A perfect storm: The effect of natural disasters on child health

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Abstract

Typhoons and their accompanying flooding have destructive effects, including an increase in the risk of waterborne disease in children. Using a spatial regression discontinuity design, I explore the immediate to short-term effects of flooding as a result of Typhoon Labuyo on the incidence of diarrhea and acute respiratory infection in the Philippines by comparing children living in a flooded barangay (town) to children living just outside of the flooded area. I build on the existing literature by accounting for both incidence and intensity of the typhoon's flooding in my model. I construct this new flooding measure using programming techniques and ArcGIS by manipulating data collected by the University of Maryland's Global Flood Monitoring System. This data as well as health data from the 2013 Philippines National Demographic Health Surveys were collected the day after Typhoon Labuyo left the Philippines, providing a unique opportunity to explore the immediate impact of the typhoon on child health. Most of my results are insignificant, but subgroup analyses show that the effect of flooding on waterborne disease incidence is less impactful in the immediate term following a flood and more impactful in the medium-term. This is important, because understanding the detrimental health effects of flooding is of utmost importance, especially because climate change will only increase the frequency and intensity of natural disasters.

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1 Introduction

About 40-50 typhoons (also known as hurricanes in North America; all typhoons and hurricanes will be referred to as typhoons hereafter) hit the world each year, bringing floods and fast winds: faster than 74 miles per hour (National Hurricane Center and Central Pacific Hurricane Center, 2021; United States Geological Survey, 2021). In the past 20 years, they have affected about 726 million people and have killed more than 12,000 people worldwide (World Health Organization, 2021a). This statistic is also alarming because over the past 30 years, the proportion of the world's population living near the coast in typhoon-endemic regions has grown almost 200% (World Health Organization, 2021a). In the western Pacific region of the world, typhoons are especially impactful as tropical storms are endemic to the region. The Philippines is particularly vulnerable to typhoons due to its location at the center of the Ring of Fire, an area in the Pacific Ocean in which 75% of typhoons originate (Commission on Audit, 2014). The Philippines is hit by about 20-30 typhoons each year, one-fourth of these with winds faster than 124 miles per hour (Commission on Audit, 2014). These disasters will only worsen with time, as the incidence and severity of typhoons are expected to increase with rising global surface temperatures (United States Geological Survey, 2021).

From a health perspective, typhoons have both short- and long-term effects, primarily due to the heavy flooding that occurs during the typhoon and in the subsequent weeks and months following the event (Waddell et al., 2021). One such short-term effect is waterborne disease incidence. Over 95% of cases of waterborne disease can be avoided through simple investments in sanitation and access to clean water, yet these diseases continue to be a leading cause of morbidity (incidence) and mortality (death), especially for children. Since 2001, over 3.4 million people die from a waterborne disease globally, and about 4,000 children die per day from these preventable diseases (World Health Organization, 2021a). In the Philippines, acute respiratory infection (ARI) and diarrhea are the first- and second-leading cause of death among children (14.3 and 8.5 cases per 1,000 children) (Baltazar et al., 2002).

Floodwater is often contaminated by raw sewage and in turn, floodwater often contaminates food and clean water. Thus, consumption of contaminated food and water increases the likelihood of children contracting a waterborne disease. This is especially concerning for children whose water comes from a non-piped source, because these sources are particularly susceptible to contamination. Children residing in developing countries like the Philippines are especially vulnerable, as poor drainage and substandard sanitation facilities increase the risk of exposure to waterborne disease pathogens.

To better understand the effect of flooding on child health, I will explore the immediate-term impacts of flooding as a result of Typhoon Labuyo, a typhoon that hit the Philippines on August 12, 2013. By estimating the causal impact of flooding in the Philippines on waterborne disease incidence, I add to the existing literature on the human impacts of climate change. I do this using satellite-based flooding data from the University of Maryland's NASA-funded Global Flood Monitoring System (GFMS), which measures both intensity of flooding and incidence of flooding accurate to the 1/8th degree of latitude and longitude and the 2013 Philippine National Demographic and Health Survey (NDHS). Both datasets are at the town (barangay) level (the smallest geographical unit in the Philippines) and collect data the day after the typhoon hit (Philippine Statistics Authority (PSA) [Philippines] & ICF International, 2014; University of Maryland, 2018). By studying the impact of flooding on one of the most vulnerable countries, this impact will provide insight on countries with a high probability of facing multiple natural disasters each year.

2 Literature Review

The link between the effect of flooding on disease incidence is well established (Sajid & Bevis, 2021; Yonson, 2018). Sajid and Bevis (2021) explores the causal impact of flood exposure on child health in Pakistan from 2003-2017. The authors use flood maps collected by NASA's Terra and Aqua satellites to create the first satellite-based measure of flooding with a spatial resolution of 250 meters (about 0.16 mile). Previous studies had used rainfall or self-reported measures of flooding as a proxy for flood exposure. Sajid and Bevis use data from the 2006-2007, 2012-2013, and 2017-2018 Pakistan NDHS to examine two channels of the effect of flooding on child health: the communicable disease pathway and the agricultural pathway. For the first pathway, they argue that flooding negatively impacts child health through incidence of waterborne illness. For the latter pathway, they argue that floodwater improves the fertility of arable land, though flooding may worsen the land and destroy existing crops if sufficiently intense. Thus, the quantity and quality of food may increase or decrease depending on the severity of a flood, and therefore flooding may positively or negatively impact child dietary health generally. The authors find that incidence of diarrhea increases with flooding at the 1% confidence level when a flood event takes place more than 3 months after the flood season and at the 5% confidence level when a flood event takes place within 1-3 months after the flood season. They also find that the quantity of food consumed (measured using meal frequency) increases with flooding at the 5% level when a flood event takes place more than 3 months after the flood season. Results from both the disease and agricultural pathways are insignificant when a flood event takes place during the flood season. However, these insignificant results may have been driven by the fact that the authors' flood measure only measured incidence of flooding, without accounting for intensity of flooding.

In a case study of Cagayan de Oro City in the Philippines, Yonson (2018) explores the effect of flooding as a result of Tropical Storm Washi in 2011 on disease incidence. The author also studies the effect of flooding on economic outcomes, but only for individuals residing in urban households. In children under 5, the relationship between exposure to a flood and incidences of diarrheal disease was insignificant. This insignificant result may have been driven becuase of the focus on urban households. In contrast to urban households, it is likely that rural households obtain their water from a non-piped source. Children living in rural areas may therefore be more sensitive to floods in terms of contracting diarrhea. Additionally, because the author examines the effects of a tropical storm in the Philippines, there is still an opportunity to explore other more severe (yet still prevalent) tropical cyclones such as typhoons and their effect on incidences of diarrhea in children.

A growing body of literature has focused on the causal impact of flood exposure on child health relating to rare natural events (Rosales-Rueda, 2018). Rosales-Rueda (2018) explores the effect of flooding as a result of the 1997-1998 El Niño, a natural disaster event associated with heavy rainfall and severe flooding in South America, on low-income children's health and human capital outcomes in Ecuador. By treating El Niño as a natural experiment and exploiting variation in the number of months a child in utero is exposed to flooding, she finds that children exposed to severe floods in utero are shorter in stature five and seven years later at the 5% confidence level and have lower test scores on cognitive exams at the 10% confidence level. There is room to explore the effects of other natural disasters on child health, particularly with respect to disease.

The link between access to protected water sources and waterborne disease incidence is also well established (Capuno, Tan, & Fabella, 2015). Capuno, Tan, and Fabella (2015) use propensity score matching on observables to measure the impact of access to piped water on incidence of child (under 5 years old) diarrhea in rural households using data from the 1993, 1998, 2003, and 2008 Philippine NDHS. The authors run separate regressions for each of the four surveys. However, their results are only significant for the 2008 survey. Additionally, because the children in the study are balanced on observables, there is still a chance that children in the control and treatment group are not balanced on unobservable characteristics, potentially resulting in selection bias.

I contribute to the literature of natural disasters and child health by exploring the effect of flooding (as a result of a typhoon) on child waterborne disease incidence. Typhoons are not only more destructive and intense than higher-than-average rainfall or El Niño, but they also sustain the length of time a flood persists in an area because they often destroy existing infrastructure. Additionally, because the 2013 Philippine NDHS started its interviewing process immediately after Typhoon Labuyo left the Philippines (August 12, 2013) and my measure for flooding captures the amount of flooding experienced 30 minutes after Typhoon Labuyo left the Philippines, I am able to precisely measure both the incidence and intensity of flooding experienced by children at the barangay level. Thus, Typhoon Labuyo hitting the Philippines provides me a unique opportunity to examine a natural experiment.

3 Setting and Context

3.1 The Philippines

Like many developing countries, poor health is inextricably linked with poverty in the Philippines. Illnesses and deaths from waterborne disease impact the most vulnerable: incidence of waterborne disease severely affects infants and children under 5 years old (Philippines Department of Health, 2019). Acute respiratory infection (ARI) and diarrhea are the first- and second-leading cause of death among children (14.3 and 8.5 cases per 1,000 children) (Baltazar et al., 2002). Moreover, diarrhea accounts for 9% of the total deaths among children below 5 years old (Philippines Department of Health, 2019).

The Philippines is especially vulnerable to natural disasters, particularly typhoons (and the floods that accompany them) due its location in the center of the Pacific Typhoon Belt. This is an area in the western Pacific Ocean where 75% of the world's typhoons form. Typhoons and flooding comprised 80% of the natural disasters in the Philippines in the past 50 years (CFE-DM, 2018). These disasters occur frequently: about 20 typhoons make landfall in the Philippines each year, more than anywhere else in the world (PAGASA, 2022). Flooding occurs most frequently from July through October (peak typhoon season), and 70% of all the typhoons that hit the Philippines develop during this period (PAGASA, 2022). Typhoons also occur with great intensity: damages from the typhoon season cost 4% of the country's real annual gross domestic product on average (National Disaster Risk Reduction and Management Center, 2013). Quantifying the impact of flooding in the Philippines will give insight into the effect of flooding on child health in countries most vulnerable to flooding along the Pacific Typhoon Belt.

The Philippine is divided into 17 administrative regions, 81 provinces; 167 cities, 1,495 municipalities and 42,008 barangays (towns) (Philippines Department of Health, 2019). This analysis is conducted at the barangay level, the smallest geographical and governmental unit in the Philippines.

3.2 Typhoon Labuyo

The specific flooding incident I examine is Typhoon Labuyo: the first Category 4 super typhoon (winds of between 130-156 miles per hour) of the 2013 typhoon season (Riebeek, 2013). Typhoon Labuyo made landfall on August 11, 2013 at approximately 1900 UTC and left on August 12, 2013 at approximately 1430 UTC (Riebeek, 2013). See Figure 1 for a more detailed storm track map. The Philippine Atmospheric, Geophysical and Astronomical Services Administration (PAGASA), the government agency responsible for informing and protecting citizens from natural disasters, first categorized Typhoon Labuyo as a typhoon on August 10, 2013 at 1500 UTC, just over 24 hours before the typhoon hit the Philippines (Rappler.com, 2013). While this may or may not be a sufficient amount of time for a household to evacuate, government reports after Typhoon Labuyo left the Philippines state that households were only evacuated once the typhoon had already made landfall; that is, no households were evacuated in anticipation of the typhoon (National Disaster Risk Reduction and Management Center, 2013). Thus, Typhoon Labuyo can be treated as an unexpected event.

The total cost of damages amounted to ₱932,338,896 ($19,212,092) (National Disaster Risk Reduction and Management Center, 2013). One advantage of this setting is that while Typhoon Labuyo was damaging, very few flood-related deaths occurred: there were 8 causalities, many of whom were middle aged and none of whom were children 2-4 years old. Additionally, deaths were spread across municipalities, further reducing concern for potential survivorship bias in the estimate.

281,686 families were affected in 569 barangays of Regions I, II, III, V, and the Cordillera Administrative Region (CAR) (National Disaster Risk Reduction and Management Center, 2013). Many individuals faced home damage and persistent flooding throughout the length of Typhoon Labuyo. Another advantage of this setting is that more generally, typhoons most frequently hit the northern regions of the country, making this setting appropriate in studying the area most subject to flooding (Warren, 2014).

4 Econometric Specification

4.1 Logistic model

A logistic model of the effect of flooding on child waterborne disease incidence is specified below:

$$y_i = \beta_0 + \beta_1 flood_i + \beta_2 days_i + \beta_3 days_i^2 + \beta_4 X_i + \varepsilon_i$$

In this equation, y_i is an indicator for whether a child i contracted diarrhea or ARI. $flood_i$ is a continuous measure of the flooding a child experiences, ranging from 0 to 325.1459 millimeters above the average water level over 13 years. X_i is a vector of child-, mother-, and household-level control variables used in the summary statistics table (excluding diarrhea and ARI, see Tables 3a and 3b). $days_i$ is number of days between the child's survey date and the date of the typhoon, ranging from 0 to 49, and $days_i^2$ is days squared. $days_i$ and $days_i^2$ are included in the model because it is likely that the risk of contracting a waterborne disease will peak at a certain point, particularly when there has been standing water for some time. Moreover, the later the child is surveyed, the more likely floodwater will have dispersed and less likely he/she will be at risk for contracting a waterborne disease. Dummy variables for each child age (0-4) are included in the model rather than a continuous measure of age, as disease incidence is likely to differ greatly by age of child, falling steadily with age.

Standard errors are clustered at the barangay level. I do not consider barangay fixed effects as the unit of observation for flooding is at the barangay level.

The coefficient on $flood_i$ measures the difference in the log odds of y_i that a child will contract a waterborne disease between children living in areas exposed and not exposed to flooding. Children exposed to flooding will be more likely to contract a waterborne disease than children who were not because the floodwater itself may be contaminated with raw sewage and other pollutants, and the floodwater may contaminate existing sources of water that children consume.

Though Typhoon Labuyo can be regarded as a natural experiment, the logistic model does not solve the problem of endogeneity. For example, it is possible that the logistic model is not accounting for omitted variable bias, and some variable is separately affecting both flooding and disease (such as quality of drainage systems in a barangay). This issue necessitates a model that can address this bias.

4.2 Spatial Regression Discontinuity Design

4.2.1 Background and Motivation

The spatial regression discontinuity design measures the impact of flooding on incidence of waterborne disease by comparing children exposed to flooding to children who are not exposed to flooding but live just outside of a flooded area[1]. For children living in households that are near a flooded area but do not experience flooding, they do not get exposed to flooding and will therefore have a lower chance of contracting a waterborne disease than children living in the nearby flooded area. Because households did not anticipate exposure to Typhoon Labuyo's flooding, the probability that a child lives in a flooded or nonflooded area is approximately the same. Consequently, these children can be regarded as identical, balanced in observables and unobservables or "statistically exchangable" because they live

[1] A similar specification was used by Melissa Dell to compare outcomes between indigenous communities in Peru across a border (Dell, 2010).

very near to one another. By assuming that children who experience and who do not experience flooding are the same except for their place of residence (and therefore its proximity to a flooded area), the only difference between these children is exposure to flooding. Additionally, by assuming that the only change occurring at the "flood border", or the contour separating a flooded area from a nonflooded area, is exposure or no exposure to flooding, flooding is not endogenous to some other simultaneously occurring event. Thus, I can compare incidence of waterborne disease among children living in flooded areas and children just outside the flood border to identify the causal effect of flooding on incidence of waterborne disease. I expect there to be a discontinuous jump right at the border because flooding (as defined in my dataset) takes into account streamflow and inundation levels, so flooded areas are well-defined (University of Maryland, 2018). This model addresses the aforementioned endogeneity issue because children exposed or not exposed to flooding are assumed to be the same in terms of baseline characteristics.

4.2.2 Linear Specification

My main specification is a local linear regression under a sharp spatial regression discontinuity design. While a logistic regression is typically used when the outcome variable is binary, traditional regression discontinuity designs and spatial regression discontinuity designs use the local linear regression as the standard in the literature, in part because of their interpretability (Lee & Lemieux, 2010). However, I later discuss the local logistic regression and present results from this specification in the appendix. The linear specification is presented below:

$$y_i = \beta_0 + \beta_1 distance_i + \beta_2 flood_i + \beta_3 distance_i * flood_i + \beta_4 days_i + \beta_5 days_i^2 + \beta_6 X_i + \varepsilon_i$$

In this equation, y_i is an indicator for whether a child i contracted diarrhea or ARI. $distance_i$ is a continuous measure of the distance a child lives from a flood border (negative if a child lives in a nonflooded area and positive if a child lives in a flooded area). I choose a linear specification because it is likely that incidence of waterborne disease increases the closer a child not exposed to flooding lives to the flood border and also increases (albeit less) the farther a child exposed to flooding lives from a nonflooded area. $flood_i$ is either a dummy indicating if a child lived in a barangay that experienced flooding in millimeters. X_i is a vector of child-, mother-, and household-level control variables used in the summary statistics table (excluding diarrhea and ARI, see Table 3a and 3b). $days_i$ is the number of days between the child's survey date and the date of the typhoon and $days_i^2$ is days squared. Standard errors are clustered at the barangay level. I use a threshold of 10.371 miles (diarrhea) or 7.777 miles (ARI) from a flooded border, which is calculated using a bandwidth selector developed by Calonico, Cattaneo, and Titiunik for a sharp regression discontinuity design (Calonico et al., 2014)[2].

The coefficient on $flood_i$ (β_2) measures the additional impact of flooding on the average likelihood a child will contract a waterborne disease between children living in areas exposed and not exposed to flooding, or the discontinuity. The coefficient on $distance_i$ (β_1) measures the effect of distance or proximity from a flood border on the likelihood a child will contract a waterborne disease. The coefficent on $distance_i * flood_i$ (β_3) measures the additional effect of distance from a flood border on the likelihood a child contracts a waterborne disease conditional on a child living in a flooded area.

I expect that β_2 will be positive because it is likely that there will be a jump in the likelihood of contracting a waterborne disease once a child lives in a flooded area. I expect that β_1 will be positive, as it is likely that for children living in a nonflooded area, as the distance from a flood border becomes less negative (i.e., a child lives closer to the flood border, when $distance_i = 0$), the likelihood that a child will be exposed to flooding and therefore the likelihood the child will contract a waterborne disease increases. At the same time, for children living in a flooded area, as the distance from a flood border increases (i.e., the farther a child lives away from a nonflooded area), it is likely that they will be deeper in

[2] This method builds on previous methods of finding mean squared error-optimal bandwidth choices for the regression discontinuity point estimator) by accounting for asymptotic bias, improving the probability that an estimator is close to its "true value".

a flood zone, and thus the likelihood the child will contract a waterborne disease increases. Last, I expect that β_3 will be positive because the deeper a child lives in a flooded area, the more likely he/she will be exposed to more severe flooding and contract a waterborne disease.

See Figure 3a for a graphical representation of this model and the discontinuity.

4.2.3 Logistic Specification

My secondary specification is a local logit regression under a sharp spatial regression discontinuity design[3], described below:

$$\Lambda(y_i) = \frac{e^{\beta_0+\beta_1 distance_i+\beta_2 flood_i+\beta_3 distance_i * flood_i}}{1+e^{\beta_0+\beta_1 distance_i+\beta_2 flood_i+\beta_3 distance_i * flood_i}}$$

The equation showing changes above and below the flooded border ($distance_i = 0$) is shown below:

$$\Lambda(y_i) = \begin{cases} \dfrac{e^{\beta_0+\beta_1 distance_i}}{1+e^{\beta_0+\beta_1 distance_i}} & \text{if } distance_i < 0 \\[2ex] \dfrac{e^{\beta_0+\beta_1 distance_i+\beta_2+\beta_3 distance_i}}{1+e^{\beta_0+\beta_1 distance_i+\beta_2+\beta_3 distance_i}} & \text{if } distance_i > 0 \end{cases}$$

The coefficient on $flood_i$ (β_2) measures the difference in the log odds of y_i that a child will contract a waterborne disease between children living in areas exposed and not exposed to flooding and factors into the estimate of the "discontinuity". The coefficient on $distance_i$ (β_1) measures the effect of distance from a flood border on the log odds of y_i that a child will contract a waterborne disease. The coefficent on $distance_i * flood_i$ (β_3) measures the additional effect of distance from a flood border on the log odds of y_i conditional on a child living in a flooded area.

See Figure 3b for a graphical representation of this model and the discontinuity.

[3] Outlined in Wooldridge's *Econometric Analysis of Cross Section and Panel Data* (Wooldridge, 2011).

4.2.4 Strengths and Limitations

The spatial regression discontinuity design addresses the endogeneity problem found in the simple logit model by taking omitted variable bias into account. By considering children living within some narrow bandwidth of a flood zone, the two groups of comparison are virtually identical except for exposure to flooding (exchangability assumption). Because we assume that children could not have responded in expectation of Typhoon Labuyo by moving to a nonflooded area, "assignment" to a flooded or nonflooded area is (locally) randomized (behavioral assumption). Additionally, we assume that any discontinuity in the probability of contracting a waterborne disease is only a result of flooding (continuity assumption). Thus, we can treat Typhoon Labuyo as a randomized experiment, estimating the effect of flooding on child waterborne disease incidence by exploiting variation in the distance a child lives from a flooded area, as these children are likely to have similar characteristics. The spatial regression discontinuity design's ability to control for confounding factors makes it a significant improvement in identification compared to the logit model.

Having said that, the spatial regression discontinuity design is limited in its generalizability because it only considers children living within some threshold of a flood border, so any effect of flooding is inherently a local one. Thus, this design can say little about children living far from the flood border. This is particularly important for the children living in a flooded area but far away from the flood border, as they are likely to experience the most severe effects of flooding. It is probable that the local effect of flooding on health underestimates the general effect, and at worst, the local effect of flooding on health can be quite different from the general population. Additionally, the design is only as good as we are able to observe the distance a child lives from a flood border. We are only able to observe the location of children at the barangay level, not at the household level.

4.2.5 Validating the Design

The three assumptions I make in this design are the continuity, exchangability, and behavioral assumption. Both the exchangability and behavioral assumptions are implied if the continuity assumption holds, so this design can be validated if support for the continuity assumption is reasonable.

The continuity assumption states that absent any flooding, incidence of waterborne disease would be a smooth function of distance. In other words, there does not exist any discontinuity or jump at the flood border other than flooding. Omitted variable bias can therefore be ruled out at the flood border. Generally, it is unlikely that the continuity assumption would not hold in this setting because "assignment" to a flooded or nonflooded barangay is determined by the typhoon.

One possible violation of this assumption is if a child lives in a household that is a beneficiary of Pantawid Pamilyang Pilipino Program (4Ps), a conditional cash transfer program in the Philippines that aims to support poor families in an effort to escape the poverty trap by promoting health, nutrition, and education (Department of Social Welfare and Development, 2021). Families who are within 110% of their provincial poverty threshold and have at least one child or a pregnant member of their household qualify to receive 4Ps. In addition to receiving a cash grant, families also receive nutrition counseling, access to services at health centers to manage childhood diseases, and disaster preparedness counseling (Department of Social Welfare and Development, 2021). Families who are beneficiaries of 4Ps might have responded to warnings about Typhoon Labuyo differently from nonbeneficiaries. This is an issue if there is some overlap between children living in households that qualify for 4Ps and children living in nonflooded areas, because if nonflooded households have generally better health habits, the discontinuity between children living in nonflooded and flooded areas may be attributed to participation in 4Ps, rather than exposure to flooding. Therefore, the estimate of the discontinuity between children living in nonflooded and flooded areas would overestimate the true effect of flooding on the probability a child would contract a waterborne disease.

Cattaneo et al. (2019) create a test to check for possible manipulation at a cutoff by examining the density distribution of the running variable (i.e., $distance_i$), and look for a discontinuity in the density function on either side of the cutoff absent of the treatment ($flooding_i$). The ideal scenario is that there is an equal distribution of children above and below the cutoff ($distance_i = 0$). Figure 4a shows the density tests for both diarrhea (10.371 mile threshold) and ARI (7.777 mile) using the method of Cattaneo et al. For diarrhea, the difference in estimated densities at the flood border is -2.3014 with a p-value of 0.0214. For ARI, the difference in estimated densities at the the flood border is -1.4097 with a p-value of 0.1586. Further, Figure 4b shows the distribution of $distance_i$ in a histogram. Overall, these tests reveal that the distribution of children living in barangays skews to the right, implying that more children that are within some threshold of the flood border live in flooded areas. However, this may be less of a concern because even though there are some barangays who were not exposed to flooding as a result of the typhoon, it is more likely that more barangays would be flooded rather than not, especially given that Typhoon Labuyo was a super typhoon.

Additionally, I check for balance across children living in flooded and nonflooded areas, Tables 5a and 5b report summary statistics at the corresponding thresholds for diarrhea and ARI for various child, mother, household, and socioeconomic indicators using the 2013 Philippine NDHS data. It compares children who were living in barangays that experienced (or did not experience) flooding. For the threshold for diarrhea (Table 5a), children living in flooded areas were no more likely to contract diarrhea than children that were not exposed to the flood. Additionally, children living in flooded areas have older mothers, are welathier, are more rural, and have greater access to electricity at the 1-5% significance level. For the threshold for ARI (Table 5b), children living in flooded areas were less likely than children living in nonflooded areas to contract ARI at the 5% significance level. Comparisons across children show that children living in flooded areas were wealthier, had more access to electricity, and additionally have fewer children living in their household at the 1-5% significance level. Overall, children in flooded areas were well-off on average compared to children living in nonflooded areas.

5 Data and Measurement

5.1 Flooding Data

I match latitude and longitude data from the Philippine Statistics Authority to flood detection/intensity estimates from the University of Maryland's NASA-funded Global Flood Monitoring System (GFMS) (University of Maryland, 2018). This system contains information on flood detection/intensity estimates, collected during NASA's Tropical Rainfall Measuring Mission. These estimates are based on real-time precipitation sensors measured via satellite and processed by NASA's Multi-satellite Precipitation Analysis algorithm. The data reflect the amount of flooding at 1 km resolution, with precision to the 1/8th (0.125) degree of latitude and longitude.

Flooding intensity is defined as the depth in millimeters of the surface water above the flood threshold over 13 years. The flood threshold is the 95th percentile value in the distribution of water after identifying the natural surface water in an area over 13 years (i.e., 95% of the time, the level of water is below that value) (University of Maryland, 2018). Additionally, the flood threshold has to be above 3 millimeters and flooding is identified as being a minimum of 10 millimeters above the flood threshold. This is so that small absolute levels of water above the normal amount are not counted as flooding even though these levels may be large relative to the typical levels of water in the area. From these data, I create a visualization of global flooding experienced on August 12, 2013 at 1500 UTC (30 minutes after Typhoon Labuyo left the Philippines) (see Figure 2a and 2b).

To construct my flooding measure, I first assign latitude and longitude values to every child's barangay in the Philippine NDHS. I create a location ID for each barangay in accordance with the Unified Accounts Code Structure (UACS), the Philippine government's official location classification system (Unified Accounts Code Structure, 2014a). I then identify each barangay's name by its UACS code (UACS data) and assign to it a latitude and longitude value (at the barangay's centroid, the representative center) in decimal coordinate form (PhilAtlas, 2022).

After assigning a latitude and longitude to each barangay, I match the University of Maryland's flooding data to each barangay. The data report the amount of flooding for each pixel (a distance of approximately 8 by 8 miles). I assign an upper and a lower latitude and an upper and a lower longitude to each pixel to establish decimal coordinate boundaries for a given pixel. This information is then matched to the latitude and longitude of each barangay in the Philippine NDHS. Last, I assign the amount (in millimeters) of flooding experienced to each barangay based on its corresponding pixel value to create my flooding measure, variable *flood*.

5.2 Distance Data

To construct my distance measure, I plot each pixel of flooding using the latitude and longitude data mentioned prior in ArcGIS Pro and find the distance from each barangay centroid to the nearest flood border. Figure 6 shows visualizations of this process. The top image shows a plot of a set of barangays and their corresponding centroids. I use an algorithm on ArcGIS to calculate the shortest geodesic distance (the distance along the curved surface of the Earth) from each centroid to a flooded area. This process is slightly different for barangays that are flooded versus nonflooded. The bottom two pictures show this process. For a barangay that is not flooded (i.e., A), I calculate the shortest distance from its centroid to the nearest flooded area (solid pattern). For a barangay that is flooded (i.e., B), I calcuate the shortest distance from its centroid to the nearest nonflooded area (striped pattern). This effectively determines each barangay's distance to the nearest flood border.

I then match the ArcGIS barangay data to every observation in the NDHS data, assigning *distance* to each child. If a child is living in a nonflooded barangay, his/her corresponding distance value is negative. If a child is living in a flooded barangay, his/her corresponding distance value is positive so that the cutoff occurs when distance is 0 (at the flood border), in accordance with the literature (Lee & Lemieux, 2010).

5.3 Health Data

Data relating to child health come from the 2013 Philippine NDHS and was collected from August 12, 2013 to September 24, 2013 (Philippine Statistics Authority (PSA) [Philippines] & ICF International, 2014a). This cross-sectional survey is designed to assess the demographic and health status of the Philippines, so it contains rich data from all barangays in the country. Information at the barangay level allows me to directly compare child health differences in flooded and nonflooded barangays. The Philippine NDHS is suited to analysis of child health because it is collected at the household level, providing substantial information on demographic information of mothers and their children, child health, and maternal health. Households were sampled through a stratified two-stage sample design: using systematic random sampling, 800 enumeration areas were selected (distributed by region and urban/rural residence) and 20 housing units were selected from each enumeration area. The survey covered a national sample of about 13,000 households and 14,000 women 15 to 49 years old. In this study, I use two measures of child health: incidence of diarrhea and incidence of acute respiratory illness (common waterborne diseases contracted after a flood event) within the last two weeks of being interviewed. I do not consider children who are not living (the cause and time of death is unspecified) and children who were interviewed less than two weeks after Typhoon Labuyo hit.[4].

[4]More detailed code of the specific methodologies to construct these variables can be found on the author's GitHub. Link: `https://github.com/cheyennedq/typhoon_health_PH`

6 Results

6.1 Logit Results

Table 7 reports the results of the logit model for diarrhea and ARI.

The coefficient on $flooding_i$ is insignificant for all of the equations. However, the coefficients on the controls that are significant align with the literature and with what we would expect. In equations 2 and 3, the estimates for 3- and 4-year olds are negative and significant at the 1-10% level, respectively. This implies that when a child is 3 years old, the odds of incidence of diarrhea decreases by a factor of 0.558 ($e^{-0.5833}$), and for 4-year olds, the odds of incidence of diarrhea decreases by a factor of 0.262 ($e^{-1.3384}$). This is aligned with the literature previously mentioned: disease incidence falls with age, and young children are especially vulnerable to disease. To note, the range in the age of children for this data is 0-4 years, so I am limited to exploring the relationship between diarrhea and age for this subset of children.

In equation 3, the coefficient on household type is positive and significant at the 10% significance level, implying that living in a rural area increases the odds of diarrhea by a factor of 1.520 ($e^{0.4186}$). This coefficient is only significant in the model with clustered standard errors, which is reasonable because living in a rural or urban area may be correlated within barangays but independent across barangays.

In equations 5 and 6, the coefficient on sex of child (i.e., if a child is female or not) is significant at the 5% significance level. Interestingly, this implies that the odds that girls contract ARI are significantly less than the odds compared to boys (or the odds for girls decrease by a factor of 0.508 ($e^{-0.6768}$).

Additionally, in equation 4, the estimate for 1-year olds is positive and significant at the 10% significance level, implying that when a child is 1, the odds of incidence of ARI increases by a factor of 2.049 ($e^{0.7172}$), which is again aligned with the literature. Further, in this equation, the coefficient for wealth is negative and significant at the 10% significance level, implying that as a child's household increases in quintile, the odds of contracting ARI decrease by a factor of 0.761 ($e^{-0.2730}$).

The estimates for $flooding_i$ for all equations are also insignificant for the OLS model (see Appendix Table A). For the variables that are significant, there is a simliar relationship as in the logit model. More of the estimates for 1-year olds are significant and positive. There is also a significant negative relationship between access to protected water and incidence of disease, which is coherent because protected water sources decrease the likelihood of contamination and thus reduce exposure to fecal consumption.

6.2 Spatial Regression Discontinuity Design Results

Table 8 reports the results of the spatial regression discontinuity design for diarrhea and ARI.

The main estimate of interest (the coefficient on $flooding_i$) is insignificant for all of the equations. However, for diarrhea (equations 1-3), the estimates for the interaction of flooding and distance are positive and significant. In equation 1, the estimate on the interaction term is 0.0152 and significant at the 5% significance level., implying that children living in flooded areas experience an additional 1.52 percentage point increase (24.01%) in the likelihood of contracting diarrhea. For equations 2 and 3, the estimate is significant at the 1-5% significance level, and children experience an additional 1.78 percentage point increase (5.38%) in the likelihood of contracting diarrhea.

Additionally, for equations 2 and 3, the coefficient on water source is negative and signficant at the 1-10% significance level, implying that children who have access to protected water sources experience a 1.78 percentage point decrease (35.43%) in the likelihood of contracting diarrhea, which is in alignment with the literature.

For ARI, the coefficients on the interaction term are negative and significant for equations 4-6. In equation 4, the estimate on the interaction term is 0.0177 and significant at the 10% significance level., implying that children living in flooded areas experience an additional

1.77 percentage point decrease (16.75%) in the likelihood of contracting ARI. For equations 5 and 6, the estimate is significant at the 10% significance level, and children experience an additional 1.84 percentage point decrease (37.70%) in the likelihood of contracting ARI. This relationship is the opposite relationship observed for diarrhea. This may be because if a child lives deeper in a flood zone, the effect of distance (or proximity away from a flood border) may have less of an effect on incidence of ARI.

In equations 5 and 6, the coefficient on sex of child (i.e., if a child is female or not) is significant at the 5% significance level. Again, this implies that the likelihood that girls contract ARI is significantly less than boys. This brings up the question of gender differences in disease incidence, a potential area to explore in future work. Last, for equation 6, the coefficient on participation in 4Ps is negative and significant at the 5% significance level, which is in alignment with my previous predictions.

The estimates for $flooding_i$ for all equations are also insignificant for the local logit regression model (see Appendix Table B). The contrasting relationship between the coefficients on the interaction term for diarrhea versus ARI is also observed. For the variables that are significant, there is a simliar relationship as in the logit model. More of the participation in 4Ps are significant and negative. There is also a significant positive relationship between access to protected water and incidence of disease.

7 Discussion

Overall, my main results were not significant. This may be because of a variety of factors. To start, the thresholds of 10.731 and 7.777 miles are around the same size as the resolution of my flood measure (8 miles). Thus, there is only so much precision that I have in detecting an effect. This is one of the challenges of using a spatial design because it relies on the precision of the satellite data. While the University of Maryland's NASA data is one of the best sources for this information, there is limited precision that the satellite has. Thus, to improve this analysis, it requires better satellite data or survey data on the ground that reports flood levels at the barangay level.

Additionally, my measure of distance may have some imprecision because I used the shortest distance to the nearest flood border. However, we can imagine a scenario where a child lives in a barangay surrounded by many flooded areas. For this scenario, a child is probably more likely to experience more intense flooding, but my measure does not differentiate between this hypothetical child and another child who lives the same distance from a flooded border but is not around more flooded areas. Additionally, because the traditional spatial model requires flooding to be binary, I do not consider intensity of flooding in my design.

An external factor not considered in this model is evacuation. Households may have responded in anticipation to the flood by evacuating to a nonflood area and thus, did not experience flooding though they live in a flooded area. As mentioned earlier, though, government reports do not show that households evacuated until the typhoon hit.

Last, I only consider time trends by controlling for the number of days between a child's survey date and when Typhoon Labuyo hit. However, ideally I would want to examine the effect of flooding on child health at once instance of time. Additionally, it is possible that the relationship between flooding and waterborne disease incidence is less prominent during the immediate period following a flood. Thus, the effect of flooding might take longer to see and the relationship between flooding and waterborne disease incidence may be more impactful in the medium term following a flood. Figures 9a and 9b show a subgroup analysis, comparing samples of children who were surveyed 2-4 weeks after a flood (short-term) and children who were surveyed more than 4 weeks after a flood (medium-term). I use time thresholds defined in the medical literature (Joshi et al., 2011).

For diarrhea, we see that the main coefficients of interest are insignificant for the short-term and are signifcant at the 0.1-10% significance level for the medium-term.

8 Conclusion

My study builds on the existing literature of the effects of climate change on human outcomes by examining the effect of flooding as a result of natural disasters on child health. By using a spatial regression discontinuity design, my analysis exploits variation in the distance from a flooded area to where a child lives to substantiate the claim that flooding (as a result of a natural disaster event) increases incidence of waterborne disease. Though my results are insignificant, I find signficance when conducting subgroup analyses by days after the flood. I also contribute a previously unused data source in the literature: the University of Maryland's Global Flood Monitoring System, which measures both incidence and intensity of flooding. I document new methods for future researchers to access and manipulate this data, as it is contained on a rather difficult to process format. I identify the relationship between flooding and child incidence of waterborne disease through 3 models: an OLS, logit, and spatial regression discontinuity design.

These results are especially important given the rise of natural disasters, including typhoons, around the world as weather patterns change. For countries like the Philippines that are especially vulnerable to natural disaster events, these effects can be devastating on both children and individuals in general. The development of models that explore different ways to define distance from a flooded area is a particularly central area for future research, as well as gender differences in contracting disease.

Appendix

Figure 1: NASA visualization of the accumulated rainfall in the Philippines on August 12, 2013 at 1500 UTC, 30 minutes after Typhoon Labuyo left the Philippines (NASA's Goddard Space Flight Center, 2013)

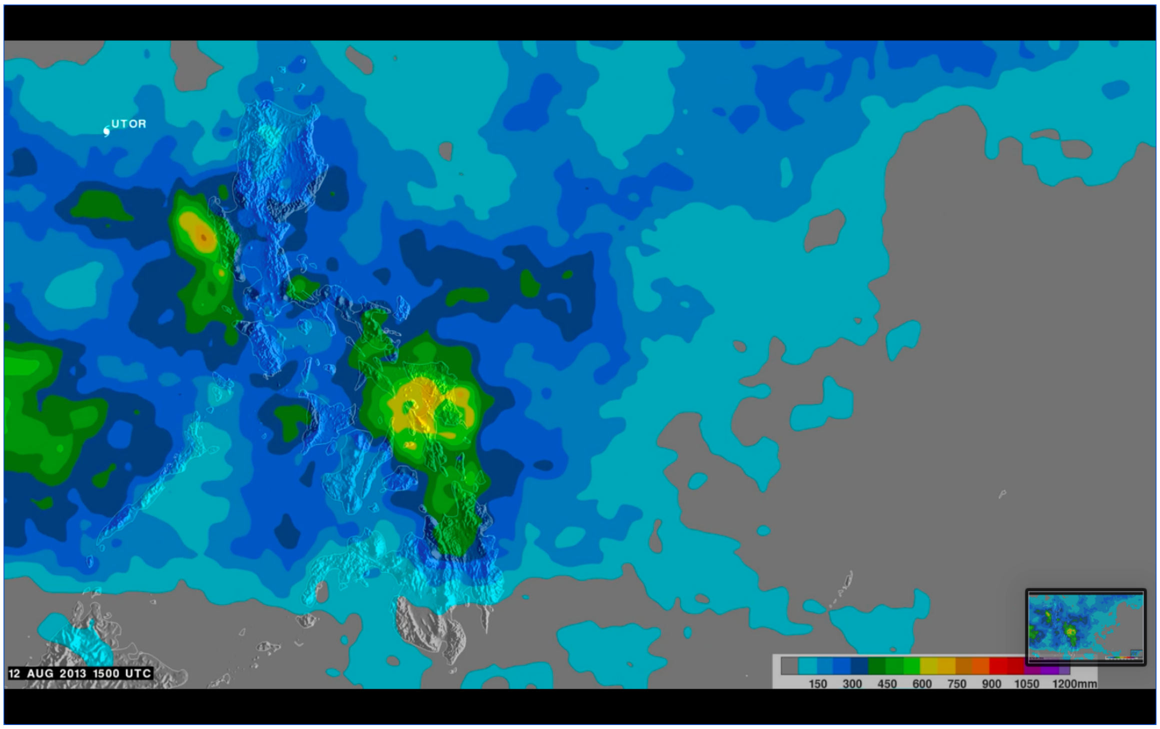


Figure 2a: Visualization of global flooding constructed from the University of Maryland's flooding data (generated by the author using ArcGIS)

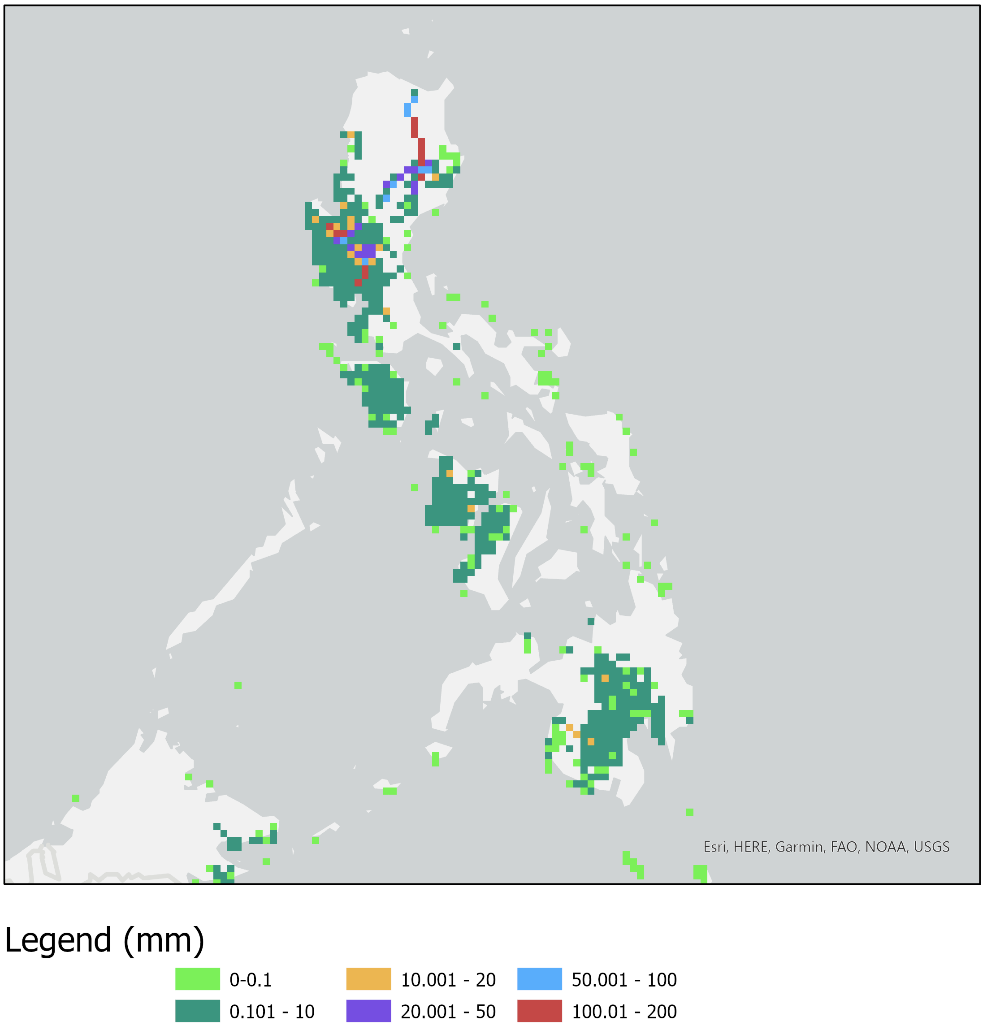
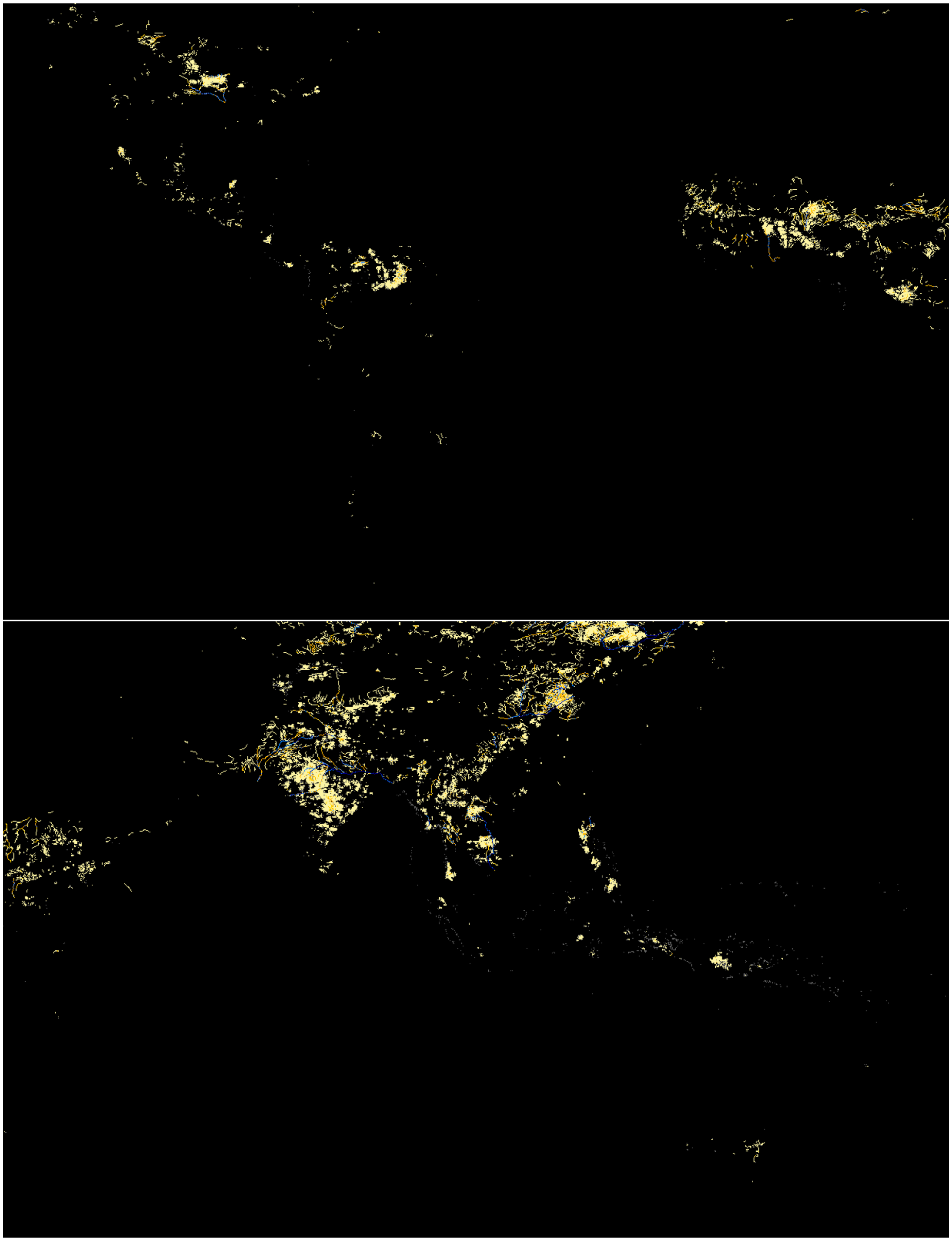
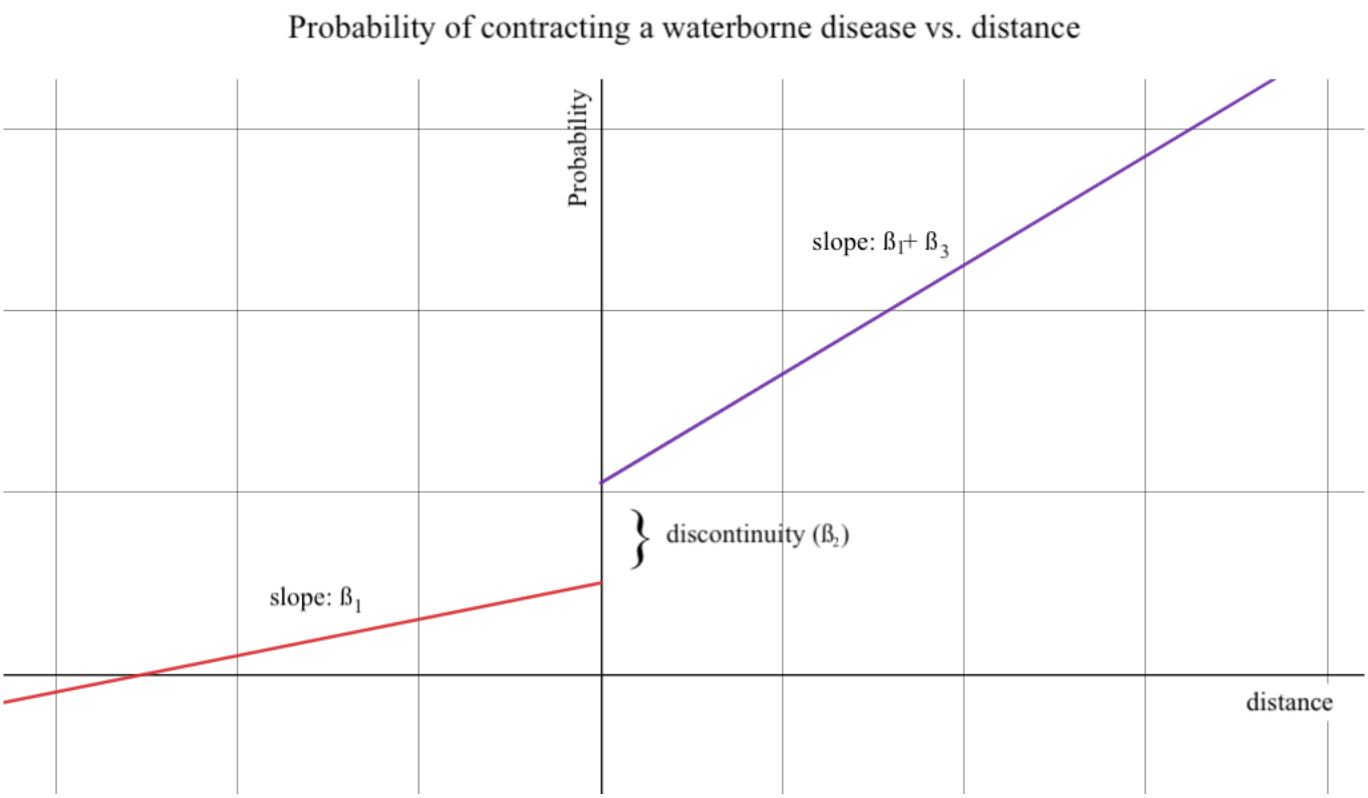


Figure 2b: Visualization of global flooding constructed from the University of Maryland's flooding data (author's code)



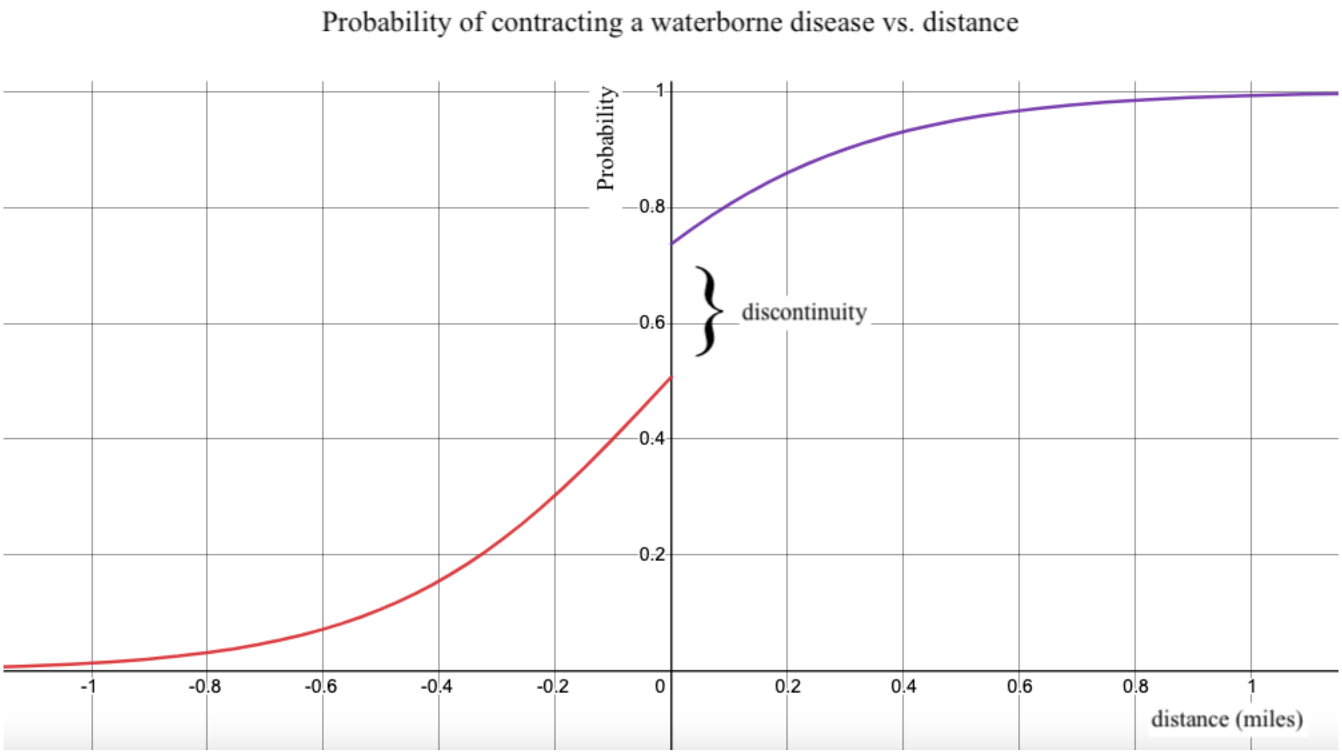
Legend: 0 millimeters (mm): black, 0.1 mm: light yellow, 10 mm: yellow, 20 mm: gold, 50 mm: light blue, 100 mm: cyan, 200 mm: navy

Figure 3a: Graph of the local linear regression under a sharp spatial regression discontinuity design



The value of the discontinuity is β_2. Intuitively, this represents the jump in the probability that a child will contract a waterborne disease when he/she is living in a flooded area.

Figure 3b: Graph of the local logit regression under a sharp spatial regression discontinuity design



The value of the discontinuity is the difference between the subfunctions evaluated at $distance_i = 0$:

$$\frac{e^{\beta_0+\beta_2}}{1+e^{\beta_0+\beta_2}} - \frac{e^{\beta_0}}{1+e^{\beta_0}}$$

Intuitively, this represents the jump in the probability that a child will contract a waterborne disease when he/she is living in a flooded area.

Figure 4a: Density discontinuity test for diarrhea and ARI (Cattaneo et al., 2019)

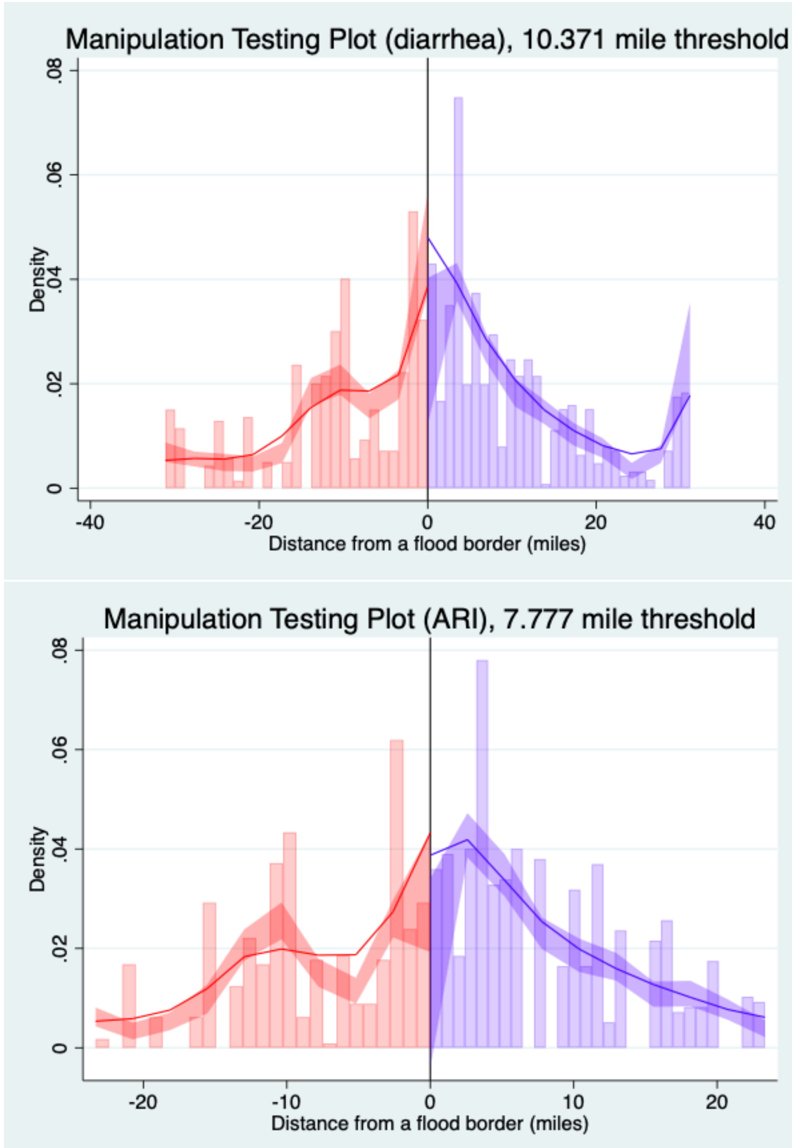


Figure 4b: Distribution of $distance_i$

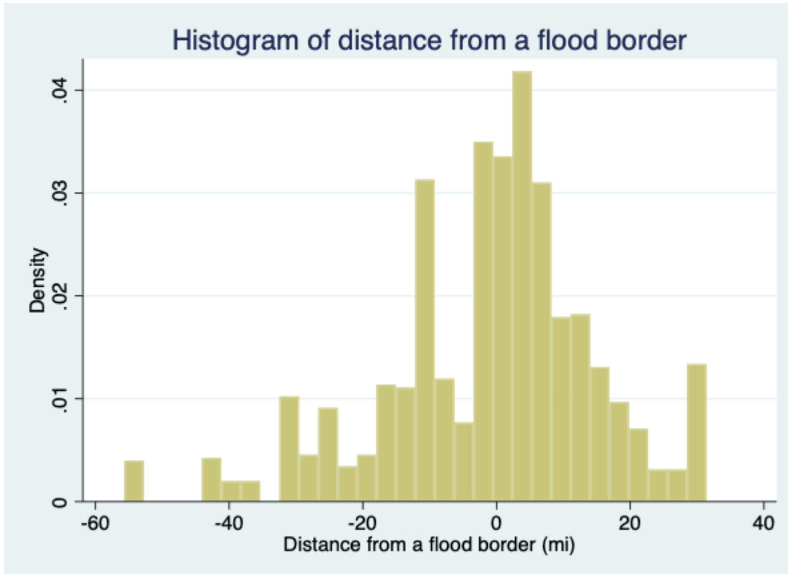


Table 5a: Summary statistics of 2013 child outcome means for children living in barangays that do not experience flooding and do experience flooding (10.371 mile threshold [diarrhea])

	No flooding	*Flooded*	*T-test*
Age of child	2.022	2.000	0.020
	(-1.427)	(-1.465)	[-0.17]
Sex of child (1=female)	0.496	0.477	0.019
	(-0.501)	(-0.500)	[-0.49]
Age of mother (years)	30.580	29.550	1.051*
	(-6.559)	(-6.754)	[-1.98]
Education of mother (years)	10.440	10.190	0.274
	(-3.390)	(-3.047)	[-1.08]
Oral rehydration knowledge[a]	0.918	0.889	0.029
	(-0.275)	(-0.315)	[-1.21]
Wealth (quintiles)[b]	2.735	3.026	−0.280**
	(-1.293)	(-1.299)	[-2.72]
Number of children in household	3.168	2.782	0.379**
	(-1.988)	(-1.711)	[-2.61]
Household type[c]	0.198	0.290	−0.091**
	(-0.399)	(-0.454)	[-2.65]
Has elecricity	0.851	0.909	−0.054*
	(-0.357)	(-0.288)	[-2.11]
Water source[d]	0.944	0.935	0.009
	(-0.230)	(-0.246)	[-0.46]
Toilet facility type[e]	0.037	0.026	0.011
	(-0.190)	(-0.159)	[-0.84]
Beneficiary of 4P[f]	0.276	0.308	-0.031
	(-0.448)	(-0.892)	[-0.52]
Diarrhea[g]	0.060	0.080	-0.020
	(-0.237)	(-0.272)	[-0.99]
Observations	268	388	656

t-statistics are in brackets. +p<0.1; *p<0.05; **p<0.01; ***p<0.001

a Recoded Philippines NDHS data from 0: have not heard of oral rehydration, 1: used oral rehydration, 2: heard of oral rehydration to 0: have not heard of oral rehydration, 1: used or heard of oral rehydration.
b Wealth index by quintile (1 = Poorest, 2 = Poorer, 3 = Middle, 4 = Richer, 5 = Richest). This is a DHS measure constructed by weighting data on household assets such as televisions, transportation, and other household characteristics.
c Urban (0), rural (1)
d Recoded data from various water source categories to protected and non-protected water sources as defined by the DHS (World Health Organization, 2021b).
e Is a beneficiary of Pantawid Pamilyang Pilipino Program (4Ps) (1) or not (0)
f Recoded data from various toilet facility types to improved and not improved toilet facilities as defined by the DHS (World Health Organization, 2021b).
g Recoded data from 0: child did not have diarrhea, 2: child had diarrhea in the last 24 hours to 0: child did not have diarrhea, 1: child had diarrhea in the last 2 weeks.

Table 5b: Summary statistics of 2013 child outcome means for children living in barangays that do not experience flooding and do experience flooding (7.777 mile threshold [ARI])

	No flooding	*Flooded*	*T-test*
Age of child	2.000	2.039	-0.041
	(-1.440)	(-1.470)	[-0.31]
Sex of child (1=female)	0.458	0.481	-0.022
	(-0.500)	(-0.500)	[-0.50]
Age of mother (years)	30.240	29.470	0.794
	(-6.370)	(-6.823)	[-1.32]
Education of mother (years)	10.240	10.120	0.153
	(-3.320)	(-3.019)	[-0.54]
Oral rehydration knowledge[a]	0.901	0.884	0.016
	(-0.299)	(-0.320)	[-0.57]
Wealth (quintiles)[b]	2.620	2.985	-0.354^{**}
	(-1.309)	(-1.271)	[-3.04]
Number of children in household	3.115	2.783	0.324^{*}
	(-1.933)	(-1.718)	[-2.00]
Household type[c]	0.203	0.276	-0.071
	(-0.403)	(-0.448)	[-1.83]
Has elecricity	0.812	0.896	-0.078^{*}
	(-0.391)	(-0.306)	[-2.53]
Water source[d]	0.932	0.932	0.001
	(-0.252)	(-0.253)	[-0.02]
Toilet facility type[e]	0.047	0.030	0.017
	(-0.212)	(-0.170)	[-1.03]
Beneficiary of 4P[f]	0.260	0.320	-0.058
	(-0.440)	(-0.941)	[-0.81]
ARI[g]	0.078	0.039	0.040^{*}
	(-0.269)	(-0.193)	[-1.97]
Observations	192	339	531

t-statistics are in brackets. +p<0.1; *p<0.05; **p<0.01; ***p<0.001

a Recoded Philippines NDHS data from 0: have not heard of oral rehydration, 1: used oral rehydration, 2: heard of oral rehydration to 0: have not heard of oral rehydration, 1: used or heard of oral rehydration.
b Wealth index by quintile (1 = Poorest, 2 = Poorer, 3 = Middle, 4 = Richer, 5 = Richest). This is a DHS measure constructed by weighting data on household assets such as televisions, transportation, and other household characteristics.
c Urban (0), rural (1)
d Recoded data from various water source categories to protected and non-protected water sources as defined by the DHS (World Health Organization, 2021b).
e Is a beneficiary of Pantawid Pamilyang Pilipino Program (4Ps) (1) or not (0)
f Recoded data from various toilet facility types to improved and not improved toilet facilities as defined by the DHS (World Health Organization, 2021b).
g Recoded data from 0: child did not have ARI, 1: child had ARI in the last 2 weeks as defined by the DHS (Demographic and Health Surveys Program, 2021).

Figure 6: Visualizations of the ArcGIS plot used to find the distance (mi) from a barangay to a flooded area (generated by the author using ArcGIS).

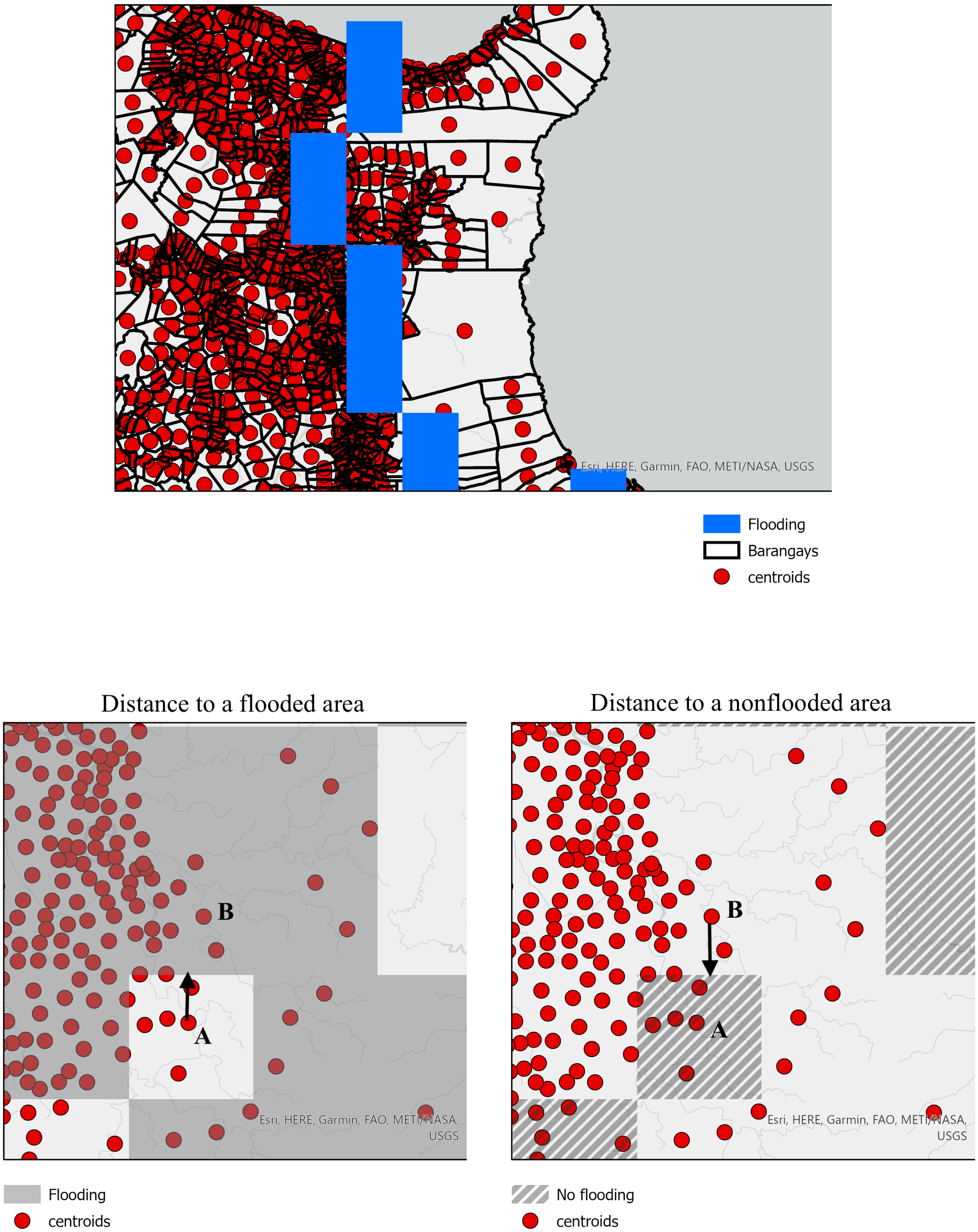


Table 7: Diarrhea incidences and acute respiratory infection incidences (Logit)

	Diarrhea			**ARI**		
	Simple Logit (no controls)	Logit (with controls)	Logit (with controls and clustered errors)	Simple Logit (no controls)	Logit (with controls)	Logit (with controls and clustered errors)
	(1)	(2)	(3)	(4)	(5)	(6)
Flooding (mm)	0.0051	0.0052	0.0052	−0.0090	−0.0092	−0.0092
	(0.0033)	(0.0035)	(0.0035)	(0.0085)	(0.0082)	(0.0081)
Days[a]		−0.0284	−0.0284		−0.0199	−0.0199
		(0.0969)	(0.1061)		(0.1126)	(0.1280)
Days squared[b]		0.0003	0.0003		0.0007	0.0007
		(0.0018)	(0.0020)		(0.0020)	(0.0024)
Age 1		0.4468	0.4468		0.7172+	0.7172
		(0.2902)	(0.2738)		(0.4017)	(0.4403)
Age 2		−0.0381	−0.0381		0.3202	0.3202
		(0.3338)	(0.3631)		(0.4369)	(0.5112)
Age 3		−0.7511*	−0.7511+		0.2355	0.2355
		(0.3734)	(0.3907)		(0.4319)	(0.3866)
Age 4		−1.3384**	−1.3384**		−0.1040	−0.1040
		(0.4723)	(0.4898)		(0.4684)	(0.5451)
Sex of child[c]		−0.2522	−0.2522		−0.6768*	−0.6768*
		(0.2231)	(0.2134)		(0.2753)	(0.2825)
Age of mother (years)		−0.0048	−0.0048		0.0022	0.0022
		(0.0222)	(0.0203)		(0.0263)	(0.0245)
Education of mother (years)		−0.0301	−0.0301		0.0125	0.0125
		(0.0413)	(0.0383)		(0.0491)	(0.0487)
Oral rehydration knowledge[d]		−0.1337	−0.1337		0.1374	0.1374
		(0.3568)	(0.4044)		(0.4589)	(0.6483)
Wealth (quintiles)		−0.1610	−0.1610		−0.2730+	−0.2730
		(0.1193)	(0.1234)		(0.1459)	(0.1662)
Number of children in household		0.0239	0.0239		−0.0164	−0.0164
		(0.0803)	(0.0696)		(0.0962)	(0.1150)
Household type[e]		0.4186	0.4186+		−0.1089	−0.1089
		(0.2630)	(0.2440)		(0.3408)	(0.3451)
Has elecricity[f]		0.4047	0.4047		0.2393	0.2393
		(0.3937)	(0.4043)		(0.4696)	(0.4893)
Water source[g]		−0.7078	−0.7078			
		(0.4386)	(0.5011)			
Toilet facility type[i]		−1.2550	−1.2550		−0.3507	−0.3507
		(1.0355)	(0.8971)		(0.7652)	(0.5122)
Beneficiary of 4P[h]		0.0150	0.0150		−0.5221	−0.5221
		(0.1385)	(0.1012)		(0.3478)	(0.3686)
Constant	−2.5330***	−0.5833	−0.5833	−2.8528***	−2.3433	−2.3433
	(0.1139)	(1.3821)	(1.4491)	(0.1341)	(1.6723)	(1.9253)
Observations	656	654	654	531	493	493
Pseudo R^2	0.0290	0.0889	0.0889	0.0272	0.1207	0.1207

+p<0.1; *p<0.05; **p<0.01; ***p<0.001

a Days ranges from 0 to 49.
b The DHS data from the Philippines only has information on children between the ages 0-4 for the regions of interest.
c Indicator variable. 0 is male and 1 is female.
d Indicator for head of household possessing knowledge of oral rehydration. 0 is no knowledge and 1 is knowledge or use or oral rehydration.
e Indicator variable. Urban (0), rural (1).
f Indicator variable. Has no electricity (0), has electricity (1).
g Indicator variable. Water source is unprotected (0), or protected (1). Omitted in the ARI model due to lack of variation.
h Is a beneficiary of Pantawid Pamilyang Pilipino Program (4Ps) (1) or not (0)
i Recoded data from various toilet facility types to improved and not improved toilet facilities as defined by the DHS (World Health Organization, 2021b).

Table 8: Diarrhea incidences and acute respiratory infection incidences (Linear SRDD)

	Diarrhea			ARI		
	Simple SRDD (no controls)	SRDD (with controls)	SRDD (with controls and clustered errors)	Simple SRDD (no controls)	SRDD (with controls)	SRDD (with controls and clustered errors)
	(1)	(2)	(3)	(4)	(5)	(6)
Distance	0.0008	−0.0015	−0.0015	0.0109	0.0114	0.0114
	(0.0045)	(0.0047)	(0.0039)	(0.0086)	(0.0090)	(0.0094)
Flooding (indicator)	−0.0546	−0.0502	−0.0502	−0.0419	−0.0432	−0.0432
	(0.0356)	(0.0364)	(0.0338)	(0.0366)	(0.0373)	(0.0392)
Flooding ∗ distance	0.0152*	0.0178**	0.0178*	−0.0177+	−0.0184+	−0.0184+
	(0.0066)	(0.0068)	(0.0076)	(0.0104)	(0.0108)	(0.0102)
Days[a]		−0.0093	−0.0093		0.0085	0.0085
		(0.0095)	(0.0091)		(0.0089)	(0.0075)
Days squared[b]		0.0002	0.0002		−0.0001	−0.0001
		(0.0002)	(0.0002)		(0.0002)	(0.0001)
Age 1		0.0251	0.0251		0.0303	0.0303
		(0.0318)	(0.0334)		(0.0310)	(0.0272)
Age 2		0.0211	0.0211		0.0318	0.0318
		(0.0340)	(0.0376)		(0.0331)	(0.0359)
Age 3		−0.0281	−0.0281		0.0013	0.0013
		(0.0314)	(0.0336)		(0.0305)	(0.0218)
Age 4		−0.0263	−0.0263		0.0203	0.0203
		(0.0317)	(0.0281)		(0.0305)	(0.0252)
Sex of child[c]		−0.0106	−0.0106		−0.0425*	−0.0425*
		(0.0202)	(0.0187)		(0.0197)	(0.0199)
Age of mother (years)		0.0014	0.0014		−0.0015	−0.0015
		(0.0020)	(0.0018)		(0.0020)	(0.0014)
Education of mother (years)		−0.0005	−0.0005		−0.0014	−0.0014
		(0.0041)	(0.0034)		(0.0040)	(0.0027)
Oral rehydration knowledge[d]		−0.0551	−0.0551		0.0467	0.0467
		(0.0354)	(0.0486)		(0.0330)	(0.0287)
Wealth (quintiles)		−0.0131	−0.0131		0.0099	0.0099
		(0.0111)	(0.0103)		(0.0109)	(0.0107)
Number of children in household		−0.0053	−0.0053		0.0080	0.0080
		(0.0079)	(0.0063)		(0.0078)	(0.0095)
Household type[e]		0.0269	0.0269		−0.0185	−0.0185
		(0.0251)	(0.0250)		(0.0245)	(0.0228)
Has elecricity[f]		0.0296	0.0296		0.0104	0.0104
		(0.0381)	(0.0419)		(0.0342)	(0.0320)
Water source[g]		−0.1172**	−0.1172+			
		(0.0454)	(0.0650)			
Toilet facility type[i]		0.0023	0.0023		0.0449	0.0449
		(0.0621)	(0.0403)		(0.0555)	(0.0383)
Beneficiary of 4P[h]		0.0164	0.0164		−0.0199	−0.0199*
		(0.0143)	(0.0112)		(0.0128)	(0.0081)
Constant	0.0633*	0.3308*	0.3308*	0.1057***	−0.0488	−0.0488
	(0.0255)	(0.1371)	(0.1306)	(0.0270)	(0.1280)	(0.1119)
Observations	656	654	654	531	493	493
Adjusted R^2	0.0142	0.0222	0.0521	0.0073	0.0451	0.0451

+p<0.1; *p<0.05; **p<0.01; ***p<0.001

a Days ranges from 0 to 49.
b The DHS data from the Philippines only has information on children between the ages 0-4 for the regions of interest.
c Indicator variable. 0 is male and 1 is female.
d Indicator for head of household possessing knowledge of oral rehydration. 0 is no knowledge and 1 is knowledge or use or oral rehydration.
e Indicator variable. Urban (0), rural (1).
f Indicator variable. Has no electricity (0), has electricity (1).
g Indicator variable. Water source is unprotected (0), or protected (1). Omitted for ARI due to lack of variation.
h Is a beneficiary of Pantawid Pamilyang Pilipino Program (4Ps) (1) or not (0)
i Recoded data from various toilet facility types to improved and not improved toilet facilities as defined by the DHS (World Health Organization, 2021b).

Table 9a: Subgroup analysis of diarrhea for recently and later surveyed children (Linear SRDD)

		Short term (2-4 weeks)			Medium term (> 4 weeks)	
	Simple SRDD (no controls)	SRDD (with controls)	SRDD (with controls and clustered errors)	Simple SRDD (no controls)	SRDD (with controls)	SRDD (with controls and clustered errors)
	(1)	(2)	(3)	(4)	(5)	(6)
Distance	−0.0033	−0.0047	−0.0047	0.0003	−0.0024	−0.0024
	(0.0077)	(0.0081)	(0.0080)	(0.0054)	(0.0057)	(0.0037)
Flooding (indicator)	−0.0415	−0.0336	−0.0336	−0.0915+	−0.0944+	−0.0944*
	(0.0486)	(0.0510)	(0.0487)	(0.0527)	(0.0547)	(0.0414)
Flooding ∗ distance	0.0144	0.0160	0.0160	0.0348***	0.0383***	0.0383**
	(0.0097)	(0.0103)	(0.0110)	(0.0105)	(0.0116)	(0.0118)
Constant	0.0710*	0.4184	0.4184	0.0339	0.7958	0.7958
	(0.0358)	(0.4533)	(0.4080)	(0.0357)	(0.9435)	(0.8052)
Days[a]		−0.0275	−0.0275		−0.0130	−0.0130
		(0.0448)	(0.0377)		(0.0551)	(0.0438)
Days squared[b]		0.0006	0.0006		0.0002	0.0002
		(0.0011)	(0.0009)		(0.0008)	(0.0006)
Age 1		0.0318	0.0318		0.0055	0.0055
		(0.0446)	(0.0490)		(0.0461)	(0.0423)
Age 2		0.0351	0.0351		0.0015	0.0015
		(0.0515)	(0.0643)		(0.0423)	(0.0452)
Age 3		−0.0219	−0.0219		−0.0190	−0.0190
		(0.0449)	(0.0498)		(0.0436)	(0.0425)
Age 4		−0.0105	−0.0105		−0.0515	−0.0515+
		(0.0480)	(0.0478)		(0.0399)	(0.0300)
Sex of child[c]		0.0025	0.0025		−0.0171	−0.0171
		(0.0285)	(0.0260)		(0.0287)	(0.0375)
Age of mother (years)		0.0022	0.0022		0.0002	0.0002
		(0.0029)	(0.0026)		(0.0028)	(0.0025)
Education of mother (years)		0.0006	0.0006		−0.0008	−0.0008
		(0.0055)	(0.0041)		(0.0060)	(0.0061)
Oral rehydration knowledge[d]		−0.0494	−0.0494		−0.0696	−0.0696
		(0.0490)	(0.0657)		(0.0509)	(0.0764)
Wealth (quintiles)		−0.0244	−0.0244+		−0.0008	−0.0008
		(0.0152)	(0.0144)		(0.0165)	(0.0135)
Number of children in household		−0.0094	−0.0094		−0.0083	−0.0083
		(0.0119)	(0.0095)		(0.0101)	(0.0085)
Household type[e]		0.0373	0.0373		0.0035	0.0035
		(0.0364)	(0.0330)		(0.0354)	(0.0333)
Has elecricity[f]		0.0512	0.0512		−0.0044	−0.0044
		(0.0546)	(0.0555)		(0.0530)	(0.0575)
Water source[g]		−0.0532	−0.0532		−0.4464***	−0.4464+
		(0.0560)	(0.0502)		(0.0970)	(0.2451)
Toilet facility type[i]		0.0045	0.0045		0.0105	0.0105
		(0.0782)	(0.0500)		(0.1329)	(0.0499)
Beneficiary of 4P[h]		0.0347	0.0347		0.0094	0.0094
		(0.0269)	(0.0325)		(0.0153)	(0.0094)
Observations	399	399	399	257	255	255
Adjusted R^2	0.0019	-0.0081	0.0426	0.0543	0.1048	0.1753

+p<0.1; *p<0.05; **p<0.01; ***p<0.001

a Days ranges from 0 to 49.
b The DHS data from the Philippines only has information on children between the ages 0-4 for the regions of interest.
c Indicator variable. 0 is male and 1 is female.
d Indicator for head of household possessing knowledge of oral rehydration. 0 is no knowledge and 1 is knowledge or use or oral rehydration.
e Indicator variable. Urban (0), rural (1).
f Indicator variable. Has no electricity (0), has electricity (1).
g Indicator variable. Water source is unprotected (0), or protected (1). Omitted for ARI due to lack of variation.
h Is a beneficiary of Pantawid Pamilyang Pilipino Program (4Ps) (1) or not (0)
i Recoded data from various toilet facility types to improved and not improved toilet facilities as defined by the DHS (World Health Organization, 2021b).

Table 9b: Subgroup analysis of ARI for recently and later surveyed children (Linear SRDD)

	Short term (2-4 weeks)			Medium term (> 4 weeks)		
	Simple SRDD (no controls)	SRDD (with controls)	SRDD (with controls and clustered errors)	Simple SRDD (no controls)	SRDD (with controls)	SRDD (with controls and clustered errors)
	(1)	(2)	(3)	(4)	(5)	(6)
Distance	−0.0084 (0.0110)	−0.0070 (0.0125)	−0.0070 (0.0132)	0.0296* (0.0138)	0.0289+ (0.0161)	0.0289+ (0.0150)
Flooding (indicator)	0.0166 (0.0425)	0.0199 (0.0474)	0.0199 (0.0395)	−0.1261+ (0.0677)	−0.1309+ (0.0759)	−0.1309 (0.0786)
Flooding ∗ distance	−0.0038 (0.0127)	−0.0057 (0.0138)	−0.0057 (0.0143)	−0.0223 (0.0183)	−0.0178 (0.0207)	−0.0178 (0.0164)
Constant	0.0539+ (0.0323)	−0.1116 (0.3801)	−0.1116 (0.4738)	0.1641*** (0.0480)	−0.6788 (1.2073)	−0.6788 (0.7236)
Days[a]		0.0108 (0.0374)	0.0108 (0.0484)		0.0531 (0.0703)	0.0531 (0.0412)
Days squared[b]		−0.0002 (0.0009)	−0.0002 (0.0012)		−0.0008 (0.0010)	−0.0008 (0.0006)
Age 1		0.0318 (0.0359)	0.0318 (0.0338)		0.0039 (0.0611)	0.0039 (0.0468)
Age 2		−0.0044 (0.0409)	−0.0044 (0.0337)		0.0568 (0.0579)	0.0568 (0.0620)
Age 3		−0.0009 (0.0359)	−0.0009 (0.0259)		−0.0013 (0.0600)	−0.0013 (0.0444)
Age 4		0.0394 (0.0372)	0.0394 (0.0381)		−0.0177 (0.0546)	−0.0177 (0.0316)
Sex of child[c]		−0.0296 (0.0225)	−0.0296 (0.0270)		−0.0526 (0.0392)	−0.0526 (0.0332)
Age of mother (years)		−0.0021 (0.0023)	−0.0021 (0.0016)		−0.0003 (0.0039)	−0.0003 (0.0020)
Education of mother (years)		−0.0006 (0.0045)	−0.0006 (0.0033)		−0.0064 (0.0083)	−0.0064 (0.0050)
Oral rehydration knowledge[d]		0.0426 (0.0387)	0.0426* (0.0200)		0.0633 (0.0642)	0.0633 (0.0825)
Wealth (quintiles)		0.0124 (0.0123)	0.0124 (0.0119)		0.0035 (0.0221)	0.0035 (0.0219)
Number of children in household		0.0154+ (0.0092)	0.0154 (0.0105)		−0.0064 (0.0147)	−0.0064 (0.0161)
Household type[e]		−0.0000 (0.0290)	−0.0000 (0.0243)		−0.0911+ (0.0504)	−0.0911* (0.0442)
Has elecricity[f]		−0.0004 (0.0400)	−0.0004 (0.0371)		0.0165 (0.0678)	0.0165 (0.0595)
Water source[g]						
Toilet facility type[i]		0.0707 (0.0580)	0.0707 (0.0664)		−0.0468 (0.1608)	−0.0468 (0.0401)
Beneficiary of 4P[h]		−0.0200 (0.0201)	−0.0200 (0.0142)		−0.0151 (0.0188)	−0.0151 (0.0094)
Observations	399	399	399	257	255	255
Adjusted R^2	0.0019	-0.0081	0.0426	0.0543	0.1048	0.1753

+p<0.1; *p<0.05; **p<0.01; ***p<0.001

a Days ranges from 0 to 49.
b The DHS data from the Philippines only has information on children between the ages 0-4 for the regions of interest.
c Indicator variable. 0 is male and 1 is female.
d Indicator for head of household possessing knowledge of oral rehydration. 0 is no knowledge and 1 is knowledge or use or oral rehydration.
e Indicator variable. Urban (0), rural (1).
f Indicator variable. Has no electricity (0), has electricity (1).
g Indicator variable. Water source is unprotected (0), or protected (1). Omitted for ARI due to lack of variation.
h Is a beneficiary of Pantawid Pamilyang Pilipino Program (4Ps) (1) or not (0)
i Recoded data from various toilet facility types to improved and not improved toilet facilities as defined by the DHS (World Health Organization, 2021b).

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Appendix

Appendix Table A: Diarrhea incidences and acute respiratory infection incidences (OLS)

	Diarrhea			ARI		
	Simple OLS (no controls)	OLS (with controls)	OLS (with controls and clustered errors)	Simple OLS (no controls)	OLS (with controls)	OLS (with controls and clustered errors)
	(1)	(2)	(3)	(4)	(5)	(6)
Flooding (mm)	0.0005	0.0005	0.0005	−0.0003	−0.0003	−0.0003+
	(0.0003)	(0.0003)	(0.0004)	(0.0003)	(0.0003)	(0.0002)
Days[a]		−0.0024	−0.0024		−0.0020	−0.0020
		(0.0066)	(0.0071)		(0.0055)	(0.0069)
Days squared[b]		0.0000	0.0000		0.0001	0.0001
		(0.0001)	(0.0001)		(0.0001)	(0.0001)
Age 1		0.0443+	0.0443		0.0377+	0.0377+
		(0.0237)	(0.0274)		(0.0199)	(0.0227)
Age 2		−0.0039	−0.0039		0.0164	0.0164
		(0.0248)	(0.0288)		(0.0208)	(0.0236)
Age 3		−0.0477*	−0.0477*		0.0113	0.0113
		(0.0237)	(0.0228)		(0.0200)	(0.0166)
Age 4		−0.0629**	−0.0629**		−0.0021	−0.0021
		(0.0240)	(0.0197)		(0.0201)	(0.0208)
Sex of child[c]		−0.0190	−0.0190		−0.0321*	−0.0321*
		(0.0153)	(0.0146)		(0.0128)	(0.0135)
Age of mother (years)		−0.0003	−0.0003		0.0000	0.0000
		(0.0015)	(0.0014)		(0.0013)	(0.0012)
Education of mother (years)		−0.0019	−0.0019		0.0008	0.0008
		(0.0028)	(0.0026)		(0.0024)	(0.0025)
Oral rehydration knowledge[d]		−0.0094	−0.0094		0.0052	0.0052
		(0.0271)	(0.0337)		(0.0228)	(0.0338)
Wealth (quintiles)		−0.0110	−0.0110		−0.0124+	−0.0124
		(0.0082)	(0.0085)		(0.0069)	(0.0080)
Number of children in household		0.0018	0.0018		−0.0014	−0.0014
		(0.0056)	(0.0049)		(0.0047)	(0.0058)
Household type[e]		0.0300	0.0300		−0.0049	−0.0049
		(0.0188)	(0.0186)		(0.0158)	(0.0161)
Has elecricity[f]		0.0284	0.0284		0.0113	0.0113
		(0.0268)	(0.0280)		(0.0225)	(0.0232)
Water source[g]		−0.0627+	−0.0627		0.0631*	0.0631***
		(0.0373)	(0.0509)		(0.0314)	(0.0125)
Toilet facility type[i]		−0.0537	−0.0537*		−0.0198	−0.0198
		(0.0423)	(0.0257)		(0.0356)	(0.0233)
Beneficiary of 4P[h]		0.0009	0.0009		−0.0122	−0.0122*
		(0.0098)	(0.0072)		(0.0082)	(0.0052)
Constant	0.0733***	0.2281*	0.2281*	0.0541***	0.0303	0.0303
	(0.0080)	(0.0996)	(0.1069)	(0.0067)	(0.0837)	(0.0947)
Observations	1211	1208	1208	1211	1208	1208
Adjusted R^2	0.0012	0.0201	0.0347	0.0002	0.0041	0.0189

+p<0.1; *p<0.05; **p<0.01; ***p<0.001

a Days ranges from 0 to 49.
b The DHS data from the Philippines only has information on children between the ages 0-4 for the regions of interest.
c Indicator variable. 0 is male and 1 is female.
d Indicator for head of household possessing knowledge of oral rehydration. 0 is no knowledge and 1 is knowledge or use or oral rehydration.
e Indicator variable. Urban (0), rural (1).
f Indicator variable. Has no electricity (0), has electricity (1).
g Indicator variable. Water source is unprotected (0), or protected (1).
h Is a beneficiary of Pantawid Pamilyang Pilipino Program (4Ps) (1) or not (0)
i Recoded data from various toilet facility types to improved and not improved toilet facilities as defined by the DHS (World Health Organization, 2021b).

Figure 5: Diarrhea incidences and acute respiratory infection incidences (Logit SRDD)

	Diarrhea			ARI		
	Simple SRDD (no controls)	SRDD (with controls)	SRDD (with controls and clustered errors)	Simple SRDD (no controls)	SRDD (with controls)	SRDD (with controls and clustered errors)
	(1)	(2)	(3)	(4)	(5)	(6)
Distance	0.0146	−0.0209	−0.0209	0.1707	0.1813	0.1813
	(0.0757)	(0.0830)	(0.0785)	(0.1637)	(0.1718)	(0.1657)
Flooding (indicator)	−0.8053	−0.8026	−0.8026	−0.4888	−0.3734	−0.3734
	(0.5965)	(0.6423)	(0.6712)	(0.6736)	(0.7068)	(0.5871)
Flooding ∗ distance	0.1919+	0.2470*	0.2470*	−0.3678+	−0.4056+	−0.4056*
	(0.1008)	(0.1104)	(0.1125)	(0.2189)	(0.2316)	(0.2002)
Days[a]		−0.1313	−0.1313		0.2212	0.2212
		(0.1544)	(0.1481)		(0.2118)	(0.2096)
Days squared[b]		0.0022	0.0022		−0.0034	−0.0034
		(0.0030)	(0.0027)		(0.0040)	(0.0037)
Age 1		0.3372	0.3372		0.6095	0.6095
		(0.4516)	(0.4280)		(0.6794)	(0.5867)
Age 2		0.3314	0.3314		0.5504	0.5504
		(0.5012)	(0.5268)		(0.6919)	(0.6485)
Age 3		−0.4774	−0.4774		−0.0395	−0.0395
		(0.5248)	(0.6112)		(0.7231)	(0.5902)
Age 4		−0.5031	−0.5031		0.3601	0.3601
		(0.5490)	(0.5313)		(0.6919)	(0.5800)
Sex of child[c]		−0.1472	−0.1472		−0.9171*	−0.9171+
		(0.3173)	(0.2848)		(0.4524)	(0.4933)
Age of mother (years)		0.0197	0.0197		−0.0410	−0.0410
		(0.0318)	(0.0275)		(0.0422)	(0.0308)
Education of mother (years)		−0.0161	−0.0161		−0.0396	−0.0396
		(0.0629)	(0.0496)		(0.0879)	(0.0574)
Oral rehydration knowledge[d]		−0.7722+	−0.7722		1.6451	1.6451
		(0.4696)	(0.5005)		(1.0740)	(1.3068)
Wealth (quintiles)		−0.2102	−0.2102		0.1279	0.1279
		(0.1739)	(0.1505)		(0.2270)	(0.2240)
Number of children in household		−0.0806	−0.0806		0.2729	0.2729
		(0.1238)	(0.0938)		(0.1715)	(0.2282)
Household type[e]		0.4164	0.4164		−0.3666	−0.3666
		(0.3864)	(0.3986)		(0.5640)	(0.5965)
Has elecricity[f]		0.5046	0.5046		−0.2656	−0.2656
		(0.5939)	(0.6476)		(0.7858)	(0.7555)
Water source[g]		−1.3887**	−1.3887*			
		(0.5395)	(0.5662)			
Toilet facility type[i]		0.1252	0.1252		0.4299	0.4299
		(1.1069)	(0.7694)		(0.9417)	(0.6407)
Beneficiary of 4P[h]		0.2166	0.2166*		−1.3404+	−1.3404+
		(0.1743)	(0.1077)		(0.7273)	(0.8014)
Constant	−2.6931***	0.7247	0.7247	−2.0770***	−5.7300+	−5.7300+
	(0.4141)	(2.1035)	(1.8997)	(0.4334)	(3.1498)	(3.1614)
Observations	656	654	654	531	493	493
Adjusted R^2	0.0318	0.0937	0.0937	0.0313	0.1179	0.1179

+p<0.1; *p<0.05; **p<0.01; ***p<0.001

a Days ranges from 0 to 49.
b The DHS data from the Philippines only has information on children between the ages 0-4 for the regions of interest.
c Indicator variable. 0 is male and 1 is female.
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e Indicator variable. Urban (0), rural (1).
f Indicator variable. Has no electricity (0), has electricity (1).
g Indicator variable. Water source is unprotected (0), or protected (1). Omitted for ARI due to lack of variation.
h Is a beneficiary of Pantawid Pamilyang Pilipino Program (4Ps) (1) or not (0)
i Recoded data from various toilet facility types to improved and not improved toilet facilities as defined by the DHS (World Health Organization, 2021b).