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

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May 2021

Abstract

Stay-at-home and other restricted movement measures are common short run policy responses to threat of viral epidemics. In this paper, I seek to find out how quarantines or restricted movement measures impact enrollment rates of school-aged children in the long-term. Sierra Leone serves as a perfect natural experiment as 30% of the population was quasi-randomly quarantined as a result of the Ebola epidemic. To undergo this analysis, I perform a difference in differences analysis between individuals who quarantined or faced restricted movement measures as a result of Ebola and individuals who didn't face such measures. I find that students affected by quarantine faced approximately 29% lower enrollment rate gains 3 years later than they would have been if not affected by quarantine. I also find that this result is driven by quarantine rather than other measures of the impact of Ebola such as market closures. This result implies that approximately 25,000 students in Sierra Leone did not enroll as a consequence of the Ebola quarantine. Most of this result is due to a lower rate of first-time enrollment rather than dropouts. I then find that these students who never enrolled will have lower aggregate consumption and, thus, worse long-term living standards later in life.

1 Introduction

Lockdowns and quarantine measures have been implemented across the globe as a result of the COVID-19 pandemic. Stay at home and other movement restrictions have been put in place in order to prevent the spread of the virus; however, the impacts of such measures are not well understood. Here, I seek to uncover the impact of these measures on school enrollment by using the Ebola epidemic in Sierra Leone as a natural experiment.

The Ebola epidemic, which took place from 2014 - 2016, led to major loss of life and socioeconomic disruptions in West Africa. Sierra Leone was one of the countries most affected with 14,124 cases reported and 3,956 deaths before being declared Ebola-free by the World Health Organization (WHO) on March 17, 2016. A weak economy, poor healthcare systems, and rampant food insecurity amplified the harm of this virus.

During this epidemic in Sierra Leone, schools were closed for approximately 9 months across the country (from June 2014 to April 2015). Although these school closures set back students from continuing to advance in their curriculum, they didn't lead to a noticeable impact on enrollment in the subsequent 3 schooling periods. These schooling periods typically last 9 months from September to July; however, the 2 periods following the school closures ran from April 2015 to December 2015 and January 2016 to July 2016 before returning to the typical schedule in the 2016-2017 school year.

Throughout 2014 and 2015, certain hotspots for Ebola were placed under quarantine. This peaked in late 2014 when over a third of the Sierra Leone population was placed under such orders. These orders only worsened the population's food insecurities and economic woes, and many people were reported to have broken quarantine to obtain food.

In regard to the education system in Sierra Leone, all children are legally required to undergo 6 years of primary education and 3 years of junior secondary school (JSS). Many students also take an additional 3 to 4 years of senior secondary school (SSS) following completion of JSS. Education in Sierra Leone has suffered as a result of shortages of schools and teachers. It is estimated that 43.3% of Sierra Leone's population never completed primary school and only 12.3% make it all the way through secondary school

(Statistics Sierra Leone 2019). This is important as each additional year of schooling is estimated to increase wages by more than 14% for women, and by more than 10% for men across Sub-Saharan Africa (Filmer and Rogers 2018).

With this in mind, I attempt to uncover the impact of quarantining and viral epidemics on enrollment rates in subsequent years. I first explore the current literature on viral epidemics' impacts on schooling and the impacts of the Ebola epidemic in West Africa. I then turn to the Sierra Leone Integrated Household Survey (SLIHS) 2018 (Statistics Sierra Leone et al.) and analyze enrollment rates between children who were placed under quarantine and those who weren't over 5 schooling periods that consisted of 1 schooling period before Ebola and 4 schooling periods after Ebola. I perform a difference in differences analysis to isolate the effect of quarantining on enrollment over the following 4 schooling periods. I then control for potential violations of the parallel trends assumption by adding controls for potential variables that may effect enrollment trends. I also check that other measures of Ebola impact don't effect school enrollment in order to verify that it is, indeed, quarantine that is the culprit of the lower enrollment rather than general effects of Ebola. Finally, I then try to uncover the mechanism by which quarantines can lead to lower enrollment, as well as the implications of this lower enrollment.

I find that children who were placed under quarantine orders had lower enrollment in following years as many of these children may have entered the workforce in order to provide supplementary income for their household and children interacted less with each other leading to less interest in schooling. I also find that other other responses to the Ebola epidemic such as workplace, hospital, and market closures didn't have a strong effect on enrollment. Finally, I find that this lower enrollment leads to lower aggregate consumption later in life for those who never enrolled. This has tremendous policy implications for uncovering the full extent of the harm caused by restricted movement measures during viral epidemics, such as the current COVID-19 crisis.

2   Literature Review

Before the dawn of COVID-19, there was little research conducted on the effects of viral epidemics on schooling decisions. Much of the research surrounding the Ebola epidemic in West Africa focuses on short-term impacts on households and firms taking place during the time of the epidemic. For instance, Bowles, Hjort, Melvin, and Werker (2016) investigated the impact of Ebola in Liberia on its jobs and economic activity during the outbreak. They found that Liberia suffered job losses focused in regions hit especially hard by the epidemic. Gonzalez-Torres and Esposito (2016) found that the Ebola outbreak led to increased rates of civil violence across Western Africa during its duration. Many other works investigate questions of employment and economic activity during the Ebola crisis and find similar results to Bowles et al.

Other works surrounding the Ebola epidemic include investigations of the impact of the outbreak on public attitude. For instance, Flückiger, Ludwig, and Sina Önder (2019) found that regions affected the most by Ebola were met by greater trust in government authorities. These works often exploit the quasi-random nature of regions heavily affected by Ebola. This will prove similar to my methodology as I exploit the quasi-random assignment of Ebola induced quarantine in Sierra Leone to isolate its effects on education outcomes.

Unlike the above research, much less work has been done investigating the long run economic consequences of individuals and households affected by this Ebola outbreak, especially in regard to education. Most similar to my study, Bandiera et al. (2018) conducted a series of surveys of 4,700 women aged 12-25 in Sierra Leone across 200 villages. The baseline survey was conducted in 2014, just as the first cases of Ebola were being reported. The endline survey was conducted in 2016, 6 months after new cases of Ebola were reportedly at or near 0. There was also a survey conducted over the phone in 2015 with prominent members of each village regarding the impact of Ebola on their villages. These surveys were focused on the impact of an Empowerment and Livelihood for Adolescents (ELA) program which was implemented in a randomly selected 150 of the 200 villages with the other 50 villages serving as a control group. Bandiera et al.

found that control villages with greater disruptions as a result of Ebola had a 16% drop in school enrollment among women. The paper also found this adverse effect was almost entirely mitigated by ELA programs.

Bandiera et al.'s follow-up paper in 2020 focused on how school closures in Sierra Leone led to more time socializing with men, higher rates of pregnancy, and lower rates of enrollment among young women. This paper established a follow-up survey finding that the patterns established in Bandiera's 2018 findings were long-lasting. Similar to the other paper, Bandiera et al. also points to the ELA program as a means of mitigating these effects. This paper provides more detail on how enrollment rates were affected by the school closures, claiming female enrollment rates fell by 17% following the Ebola epidemic.

Overall, these papers find that female school age children in regions where Ebola had a large impact on school openings and primary health units faced lower enrollment due to increased time spent socializing with men as well as increased rates of pregnancy. This is an important result and informs my hypothesis that those who experience quarantine as a result of Ebola are less likely to enroll in school following the crisis.

My study, however, investigates a rather different question. Instead of perceiving the time during school closures as time where women are likely to socialize with men and not enroll in following years, I seek to investigate whether individuals who were placed under quarantine orders experienced lower enrollment following the Ebola epidemic. My 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.

In regard to the efficacy of my data, it is the result of a survey conducted jointly by Statistics Sierra Leone, The World Bank, and the Government of Sierra Leone which took place from January to December 2018. These organizations produced a report of this data in 2019 which discusses and visualizes the raw data collected pertaining to poverty, education, and impacts of Ebola.

This report found that enrollment rates increased after the nine-month school closures

for both male and female respondents. This is a fascinating result and contradicts the enrollment trend results of the above papers by Bandiera et al. I consult this report to verify some of my findings, extrapolate my findings to the whole of the Sierra Leone population, and provide better context to the data.

Regarding the implications of children not enrolling in school in Sierra Leone, Filmer and Rogers (2018) investigated the impacts of education on Sub-Saharan Africa. They estimate that 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 higher probability of employment, greater productivity, higher earnings, and reduced poverty. Later in the paper, I attempt to replicate some of these findings with my data using an instrumental variables (IV) estimation of the effect of ever enrolling on income, income stability, food stability, and relative wealth.

3 Data

The data used for this analysis is from the Sierra Leone Integrated Household Survey (SLIHS) 2018. This survey was conducted from January to December 2018 and included 40,680 individuals across all 14 districts, 149 Chiefdoms, and 513 sections. There were 6,840 households surveyed with 10 households being surveys in each of 684 clusters. The primary variables of interest are the dummy variables that are responses to the survey questions in Table 1.

Table 1: Variables of Interest

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)

Enrolled was asked for the following 5 schooling periods: Sept 2013 to July 2014, Apr 2015 to Dec 2015, Jan 2016 to July 2016, Sept 2016 to July 2017, and Sept 2017 to July 2018. As such, we have access to 1 schooling period before Ebola and 4 schooling periods

after Ebola. The question regarding quarantine was asked to the head of the household, while the enrollment question was asked to each member of the household.

Although the survey was collected at a single point in time, I have the equivalent of panel data that I will use to look at enrollment over time. Poor memory shouldn't significantly impact the results of this enrollment data since whether an individual enrolled or not in a school year is a significant life event that is not easily forgotten within 5 years. Further, the enrollment rates that we measure for students aged 6-14 in the first schooling period are closely aligned with those of the SLIHS 2011 survey for the 2011 schooling period.

The age at which students enroll for the first time as well as graduate or dropout widely varies as shown by Figure 1. I 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 1: Enrollment rate by Age (Cohort Bounded by Vertical Lines)
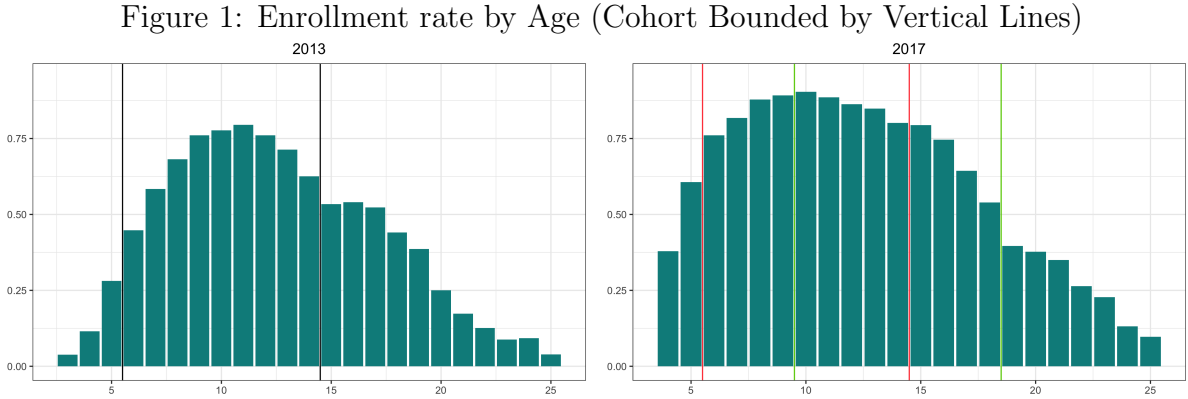
There are 2 ways that one may be interested in tracking the enrollment of students: track the 7821 individuals aged 6 - 14 at the start of the 2013 school year (labeled green in the right panel of Figure 1), and track the individuals aged 6 - 14 in each schooling period, dropping those who age out of the window and appending those who age into the window (labeled orange in the right panel of Figure 1). Going forward I will primarily focus on the fixed-age window sample as to restrict our sample to school-age children as defined by the WHO; however, I will also include results for the cohort specification.

Other benefits of this 6-14 age specification is that age 6 is when close to 50% of the population had enrolled and individuals age 14 are unlikely to have graduated by 14

with the fixed-age range specification or even 18 with the cohort specification. Thus, the changes in enrollment over time will be mostly comprised by 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 respondents. Specifically, 4 other questions were asked regarding health care facility closures, job closures, and market closures. This data is important as it allows me to control for the impact of Ebola on households as measured by these variables. Therefore, we can isolate the impact of quarantine or restricted movement measures independent of the overall effect of the Ebola epidemic on a household. These variables and their corresponding questions are listed in Table 2.

Table 2: Ebola-induced Closure Variables

Variable Name	Survey Question
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?

Initial analysis of the enrollment over time by quarantine or control groupings in Figure 2 indicates that enrollment rates for those who didn't experience quarantine were lower than for those who experienced quarantine initially; however, two schooling periods later, those who didn't 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 didn't experience quarantine. This supports the hypothesis that being forced to quarantine by the Ebola outbreak negatively impacted enrollment rates in subsequent years. Similar results are found with the cohort specification as indicated in figure 7 in the Appendix.

I performed the same analysis as the quarantine grouping for the other four Ebola exposure dummy variables in Figure 9 in the Appendix. The differences in enrollment

Figure 2: Enrollment Over Time, Quarantine Vs. Control
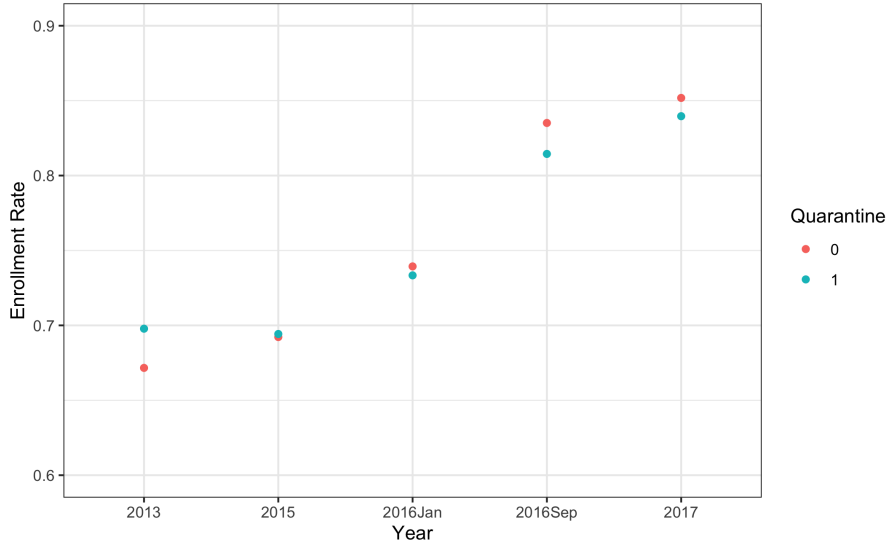
rates over time are much less pronounced. For health care facility closures, the gap widens in 2015 but returns to near normal levels for the January 2016 School year. For job closures, The gap widens for 2015 through September 2016 school years but at a lower rate than quarantine and a diminishing rate for the 2016 school years. I include this figure for the cohort specification in Figure 8 of the Appendix. The overall trends of enrollment are similar for this specification.

4 Empirical Strategy

In this section, I will describe my attempt to isolate the effect of being quarantined or facing restricted movement orders on enrollment trends over time. I first do this through a simple difference in differences approach before verifying that the necessary assumptions of this approach hold.

I seek to determine whether being quarantined as a result of the Ebola epidemic had a negative effect on enrollment in years after the crisis. Since it is possible that quarantining could serve as a proxy for the overall impact that Ebola had on a household, I will perform the same analyses with the other 4 Ebola exposure dummies relating to hospital, work, and market closures in place of the quarantine dummy. I perform a difference in differences analysis as it allows me to isolate the effect of the one-time shock of the

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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, a majority of the fixed effects of the students will be accounted for, while the overall enrollment trends in Sierra Leone can also be accounted for.

I estimate the shock of Ebola was greatest from the end of the school period in 2013 to the beginning of the school period in 2015, but that there were still impacts of this crisis playing out until before the school year beginning in September 2016. We see from Figure 2 that this difference in enrollment trends widens across the first three schooling periods before narrowing closer to its original 2013 level in 2017. Therefore, I expect strengthening results for the first 3 periods before a weakened result for the final 2017 period.

I 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 the pre- to post-Ebola schooling period, and u_{it} is the residual term. I later add level effects for age, female, urban, has father, father education, log welfare and district (will be described in further detail below) in order to increase the precision of my estimates. I find that my results mildly strengthen when level effects are included.

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 quar-

antined 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 don't have enough data to analyze enrollment trends pre-Ebola, our model controls for the fixed effects of enrollment between these two groups 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, I will now add controls for time trends of enrollment.

Here, I check for omitted variable bias. I do this by controlling for variables that may affect the change in enrollment trends over time. I control for the following variables: age, female, urban, has father, father education, log welfare, late region, and district. 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. I use father education instead of mother education as it was especially difficult for female children to receive education in Sierra Leone in the past, when school-age children's parents would have been school-age. welfare is defined as the aggregate consumption after controlling for purchasing power. This is used over income as income is very difficult to measure due to most economic activity occurring through self-employed individuals that is very difficult to track. Aggregate consumption is also most likely a more reliable indicator of long-term living standards than income. For a more in-depth description of how the welfare variable was formulated, see Statistics Sierra Leone and The World Bank 2018. late region is defined as a region that had over

50% of students claim that their schools didn't open on time during the 2015 school year following the worst of the Ebola epidemic. District is a collection of 14 dummies that are 1 if an individual lives in that district. I lose 94-101 observations due to a lack of responses to survey questions concerning the above controls.

I use the following model:

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

Where δ_k is the effect on enrollment of the control variable $control_k$ and 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.

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. I first assume parallel trend assumptions hold. I then include level effects and time-trend effects to control for biased assignment into the quarantine grouping. Finally, I verify that it is quarantine and restricted movement measures that lead to lower enrollment instead of general Ebola effects.

5.1   Main Results

First, we'll turn to the simple difference in differences result where we assume parallel trends would occur had the quarantine and restricted movement measures occurred. Table 3 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 2 Post-Ebola schooling periods and at the 1% level for the final 2 schooling periods. This indicates that had individuals not been impacted by Ebola to the point in which they had to quarantine, they would have experienced higher enrollment rates.

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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. I leave in the Constant so that enrollment rates can be constructed for each 4 groupings by time. Similar estimates are obtained for the cohort specification in Table 9 in the Appendix.

Table 3: DID Regression: Quarantine No Controls

	Dependent variable:			
	enrolled			
	2015	2016Jan	2016Sep	2017
	(1)	(2)	(3)	(4)
Quarantine	0.026**	0.026**	0.026**	0.026**
	(0.011)	(0.011)	(0.011)	(0.011)
POST	0.021***	0.068***	0.163***	0.180***
	(0.006)	(0.007)	(0.007)	(0.007)
POST : Quarantine	−0.024**	−0.032**	−0.047***	−0.038***
	(0.011)	(0.013)	(0.012)	(0.012)
Constant	0.672***	0.672***	0.672***	0.672***
	(0.006)	(0.006)	(0.006)	(0.006)
Observations	16,149	16,655	16,656	17,043

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

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 almost a 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 children are in the school-age range of 6-14. I estimate that 29.6% of these school age children were affected by quarantine. Thus, approximately 546,684 school age children were impacted by Ebola to the point in which they were placed under

quarantine. Therefore, I estimate that over 25,000 school age children in Sierra Leone did not enroll in school due to the Ebola epidemic and resulting quarantine ($546,684 \times 0.047$).

I put this same regression for the other Ebola exposure dummy variables in the Appendix. 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 as a result of Ebola. This suggests that quarantining is the primary cause of this depressed enrollment. I will further verify that this is the case in the next section.

I also ran this regression with level controls for age, female, urban, has father, father education, welfare, late region, and district. The results strengthened with all four time periods becoming significant at the 1% level.

Now, I will now 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. Table 4 indicates that we get statistically significant results for all 4 time periods with stronger results in the second schooling period and weaker results in the fourth schooling period. Thus, the assignment of the subjects with varying age, female, urban, has father, father education, welfare, late region, and district variables to the control and treatment groups does not explain our main results.

I 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, most 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 and increased interest in schooling from those without fathers who most likely wouldn't have gone to school if not for recent policy pushing schooling. Despite this, our result supports that the assignment of quarantining to certain regions or ages doesn't significantly impact our main results. These results also hold for Table 10 the cohort specification in the Appendix.

Table 4: DiD Regression: Quarantining with Controls

	Dependent variable:			
	enrolled			
	2015	2016Jan	2016Sep	2017
	(1)	(2)	(3)	(4)
POST	−0.136	−0.007	0.398***	0.607***
	(0.093)	(0.105)	(0.102)	(0.104)
POST : Quarantine	−0.024**	−0.034***	−0.045***	−0.032**
	(0.011)	(0.013)	(0.013)	(0.013)
POST : Female	0.024**	0.027**	0.025**	0.035***
	(0.010)	(0.011)	(0.011)	(0.011)
POST : Urban	−0.058***	−0.070***	−0.086***	−0.101***
	(0.013)	(0.015)	(0.014)	(0.014)
POST : Has Father	−0.047***	−0.037***	−0.030***	−0.035***
	(0.010)	(0.011)	(0.011)	(0.011)
POST : Father Educ	0.001	0.001	−0.004	−0.009**
	(0.003)	(0.004)	(0.003)	(0.004)
POST : Age	0.033***	0.027***	−0.008***	−0.018***
	(0.002)	(0.003)	(0.003)	(0.003)
POST : Log Welfare	−0.017	−0.018	−0.010	−0.020*
	(0.011)	(0.012)	(0.012)	(0.012)
POST : Late Region	−0.033*	−0.020	−0.005	0.004
	(0.019)	(0.022)	(0.022)	(0.023)
Observations	16,055	16,557	16,558	16,942

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

Only included POST and POST interactions

5.2   Robustness Check

Here, I will run tests to determine whether quarantining was the reason for the change in enrollment or if it was the overall impact of Ebola. We've already seen that other Ebola impact variables don't yield significant results in reducing enrollment over time; however, I will further investigate this issue by running tests with quarantine as well as the other Ebola impact variables.

I will now investigate whether adding in all of the Ebola exposure variables affect our estimate. This is to further investigate whether the enrollment trend change is caused by quarantine or Ebola as a whole. Table 5 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 and restricted movement is leading to lower enrollment seemingly 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 is also positive results of market closures on schooling in the final two schooling periods which will be eliminated when adding controls in the next regression. The impact of quarantine on the enrollment in post-Ebola periods also holds for all periods for the cohort specification as shown in Table 12.

I will now investigate whether adding in all of the controls of the Ebola exposure variables affect our estimate. Table 6 indicates that the results hold for the final 3 schooling periods after adding in all control variables; however, this result weakens to being significant at the 10% level in the first period. This is likely due to Ebola impacting enrollment rates in the first period back as there were still concerns in regions impacted heavily by Ebola as to whether it was safe to return to school. Those who didn't enroll as a result of Ebola in the first period were likely to have faced quarantine as well, and thus, the results for quarantine weakened.

Other results of note are that the significant positive results of the market closures on enrollment vanish while the effect of hospital closures on enrollment strengthens in the

Table 5: DiD Regression: Quarantining 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	16,655	16,656	17,043

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

Only included POST interactions

first schooling period. Female, urban, and has father also remained significant from the tests with all controls and quarantine excluding the other Ebola impact measures. Similar results are seen using the cohort specification as shown by Table 11 in the Appendix.

Table 6: DiD Regression: All Controls and Ebola Impact Variables

	Dependent variable:			
	enrolled			
	2015	2016Jan	2016Sep	2017
	(1)	(2)	(3)	(4)
POST	0.169*	0.238**	0.310***	0.428***
	(0.090)	(0.102)	(0.099)	(0.102)
POST:quarantine	−0.024*	−0.036**	−0.057***	−0.045***
	(0.013)	(0.015)	(0.015)	(0.015)
POST:hospital closure	−0.032*	−0.019	−0.023	−0.019
	(0.017)	(0.019)	(0.019)	(0.020)
POST:job closure	0.015	−0.014	−0.001	−0.002
	(0.018)	(0.020)	(0.020)	(0.020)
POST:buy market closure	0.011	0.012	0.037	0.040
	(0.021)	(0.024)	(0.024)	(0.024)
POST:sell market closure	−0.001	0.031	0.010	0.009
	(0.019)	(0.023)	(0.022)	(0.023)
POST:female	0.027***	0.029***	0.025**	0.035***
	(0.010)	(0.011)	(0.011)	(0.011)
POST:urban	−0.047***	−0.055***	−0.083***	−0.101***
	(0.013)	(0.015)	(0.014)	(0.014)
POST:has father	−0.064***	−0.051***	−0.026**	−0.027**
	(0.010)	(0.011)	(0.011)	(0.011)
POST:father educ	−0.0004	−0.001	−0.004	−0.008**
	(0.003)	(0.004)	(0.003)	(0.004)
POST:log welfare	−0.015	−0.017	−0.011	−0.022*
	(0.011)	(0.012)	(0.012)	(0.012)
POST:late region	−0.028	−0.015	−0.007	0.0005
	(0.019)	(0.022)	(0.022)	(0.023)
Observations	16,055	16,557	16,558	16,942

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

Only included POST interactions and omitted District results

6 Causes and Implications

Having shown that quarantining as a result of Ebola leads to lower enrollment in subsequent years, I will now turn to investigate how this lower enrollment affects these children in the long run. First, I will look into the cause of this drop in enrollment (dropouts or lack of first time enrollment). Then, I will investigate the implications of these results with regard to stability in income, stability in food, and relative wealth.

6.1 Causes

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

Turning to the results, on the right panel of Figure 4, 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 weren't enrolled in the prior year enroll in the next year. Concerning at the count of students who dropped out vs. enrolled for the first time in 6.1, 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.

I 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 5. The green bars in the 2015 graph less the small orange bars indicates enrollment rates by

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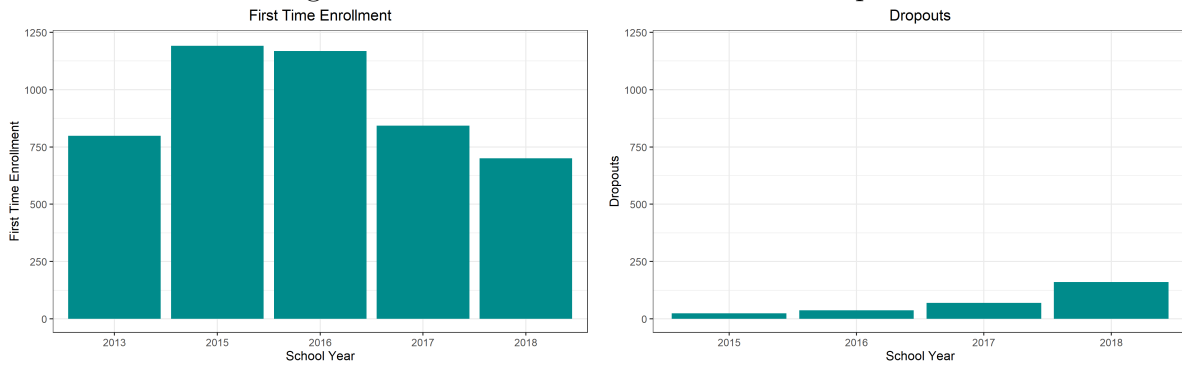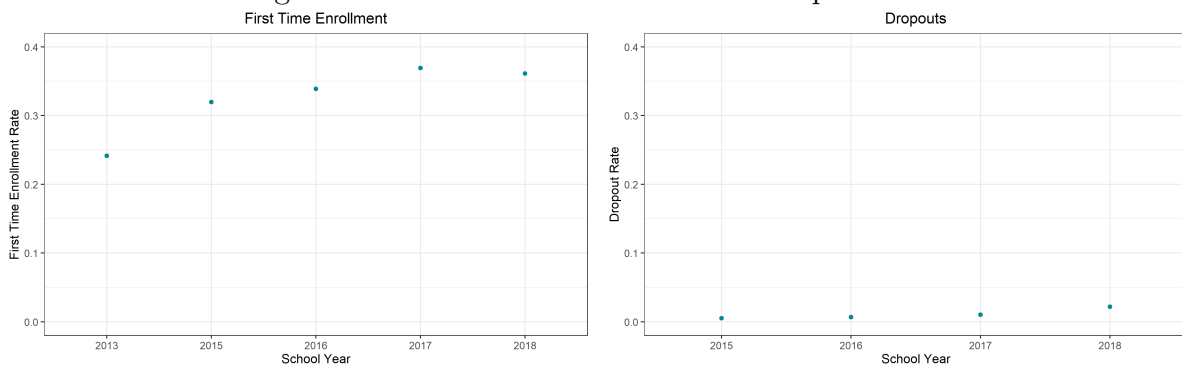Figure 3: First Time Enrollments Vs. Dropouts

Figure 4: First Time Enrollment Vs. Dropout Rates

age from 2013. The blue bars indicate the first time enrollments. It is clear that dropouts play a much smaller role in shifting enrollment patterns than first time enrollment. These first time enrollments are what let so such a massive increase in enrollment across age groups from 2013 to 2017.

This result is interesting 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 than keeping children enrolled.

For this analysis, however, it indicates that a negligible amount of the time trends in enrollment are due to dropouts. Thus, I 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.

Further, the SLIHS 2018 surveys asks each student who has never been enrolled for the reason that the respondent has never attended school. I first look into whether those who

Figure 5: First Time Enrollment and Dropouts by Age Over Time
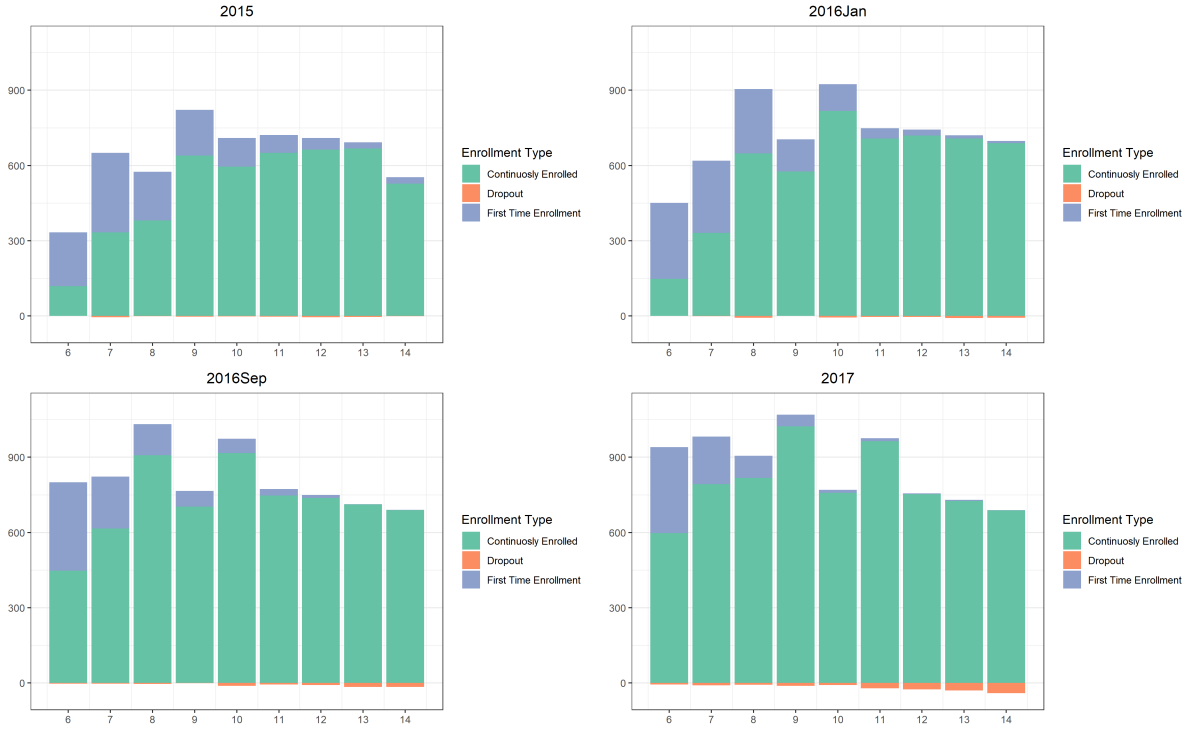
quarantined never attended school for different reasons than those who never quarantined. Figure 6 indicates that those who quarantined were more likely to have worked instead of attending school, were burdened by the cost of school, and were unwilling to travel the long distance to school. With this, I will further investigate whether those who quarantined faced lower enrollment due to working, school cost, and distance to school.

I attempted to isolate why quarantine was leading to lower enrollment by looking at whether certain groups who quarantined faced worse enrollment after the Ebola epidemic than other groups. In order to do this, I looked at the triple interaction terms between POST, quarantine, and the one of the following variables: school cost, school type, work type, and urban. None of these mechanisms proved statistically significant results, and are thus relegated to the Appendix. Other mechanisms such as a lost interest among students and parents due to less interaction as a result of restricted movement measures couldn't be tested. Although these reasons were listed as reasons to not enroll for those who didn't quarantine over those who did, we don't have a prior that could be tested. Thus, it is possible that this was the case to a higher degree before the Ebola epidemic.

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Figure 6: Reasons Not Attending by Quarantine
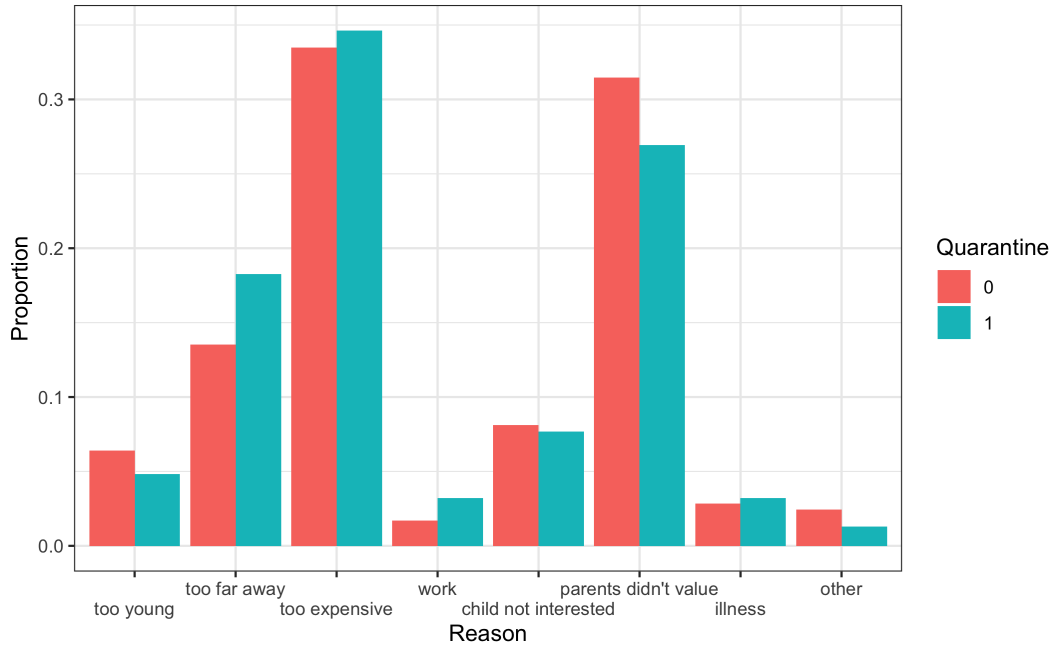
6.2 Implications Methodology

Continuing to use the survey data from SLIHS 2018, we do not have data for sufficient years after the Ebola pandemic to directly investigate the effect of quarantine on long-term earning potential 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 World Bank uses ages 15+ to indicate the labor force participation rate in Sierra Leone and labels age 64 as the oldest adult working age, thus in order to look at the effects of enrollment on an individual during his or her working years, I subset to only include individuals between the ages of 15 and 64 at the time of being surveyed who know their father (in order to use father education as an instrument).

I then use an instrumental variable (IV) estimation with father education as an instrument to control for endogeneity between whether an individual was ever enrolled and an individual's aggregate consumption (log welfare). I use these outcome variables as a proxy for income because in Sierra Leone, many workers are self employed or engage in informal work making their incomes difficult to calculate.

I also have the following controls in my model: female, urban, has father, age, and district. As usual, district is omitted from the results table as there are 14 districts

Father education serves as a good instrument as it is highly correlated with one's own education, and thus, leads to a strong first stage. Additionally, it also serves as a good instrument as one would expect father education to have negligible effects on one's earnings other than through the increased earning potential gained through one's education. Thus, father education shouldn't have an impact on one's income stability, food stability, or relative wealth, other than through one's education, and it satisfies the exclusion restriction.

I use the following model for the IV estimation:

First Stage

$$EverEnrolled_i = \pi_0 + \pi_1(FatherEducation_i) + \sum_{k=1}^{18} \eta_k(control_k) + \sigma_i$$

Second Stage

$$LogWelfare_i = \beta_0 + \beta_1 Ever\widehat{Enrolled}_i + \sum_{k=1}^{18} \gamma_k(control_k) + \epsilon_i$$

where $EverEnrolled_i$ is a dummy indicating whether an individual was ever enrolled in school at any level, π_1 is the impact of father education on the chance one will have ever enrolled, η_k is the impact of the control $control_k$ on the chance that an individual will ever enroll, σ_i is the residual term in the first stage, $LogWelfare$ is the log of aggregate consumption after controlling for purchasing power, $Ever\widehat{Enrolled}_i$ is our OLS estimation of whether an individual was enrolled from our first stage, β_1 is our main variable of interest as it is the impact that our estimated value of ever enrolling has on our outcome variable, and ϵ_i is the residual term in the second stage.

I precede this IV estimation with an ordinary least squares (OLS) estimation with the same controls, measuring the impact of ever enrolling directly on these three well-being outcomes. This model is the same as the second stage model except I use an individual's actual enrollment dummy instead of the first stage estimate. This ensures that our results hold directly and aren't just a result of father education.

Following this result, I perform a robustness check by running an IV test instrumenting

distance to the nearest primary school instead of father education. This result should also satisfy the exclusion restriction as how close the nearest primary school shouldn't effect one's earnings and, thus, aggregate consumption other than through enrolling in school. It also serves as a good robustness check as it is highly correlated with whether an individual ever enrolled in primary school and will, therefore, have a strong first stage.

6.3   Implication Results

From the left column of Table 7, we see that ever enrolling leads to significantly more aggregate consumption throughout one's life. With this result verified, let us turn to the IV regression results.

It is apparent from the highly significant estimate in the first stage that father education has good prediction power of whether an individual was ever enrolled and we have a strong first stage. This regression suggests that not enrolling in school has significant long run impacts on the well-being of the population of Sierra Leone. These findings are in line with those of Filmer and Rogers (2018) which find that education in Sub-Saharan Africa improves probability of employment, a reduction in poverty, and higher earnings.

This supports the harsh implications of my earlier findings since a majority of the effects of quarantining were faced by a lack of first-time enrollment. Therefore, quarantines and restricted movement measures will lead to many of the estimated 25,000 students who don't enroll having lower earnings and overall well-being than would have otherwise occurred if not for these measures.

6.4   Robustness Check

To verify the robustness of my results, I also run the same two stage regression with spouse education as the instrument instead of father education. Figure 8 indicates that our initial results hold. We also see that we have a highly significant value in our first stage indicating that we have a strong first stage. Thus, it holds that individuals who never enroll in school face lower aggregate consumption and, presumably, worse well-being later in life. Furthermore, quarantining also serves to impact these three outcomes

Table 7: IV Regression: Enrollment On Life Outcomes; Father Education Instrument

	log_welfare	ever_enrolled	log_welfare
	OLS	First Stage	Second Stage
	(1)	(2)	(3)
Ever Enrolled	0.171***		4.588***
	(0.009)		(0.726)
Father Education		0.065***	
		(0.002)	
Female	0.012	−0.144***	0.660***
	(0.007)	(0.006)	(0.110)
Urban	0.311***	0.255***	−0.991***
	(0.009)	(0.007)	(0.226)
Has Father	−0.165***	0.101***	−0.722***
	(0.010)	(0.008)	(0.099)
Age	0.003***	−0.012***	0.058***
	(0.0003)	(0.0002)	(0.009)
Observations	20,195	20,195	20,195

Dependent variable:

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

through its impact on enrollment trends.

Table 8: IV Regression: Enrollment On Life Outcomes; Distance Primary Instrument

| | log_welfare | ever_enrolled | log_welfare |
| | OLS | First Stage | Second Stage |
	(1)	(2)	(3)
Ever Enrolled	0.171***		4.441***
	(0.009)		(0.680)
Distance Primary		−0.015***	
		(0.001)	
Female	0.012	−0.147***	0.636***
	(0.007)	(0.006)	(0.103)
Urban	0.311***	0.282***	−0.947***
	(0.009)	(0.007)	(0.212)
Has Father	−0.165***	0.125***	−0.697***
	(0.010)	(0.008)	(0.093)
Age	0.003***	−0.012***	0.056***
	(0.0003)	(0.0002)	(0.009)
Observations	20,195	20,200	20,200

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

7 Conclusion

I have shown through these various tests that the exposure to quarantine or "time when they didn't let people go where they wanted" decreased enrollment independent of one's overall exposure to Ebola as well as other characteristics that may effect enrollment over time. The overall exposure to Ebola leads to a drop in enrollment in the 2015 school year before Sierra Leone was officially declared Ebola free and concerns about Ebola remained. Following the 2015 school year, only having been quarantined displayed any significant declines in enrollment trends, even when controlling for confounding factors. Unlike the other Ebola exposure indicators, This effect grew over the first three time periods, peaking in the 2016Sep (the third school period after schools reopened) before falling in the final, 2017 school year.

What could possibly cause this drop in enrollment? Perhaps those with restricted movements were more likely to stay and help with the family's farm and didn't enroll in school thereafter. Perhaps family's faced more economic strife after having restricted

movement and therefore, students dropped out to help by providing supplementary income. Perhaps quarantining struck more fear into interacting with other students even after the Ebola outbreak than the other Ebola exposure indicators. Although this paper wasn't able to isolate the mechanisms in which quarantining and restricted movement measures effected enrollment, there are many possibilities to explore in the future.

Going forward, I wish to investigate why these measures led to lower enrollment and isolate which groups these measures impacted the most. I have shown that certain school types and whether a region was urban or rural didn't significantly impact the overall effect of quarantining on enrollment. I will also look more closely into the district-wide responses of the quarantine answer and compare them to publicly announced district-wide lockdowns. This could verify my above findings at a regional level with verifiable lockdowns, but won't allow the same level of individual controls. Also, this would ignore whether an individual was aware of the lockdown or followed the order.

This paper should serve to spark more interest into examining the negative externalities associated with lockdowns and restricted movement measures 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 and potentially other impacts.

8 References

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9 Appendix

9.1 Cohort Specification Results

Figure 7: Enrollment Over Time, Quarantine Vs. Control
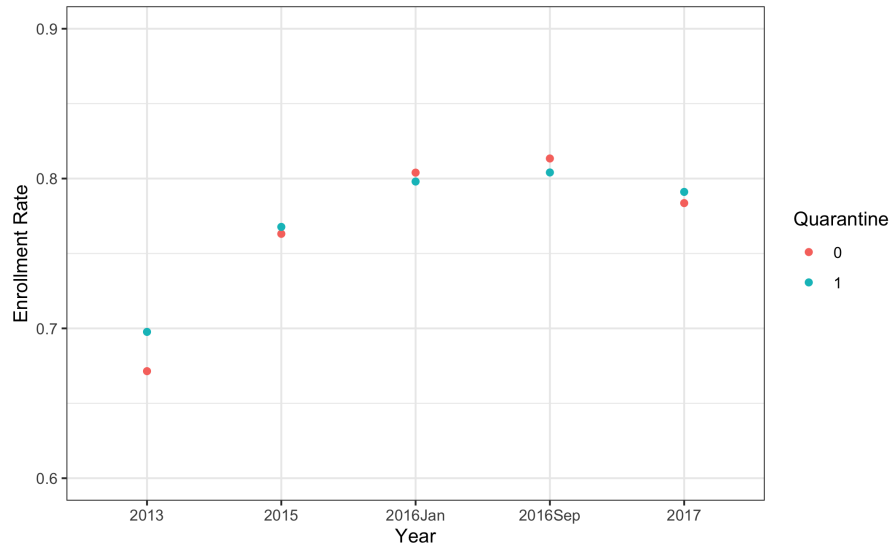
Figure 8: Enrollment Over Time, Other Ebola Exposure Indicators
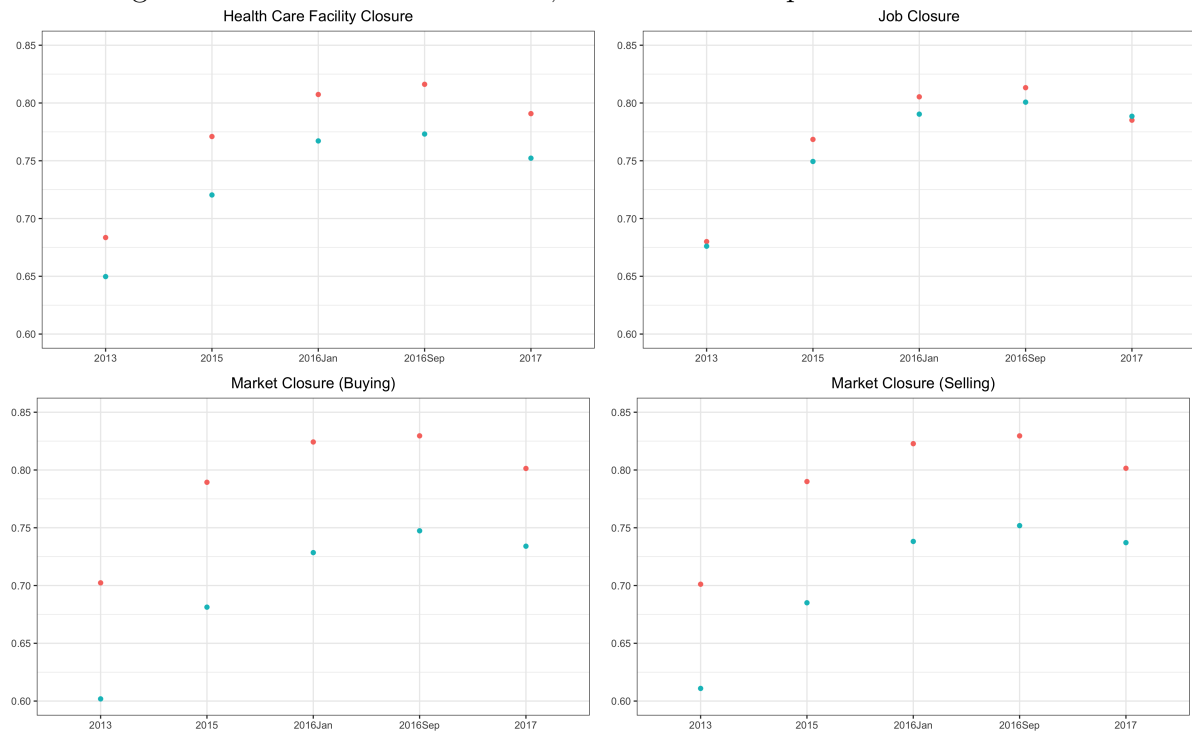
9.2 Other Ebola impact variable DiD Results.

Table 9: DID Regression: Quarantining no Controls

	Dependent variable:			
	enrolled			
	2015	2016Jan	2016Sep	2017
	(1)	(2)	(3)	(4)
quarantine	0.026**	0.026**	0.026**	0.026**
	(0.011)	(0.011)	(0.011)	(0.011)
POST	0.092***	0.133***	0.142***	0.112***
	(0.004)	(0.005)	(0.005)	(0.006)
POST:quarantine	−0.022***	−0.032***	−0.036***	−0.019*
	(0.007)	(0.008)	(0.010)	(0.010)
Constant	0.671***	0.671***	0.671***	0.671***
	(0.006)	(0.006)	(0.006)	(0.006)
Observations	15,642	15,642	15,642	15,642

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

Figure 9: Enrollment Over Time, Other Ebola Exposure Indicators

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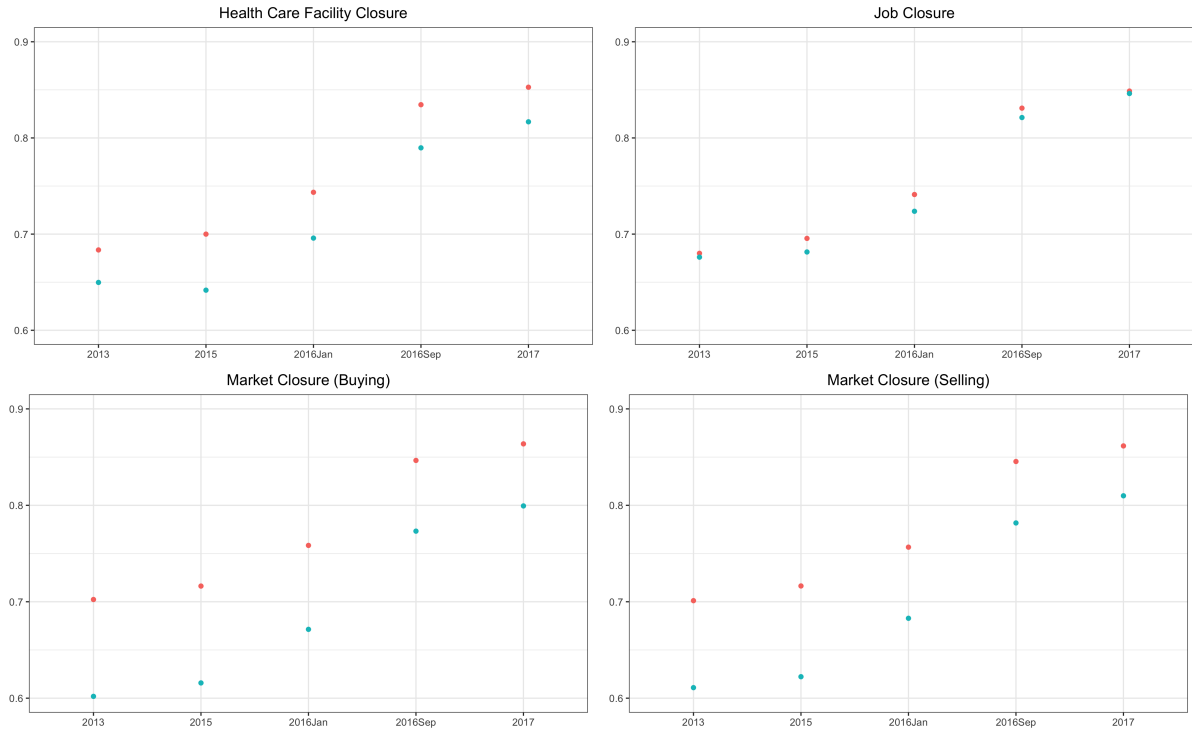
Table 10: DiD Regression: Quarantining with Controls

	Dependent variable:			
	enrolled			
	2015	2016Jan	2016Sep	2017
	(1)	(2)	(3)	(4)
POST	0.465***	0.770***	0.949***	0.981***
	(0.061)	(0.072)	(0.077)	(0.085)
POST : Quarantine	−0.018**	−0.027***	−0.035***	−0.024**
	(0.007)	(0.009)	(0.010)	(0.011)
POST : Female	0.002	0.005	−0.008	−0.008
	(0.007)	(0.008)	(0.008)	(0.009)
POST : Urban	−0.028***	−0.043***	−0.048***	−0.048***
	(0.008)	(0.010)	(0.010)	(0.011)
POST : Has Father	−0.018***	−0.012	−0.006	0.003
	(0.007)	(0.008)	(0.009)	(0.009)
POST : Father Educ	0.003	−0.001	−0.003	−0.007**
	(0.002)	(0.003)	(0.003)	(0.003)
POST : Age	−0.026***	−0.043***	−0.055***	−0.063***
	(0.001)	(0.002)	(0.002)	(0.002)
POST : Log Welfare	−0.011	−0.013	−0.012	−0.001
	(0.007)	(0.008)	(0.009)	(0.010)
POST : Late Region	−0.021*	0.005	−0.015	−0.022
	(0.012)	(0.015)	(0.017)	(0.018)
Observations	15,556	15,556	15,556	15,556

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

Only included POST and POST interactions

Table 11: DiD: All controls and Ebola Vars

	Dependent variable:			
	enrolled			
	2015	2016Jan	2016Sep	2017
	(1)	(2)	(3)	(4)
POST	0.209***	0.316***	0.373***	0.297***
	(0.060)	(0.073)	(0.080)	(0.088)
POST : Quarantine	−0.016*	−0.031***	−0.041***	−0.033**
	(0.009)	(0.011)	(0.012)	(0.013)
POST : Hospital Closure	−0.012	−0.004	−0.013	−0.022
	(0.011)	(0.014)	(0.016)	(0.017)
POST : Job Closure	−0.002	−0.007	−0.008	0.003
	(0.012)	(0.015)	(0.016)	(0.017)
POST : Buy Market Closure	0.019	0.011	0.038*	0.046**
	(0.014)	(0.018)	(0.019)	(0.021)
POST. :Sell Market Closure	−0.018	0.005	−0.009	−0.016
	(0.013)	(0.017)	(0.019)	(0.020)
POST : Female	−0.003	−0.002	−0.017*	−0.018*
	(0.007)	(0.008)	(0.009)	(0.010)
POST : Urban	−0.036***	−0.053***	−0.061***	−0.062***
	(0.008)	(0.010)	(0.012)	(0.013)
POST : Has Father	−0.001	0.016*	0.029***	0.042***
	(0.007)	(0.008)	(0.009)	(0.010)
POST : Father Education	0.004	0.001	−0.001	−0.005
	(0.002)	(0.003)	(0.003)	(0.003)
POST : Log Welfare	−0.015**	−0.020**	−0.021**	−0.011
	(0.007)	(0.009)	(0.010)	(0.011)
POST : Late Region	−0.024*	−0.003	−0.024	−0.033*
	(0.013)	(0.016)	(0.018)	(0.020)
Observations	15,556	15,556	15,556	15,556

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

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Table 12: DiD Regression: Quarantining with Ebola Control Variables

	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

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

Only included POST interactions

Table 13: DiD Regression: Primary Health Facility Closure

	Dependent variable:			
	enrolled			
	2015	2016Jan	2016Sep	2017
	(1)	(2)	(3)	(4)
Hospital Closure	−0.034**	−0.034**	−0.034**	−0.034**
	(0.016)	(0.016)	(0.016)	(0.016)
POST	0.087***	0.124***	0.133***	0.107***
	(0.004)	(0.004)	(0.005)	(0.005)
POST : Hospital Closure	−0.017*	−0.006	−0.009	−0.005
	(0.010)	(0.012)	(0.013)	(0.015)
Constant	0.684***	0.684***	0.684***	0.684***
	(0.006)	(0.006)	(0.006)	(0.006)
Observations	15,642	15,642	15,642	15,642

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

Table 14: DiD Regression: Job Closure

	Dependent variable:			
	enrolled			
	2015	2016Jan	2016Sep	2017
	(1)	(2)	(3)	(4)
Job Closure	−0.004	−0.004	−0.004	−0.004
	(0.013)	(0.013)	(0.013)	(0.013)
POST	0.088***	0.125***	0.133***	0.105***
	(0.004)	(0.005)	(0.005)	(0.006)
POST : Job Closure	−0.015*	−0.011	−0.009	0.007
	(0.008)	(0.010)	(0.011)	(0.012)
Constant	0.680***	0.680***	0.680***	0.680***
	(0.006)	(0.006)	(0.006)	(0.006)
Observations	15,642	15,642	15,642	15,642

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

Table 15: DiD Regression: Market for Buying Closure

	Dependent variable:			
	enrolled			
	2015	2016Jan	2016Sep	2017
	(1)	(2)	(3)	(4)
buy market closure	−0.100***	−0.100***	−0.100***	−0.100***
	(0.013)	(0.013)	(0.013)	(0.013)
POST	0.087***	0.122***	0.127***	0.099***
	(0.004)	(0.005)	(0.005)	(0.006)
POST : Buy Market Closure	−0.008	0.005	0.018*	0.033***
	(0.008)	(0.010)	(0.011)	(0.012)
Constant	0.702***	0.702***	0.702***	0.702***
	(0.006)	(0.006)	(0.006)	(0.006)
Observations	15,642	15,642	15,642	15,642

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

Table 16: DiD Regression: Market for Selling Closure

	Dependent variable:			
	enrolled			
	2015	2016Jan	2016Sep	2017
	(1)	(2)	(3)	(4)
Sell Market Closure	−0.090***	−0.090***	−0.090***	−0.090***
	(0.013)	(0.013)	(0.013)	(0.013)
POST	0.089***	0.122***	0.128***	0.100***
	(0.004)	(0.005)	(0.005)	(0.006)
POST : Sell Market Closure	−0.015*	0.006	0.013	0.026**
	(0.008)	(0.010)	(0.011)	(0.012)
Constant	0.701***	0.701***	0.701***	0.701***
	(0.006)	(0.006)	(0.006)	(0.006)
Observations	15,642	15,642	15,642	15,642

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

9.3 School Cost with Quarantine DiD Regression Results

The cost of schools was defined by section to include the average cost that would be faced to a student not enrolled should he choose to enroll. High cost schools are those in sections where the average cost of schooling is above the 75th percentile of sectional school costs. Table 17 Indicates that those who quarantined at the high cost schools faced worse enrollment in the first year following the pandemic at the 10% significance level; however, this effect was lost in the final three periods.

Table 17: DID School Cost Triple Interaction

	Dependent variable:			
	enrolled			
	2015	2016Jan	2016Sep	2017
	(1)	(2)	(3)	(4)
Quarantine	0.048***	0.048***	0.048***	0.048***
	(0.013)	(0.013)	(0.013)	(0.013)
POST	0.080***	0.127***	0.142***	0.118***
	(0.005)	(0.006)	(0.006)	(0.007)
High Cost	0.112***	0.112***	0.112***	0.112***
	(0.013)	(0.013)	(0.013)	(0.013)
POST : Quarantine	−0.011	−0.028***	−0.036***	−0.023**
	(0.008)	(0.009)	(0.011)	(0.012)
Quarantine : High Cost	−0.040	−0.040	−0.040	−0.040
	(0.028)	(0.028)	(0.028)	(0.028)
POST : High Cost	0.040***	0.019*	−0.001	−0.021
	(0.010)	(0.011)	(0.012)	(0.013)
POST : Quarantine : High Cost	−0.032*	−0.010	−0.0003	0.008
	(0.019)	(0.022)	(0.024)	(0.026)
Constant	0.639***	0.639***	0.639***	0.639***
	(0.008)	(0.008)	(0.008)	(0.008)
Observations	15,642	15,642	15,642	15,642

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

9.4 School Type with Quarantine DiD Regression Results

Here I look into whether the type of school makes a difference in whether quarantining led to lower enrollment. 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. I 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 18 indicates that there were no statistically significant results and that those who quarantined faced lower enrollment across all school types. For reference, quarantine:POST uses local gov't as the baseline and there were 602, 4666, 1764, 749, 7, and 33 students for which the respective schooling types were dominate in their region

Table 18: DID School Type Triple Interaction

	Dependent variable:			
	enrolled			
	2015	2016Jan	2016Sep	2017
	(1)	(2)	(3)	(4)
Quarantine : POST	−0.022	−0.050	−0.014	−0.030
	(0.030)	(0.038)	(0.044)	(0.047)
Quarantine : POST : Central Gov't	0.012	0.029	−0.012	0.019
	(0.032)	(0.040)	(0.046)	(0.049)
Quarantine : POST : Religious	−0.010	0.017	−0.026	0.009
	(0.032)	(0.041)	(0.047)	(0.051)
Quarantine : POST : Community	0.014	0.036	−0.032	0.004
	(0.039)	(0.049)	(0.056)	(0.060)
Quarantine : POST : NGO	−0.178	−0.350	−0.386*	−0.370*
	(0.182)	(0.223)	(0.224)	(0.224)
Quarantine : POST : Private Person	−0.094	−0.219	−0.008	0.046
	(0.069)	(0.223)	(0.288)	(0.288)
Observations	15,642	15,642	15,642	15,642

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

Only included POST:quarantine interactions