times POST_t) + \sum_{k=1}^{15} \eta_k(control_{k,i} \times POST_t) + u_{it}$ where only *EVD Per 1000*, *Urban*, and *District* control trend effects were included. The "All Controls" model is as follows: $Y_{it} = \alpha + \gamma(Q_i) + \sum_{k=1}^{21} \delta_k(control_{k,i}) + \lambda(POST_t) + \beta(Q_i \times POST_t) + \sum_{k=1}^{21} \eta_k(control_{k,i} \times POST_t) + u_{it}$. Y_{it} is *Enrolled* and Q_i is *Quarantine* as defined in *Empirical Methodology.* The 21 controls include the controls in this table as well as the district level controls. Observations include the 7,821 individuals age 6-14 in 2013 summed with the number of kids age 6-14 in the 2016Sep school year. Standard errors are clustered on the SLIHS cluster level.

5.2 Regional Lockdowns or Home Quarantines

Here, we will test whether quarantines were the reason for the depressed enrollment or if lockdowns caused by Ebola were the main culprit. We have already seen in tables A.8 - A.11 that regional, EVD-induced closures do not lead to a reduction in enrollment over time; however, we will further investigate this issue by running tests with *Quarantine* controlling for other Ebola impact variables.

We will now examine whether adding in all of the Ebola-induced closure variables affect our estimate. This is to further investigate whether the enrollment trend change is caused by *Quarantine* or Ebola as a whole. In this analysis and others from here on out, we cluster standard errors by individual as we have fixed and trend effects at the section level. Table 6 indicates that adding in additional controls for the impact of Ebola strengthens the estimate for quarantine's impact on enrollment across all schooling periods. Thus, quarantining leads to lower enrollment independent of whether an individual was in an area where businesses, primary health units, and markets were forced to close.

Other results of note are that hospital closures had weakly negative effects as did job closures for the final three schooling periods. There are also positive results of market closures on schooling in the final two schooling periods which will be eliminated when adding back our controls from before. The impact of *Quarantine* on the enrollment in post-Ebola periods also holds for all periods for the cohort specification as shown in Table A.12. Further, our results hold when adding back our controls from earlier. Those results are shown in Table A.13 for the fixed-age specification and A.14 for the cohort specification.

Having verified that other closures that coincide with lockdown measures are not driving the decrease in enrollment, we now turn to verify that individuals that answered yes to quarantining were referring to household-level quarantines rather than restrictions on inter-district travel. Although the entire population underwent 3 day curfews, only 7 districts went under isolation orders (Kamara 2014) (Mackey 2014). These measures restricted inter-district travel to essential workers. We have already shown in table A.3 individuals in isolated

Table 6: Quarantine on Enrollment, with Ebola Control Variables

	Dependent variable:			
	Enrolled			
	2015	2016Jan	2016Sep	2017
	(1)	(2)	(3)	(4)
POST	0.021***	0.065***	0.157***	0.173***
	(0.007)	(0.007)	(0.007)	(0.007)
POST : Quarantine	−0.025**	−0.038***	−0.063***	−0.058***
	(0.013)	(0.014)	(0.014)	(0.014)
POST : Hospital Closure	−0.029*	−0.017	−0.020	−0.017
	(0.018)	(0.020)	(0.020)	(0.020)
POST : Job Closure	0.0004	−0.033	−0.027	−0.032
	(0.018)	(0.021)	(0.020)	(0.020)
POST : Buy Market Closure	0.023	0.033	0.055**	0.052**
	(0.021)	(0.025)	(0.024)	(0.024)
POST : Sell Market Closure	−0.003	0.032	0.033	0.047**
	(0.020)	(0.023)	(0.022)	(0.023)
Observations	16,149	16,656	16,656	17,043
R^2	0.018	0.019	0.046	0.055
Note:				*p<0.1; **p<0.05; ***p<0.01

We only display *POST* and *POST* interactions. We employ the following model: $Y_{it} = \alpha + \gamma(Q_i) + \sum_{k=1}^{4} \delta_k(closure_{k,i}) + \lambda(POST_t) + \beta(Q_i \times POST_t) + \sum_{k=1}^{4} \eta_k(closure_{k,i} \times POST_t) + u_{it}$ where Y_{it} is *Enrolled* and Q_i is *Quarantine* as defined in *Empirical Methodology.* The 4 closures in the table correspond to the answers of the survey questions in Table A.2. Observations include the 7,821 individuals age 6-14 in 2013 summed with the number of kids age 6-14 in the corresponding school year. Standard errors are clustered on the individual level.

districts don't claim to quarantine at a much higher rate than individuals in districts that did not face isolation measures.

Further, we institute a new dummy variable: *Iso* which is 1 if an individual lives in a district that faced isolation measures at any point throughout the Ebola outbreak and 0 otherwise. Running a difference-in-differences in table A.15, we see that merely living in a district that faced these broad restricted movement measures doesn't lead to significantly lower enrollment.

As further evidence, the Western Area Urban district, in which Freetown resides, never faced isolation measures; however, security forces vigilantly quarantined homes in which a resident was believed to be infected by quarantine. When we restrict our sample to those in this district, we find in Table A.16 that quarantining results in a 2-4x greater impact on enrollment than our initial results. Therefore, we are confident that respondents answering that they had quarantined are referring to not being able to leave their home rather than more broad regional movement-restrictions.

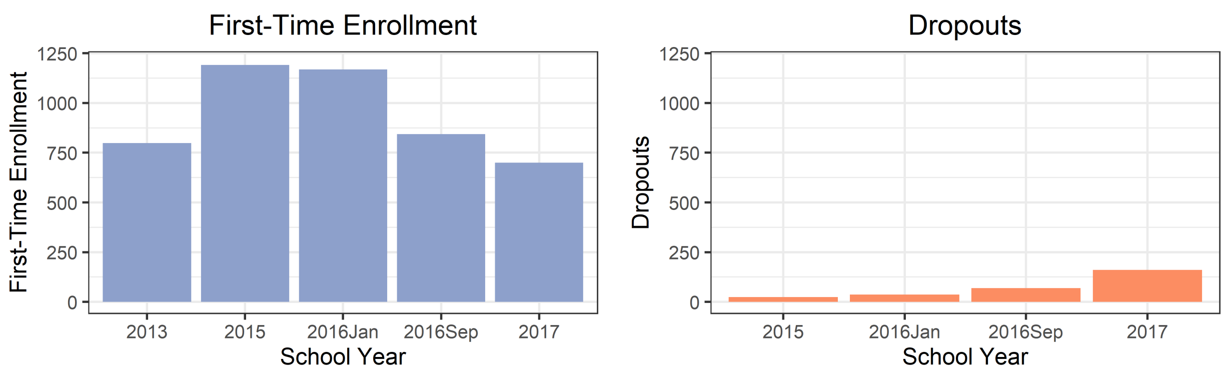
5.3 Dropouts or Lower First-time Enrollment

We now seek to determine whether this drop in enrollment was a result of dropouts or a decline in first-time enrollment. We first subset the 6-14 age individuals to those who were enrolled in 2013 (the pre-Ebola school year). We then assume that they dropped out if they did not enroll in the following school year. To investigate first-time enrollment, we subset the individuals who weren't enrolled in 2013 and determine what school period (if any) they enrolled. In 2013, we assume that those enrolled in the first year of primary school were first-time enrollments. We then repeat this procedure for all schooling periods to get a count of first-time enrollment and dropouts for each schooling period. It is of note that we cannot obtain a measure of dropouts for the 2013 schooling period as we do not know whether individuals were enrolled in the year prior.

Turning to the results, on the right panel of Figure 5, we see that a very small percentage of students who were enrolled drop out each year. On the left panel, we see that over a fourth of students who were not enrolled in the prior year enroll in the next year. Concerning the count of students who dropped out vs. enrolled for the first-time in 5.3, there are far more students enrolling after not being enrolled in the year prior than there are students dropping out. Thus, most of the time trends in enrollment observed through our difference-in-differences are due to these newly enrolled students.

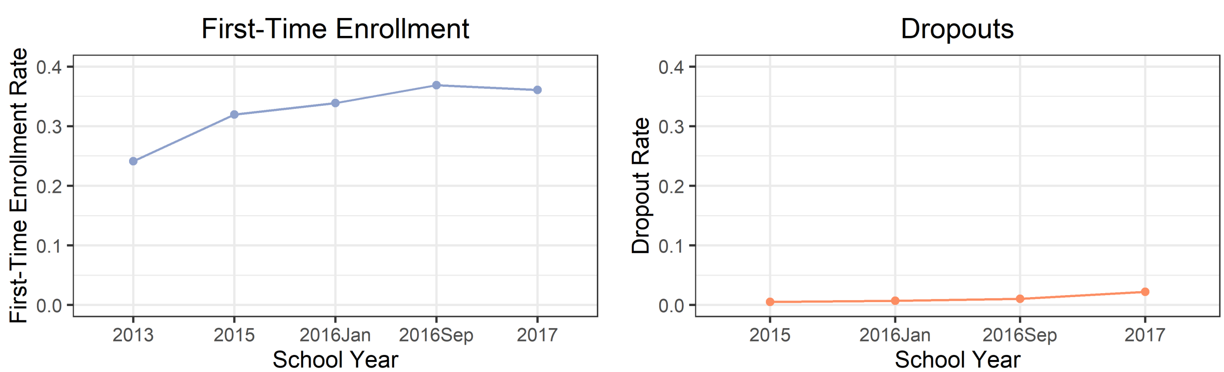
Furthermore, we also tracked the new enrollments, dropouts, and continued enrollment for all 5 schooling periods to better visualize how school enrollment evolved over time in Figure 6. The green bars in the 2015 graph less the small orange bars indicate enrollment by

Figure 4: First-Time Enrollments Vs. Dropouts, Number of Students



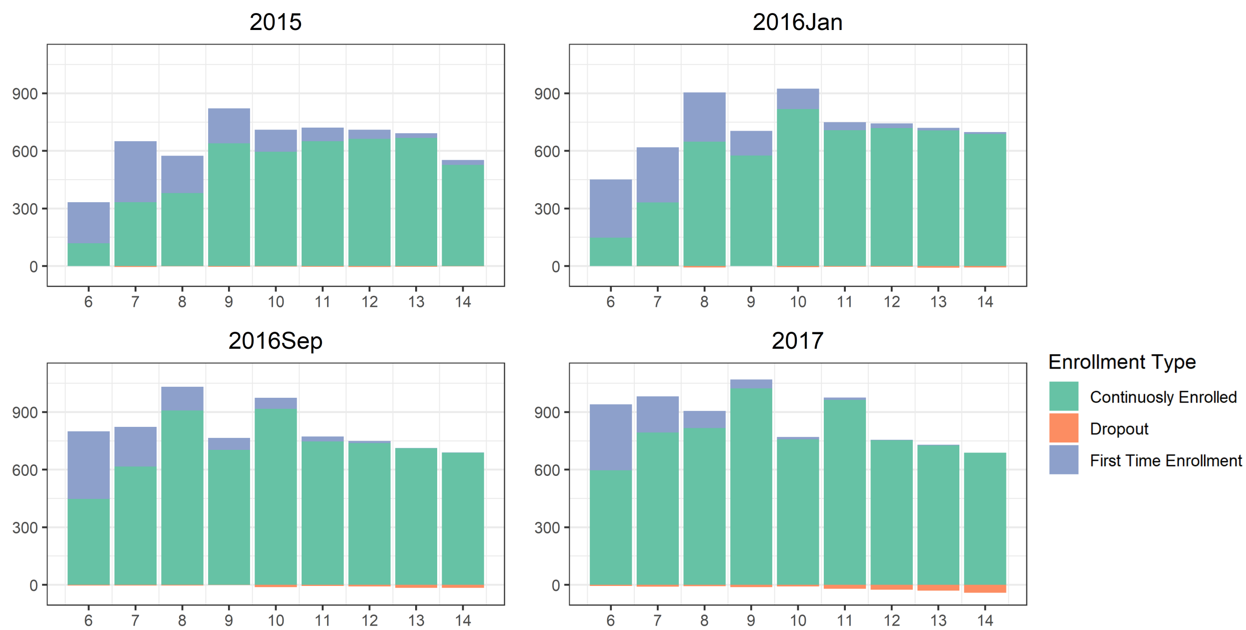
On the left graph, we have the number of first-time enrolled students age 6-14 by school year represented by the blue bars. On the right, we have the number of students age 6-14 who were enrolled in the previous year, but dropped out in the school year on the x-axis. There are only 4 years observable for dropouts as there is no way to know if kids were enrolled in the year prior to 2013. First-time enrollment is observable for all 5 school years as we define it as students entering the class corresponding to the first year of schooling in primary school.

Figure 5: First-Time Enrollment Vs. Dropout, Rates



On the left graph, we have the rate at which students age 6-14 who were not enrolled in prior years enroll for the first time by school year represented by the blue line. On the right, we have the rate at which students age 6-14 who were enrolled in the previous year dropped out in the school year on the x-axis. There are only 4 years observable for the dropout rate as there is no way to know if kids were enrolled in the year prior to 2013. The first-time enrollment rate is observable for all 5 school years as we define it as the students entering the class corresponding to the first year of schooling in primary school over the total number of kids who have never enrolled prior (those who start grade 2 and above in year 2013 are assumed to have enrolled prior).

Figure 6: First-Time Enrollment and Dropouts by Age Over Time



The y-axis represents the number of students while the x-axis represents the age of the students. On the upper right graph, the green bars represent the students that were enrolled in 2013 and 2015. The blue bars represent those who enrolled for the first time in 2015. The difficult to observe orange bars below the green bars represent those who were enrolled in 2013 but not in 2015. This continues for the following three graphs with the green bars representing those who were enrolled in the prior year as well as the current year, the blue bars representing those who enrolled for the first time in the current year, and the orange bars representing those who were enrolled in the prior year, but not the current year.

age in 2013, whereas the blue bars indicate the first-time enrollments in 2015. It is clear that dropouts play a much smaller role in shifting enrollment patterns than first-time enrollment. These first-time enrollments are what led to such a vast increase in enrollment across age groups from 2013 to 2017.

This result is fascinating and has many implications beyond the scope of this paper. It indicates that in Sierra Leone, once in school, very few students dropout. Therefore, it seems that a greater effort should be placed on getting children to enroll in school for the first time, rather than focusing on keeping children enrolled.

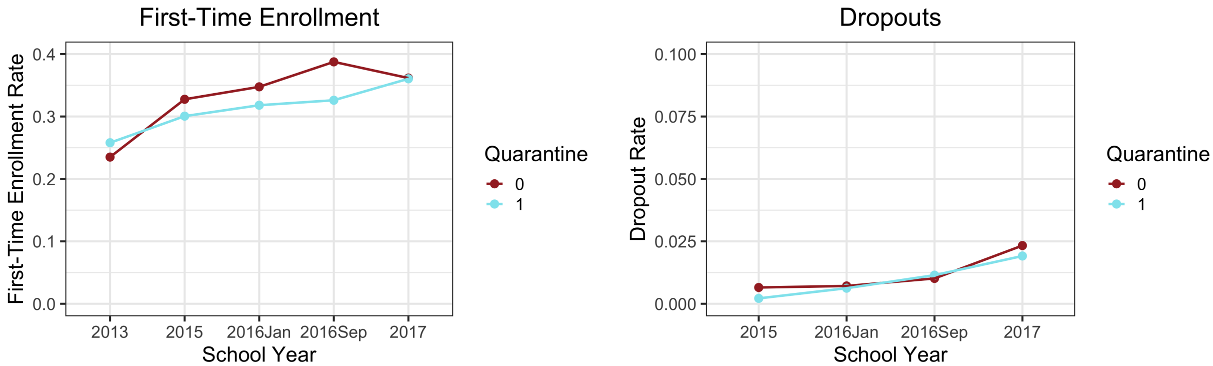
For this analysis, however, it indicates that a negligible amount of the trends in enrollment are due to dropouts. Thus, we will mainly investigate the impact of having ever enrolled in school on future outcomes. This is because we can assume that quarantining mainly impacts first-time enrollment which directly affects whether an individual was ever enrolled in school.

To verify that first-time enrollment was lower among those who quarantined, in Figure 7 we find that those who quarantined faced higher first-time enrollment in 2013. Following Ebola and subsequent movement restriction measures, they faced lower first-time enrollment rates than those who did not quarantine. We also find that dropout rates increased for those who quarantined relative to those who did not over the first 3 schooling periods following Ebola, however, all dropout rates were below 2.5%. Thus, they do not play as large a role in impacting overall enrollment rates.

Breaking the first-time enrollment rates down by age, we find in Figure A.4 that there is no specific age group in which first-time enrollment among the group which did not quarantine far exceeds the quarantine group. Rather, it appears that quarantine negatively affected the enrollment across all children aged 6-14.

Overall, the fact that quarantine led to lower first-time enrollment points to social isolation and stigma as mechanisms by which quarantining led to this drop in enrollment. Students who weren't integrated into the school system prior to having quarantined faced difficulties in joining following the Ebola crisis. We explore these mechanisms more in the

Figure 7: First-Time Enrollments and Dropouts, Quarantine and Control



On the left graph, we have the rate of first-time enrollment from kids age 6-14 by school year with those who did not quarantine represented by the dark brown line and those who did quarantine represented by the light blue line. On the right, we have the rate at which students age 6-14 who were enrolled in the previous year dropped out in the school year on the x-axis with the dark brown line representing those who did not quarantine and the light blue line representing those who did quarantine. There are only 4 years observable for dropouts as there is no way to know if kids were enrolled in the year prior to 2013. First-time enrollment is observable for all 5 school years as we define it as students entering the class corresponding to the first year of schooling in primary school.

next section.

6 Causes and Implications

Having shown that quarantining leads to lower first-time enrollment in subsequent years, we will now turn to investigate what is causing quarantine to have this profound effect on enrollment, as well as how this effects children in the long run. We start by demonstrating how stigma and social isolation are mechanisms through which quarantine is leading to lower enrollment. Next, we analyze what regions were affected the most. Finally, we will investigate the implications of these results with regard to aggregate consumption during one's prime-working age.

6.1 Causes

We first explore how attendance within one's family affects school enrollment. Specifically, we look into whether having the oldest child in a family enrolled prior to the epidemic led to diminished effects of quarantine. One might expect this to be true since if one has the precedent of an older sibling attending school, then he or she may be less deterred by quarantine. This would support the conjecture that quarantine led to less interaction with other families who may have influenced change within one's family towards the importance of schooling.

For this analysis, we will employ two new variables: *No Oldest Att 2013* which is a dummy variable assigned 1 if an individual's oldest sibling was not attending school in 2013, and *HH Head Age* which is the age of the head of the household in which the individual belongs. If an individual is the oldest sibling, *No Oldest Att 2013* is assigned 0. If there are no children of school age but grandchildren of school age in one's household, the oldest grandchild is considered the oldest sibling. We include the control for the household head's age since the older the oldest sibling, the older the head of the household head will be on average which may impact one's likelihood of enrollment. We employ the following model:

$$\begin{aligned} Y_{it} =& \alpha + \gamma(Q_i) + \zeta(NOA_i) + \delta(HHHage_i) + \lambda(POST_t) + \beta(Q_i \times POST_t) + \\ & \phi(NOA_i \times POST_t) + \eta(HHHage_i \times POST_t) + \psi(Q_i \times POST_t \times NOA_i) + u_{it} \end{aligned}$$

where NOA_i is the *No Oldest Att 2013* dummy of individual i, $HHHage_i$ is the *HH Head Age* of individual i, and the rest of the variables are defined the same as earlier in the paper. We use the fixed-age specification in which we restrict the sample to students age 6-14 in each school year.

Table 7 indicates that those who did not have their oldest sibling attending in 2013, prior to the epidemic, faced between 5.5% and 8.3% lower enrollment trends. Those who did not have the precedent of the oldest sibling attending school appear to be driving the main results as the trend effect of quarantine is now close to 0 in this model. This provides evidence that individuals who faced quarantine were less likely to be influenced by social pressures outside of one's household. Children who were in a household that had not decided that school was

Table 7: Quarantine and Oldest Sibling Enrollment on Individual Enrollment

	Dependent variable:			
	Enrolled			
	2015	2016Jan	2016Sep	2017
	(1)	(2)	(3)	(4)
POST	−0.007	0.055**	0.187***	0.202***
	(0.022)	(0.025)	(0.024)	(0.024)
Quarantine	−0.014	−0.014	−0.014	−0.014
	(0.018)	(0.018)	(0.018)	(0.018)
NOA 2013	−0.168***	−0.168***	−0.168***	−0.168***
	(0.013)	(0.013)	(0.013)	(0.013)
HH Head Age	0.001**	0.001**	0.001**	0.001**
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
POST : Quarantine	0.013	0.024	−0.00001	0.005
	(0.018)	(0.020)	(0.019)	(0.019)
POST : NOA 2013	0.051***	0.056***	0.054***	0.057***
	(0.013)	(0.015)	(0.014)	(0.014)
Quarantine : NOA 2013	0.050**	0.050**	0.050**	0.050**
	(0.023)	(0.023)	(0.023)	(0.023)
POST : HH Head Age	−0.0003	−0.001	−0.001***	−0.001***
	(0.0004)	(0.0005)	(0.0005)	(0.0005)
POST : Quarantine : NOA 2013	−0.055**	−0.084***	−0.069***	−0.065**
	(0.023)	(0.026)	(0.025)	(0.025)
Constant	0.743***	0.743***	0.743***	0.743***
	(0.022)	(0.022)	(0.022)	(0.022)
Observations	15,193	15,669	15,669	16,033
R^2	0.020	0.025	0.053	0.064
Note:				*p<0.1; **p<0.05; ***p<0.01

This table reports the results of the following model: $Y_{it} = \alpha + \gamma(Q_i) + \zeta(NOA_i) + \delta(HHHage_i) + \lambda(POST_t) + \beta(Q_i \times POST_t) + \phi(NOA_i \times POST_t) + \eta(HHHage_i \times POST_t) + \psi(Q_i \times POST_t \times NOA_i) + u_{it}$ where Y_{it} is *Enrolled* and Q_i is *Quarantine* as defined in *Empirical Methodology*. NOA is the *No Oldest Att 2013* dummy of individual i and $HHHage_i$ is the *HH Head Age* of individual i. Observations include individuals age 6-14 in 2013 summed with the number of kids age 6-14 in the corresponding school year. Standard errors are clustered on the individual level.

of high enough value to send their first child were far less likely to have changed their view for their younger children if they were quarantined. One might suspect this is because they were more isolated and interacted less with other households that may have a more positive view of schooling. Therefore, social isolation is likely a mechanism by which quarantine is leading to lower enrollment.

In order to verify that these results were not driven by the oldest child having a higher income following schooling and, thus, reducing cost frictions in schooling, we verify that these results hold when we restrict our sample to households in which the oldest sibling either never attended school or was still in school in 2015 (the first schooling period following the EVD outbreak). in A.17, we find similar results.

Further, the SLIHS 2018 asks each household's head how much money his or her household spent on weddings in the past 12 months. In order to determine the role of stigma, we analyze whether households that did not quarantine spent any money on weddings at a higher rate than households that did quarantine. Having spent any money on weddings in the past 12 months is a good proxy for whether a household has attended or thrown a wedding in the past 12 months. Logically, households that face stigma for having been quarantined during the Ebola crisis are less likely to attend or hold weddings.

For this analysis, we will employ a new variable: *Any Wedding Expenditure*, a dummy equal to 1 if the household has spent any money on weddings in the past 12 months. We employ the following model:

$$Y_i = \alpha + \gamma(Q_i) + \sum_{k=1}^{17} \delta_k(control_{k,i}) + u_i$$

where Y_i is the *Any Wedding Expenditure* of individual i and the rest of the variables are defined the same as earlier in the paper. We omit controls that aren't on the household level or aren't relevant, leaving us with the following controls: *EVD Per 1000*, *Urban*, *Log Consumption*, and *District*. We include all 5,927 households that responded to this question in the SLIHS 2018.

Table 8: Quarantine on Any Wedding Expenditure

	Dependent variable:
	Any Wedding Expenditure
Quarantine	-0.037^{***}
	(0.010)
EVD Per 1000	0.005
	(0.003)
Urban	-0.039^{*}
	(0.022)
Log Consumption	0.020^{***}
	(0.007)
District	Y
Observations	5,927
R^2	0.004
Note:	*p<0.1; **p<0.05; ***p<0.01

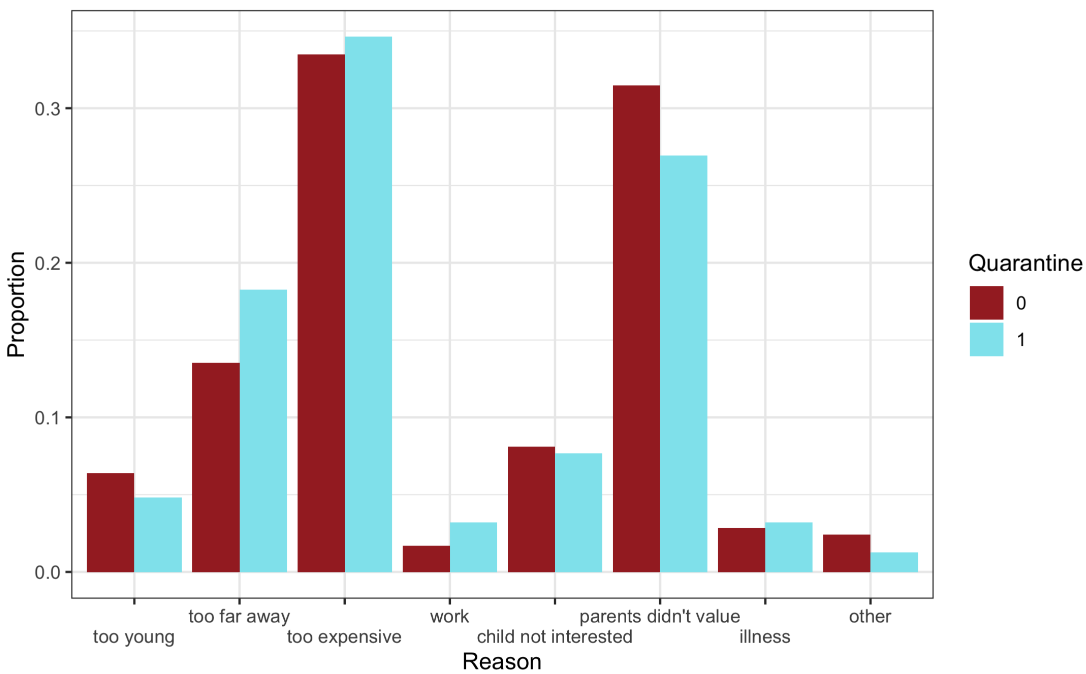
This table reports the results of the following OLS model: $Y_i = \alpha + \gamma(Q_i) + \sum_{k=1}^{17} \delta_k(control_{k,i}) + u_i$ where Y_i is the *Any Wedding Expenditure* dummy and Q_i is *Quarantine* as defined in *Empirical Methodology.* Observations include all 5,927 households that responded to this question in the SLIHS 2018. Standard errors are clustered on the SLIHS cluster level.

We find in Table 8 that, indeed, households that quarantined were 3.7% less likely to spend any money on weddings in the past 12 months after controlling for consumption and regional factors. This is a massive difference as 8.3% of those who did not quarantine spent money on a wedding in the past year. Therefore, households that faced quarantine were over 44% less likely to have spent money on a wedding than those who did not quarantine. This provides evidence that those who quarantined faced stigma that deterred them from throwing or attending weddings. This same stigma is likely to have prevented students from enrolling in school for the first time.

To further test the role stigma may have played on the reduction in enrollment, we test whether those in sections which faced over 80% of the population quarantining had a similar effect of quarantine. We get in Table A.18 no results for this subset, indicating that if a large majority of one's community faced quarantine, then quarantine didn't serve to deter enrollment. This provides supports the claim that stigma is playing a role in depressing enrollment.

We now turn to a question on the SLIHS 2018 survey that asks each child who has never been enrolled for the reason why the respondent has never attended school. We look into whether those age 6-14 who quarantined never attended school for different reasons than those who never quarantined. Figure 8 indicates that those who quarantined were more likely to have worked instead of attending school, were burdened by the cost of school, and were unwilling to travel the long distance to school. Because distance to school would have been the same before the epidemic as after (we don't find evidence that many schools permanently closed as a result of Ebola), we turn to cost as a potential mechanism in which quarantine led to lower enrollment.

Figure 8: Reasons Not Attending, Quarantine and control



The y-axis represents the ratio of those aged 6-14 in 2017 who did not attend school who answered the corresponding reasons for not attending on the x-axis. The dark brown bars represent those who did not quarantine, and the light blue bars represents those who did quarantine. The following question was asked to each kid who did not attend school: "Why did you [he/she] never attend formal school?"

In order analyze how school costs affected those who quarantined versus those that did not quarantine, we start by looking into the triple interaction terms between *POST*, *Quarantine*, and *Sch Cost*. *Sch Cost* is defined as the sectional mean of the aggregate of the school costs faced by students in 1,000 Sierra Leonean Leones (slightly less than 10 cents USD). The SLIHS divided school expenses into 10 categories and also gave the respondents an option to give the total cost of attending school without the division of costs by category. If a respondents categorized his or her spending, we aggregated the total expenses. Otherwise, we used their response corresponding to their total school expenses. This measure is aggregated at the section-level as only those who attended school answered the question. Regions in which no students went to school were omitted from this analysis as there is no way to determine their mean cost of attendance. We also include the level effect of *Log Consumption* as well as the *POST* and *Log Consumption* interaction as those with a high *Log Consumption* may attend costlier schools in more well-off regions where school enrollment is high. This will determine if those who quarantined were more likely to be deterred to enroll by the cost of school.

Our results in Table 9 indicate that school costs did not deter enrollment for those who quarantined more than those that did not quarantine in a statistically significant way in the first school year observed, however, it does in the following 3 school years. Thus, quarantine may have amplified the cost frictions in getting students to enroll. Quarantine measures may have also reduced income leading to the inability to bear these school costs.

To explore this potential mechanism further, we first analyze whether those who faced quarantine had lower consumption in 2018 (at the time of being surveyed). We do this by running a simple OLS regression of *Log Consumption* on *Quarantine* controlling for *District* and *Urban* at the household level. Since the consumption prior to quarantine is unknown, this result is determining the difference in consumption between households that quarantined and those that did not rather than the impact of quarantining on a household's consumption. We include different specifications of the model to ensure robustness.

We find in table 10 that those who quarantine face consume at similar levels to those that didn't quarantine. This provides evidence that financial burdens imposed by quarantines are not the leading cause of the drop in enrollment.

Table 9: Quarantine and School Cost on Enrollment

	Dependent variable:			
	Enrolled			
	2015	2016Jan	2016Sep	2017
	(1)	(2)	(3)	(4)
POST	0.318***	0.431***	0.536***	0.625***
	(0.089)	(0.099)	(0.093)	(0.096)
Sch Cost	0.021	0.021	0.021	0.021
	(0.014)	(0.014)	(0.014)	(0.014)
Quarantine	−0.017	−0.017	−0.017	−0.017
	(0.016)	(0.016)	(0.016)	(0.016)
Log Consumption	0.142***	0.142***	0.142***	0.142***
	(0.011)	(0.011)	(0.011)	(0.011)
POST : Sch Cost	0.078***	0.069***	0.029**	0.013
	(0.015)	(0.015)	(0.015)	(0.015)
POST : Quarantine	−0.002	−0.002	−0.025	−0.014
	(0.016)	(0.018)	(0.018)	(0.018)
Sch Cost : Quarantine	0.136***	0.136***	0.136***	0.136***
	(0.024)	(0.024)	(0.024)	(0.024)
POST : Log Consumption	−0.040***	−0.047***	−0.046***	−0.054***
	(0.011)	(0.012)	(0.012)	(0.012)
POST : Sch Cost : Quarantine	−0.048*	−0.080***	−0.070***	−0.087***
	(0.025)	(0.028)	(0.027)	(0.027)
Constant	−0.500***	−0.500***	−0.500***	−0.500***
	(0.086)	(0.086)	(0.086)	(0.086)
Observations	15,986	16,483	16,483	16,861
R^2	0.045	0.045	0.072	0.079
Note:				*p<0.1; **p<0.05; ***p<0.01

This table reports the results of the following model: $Y_{it} = \alpha + \lambda(POST_t) + \eta(LogConsumption_i) + \gamma(Q_i) + \delta(SchCost_i) + \zeta(Q_i \times SchCost_i) + \phi(POST_t \times LogConsumption_i) + \nu(POST_t \times Q_i) + \xi(POST_t \times SchCost_i) + \beta(POST_t \times Q_i \times SchCost_i) + u_{it}$ where Y_{it} is *Enrolled*, Q_i is *Quarantine*, and *LogConsumption* is the log of our aggregate consumption variable as defined in *Empirical Methodology*. *Sch Cost* is defined as the sectional mean of the aggregate of the school costs faced by student i in 1,000 Sierra Leonean Leones (slightly less than 10 cents USD). Observations include individuals age 6-14 in 2013 summed with the number of kids age 6-14 in the corresponding school year. Those in sections where no child age 6-14 attended school were omitted as no data on school costs were available. Standard errors are clustered on the individual level.

In order to further test whether households that quarantined faced greater financial burdens that may have depressed their school enrollment, we analyze the difference in medical expenditure and debt outstanding between households that quarantined and those that did

Table 10: Quarantine on Log Consumption

	Dependent variable:		
	Log Consumption		
	(1)	(2)	(3)
Quarantine	0.003	−0.011	−0.023
	(0.027)	(0.029)	(0.028)
Urban	0.383***	0.286***	0.273***
	(0.030)	(0.039)	(0.037)
EVD Per 1000		−0.001	−0.00005
		(0.005)	(0.005)
HH Size			−0.081***
			(0.003)
Late Region			−0.060*
			(0.033)
District	Y	Y	Y
Observations	6,806	5,927	5,927
R^2	0.353	0.389	0.526
Note:			*p<0.1; **p<0.05; ***p<0.01

Column 1 of this table reports the results of the following model: $Y_{it} = \alpha + \beta(Q_i) + \sum_{k=1}^{15} \delta_k(control_{k,i}) + u_{it}$ where Y_{it} is *Log Consumption* and Q_i is *Quarantine* as defined in *Empirical Methodology*. The controls are as listed in the table where *Urban* and *District* are in the model corresponding to the results displayed in column 1. *EVD Per 1000* is added as a control in column 2. Finally, we include *HH Size* and *Late Region* as controls in model 3. Observations include households that responded to the questions corresponding to the above variables. Standard errors are clustered on the SLIHS cluster level.

not. We implement the following variables: *Medical Expenditure* which is the amount of money in Sierra Leonean Leones that a household has spent on medical expenses in the past 12 months, and *Debt Outstanding* which is the amount of debt in Sierra Leonean Leones that a household has taken out but not paid back in the past 12 months. We then implement the same model from 8, substituting Y_i for *Medical Expenditure* and *Debt Outstanding*. We also include the results for the models not controlling for consumption to ensure that the through effect of quarantine impacting consumption which would in turn impact medical expenditure or debt outstanding is also minimal.

Table 11: Quarantine on Medical Expenditure and Debt Outstanding

	Dependent variable:			
	Med Exp	Debt Outstanding	Med Exp	Debt Outstanding
	(1)	(2)	(3)	(4)
Quarantine	-49.807^{***}	-0.020	-51.037^{***}	-0.020
	(12.345)	(0.027)	(12.302)	(0.027)
EVD Per 1000	10.215^{***}	0.001	10.153^{***}	0.001
	(3.702)	(0.007)	(3.836)	(0.007)
Urban	71.213^{***}	0.065^{*}	97.515^{***}	0.077^{**}
	(23.301)	(0.035)	(23.610)	(0.035)
Log Consumption	92.481^{***}	0.048^{***}		
	(19.227)	(0.015)		
District	Y	Y	Y	Y
Observations	5,927	5,927	5,956	5,956
R^2	0.086	0.094	0.061	0.090
Note:				*p<0.1; **p<0.05; ***p<0.01

This table reports the results of the following OLS model: $Y_i = \alpha + \gamma(Q_i) + \sum_{k=1}^{17} \delta_k(control_{k,i}) + u_i$ where Y_i is *Medical Expenditure* in the first column and *Debt Outstanding* in the second column. Q_i is *Quarantine* as defined in *Empirical Methodology*. Observations include all 5,927 and 5,956 households respectively that responded to the questions corresponding to the above variables in the SLIHS 2018. Standard errors are clustered on the SLIHS cluster level.

Table 11 indicates that households that quarantined actually faced less medical costs than those that did not, as well as similar debt burdens. Therefore, we don't find that households that quarantined faced more financial burdens, at least on these two dimensions, than those that did not. We also find that students from households that quarantined work at approximately the same rate as those from households that did not quarantine. Overall, it appears that while school costs may have added to the frictions created from quarantining during the Ebola crisis, the financial burdens of quarantining are not driving our main results.

6.2 Implications

Next, we looked at whether quarantine measures affected regions which were already struggling. We want to know whether quarantines widened the enrollment gaps between high-enrollment regions and those struggling to get students to enroll. In order to achieve this, we run a difference-in-differences triple-interaction test between *Quarantine*, *POST*, and *Enr Rate*. *Enr Rate* is defined as the enrollment rate of a given respondent's section (the finest region specification available in the survey) in 2013. There are 511 sections which respondents aged 6-14 with a mean of 15.3 students per section. For this test, we use the following model:

$$\begin{aligned} Y_{it} =& \alpha + \gamma(Q_i) + \zeta(ER_i) + \lambda(POST_t) + \beta(Q_i \times POST_t) + \phi(ER_i \times POST_t) + \\ & \psi(Q_i \times POST_t \times ER_i) + u_{it} \end{aligned}$$

where ER_i is the enrollment rate of individual i's section in 2013 (before the Ebola crisis) and the rest of the variables are defined the same as earlier in the paper.

The results in Table 12 indicate that in absence of quarantine, regions that faced low enrollment had increased enrollment relative to regions with high enrollment over all periods analyzed. Students who were forced to quarantine in lower enrollment regions did not face such stark increases with the gains being more than halved in the first period and the triple interaction effect remaining significant at the 5% level over the next 2 periods and at the 10% level in the final period. Thus, quarantining affected those in regions where enrollment was already low far greater than regions in which enrollment was high.

To further illustrate how quarantine affected regions already struggling with enrollment,

Table 12: Quarantine and Regional Enrollment Rate on Enrollment

	Dependent variable:			
	Enrolled			
	2015	2016Jan	2016Sep	2017
	(1)	(2)	(3)	(4)
Quarantine	-0.036^{*}	-0.036^{*}	-0.036^{*}	-0.036^{*}
	(0.021)	(0.021)	(0.021)	(0.021)
POST	0.216^{***}	0.323^{***}	0.485^{***}	0.547^{***}
	(0.026)	(0.027)	(0.032)	(0.032)
Enr Rate	0.992^{***}	0.992^{***}	0.992^{***}	0.992^{***}
	(0.014)	(0.014)	(0.014)	(0.014)
POST : Quarantine	-0.109^{***}	-0.096^{**}	-0.144^{***}	-0.080
	(0.037)	(0.046)	(0.052)	(0.057)
Quarantine : Enr Rate	0.037	0.037	0.037	0.037
	(0.027)	(0.027)	(0.027)	(0.027)
POST : Enr Rate	-0.281^{***}	-0.363^{***}	-0.464^{***}	-0.527^{***}
	(0.033)	(0.036)	(0.041)	(0.042)
POST : Quarantine : Enr Rate	0.144^{***}	0.119^{*}	0.172^{**}	0.092
	(0.049)	(0.061)	(0.067)	(0.074)
Constant	0.008	0.008	0.008	0.008
	(0.012)	(0.012)	(0.012)	(0.012)
Observations	16,149	16,655	16,655	17,040
R^2	0.215	0.210	0.243	0.241
Note:				*p<0.1; **p<0.05; ***p<0.01

This table reports the results of the following model: $Y_{it} = \alpha + \gamma(Q_i) + \delta(EnrRate_i) + \lambda(POST_t) + \beta(POST_t \times Q_i) + \eta(Q_i \times EnrRate_i) + \zeta(POST_t \times EnrRate_i) + \phi(POST_t \times Q_i \times EnrRate_i) + u_{it}$ where Y_{it} is *Enrolled* and Q_i is *Quarantine* as defined in *Empirical Methodology*. $EnrRate_i$ is the enrollment rate of the section of individual i. Observations include the 7,821 individuals age 6-14 in 2013 summed with the number of kids age 6-14 in the corresponding school year. Standard errors are clustered on the individual level.

we run the same regression as above substituting *Enr Rate* with *Low Enroll*. *Low Enroll* is a dummy variable which indicates whether an individual lives in a section within the lowest quartile of enrollment rates. These regions faced 37.5% enrollment rates and below. Table 13 indicates that *Quarantine* had a far greater effect on those living in regions struggling with school enrollment. Therefore, quarantine measures served to widen the gap of low and high-enrollment regions.

Beyond controlling for enrollment rates in 2013, we also wish to determine whether

Table 13: Quarantine and Low Enrollment Region on Enrollment

	Dependent variable:			
	Enrolled			
	2015	2016Jan	2016Sep	2017
	(1)	(2)	(3)	(4)
Quarantine	−0.004	−0.004	−0.004	−0.004
	(0.011)	(0.011)	(0.011)	(0.011)
POST	0.002	0.047***	0.134***	0.145***
	(0.007)	(0.007)	(0.007)	(0.007)
Low Enroll	−0.555***	−0.555***	−0.555***	−0.555***
	(0.015)	(0.015)	(0.015)	(0.015)
POST : Quarantine	−0.004	−0.010	−0.018	−0.014
	(0.012)	(0.013)	(0.012)	(0.012)
Quarantine : Low Enroll	0.039	0.039	0.039	0.039
	(0.032)	(0.032)	(0.032)	(0.032)
POST : Low Enroll	0.144***	0.184***	0.235***	0.283***
	(0.016)	(0.018)	(0.019)	(0.019)
POST : Quarantine : Low Enroll	−0.089***	−0.095***	−0.126***	−0.087**
	(0.030)	(0.036)	(0.037)	(0.039)
Constant	0.758***	0.758***	0.758***	0.758***
	(0.006)	(0.006)	(0.006)	(0.006)
Observations	16,149	16,655	16,655	17,040
R^2	0.137	0.139	0.170	0.170
Note:				*p<0.1; **p<0.05; ***p<0.01

This table reports the results of the following model: $Y_{it} = \alpha + \gamma(Q_i) + \delta(LowEnroll_i) + \lambda(POST_t) + \beta(POST_t \times Q_i) + \eta(Q_i \times LowEnroll_i) + \zeta(POST_t \times LowEnroll_i) + \phi(POST_t \times Q_i \times LowEnroll_i) + u_{it}$ where Y_{it} is *Enrolled* and Q_i is *Quarantine* as defined in *Empirical Methodology*. *LowEnroll* a dummy variable that is 1 if individual i is in a section that has an enrollment rate in the bottom quartile of enrollment rates (37.5% and below). Observations include the 7,821 individuals age 6-14 in 2013 summed with the number of kids age 6-14 in the corresponding school year. Standard errors are clustered on the individual level.

quarantine more negatively affected regions with an increasing enrollment trend prior to the quarantine measures. More succinctly, we wish to know whether quarantine slowed or halted the progress of regions which were experiencing gains in enrollment rates prior to Ebola. In order to investigate this issue, we turn to the SLIHS 2011 which asks respondents whether they were enrolled in school at the time of being surveyed. We similarly determine the enrollment rates of the sections in 2011 and find *Enr Dif* defined as the enrollment difference among sections from 2011 to 2013. Due to differences in the identification of certain sections, we lose slightly less than a third of our sample from an inability to accurately match sections between the two surveys. We then run the triple interaction difference-in-differences between *POST*, *Quarantine*, and *Enr Dif*.

We find in Table 14 that *Quarantine* indeed has a greater affect the more regions were experiencing high enrollment gains pre-Ebola. Regions that had been experiencing gains prior to the Ebola crisis maintained this positive trend; however, *Quarantine* starkly reduced this positive trend. Thus, having faced quarantine measures may have limited the ability of initiatives that were acting to increase enrollment in worse-off regions.

Now we turn to uncovering the implications of our findings in regard to the long-run life outcomes of the school-age children who were forced into quarantine. We are specifically concerned with the impact of having ever enrolled in school on aggregate consumption. Continuing to use the survey data from SLIHS 2018, we do not have data for sufficient years after the Ebola epidemic to directly investigate the effect of quarantine on long-run aggregate consumption through Ebola's effect on educational outcomes. However, we can estimate other effects of a similar lack of schooling on working age adults in the sample. the 2014 labor force survey in Sierra Leone defines prime-working age in Sierra Leone as 36-55 (Margolis, Rosas, Turay, and Turay 2016). Using this specification, we first simply compare the aggregate consumption of those who have had any schooling and those who have never enrolled in school. Margolis et al. find that, "there is a large jump in earnings among people with some primary relative to those with no schooling." We find a similar result as prime-age workers who have had any schooling have 53.38% higher median aggregate consumption than those who have never enrolled in school.

We then run a simple OLS regression to estimate the effect of enrolling on *Log Consumption* controlling for *Female*, *Urban*, *Has Father*, *Father Educ*, *Age*, and *District* (omitted from table for brevity). Table 15 indicates that enrolling in school leads to an 17.94% increase in aggregate consumption among prime-age workers in Sierra Leone.

Table 14: Quarantine and Regional Enrollment Difference on Enrollment

	Dependent variable:			
	Enrolled			
	2015	2016Jan	2016Sep	2017
	(1)	(2)	(3)	(4)
Quarantine	0.007	0.007	0.007	0.007
	(0.013)	(0.013)	(0.013)	(0.013)
POST	0.006	0.050^{***}	0.137^{***}	0.149^{***}
	(0.007)	(0.008)	(0.007)	(0.008)
Enr Dif	-0.532^{***}	-0.532^{***}	-0.532^{***}	-0.532^{***}
	(0.026)	(0.026)	(0.026)	(0.026)
POST : Quarantine	-0.018	-0.037^{**}	-0.049^{***}	-0.043^{***}
	(0.014)	(0.015)	(0.014)	(0.014)
Quarantine : Enr Dif	0.057	0.057	0.057	0.057
	(0.058)	(0.058)	(0.058)	(0.058)
POST : Enr Dif	0.246^{***}	0.269^{***}	0.323^{***}	0.352^{***}
	(0.030)	(0.032)	(0.030)	(0.030)
POST : Quarantine : Enr Dif	-0.137^{**}	-0.125^{*}	-0.171^{***}	-0.115^{*}
	(0.061)	(0.067)	(0.064)	(0.064)
Constant	0.750^{***}	0.750^{***}	0.750^{***}	0.750^{***}
	(0.007)	(0.007)	(0.007)	(0.007)
Observations	10,922	11,193	11,193	11,408
R^2	0.060	0.064	0.095	0.101
Note:				*p<0.1; **p<0.05; ***p<0.01

This table reports the results of the following model: $Y_{it} = \alpha + \gamma(Q_i) + \delta(EnrDif_i) + \lambda(POST_t) + \beta(POST_t \times Q_i) + \eta(Q_i \times EnrDif_i) + \zeta(POST_t \times EnrDif_i) + \phi(POST_t \times Q_i \times EnrDif_i) + u_{it}$ where Y_{it} is *Enrolled* and Q_i is *Quarantine* as defined in *Empirical Methodology*. $EnrDif$ is the difference in the enrollment rate of the section from 2013 to 2011 of individual i. Observations include individuals age 6-14 in 2013 summed with the number of kids age 6-14 in the corresponding school year. Those in sections in 2011 that did not correspond to a section in 2018 were omitted. Standard errors are clustered on the individual level.

This result appears mild in relation to those of Filmer and Rogers (2018) who found that for each additional year of schooling, wages increase by more than 14% for women, and by more than 10% for men across Sub-Saharan Africa; however, our result is still highly significant. We will now turn to identifying how many students never enrolled in response to the quarantine measures. So far, we have only calculated the differences in enrollment rates that take into account dropouts and re-enrollment that have less implications on long-term

Table 15: Log Consumption on Having Ever Enrolled

	Dependent variable:
	Log Consumption
Ever Enrolled	0.165^{***}
	(0.016)
Female	-0.014
	(0.013)
Urban	0.279^{***}
	(0.017)
Has Father	-0.184^{***}
	(0.041)
Father Educ	0.064^{***}
	(0.006)
Age	0.002^{*}
	(0.001)
Constant	7.902^{***}
	(0.058)
Observations	6,095
R^2	0.375
Note:	*p<0.1; **p<0.05; ***p<0.01

Simple OLS regression of 6,095 prime-working-age individuals age 36-55 of *Ever Enrolled* on *Log Consumption* with the above controls as well as district controls. *Ever Enrolled* is a dummy defined as one if the individual claimed to have ever enrolled in formal schooling. *Log Consumption* is the log of the aggregate consumption variable. Both are described more in the *Empirical Methodology* Section.

aggregate consumption than having never enrolled in primary school.

We first subset our sample to the 2,087 respondents aged 6-14 who had never been enrolled in school by 2013. We then run a simple OLS regression to determine the impact of *Quarantine* on *Ever Enrolled* controlling for *Age*, *Female*, *Urban*, *Has Father*, *Father Educ*, *Log Consumption*, *Late Region*, and *District* as before. *Ever Enrolled* is a dummy variable defined as one if the respondent enrolled on or prior to the year in question. For example, for the 2016Sep schooling period, Ever Enrolled is one if the respondent enrolled in 2015, 2016Jan, or 2016Sep. We will be mainly interested in 2017 for our results as it is the most recent schooling period in which we have access and those who have not enrolled by then are highly unlikely to enroll in the future.

We find in Table 16 that among those who had not been enrolled by 2013, quarantining led to 5.6% less students enrolling at any point over the next 4 schooling periods.

Table 16: Quarantine on Ever Enrolling

	Dependent variable:			
	Ever Enrolled			
	2015	2016Jan	2016Sep	2017
	(1)	(2)	(3)	(4)
Quarantine	−0.038	−0.057*	−0.066**	−0.056**
	(0.027)	(0.030)	(0.028)	(0.028)
Female	0.020	0.038*	0.035*	0.029
	(0.021)	(0.020)	(0.020)	(0.020)
Urban	0.094***	0.122***	0.116***	0.134***
	(0.031)	(0.036)	(0.033)	(0.032)
Has Father	0.014	0.051**	0.051**	0.051**
	(0.021)	(0.021)	(0.020)	(0.021)
Father Educ	0.053***	0.049***	0.048***	0.045***
	(0.010)	(0.009)	(0.008)	(0.008)
Age	−0.036***	−0.070***	−0.087***	−0.089***
	(0.004)	(0.004)	(0.004)	(0.004)
Log Consumption	0.036	0.041	0.044*	0.048*
	(0.026)	(0.027)	(0.027)	(0.026)
Late Region	−0.036	0.035	0.032	0.032
	(0.031)	(0.035)	(0.034)	(0.035)
Constant	0.242	0.797***	1.078***	1.174***
	(0.218)	(0.234)	(0.230)	(0.229)
POST : District	Y	Y	Y	Y
Observations	2,087	2,087	2,087	2,087
Note:			*p<0.1; **p<0.05; ***p<0.01	

Simple OLS regression of 2,087 individuals age 6-14 who were not in school prior to 2015 of *Quarantine* on *Log Consumption* with the above controls as well as district controls. *Ever Enrolled* and *Quarantine* are dummies that are 1 if the individual claimed to be enrolled in the corresponding school year or quarantine respectively. Both are described more in the *Empirical Methodology* Section. Standard errors are clustered on the individual level.

Of the approximately 1,846,904 children aged 6-14 in Sierra Leone, we estimate that 26.89% or 496,617 children had not been enrolled in school by 2013. Of these 496,617 children, we estimate 27.82% or 138,146 students were placed under quarantine during the Ebola crisis. Using our result in Table 16, we estimate that 5.6% or 7,736 students never enrolled as a result of quarantine. We estimate that these students will face 17.94% lower yearly aggregate consumption during their prime-working ages 36-55.

7 Conclusion

We have shown through these various tests that being forced into a household-level quarantine leads to a decrease in enrollment independent of one's overall exposure to regional lockdown measures, how many cases of Ebola were in one's chiefdom, and other individual characteristics that may affect enrollment over time. This effect grew to 5.6% in the first schooling period following Sierra Leone being declared Ebola-free and remained robust to instrumenting for quarantine with whether an individual tested positive in one's chiefdom prior to the deployment of troops to enact quarantine.

We find that stigma and the shunning of individually affected families serve as a mechanism in which quarantine depressed enrollment. Families may have been deterred to send their children back to school, worrying that their child wouldn't be received warmly after having quarantine and its resulting stigma. Similarly, the isolation caused by quarantine may also have played a role as families who underwent quarantine were not as exposed to the social pressure of sending their children to school. In fact, we find that children who did not have their oldest sibling attend school in 2013 or who where the oldest child in the family faced far greater effects of quarantine. This evidences that familial pressures and precedents were much more important in families who quarantined, perhaps since those households were isolated from other households. Therefore, the societal pressures that may have led one to sending his or her children to school were diminished.

We also find that quarantine further strained students facing high schooling costs, forcing many to not enroll. These students may belong to families facing financial struggles that were amplified by these quarantine measures.

Concerning who these quarantine measures impacted the most, we find that those in regions where enrollment was low faced the most negative impacts. We also find that school-age children in regions that were facing the greatest increases in enrollment from 2011 to 2013 were hit the hardest by quarantining. This could be due to the inability for NGO's and government assistance to reach families placed under quarantine.

Going forward, we wish to investigate further why these measures led to lower enrollment. We also wish to verify our result is not restricted to Sierra Leone and the Ebola crisis: that quarantine measures have persistent long-term impacts on enrollment across a plethora of environments.

This paper should serve to spark more interest into examining the negative externalities associated with quarantines as a response to epidemics. Policy makers should have full information as to the downsides of these measures so that they can come to the informed conclusion of whether the threat of the epidemics mitigated through such measures are worth the costs of lower school enrollment as well as other negative impacts.

References

Acemoglu, D., T. Reed, and J. A. Robinson (2014). Chiefs: Economic development and elite control of civil society in Sierra Leone. *Journal of Political Economy 122*(2), 319–368.

Adegun, O. (2014). The effects of Ebola virus on the economy of West Africa through the trade channel. *IOSR Journal of Humanities and Social Science 19*(10), 48–56.

Anderson, E.-L. and A. Beresford (2016). Infectious injustice: the political foundations of the Ebola crisis in Sierra Leone. *Third World Quarterly 37*(3), 468–486.

Bandiera, O., N. Buehren, M. Goldstein, I. Rasul, and A. Smurra (2018). The economic lives of young women in the time of Ebola.

Bandiera, O., N. Buehren, M. Goldstein, I. Rasul, and A. Smurra (2020). Do school closures during an epidemic have persistent effects? Evidence from Sierra Leone in the time of Ebola. *Working Paper*.

Bell, B. P. (2016). Overview, control strategies, and lessons learned in the CDC response to the 2014–2016 Ebola epidemic. *MMWR supplements 65*.

Bindra, T. (2014, September). Sierra Leone quarantines 2 million to fight Ebola. *Associated Press*.

Bowles, J., J. Hjort, T. Melvin, and E. Werker (2016). Ebola, jobs and economic activity in Liberia. *J Epidemiol Community Health 70*(3), 271–277.

Christensen, D., O. Dube, J. Haushofer, B. Siddiqi, and M. Voors (2021). Building resilient health systems: Experimental evidence from sierra leone and the 2014 ebola outbreak. *The Quarterly Journal of Economics 136*(2), 1145–1198.

Coy, P. (2014, September). A Primer on the Deadly Math of Ebola. *Bloomberg*.

Davidson, M. C., S. Lu, M. B. Barrie, A. Freeman, M. Mbayoh, M. Kamara, A. C. Tsai, T. Crea, G. W. Rutherford, S. D. Weiser, and J. D. Kelly (2022). A post-outbreak assessment of exposure proximity and Ebola virus disease-related stigma among community members in Kono District, Sierra Leone: A cross-sectional study. *SSM - Mental Health 2*, 100064.

Davtyan, M., B. Brown, and M. O. Folayan (2014). Addressing Ebola-related stigma: lessons learned from HIV/AIDS. *Global health action 7*(26058).

de la Fuente, A. and E. Foster (2018). Methodology for Consumption-Poverty Estimation, 2018 and Poverty Trends, 2011-2018, in Sierra Leone. *Statistics Sierra Leone, The World Bank*.

Deaton, A. and S. Zaidi (2002). *Guidelines for constructing consumption aggregates for welfare analysis*, Volume 135. World Bank Publications.

DiLorenzo, S. (2014, November). Thousands in Sierra Leone break Ebola quarantine.

Fang, L.-Q., Y. Yang, J.-F. Jiang, H.-W. Yao, D. Kargbo, X.-L. Li, B.-G. Jiang, B. Kargbo, Y.-G. Tong, Y.-W. Wang, et al. (2016). Transmission dynamics of Ebola virus disease and intervention effectiveness in Sierra Leone. *Proceedings of the National Academy of Sciences 113*(16), 4488–4493.

Filmer, D., M. Langthaler, R. Stehrer, and T. Vogel (2018). Learning to realize education's promise. *World Development Report. The World Bank*.

Flückiger, M., M. Ludwig, and A. Sina Önder (2019). Ebola and state legitimacy. *The Economic Journal 129*(621), 2064–2089.

Gire, S. K., A. Goba, K. G. Andersen, R. S. Sealfon, D. J. Park, L. Kanneh, S. Jalloh, M. Momoh, M. Fullah, G. Dudas, et al. (2014). Genomic surveillance elucidates Ebola virus origin and transmission during the 2014 outbreak. *science 345*(6202), 1369–1372.

Goldstein, D. (2021, May). Schools Are Open, but Many Families Remain Hesitant to Return. *The New York Times*.

Gonzalez-Torres, A. and E. Esposito (2017). Epidemics and conflict: Evidence from the

Ebola outbreak in Western Africa. *Working Paper*.

Haughton, J. and S. R. Khandker (2009). *Handbook on poverty+ inequality*. World Bank Publications.

Himelein, K., M. Testaverde, A. Turay, and S. Turay (2015). The socio-economic impacts of Ebola in Sierra Leone.

Huber, C., L. Finelli, and W. Stevens (2018). The economic and social burden of the 2014 Ebola outbreak in West Africa. *The Journal of infectious diseases 218*(Supplement_5), S698–S704.

James, P. B., J. Wardle, A. Steel, and J. Adams (2020). An assessment of Ebola-related stigma and its association with informal healthcare utilisation among Ebola survivors in Sierra Leone: a cross-sectional study. *BMC Public Health 20*(1), 1–12.

Kamara, M. (2014, September). Sierra Leone News : Africell Presents Second Consignment of Food to all Quarantined Homes. *Awareness Times*.

Kaner, J. and S. Schaack (2016). Understanding Ebola: the 2014 epidemic. *Globalization and health 12*(1), 1–7.

Kostova, D., C. H. Cassell, J. T. Redd, D. E. Williams, T. Singh, L. D. Martel, and R. E. Bunnell (2019). Long-distance effects of epidemics: Assessing the link between the 2014 West Africa Ebola outbreak and US exports and employment. *Health economics 28*(11), 1248–1261.

Mackey, R. (2014, November). Surge in Ebola infections leads to lockdown in eastern Sierra Leone. *The New York Times*.

Mackintosh, A., A. Ramirez, P. Atherton, M. M.-S. Victoria Collis, and C. Bart-Williams (2020). Education Workforce Supply and Needs in Sierra Leone. *Fab Inc.*.

Margolis, D., N. Rosas, A. Turay, and S. Turay (2016). *Findings from the 2014 Labor Force Survey in Sierra Leone*. World Bank Publications.

McConnell, T. (2014). Some people would rather die of Ebola than stop hugging sick loved ones. *Global Post 10*.

Meyers, K. and M. A. Thomasson (2017). Paralyzed by panic: Measuring the effect of school closures during the 1916 polio pandemic on educational attainment. Working Paper, National Bureau of Economic Research.

Nossiter, A. (2014a, October). Ebola Help for Sierra Leone Is Nearby, but Delayed on the Docks. *New York Times*.

Nossiter, A. (2014b, August). Sierra Leone Deploys Troops in Ebola Crisis. *New York Times*.

Osterholm, M., K. Moore, N. Kelley, L. Brosseau, G. Wong, F. Murphy, C. Peters, J. LeDuc, P. Russell, M. Van Herp, et al. (2015). Transmission of Ebola viruses: what we know and what we do not know. *MBio 6*(2), e00137–15.

Prescott, J., T. Bushmaker, R. Fischer, K. Miazgowicz, S. Judson, and V. J. Munster (2015). Postmortem stability of Ebola virus. *Emerging infectious diseases 21*(5), 856.

Renner-Thomas, A. (2010). *Land tenure in Sierra Leone: The law, dualism and the making of a land policy*. AuthorHouse.

Richards, P. (2016). *Ebola: how a people's science helped end an epidemic*. Zed Books Ltd.

Richards, P., G. A. Mokuwa, A. Vandi, S. H. Mayhew, and E. G. R. Team (2020). Re-analysing Ebola spread in Sierra Leone: the importance of local social dynamics. *PloS one 15*(11), e0234823.

Sankoh, O. (2019). Sierra Leone—Integrated Household Survey 2018. *Statistics Sierra Leone, The World Bank*.

Selbervik, H. (2020). Impacts of school closures on children in developing countries: Can we learn something from the past? *CMI Brief*.

Smith, W. C. (2021). Consequences of school closure on access to education: Lessons from the 2013–2016 Ebola pandemic. *International Review of Education*, 1–26.

Wahome, W. M. (2014). Quarantines in Sierra Leone: Putting people first in the Ebola crisis.

Wang, L. (2007). *Education in Sierra Leone: Present challenges, future opportunities.* The World Bank.

Wappes, J. (2018, December). US health worker monitored as DRC Ebola nears 600 cases. *CIDRAP*.

Yadav, S. and G. Rawal (2015). The Current Mental Health Status of Ebola Survivors in Western Africa. *Journal of Clinical and Diagnostic Research 9*(10), LA01–LA2.

Yao, H., A. S. Memon, D. Amaro, A. Rigole, and Y. D. Abdou (2021). Public health emergencies and school attendance: What the Ebola crisis can teach us about the coming post-COVID education landscape. *International Journal of Educational Development 85*, 102457.

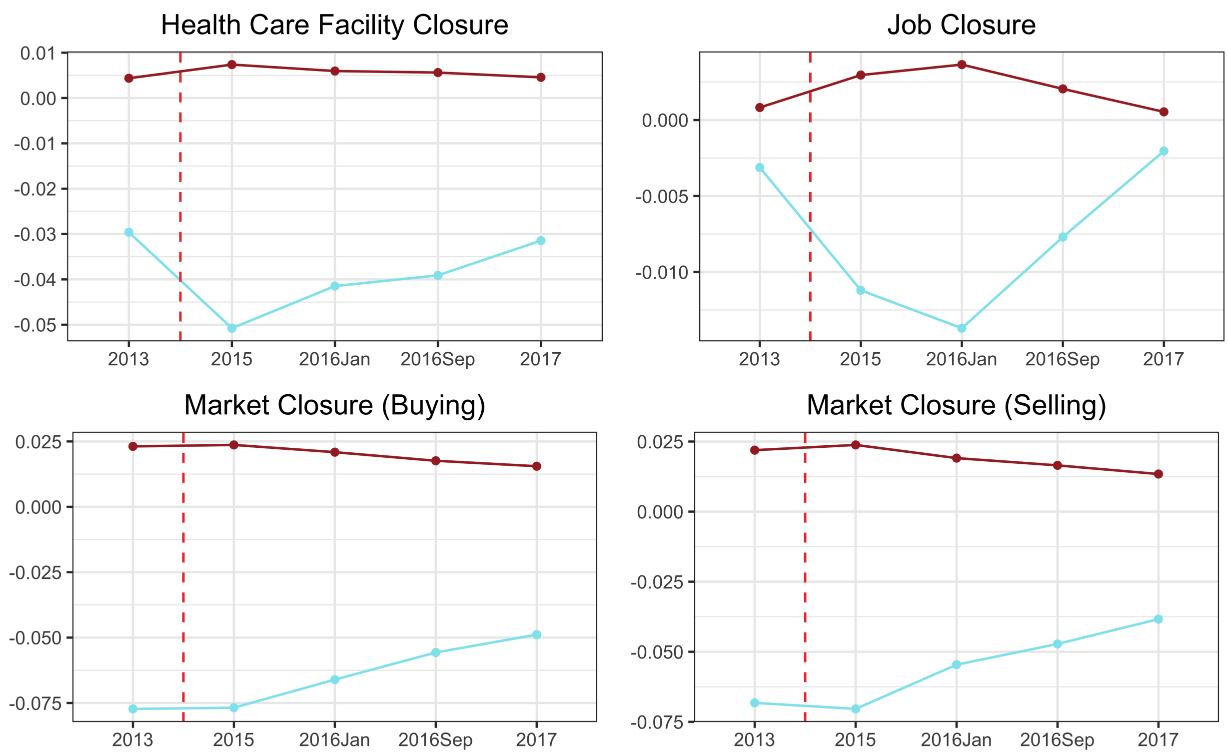
A Appendix

Table A.1: EVD per 1000 on Quarantine

	Dependent variable:
	Quarantine
EVD Per 1000	0.013^{***}
	(0.003)
Constant	0.139^{***}
	(0.018)
Observations	4,558
R^2	0.168
Note:	*p<0.1; **p<0.05; ***p<0.01

This table represents the following model: $Q_i = \alpha + \beta(EVD_i) + \sum_{k=1}^{27} \delta_k(control_{k,i}) + u_i$ where Q_i is *Quarantine*, and $control_{k,i}$ are the 27 urban × district regions specified in the SLIHS. Observations include the 7,821 individuals age 6-14 in 2013 observed twice to look at difference between enrollment before and after the Ebola outbreak. *Quarantine* and *Constant* values are repeated as they represent the effects on enrollment in 2013 (the λ and α of the above model) which is obviously the same across the four tests. Standard errors are clustered on the SLIHS cluster level.

Figure A.1: Enrollment Over Time, Other Ebola Exposure Indicators



The vertical axis represents enrollment rates of kids age 6-14 while the horizonal axis represents the school year. The dark brown line represents those who did not face the Ebola-induced closure, and the light blue line represents those who faced the Ebola-induced closure. The red, dashed line represents the start of the Ebola crisis. The corresponding survey questions were asked to the head of each of the 6,840 households and can be found in Table A.2.

Table A.2: Survey Questions Used

Variable Name	Survey Question
Quarantine	During the Ebola outbreak, did you experience quarantine or time when they didn't let people go where they wanted?
Enrolled	What class did you [NAME] attend during the following school years? (1 if indicated any class, 0 otherwise)
Hospital Closure	During the Ebola outbreak, did you experience the health care facility that you use was closed?
Job Closure	During the Ebola outbreak, did you experience your workplace or business was closed?
Buy Market Closure	During the Ebola outbreak, did you experience the market to buy food or small items was closed?
Sell Market Closure	During the Ebola outbreak, did you experience the market where you sell produce from your farm was closed?
Age	How old are you [is he/she]? (at last birthday)
Female	Is NAME male or female?
Urban	Rural/Urban
Has Father	Who/where is your [NAME's] biological father?
Father Educ	Did your [NAME's] father go to school? At which level did he stop?
Late Region	After schools were closed during Ebola, when did NAME's school open?

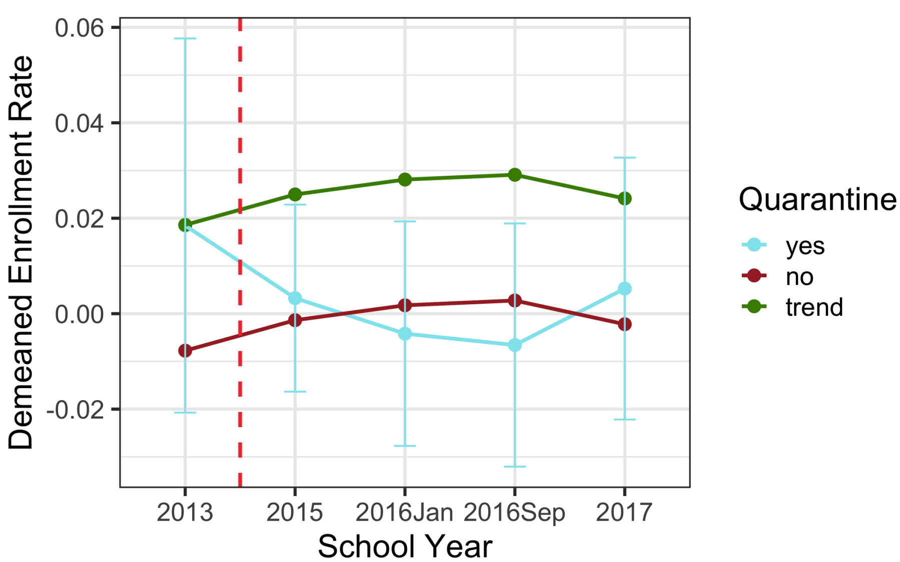
The *Quarantine* questions was asked to the heads of each of the 6,840 households and was coded such that every individual in the household had a Quarantine value of 1 if the head of the household answered yes and 0 if they answered no. The *Enrolled* question was asked to each of the 21,677 out of 40,680 respondents that answered that they had ever attended formal school and was asked for 5 schooling years from 2013-2017 (with 2 school years in 2016). If they answered no to having ever attended formal school, they received a 0 value for *Enrolled* for all 5 schooling periods. Otherwise, they received a 1 for *Enrolled* if they listed a class for the corresponding school year and a 0 otherwise. All four questions involving Ebola-induced closures were asked to the heads of each of the 6,840 households and was coded such that every individual in the household had a variable value of 1 if the head of the household answered yes and 0 if they answered no. The remaining questions were asked to each of the 40680 individual survey respondents of the SLIHS. *Has Father* coded as 0 if indicated deceased, outside household, or unknown. *Father Education* is defined as (1) no father, (2) has a father who never attended school, (3) highest educational achievement of father was primary school, (4) highest educational achievement of father was JSS or SSS, and (5) highest educational achievement of father was higher education. *Late Region* coded as 1 if any indication other than starting on time (15 April 2015).

Table A.3: Districts with Isolation Measures and Percentage of Self-Reported Quarantine

	District	Isolation	Percentage Quarantine
1	Kailahun	TRUE	0.571
2	Kenema	TRUE	0.505
3	Kono	TRUE	0.273
4	Bombali	TRUE	0.550
5	Kambia	FALSE	0.227
6	Koinadugu	FALSE	0.130
7	Port Loko	TRUE	0.103
8	Tonkolili	TRUE	0.229
9	Bo	FALSE	0.387
10	Bonthe	FALSE	0.278
11	Moyamba	TRUE	0.168
12	Pujehun	FALSE	0.170
13	Western Area Rural	FALSE	0.071
14	Western Area Urban	FALSE	0.166

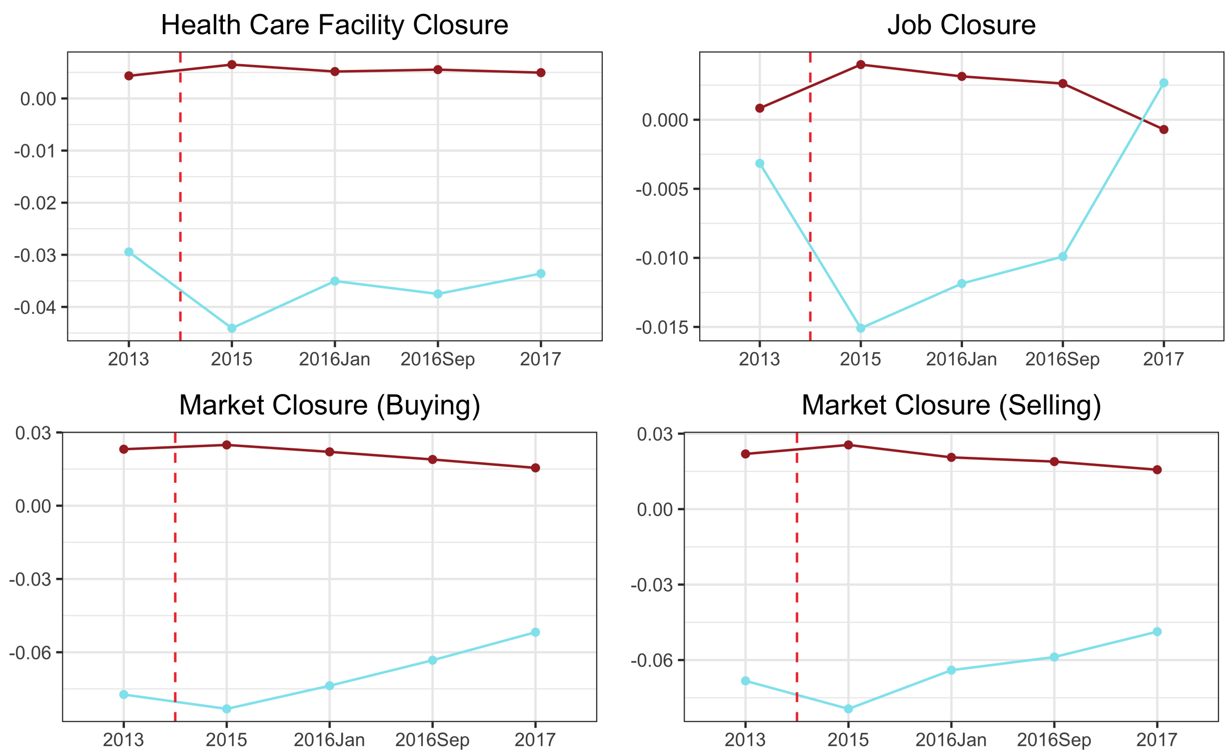
Isolation indicates whether the central government-imposed isolation measures that lasted for two weeks or longer in any of the 14 districts. *Percentage Quarantine* indicates what percentage of respondents in each district claimed to face quarantine measures in the SLIHS 2018.

Figure A.2: Enrollment Over Time, Quarantine Vs. Control, Cohort Specification



The light blue line represents the enrollment of those who claimed to face quarantine measures as a result of Ebola, and the dark brown line represents those who claimed to not have experienced quarantine. The dark green line represents what the enrollment rate would have been for the quarantine group had it followed the trends of of the group not quarantined. The red, dashed line represents the start of the Ebola crisis. This figure captures the 7821 aged 6-14 in 2013. The question of enrollment was asked to each kid, while the question of quarantine was asked to the head of each household.

Figure A.3: Enrollment Over Time, Other Ebola Exposure Indicators, Cohort Specification



This the same graphs as Figure A.1 but for the cohort specification. The vertical axis represents enrollment rates of the 7,821 kids who were age 6-14 in 2013 while the horizonal axis represents the school year. The dark brown line represents those who did not face the Ebola-induced closure, and the light blue line represents those who faced the Ebola-induced closure. The red, dashed line represents the start of the Ebola crisis. The corresponding survey questions were asked to the head of each of the 6,840 households and can be found in Table A.2.

Table A.4: DID Regression: Quarantining No Controls, Cohort Specification

	Dependent variable:			
	Enrolled			
	2015	2016Jan	2016Sep	2017
	(1)	(2)	(3)	(4)
Quarantine	0.026	0.026	0.026	0.026
	(0.020)	(0.020)	(0.020)	(0.020)
POST	0.092^{***}	0.133^{***}	0.142^{***}	0.112^{***}
	(0.007)	(0.008)	(0.009)	(0.010)
POST : Quarantine	-0.022^{**}	-0.032^{***}	-0.036^{***}	-0.019
	(0.010)	(0.012)	(0.013)	(0.014)
Constant	0.671^{***}	0.671^{***}	0.671^{***}	0.671^{***}
	(0.012)	(0.012)	(0.012)	(0.012)
Observations	15,642	15,642	15,642	15,642
R^2	0.009	0.020	0.023	0.015
Note:				*p<0.1; **p<0.05; ***p<0.01

This table represents the following model: $Y_{it} = \alpha + \gamma(Q_i) + \lambda(POST_t) + \beta(Q_i \times POST_t) + u_{it}$ where Y_{it} is *Enrolled*, Q_i is *Quarantine*, and α is *Constant* as defined in *Empirical Methodology.* Observations include the 7,821 individuals age 6-14 in 2013 observed twice to look at difference between enrollment before and after the Ebola outbreak. *Quarantine* and *Constant* values are repeated as they represent the effects on enrollment in 2013 (the λ and α of the above model) which is obviously the same across the four tests. Standard errors are clustered on the SLIHS cluster level.

Table A.5: IV Quarantine on Enrollment, Early Ebola Instrument, Cohort Specification

	Dependent variable:				
	Quarantine	Delta Enrollment			
	First Stage	*Second Stage*			
	(1)	(2)	(3)	(4)	(5)
Early Ebola	0.076^{***}				
	(0.014)				
Quarantine		-0.289^{**}	-0.380^{**}	-0.548^{***}	-0.552^{***}
		(0.136)	(0.162)	(0.187)	(0.201)
EVD Per 1000	0.006^{***}	-0.002	-0.002	-0.002	-0.0003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Female	-0.009	0.0001	0.003	-0.011	-0.012
	(0.009)	(0.007)	(0.008)	(0.010)	(0.011)
Urban	-0.017	-0.029^{***}	-0.044^{***}	-0.050^{***}	-0.050^{***}
	(0.012)	(0.009)	(0.011)	(0.013)	(0.014)
Has Father	-0.005	-0.020^{***}	-0.014	-0.009	-0.0002
	(0.010)	(0.007)	(0.009)	(0.010)	(0.011)
Father Educ	0.006^{*}	0.005^{*}	0.002	0.0003	-0.004
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
Age	0.001	-0.026^{***}	-0.043^{***}	-0.055^{***}	-0.062^{***}
	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
Log Welfare	0.007	-0.011	-0.012	-0.011	0.001
	(0.011)	(0.008)	(0.009)	(0.011)	(0.012)
Late Region	-0.087^{***}	-0.050^{***}	-0.038^{**}	-0.065^{***}	-0.062^{***}
	(0.014)	(0.016)	(0.019)	(0.021)	(0.023)
District	*Y*	*Y*	*Y*	*Y*	*Y*
Observations	7,778	7,778	7,778	7,778	7,778

Note: *p<0.1; **p<0.05; ***p<0.01

This table omitts *District* dummies which are present in both stages of the model. The first column is the first stage in the 2015 analysis. The other first stages are omitted as they share approximately 90% of the same sample and are time invariant. This table represents the following IV model with the first stage: $Q_i = \alpha + \gamma(EE_i) + \sum_{k=1}^{21} \delta_k(control_{k,i}) + u_i$ and the second stage: $Y_{it} = \alpha + \beta(\hat{Q}_i) + \sum_{k=1}^{21} \delta_k(control_{k,it}) + u_{it}$ where Y_{it} is *Delta Enrolled* (the change in enrollment for individual i from period t to 2013, and Q_i is *Quarantine* as defined in *Empirical Methodology.* The 21 controls include the controls in this table as well as the district level controls. Observations include the individuals age 6-14 in 2013.

Table A.6: DID Regression: Quarantining with Controls, Cohort Specification

	Dependent variable:			
	Enrolled			
	2015	2016Jan	2016Sep	2017
	(1)	(2)	(3)	(4)
Quarantine	0.019	0.019	0.019	0.019
	(0.016)	(0.016)	(0.016)	(0.016)
POST	0.476***	0.783***	0.977***	1.015***
	(0.076)	(0.091)	(0.098)	(0.108)
POST : Quarantine	−0.018**	−0.026**	−0.035***	−0.023*
	(0.009)	(0.011)	(0.012)	(0.013)
POST : EVD Per 1000	−0.004***	−0.004***	−0.005***	−0.004**
	(0.001)	(0.001)	(0.001)	(0.002)
POST : Female	0.002	0.006	−0.007	−0.008
	(0.007)	(0.008)	(0.009)	(0.009)
POST : Urban	−0.025***	−0.042***	−0.048***	−0.051***
	(0.009)	(0.011)	(0.012)	(0.014)
POST : Has Father	−0.017**	−0.012	−0.008	−0.001
	(0.007)	(0.008)	(0.009)	(0.010)
POST : Age	−0.026***	−0.043***	−0.055***	−0.063***
	(0.002)	(0.002)	(0.002)	(0.002)
POST : Log Welfare	−0.011	−0.015	−0.015	−0.006
	(0.009)	(0.010)	(0.011)	(0.012)
POST : Late Region	−0.027**	−0.008	−0.021	−0.016
	(0.013)	(0.018)	(0.019)	(0.020)
POST : District	Y	Y	Y	Y
Observations	15,556	15,556	15,556	15,556
R^2	0.134	0.148	0.159	0.155
Note:				*p<0.1; **p<0.05; ***p<0.01

This table only includes *POST* and *POST* interactions excluding the *District* controls for ease of display. This table reports the results of the following model: $Y_{it} = \alpha + \gamma(Q_i) + \sum_{k=1}^{21} \delta_k(control_{k,i}) + \lambda(POST_t) + \beta(Q_i \times POST_t) + \sum_{k=1}^{20} \eta_k(control_{k,i} \times POST_t) + u_{it}$ where Y_{it} is *Enrolled* and Q_i is *Quarantine* as defined in *Empirical Methodology*. The 20 controls include the controls in this table as well as the district level controls. Observations include the 7,821 individuals age 6-14 in 2013 observed twice to look at difference between enrollment before and after the Ebola outbreak. Standard errors are clustered on the SLIHS cluster level.

Table A.7: Robustness to Alternate Specifications, 2017 School Year

	Dependent variable:			
	Enrolled			
	Simple	Level Controls	FE Trend Controls	All Controls
	(1)	(2)	(3)	(4)
POST	0.142***	0.162***	0.227***	0.977***
	(0.009)	(0.010)	(0.030)	(0.098)
POST : Quarantine	−0.036**	−0.037***	−0.035***	−0.035***
	(0.013)	(0.013)	(0.013)	(0.012)
POST : EVD Per 1000			−0.004***	−0.005***
			(0.002)	(0.001)
POST : Urban			−0.076***	−0.048***
			(0.012)	(0.012)
POST : Female				−0.007
				(0.009)
POST : Has Father				−0.008
				(0.009)
POST : Age				−0.055***
				(0.002)
POST : Log Consumption				−0.015
				(0.011)
POST : Late Region				−0.021
				(0.019)
POST : District	N	N	Y	Y
Observations	15,642	15,642	15,642	15,642
R^2	0.023	0.129	0.132	0.159
Note:				*p<0.1; **p<0.05; ***p<0.01

The table shows only *POST* and *POST* interactions. The "Simple" model is as follows: $Y_{it} = \alpha + \gamma(Q_i) + \lambda(POST_t) + \beta(Q_i \times POST_t) + u_{it}$. The "Level Controls" model is as follows: $Y_{it} = \alpha + \gamma(Q_i) + \sum_{k=1}^{21} \delta_k(control_{k,i}) + \lambda(POST_t) + \beta(Q_i \times POST_t) + u_{it}$. The "FE Trend Controls" model is as follows: $Y_{it} = \alpha + \gamma(Q_i) + \sum_{k=1}^{21} \delta_k(control_{k,i}) + \lambda(POST_t) + \beta(Q_i \times POST_t) + \sum_{k=1}^{15} \eta_k(control_{k,i} \times POST_t) + u_{it}$ where only *EVD Per 1000*, *Urban*, and *District* control trend effects were included. The "All Controls" model is as follows: $Y_{it} = \alpha + \gamma(Q_i) + \sum_{k=1}^{21} \delta_k(control_{k,i}) + \lambda(POST_t) + \beta(Q_i \times POST_t) + \sum_{k=1}^{21} \eta_k(control_{k,i} \times POST_t) + u_{it}$. Y_{it} is *Enrolled* and Q_i is *Quarantine* as defined in *Empirical Methodology*. The 21 controls include the controls in this table as well as the district level controls. Observations include the 7,821 individuals age 6-14 in 2013 summed with the number of kids age 6-14 in the 2017 school year. Standard errors are clustered on the SLIHS cluster level.

Table A.8: DID Regression: Primary Health Facility Closure, Cohort Specification

	Dependent variable:			
	Enrolled			
	2015	2016Jan	2016Sep	2017
	(1)	(2)	(3)	(4)
Hospital Closure	−0.034	−0.034	−0.034	−0.034
	(0.028)	(0.028)	(0.028)	(0.028)
POST	0.087***	0.124***	0.133***	0.107***
	(0.006)	(0.007)	(0.008)	(0.008)
POST : Hospital Closure	−0.017	−0.006	−0.009	−0.005
	(0.011)	(0.015)	(0.016)	(0.018)
Constant	0.684***	0.684***	0.684***	0.684***
	(0.011)	(0.011)	(0.011)	(0.011)
Observations	15,642	15,642	15,642	15,642
R^2	0.010	0.020	0.024	0.015
Note:				*p<0.1; **p<0.05; ***p<0.01

This table represents the following model: $Y_{it} = \alpha + \gamma(H_i) + \lambda(POST_t) + \beta(H_i \times POST_t) + u_{it}$ where Y_{it} is *Enrolled*, H_i is *Hospital Closure*, and α is *Constant* as defined in *Empirical Methodology.* Observations include the 7,821 individuals age 6-14 in 2013 observed twice to look at difference between enrollment before and after the Ebola outbreak. *Hospital Closure* and *Constant* values are repeated as they represent the effects on enrollment in 2013 (the λ and α of the above model) which is obviously the same across the four tests. Standard errors are clustered on the SLIHS cluster level.

Table A.9: DiD Regression: Job Closure, Cohort Specification

	Dependent variable:			
	Enrolled			
	2015	2016Jan	2016Sep	2017
	(1)	(2)	(3)	(4)
Job Closure	−0.004	−0.004	−0.004	−0.004
	(0.023)	(0.023)	(0.023)	(0.023)
POST	0.088***	0.125***	0.133***	0.105***
	(0.006)	(0.007)	(0.008)	(0.008)
POST : Job Closure	−0.015	−0.011	−0.009	0.007
	(0.010)	(0.012)	(0.014)	(0.015)
Constant	0.680***	0.680***	0.680***	0.680***
	(0.011)	(0.011)	(0.011)	(0.011)
Observations	15,642	15,642	15,642	15,642
R^2	0.009	0.020	0.023	0.015
Note:				*p<0.1; **p<0.05; ***p<0.01

This table represents the following model: $Y_{it} = \alpha + \gamma(J_i) + \lambda(POST_t) + \beta(J_i \times POST_t) + u_{it}$ where Y_{it} is *Enrolled*, J_i is *Job Closure*, and α is *Constant* as defined in *Empirical Methodology*. Observations include the 7,821 individuals age 6-14 in 2013 observed twice to look at difference between enrollment before and after the Ebola outbreak. Standard errors are clustered on the SLIHS cluster level.

Table A.10: DID Regression: Market for Buying Closure, Cohort Specification

	Dependent variable:			
	Enrolled			
	2015	2016Jan	2016Sep	2017
	(1)	(2)	(3)	(4)
Buy Market Closure	-0.100^{***}	-0.100^{***}	-0.100^{***}	-0.100^{***}
	(0.024)	(0.024)	(0.024)	(0.024)
POST	0.087^{***}	0.122^{***}	0.127^{***}	0.099^{***}
	(0.007)	(0.008)	(0.008)	(0.009)
POST : Buy Market Closure	-0.008	0.005	0.018	0.033^{**}
	(0.010)	(0.013)	(0.015)	(0.016)
Constant	0.702^{***}	0.702^{***}	0.702^{***}	0.702^{***}
	(0.011)	(0.011)	(0.011)	(0.011)
Observations	15,642	15,642	15,642	15,642
R^2	0.019	0.029	0.031	0.021
Note:				*p<0.1; **p<0.05; ***p<0.01

This table represents the following model: $Y_{it} = \alpha + \gamma(BM_i) + \lambda(POST_t) + \beta(BM_i \times POST_t) + u_{it}$ where Y_{it} is *Enrolled*, BM_i is *Buy Market Closure*, and α is *Constant* as defined in *Empirical Methodology*. Observations include the 7,821 individuals age 6-14 in 2013 observed twice to look at difference between enrollment before and after the Ebola outbreak. *Buy Market Closure* and *Constant* values are repeated as they represent the effects on enrollment in 2013 (the λ and α of the above model) which is obviously the same across the four tests. Standard errors are clustered on the SLIHS cluster level.

Table A.11: DID Regression: Market for Selling Closure, Cohort Specification

	Dependent variable:			
	Enrolled			
	2015	2016Jan	2016Sep	2017
	(1)	(2)	(3)	(4)
Sell Market Closure	-0.090^{***}	-0.090^{***}	-0.090^{***}	-0.090^{***}
	(0.022)	(0.022)	(0.022)	(0.022)
POST	0.089^{***}	0.122^{***}	0.128^{***}	0.100^{***}
	(0.007)	(0.008)	(0.008)	(0.009)
POST : Sell Market Closure	-0.015	0.006	0.013	0.026^{*}
	(0.010)	(0.013)	(0.014)	(0.016)
Constant	0.701^{***}	0.701^{***}	0.701^{***}	0.701^{***}
	(0.011)	(0.011)	(0.011)	(0.011)
Observations	15,642	15,642	15,642	15,642
R^2	0.018	0.027	0.030	0.020
Note:				*p<0.1; **p<0.05; ***p<0.01

This table represents the following model: $Y_{it} = \alpha + \gamma(SM_i) + \lambda(POST_t) + \beta(SM_i \times POST_t) + u_{it}$ where Y_{it} is *Enrolled*, SM_i is *Sell Market Closure*, and α is *Constant* as defined in *Empirical Methodology*. Observations include the 7,821 individuals age 6-14 in 2013 observed twice to look at difference between enrollment before and after the Ebola outbreak. *Sell Market Closure* and *Constant* values are repeated as they represent the effects on enrollment in 2013 (the λ and α of the above model) which is obviously the same across the four tests. Standard errors are clustered on the SLIHS cluster level.

Table A.12: DID Regression: Quarantining with Ebola Control Variables, Cohort Specification

	Dependent variable:			
	Enrolled			
	2015	2016Jan	2016Sep	2017
	(1)	(2)	(3)	(4)
POST	0.093***	0.130***	0.138***	0.107***
	(0.004)	(0.005)	(0.006)	(0.006)
POST : Quarantine	−0.020**	−0.039***	−0.047***	−0.034***
	(0.008)	(0.010)	(0.011)	(0.012)
POST : Hospital Closure	−0.009	−0.002	−0.011	−0.021
	(0.011)	(0.014)	(0.016)	(0.017)
POST : Job Closure	−0.005	−0.016	−0.022	−0.014
	(0.012)	(0.015)	(0.016)	(0.017)
POST : Buy Market Closure	0.022	0.020	0.050**	0.056***
	(0.014)	(0.018)	(0.019)	(0.021)
POST : Sell Market Closure	−0.018	0.016	0.010	0.012
	(0.013)	(0.017)	(0.018)	(0.020)
Observations	15,642	15,642	15,642	15,642
R^2	0.029	0.037	0.039	0.030
Note:				*p<0.1; **p<0.05; ***p<0.01

This table only includes *POST* and *POST* interactions. This table reports the results of the following model: $Y_{it} = \alpha + \gamma(Q_i) + \sum_{k=1}^{4} \delta_k(closure_{k,i}) + \lambda(POST_t) + \beta(Q_i \times POST_t) + \sum_{k=1}^{4} \eta_k(closure_{k,i} \times POST_t) + u_{it}$ where Y_{it} is *Enrolled* and Q_i is *Quarantine* as defined in *Empirical Methodology.* The 4 closures in the table correspond to the answers of the survey questions in Table A.2. Observations include the 7,821 individuals age 6-14 counted twice, one time in 2013, and one time in the corresponding column year. Standard errors are clustered on the individual level.

Table A.13: Quarantine on Enrollment, All Controls and Ebola Closure Variables

	Dependent variable:			
	Enrolled			
	2015	2016Jan	2016Sep	2017
	(1)	(2)	(3)	(4)
POST	−0.125	−0.019	0.404***	0.633***
	(0.093)	(0.105)	(0.102)	(0.104)
POST : Quarantine	−0.024*	−0.035**	−0.055***	−0.043***
	(0.013)	(0.015)	(0.015)	(0.015)
POST : Hospital Closure	−0.028*	−0.016	−0.020	−0.016
	(0.017)	(0.019)	(0.019)	(0.019)
POST : Job Market Closure	0.012	−0.018	−0.003	−0.005
	(0.018)	(0.020)	(0.020)	(0.020)
POST : Buy Market Closure	0.007	0.010	0.035	0.034
	(0.021)	(0.024)	(0.024)	(0.024)
POST : Sell Market Closure	0.001	0.033	0.014	0.017
	(0.020)	(0.023)	(0.022)	(0.023)
POST : EVD Per 1000	−0.003	−0.004	−0.005**	−0.008***
	(0.002)	(0.002)	(0.002)	(0.002)
POST : Female	0.025**	0.028**	0.026**	0.036***
	(0.010)	(0.011)	(0.011)	(0.011)
POST : Urban	−0.055***	−0.060***	−0.079***	−0.095***
	(0.013)	(0.014)	(0.014)	(0.014)
POST : Has Father	−0.046***	−0.035***	−0.031***	−0.038***
	(0.010)	(0.011)	(0.011)	(0.011)
POST : Age	0.033***	0.027***	−0.008***	−0.018***
	(0.002)	(0.003)	(0.003)	(0.003)
POST : Log Consumption	−0.019*	−0.017	−0.014	−0.027**
	(0.011)	(0.012)	(0.012)	(0.012)
POST : Late Region	−0.029*	0.007	0.013	0.017
	(0.015)	(0.017)	(0.017)	(0.017)
POST : District	Y	Y	Y	Y
Observations	16,055	16,558	16,558	16,942
R^2	0.162	0.156	0.148	0.148

We employ following model: $Y_{it} = \alpha + \gamma(Q_i) + \sum_{k=1}^{25} \delta_k(control_{k,i}) + \lambda(POST_t) + \beta(Q_i \times POST_t) + \sum_{k=1}^{24} \eta_k(control_{k,i} \times POST_t) + u_{it}$ where Y_{it} is *Enrolled* and Q_i is *Quarantine* as defined in *Empirical Methodology*. The 25 controls include the 21 controls from the model whose results are reported in Table 4 along with the *District* controls. The other 4 controls are the closure controls whose results are reported in Table 6. Observations include the 7,821 individuals age 6-14 in 2013 summed with the number of kids age 6-14 in the corresponding school year. Standard errors are clustered on the individual level.

Table A.14: DID: All controls and Ebola Vars, Cohort Specification

	Dependent variable:			
	Enrolled			
	2015	2016Jan	2016Sep	2017
	(1)	(2)	(3)	(4)
POST	0.476***	0.780***	0.972***	1.011***
	(0.061)	(0.072)	(0.077)	(0.085)
POST : Quarantine	−0.016*	−0.031***	−0.041***	−0.033***
	(0.009)	(0.010)	(0.011)	(0.012)
POST : Hospital Closure	−0.010	−0.002	−0.010	−0.020
	(0.011)	(0.013)	(0.015)	(0.016)
POST : Job Closure	0.001	−0.003	−0.004	0.006
	(0.012)	(0.014)	(0.015)	(0.016)
POST : Buy Market Closure	0.014	0.004	0.030*	0.039**
	(0.014)	(0.017)	(0.018)	(0.019)
POST : Sell Market Closure	−0.014	0.012	−0.001	−0.009
	(0.013)	(0.016)	(0.017)	(0.019)
POST : EVD Per 1000	−0.004***	−0.004***	−0.005***	−0.004**
	(0.001)	(0.001)	(0.001)	(0.001)
POST : Female	0.002	0.006	−0.007	−0.007
	(0.007)	(0.008)	(0.008)	(0.009)
POST : Urban	−0.026***	−0.040***	−0.045***	−0.048***
	(0.008)	(0.009)	(0.010)	(0.011)
POST : Has Father	−0.017**	−0.013	−0.008	−0.001
	(0.007)	(0.008)	(0.008)	(0.009)
POST : Age	−0.026***	−0.043***	−0.055***	−0.063***
	(0.001)	(0.002)	(0.002)	(0.002)
POST : Log Consumption	−0.011	−0.015*	−0.016*	−0.007
	(0.007)	(0.008)	(0.009)	(0.010)
POST : Late Region	−0.027***	−0.008	−0.020	−0.016
	(0.010)	(0.012)	(0.013)	(0.014)
POST : District	Y	Y	Y	Y
Observations	15,556	15,556	15,556	15,556
R^2	0.137	0.151	0.161	0.158
Note:				*p<0.1; **p<0.05; ***p<0.01

This table only includes *POST* and *POST* interactions. This table reports the results of the following model: $Y_{it} = \alpha + \gamma(Q_i) + \sum_{k=1}^{25} \delta_k(control_{k,i}) + \lambda(POST_t) + \beta(Q_i \times POST_t) + \sum_{k=1}^{24} \eta_k(control_{k,i} \times POST_t) + u_{it}$ where Y_{it} is *Enrolled* and Q_i is *Quarantine* as defined in *Empirical Methodology*. The 25 controls include the 21 controls from the model whose results are reported in Table 4 along with the *District* controls. The other 4 controls are the closure controls whose results are reported in Table 6. Observations include the 7,821 individuals age 6-14 in 2013 observed twice to look at difference between enrollment before and after the Ebola outbreak. Standard errors are clustered on the individual level.

Table A.15: District Isolation on Enrollment

	Dependent variable:			
	Enrolled			
	2015	2016Jan	2016Sep	2017
	(1)	(2)	(3)	(4)
Iso	0.002	0.002	0.002	0.002
	(0.011)	(0.011)	(0.011)	(0.011)
POST	0.019^{***}	0.071^{***}	0.152^{***}	0.166^{***}
	(0.007)	(0.008)	(0.008)	(0.008)
POST : Iso	-0.011	-0.025^{**}	-0.005	0.005
	(0.010)	(0.012)	(0.011)	(0.012)
Constant	0.678^{***}	0.678^{***}	0.678^{***}	0.678^{***}
	(0.007)	(0.007)	(0.007)	(0.007)
Observations	16,149	16,656	16,656	17,043
R^2	0.0003	0.004	0.030	0.040
Note:				*p<0.1; **p<0.05; ***p<0.01

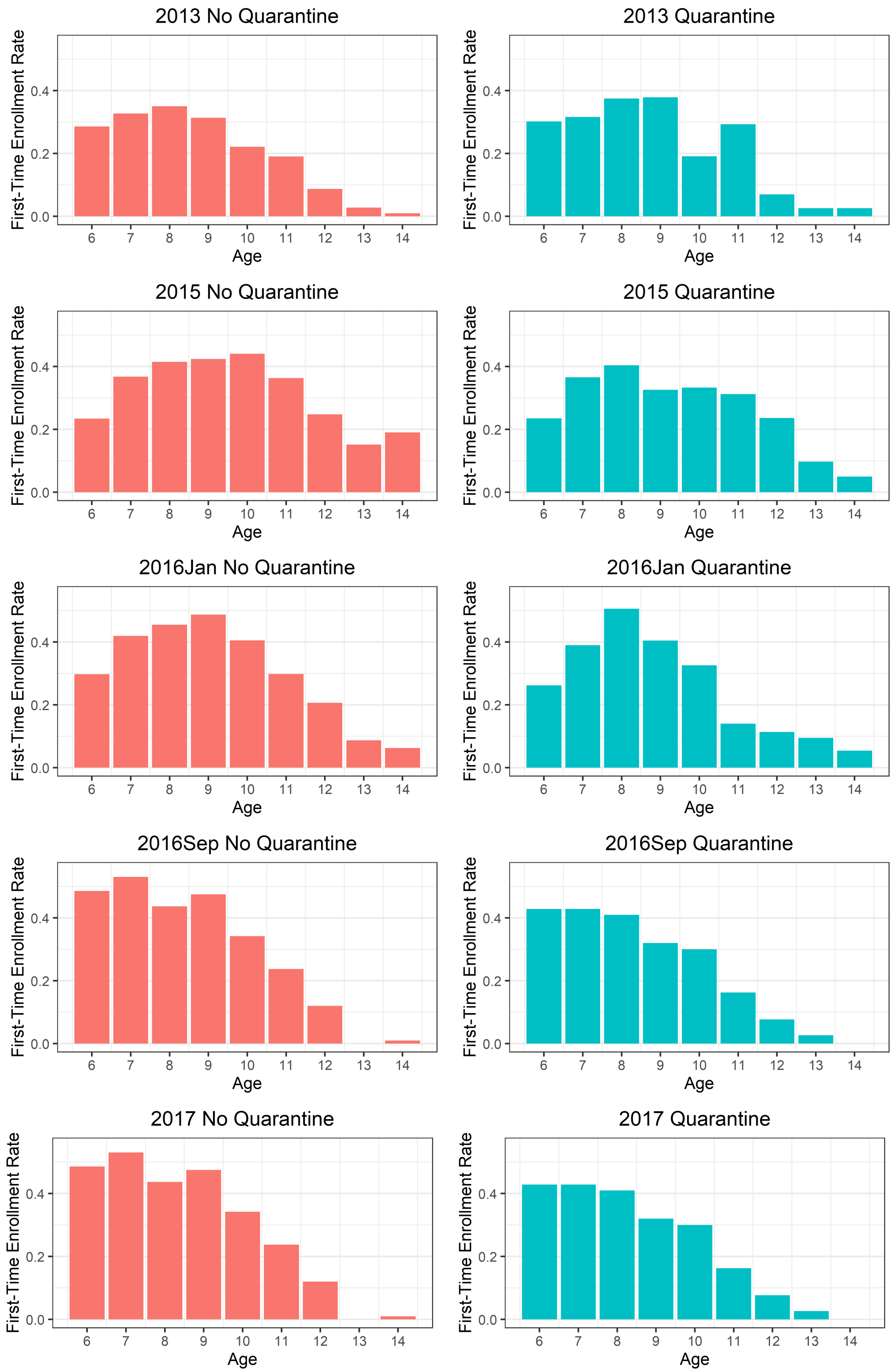
This table represents the following model: $Y_{it} = \alpha + \gamma(Iso_i) + \lambda(POST_t) + \beta(Iso_i \times POST_t) + u_{it}$ where Y_{it} is *Enrolled*, Iso_i is *Iso*, and α is *Constant* as defined in *Empirical Methodology.* Observations include the 7,821 individuals age 6-14 in 2013 summed with the number of kids age 6-14 in the corresponding school year. *Quarantine* and *Constant* values are repeated as they represent the effects on enrollment in 2013 (the λ and α of the above model) which is obviously the same across the four tests. Standard errors are clustered on the individual level.

Table A.16: Quarantine on Enrollment in Freetown

	Dependent variable:			
	Enrolled			
	2015	2016Jan	2016Sep	2017
	(1)	(2)	(3)	(4)
Quarantine	0.109***	0.109***	0.109***	0.109***
	(0.025)	(0.025)	(0.025)	(0.025)
POST	0.068***	0.110***	0.173***	0.182***
	(0.013)	(0.014)	(0.013)	(0.013)
POST : Quarantine	−0.048*	−0.094***	−0.083***	−0.091***
	(0.027)	(0.032)	(0.028)	(0.027)
Constant	0.758***	0.758***	0.758***	0.758***
	(0.012)	(0.012)	(0.012)	(0.012)
Observations	2,884	2,880	2,880	2,910
R^2	0.013	0.021	0.058	0.064
Note:				*p<0.1; **p<0.05; ***p<0.01

This table represents the following model: $Y_{it} = \alpha + \gamma(Q_i) + \lambda(POST_t) + \beta(Q_i \times POST_t) + u_{it}$ where Y_{it} is *Enrolled*, Q_i is *Quarantine*, and α is *Constant* as defined in *Empirical Methodology.* Observations include the 1447 individuals age 6-14 in 2013 in Freetown summed with the number of kids age 6-14 in the corresponding school year. *Quarantine* and *Constant* values are repeated as they represent the effects on enrollment in 2013 (the λ and α of the above model) which is obviously the same across the four tests. Standard errors are clustered on the individual level.

Figure A.4: First-Time Enrollment Rate by Age and Quarantine



On the left graphs, we have the rate of first-time enrollment for kids age 6-14 who did not quarantine and on the right, we have those that did quarantine. Each row represents a school year with the top row representing 2013 and the bottom row representing 2017.

Table A.17: DID Regression: Oldest Sibling Enrollment on Individual Enrollment, Oldest In School 2015

	Dependent variable:			
	Enrolled			
	2015	2016Jan	2016Sep	2017
	(1)	(2)	(3)	(4)
POST	−0.011	0.051**	0.184***	0.197***
	(0.022)	(0.025)	(0.024)	(0.025)
Quarantine	−0.016	−0.016	−0.016	−0.016
	(0.018)	(0.018)	(0.018)	(0.018)
NOA 2013	−0.169***	−0.169***	−0.169***	−0.169***
	(0.013)	(0.013)	(0.013)	(0.013)
HH Head Age	0.001**	0.001**	0.001**	0.001**
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
POST : Quarantine	0.012	0.023	0.0003	0.007
	(0.019)	(0.020)	(0.019)	(0.019)
POST : NOA 2013	0.052***	0.057***	0.054***	0.057***
	(0.013)	(0.015)	(0.014)	(0.014)
Quarantine : NOA 2013	0.051**	0.051**	0.051**	0.051**
	(0.024)	(0.024)	(0.024)	(0.024)
POST : HH Head Age	−0.0002	−0.001	−0.001***	−0.001***
	(0.0004)	(0.0005)	(0.0005)	(0.0005)
POST : Quarantine : NOA 2013	−0.054**	−0.083***	−0.070***	−0.066***
	(0.024)	(0.026)	(0.025)	(0.025)
Constant	0.748***	0.748***	0.748***	0.748***
	(0.022)	(0.022)	(0.022)	(0.022)
Observations	15,031	15,505	15,506	15,869
R^2	0.020	0.025	0.054	0.064
Note:				*p<0.1; **p<0.05; ***p<0.01

Table A.18: DID Regression: Main Result Subset High Quarantine Sections

	Dependent variable:			
	Enrolled			
	2015	2016Jan	2016Sep	2017
	(1)	(2)	(3)	(4)
Quarantine	−0.023	−0.023	−0.023	−0.023
	(0.098)	(0.098)	(0.098)	(0.098)
POST	−0.034	0.057	0.142*	0.143*
	(0.046)	(0.074)	(0.076)	(0.078)
Quarantine : POST	0.035	−0.015	−0.015	0.015
	(0.047)	(0.074)	(0.077)	(0.079)
Constant	0.688***	0.688***	0.688***	0.688***
	(0.097)	(0.097)	(0.097)	(0.097)
Observations	3,188	3,307	3,307	3,389
Note:				*p<0.1; **p<0.05; ***p<0.01

We employ following model: $Y_{it} = \alpha + \gamma(Q_i) + \lambda(POST_t) + \beta(Q_i \times POST_t) + u_{it}$ where Y_{it} is *Enrolled*, Q_i is *Quarantine*, and α is *Constant* as defined in *Empirical Methodology.* Observations include the 1,594 individuals age 6-14 in 2013 summed with the number of kids age 6-14 in the corresponding school year from sections in which over 80% of the population quarantined. *Quarantine* and *Constant* values are repeated as they represent the effects on enrollment in 2013 (the λ and α of the above model) which is obviously the same across the four tests. Standard errors are clustered on the SLIHS cluster level.

Table A.19: DID Regression: School Type Triple Interaction

	Dependent variable:			
	Enrolled			
	2015	2016Jan	2016Sep	2017
	(1)	(2)	(3)	(4)
POST : Quarantine	−0.042	-0.065^{**}	-0.066^{*}	−0.057
	(0.026)	(0.033)	(0.036)	(0.039)
POST : Quarantine : Central Gov't	0.023	0.035	0.038	0.048
	(0.028)	(0.035)	(0.039)	(0.042)
POST : Quarantine : Religious	0.035	0.051	0.049	0.058
	(0.029)	(0.036)	(0.040)	(0.043)
POST : Quarantine : Community	0.008	0.016	−0.029	−0.025
	(0.035)	(0.043)	(0.049)	(0.053)
POST : Quarantine : NGO	0.118	0.204^{*}	0.205^{*}	0.146
	(0.098)	(0.119)	(0.120)	(0.135)
POST : Quarantine : Private Person	0.026	0.028	0.073	0.052
	(0.051)	(0.065)	(0.072)	(0.079)
Observations	15,642	15,642	15,642	15,642
R^2	0.045	0.054	0.056	0.045
Note:				*p<0.1; **p<0.05; ***p<0.01

In this table, we look into whether the type of school makes a difference in whether quarantining led to lower enrollment. We only display the *POST : Quarantine* interactions. The idea being that different school types require different individual costs incurred among students and quarantining may have a greater impact on the ability of certain school types to operate. We aggregated the most common school type by section as individuals who never attended school would most likely attend the school type predominate in their region. Table A.19 indicates that there were no statistically significant results and that those who quarantined faced lower enrollment across all school types. For reference, there were 602, 4666, 1764, 749, 7, and 33 students for which the respective schooling types were most frequent in their region. Standard errors are clustered on the SLIHS individual level.