



Robert M. La Follette
School of Public Affairs
UNIVERSITY OF WISCONSIN-MADISON

A Cost-Benefit Analysis of Providing Sawyer PointOne Filters in La Moskitia

Prepared for

The Board of World Mission of the Moravian
Church of North America

By

Brando Flores, Sabina Huseynova,
Doris Mbaka, and Chloe Roberts

Cost-Benefit Analysis
Fall 2024

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publications@lafollette.wisc.edu

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Table of Contents

Acknowledgements	v
Abbreviations	vi
Executive Summary	vii
Introduction	1
Background.....	2
Geographical Context.....	2
Current Water Management.....	2
Sawyer Filter	2
Methodology	3
VSL.....	3
Data	3
Discount Rate	4
Objective	4
Standing.....	4
Current Policy & Alternatives	5
Current Policy	5
Alternative 1: Distribute Sawyer Filters to All Households.....	5
Alternative 2: Rigid, Narrow-Mouth Containers	5
Alternative 3: Distribute to All Households with Expanded Education.....	6
Socioeconomic Parameters	8
Health Benefits	8
Water Accessibility.....	8
Productivity	9
School Absenteeism	10
Administrative Costs	11
Acquisition Costs	11
Volunteering Costs.....	11
Administrative Costs/Data Follow-Up	11
Benefit and Cost Summary Tables	12
Results.....	14

Alternative 1: Distribute the Sawyer Filter to All Households	14
Alternative 2: Rigid, Narrow-Mouth Containers	14
Alternative 3: Distribute to All Households with Expanded Education.....	15
Sensitivity Analysis	16
Filter Attrition	16
Valuing Volunteer Time.....	16
Medical Expenses Reduction Uncertainty.....	16
Health Care Expenses Average Cost.....	16
Children VSL	16
Valuing Water Collection	17
Workdays Missed and School Day Absenteeism	17
Conclusion and Recommendations	22
Appendices	23
Appendix A: Limitations.....	23
Distribution-Follow-Up Community Survey.....	23
Standing.....	23
Assumptions.....	23
Water Collection Costs in Follow-up Data.....	23
Inconsistencies.....	24
Appendix B: Case Studies	25
Rigid Containers in India	25
Point-of-Use Water Treatment in Kenya.....	25
Appendix C: Regression Analysis.....	26
Workdays Missed.....	26
School Days Missed	26
Appendix D: Wage Calculations	28
Wage Ranges	28
Alternative 3	28
Appendix E: Estimating Medical Costs from the Dataset.....	29
Appendix F: Estimating Medical Costs from the Dataset with Stata Code.....	30
Appendix G: Estimating Reduced Costs from Young Child Mortality Through VSL.....	31

Appendix H: Estimating Reduced Costs from Young Child Mortality Through VSL with Stata Code.....	32
Appendix I: Container Costs	34
Appendix J: School Absences Formula	36
Lifetime Opportunity Cost.....	36
Education Level.....	36
Chronic Absenteeism Threshold (HCAT)	36
Base Absence Shadow Cost.....	37
Adjusted Absence Shadow Cost	37
Appendix K: Workdays Missed Formula.....	39
Appendix L: Water Collection Cost Formula.....	40
Appendix M: Alternative 2 and 3 Benefits Calculations.....	41
Alternative 2: Rigid, Narrow-Mouth Containers	41
Alternative 3: Distribute to all Households with Expanded Education.....	43
Appendix N: Triangulation	45
Appendix O: Comprehensive WASH Intervention Program Plan	47
Appendix P: Current Policy	48
Appendix Q: Monte Carlo PVBN STATA Code Current Policy.....	49
References	78

Acknowledgements

We appreciate the Board of World Mission (BWM) for granting us the opportunity to carry out this analysis. Our gratitude extends to Justin Rabbach, Brent Krueger, Debbie Collette, and Rick Nelson for their valuable contributions and active involvement in this report, providing essential data and insights. We are especially grateful to Professor Dr. Dave Weimer for his guidance, feedback, and direction, all of which have been instrumental in bringing this project to completion. Additionally, the support of BWM partners—Ona Atta Time, Aquora, and Yamnika Laya—was crucial in providing technical assistance, and we deeply appreciate their efforts.

Brando Flores
Sabina Huseynova
Doris Mbaka
Chloe Roberts



Abbreviations

DHS	Department of Health Services
BWM	Moravian Board of World Mission
H-CAT	Honduras's chronic absenteeism threshold
NPV	Net Present Value
VSL	Value of Statistical Life
WASH	Water, Sanitation, and Hygiene Program



Executive Summary

This report presents a cost-benefit analysis of three alternatives for the Moravian Board of World Mission's (BWM) distribution of Sawyer PointOne filters (Sawyer filters) in La Moskitia, Honduras. We assess the costs and the benefits of three distribution alternatives relative to the current method and level of distribution. These are: (1) distributing the Sawyer filters to the remaining households within the region; (2) distributing the Sawyer filters with rigid, narrow-mouth containers; and (3) increasing education in schools on proper filter usage and hygiene. We estimate that expanding Sawyer filters to the region of La Moskitia and providing increased education would offer the largest net benefit of \$25,000,000.

We monetize the cost and benefits of each alternative — including the reduction in diarrhea symptoms from filter usage — as the primary driver of our analysis. Most benefits derive from reduced mortality for children under five years old. Additionally, we conduct sensitivity analyses to account for the high uncertainty associated with our data. Distributing filters to all households without changing methods has the lowest net present value (NPV). Alternatively, rigid, narrow-mouth filters and expanded education offer the largest net benefits. Therefore, we recommend that BMW leaders adopt expanded education with partial or total distribution. The high NPV indicates the value of providing high-quality education with filters for reducing waterborne diseases.



Introduction

In this report, we consider the distribution of Sawyer PointOne filters to the region of La Moskitia, Honduras. The Blessings Flow project, spearheaded by the Moravian Board of World Mission (BWM), One Atta Time, and local Moravian leaders, has acknowledged the negative impacts of waterborne diseases on local communities by initiating the distribution of water filtration systems to a few communities within the region. The primary objective of this report is to evaluate the impacts of the use of Sawyer filters distributed in three ways: (1) distribute the filters to the entire region of La Moskitia with no changes to current distribution methods; (2) distribute the filters with rigid, narrow-mouth containers; or (3) distribute the filters with increased education. We evaluate these alternatives through a cost-benefit analysis by weighing the benefits against the costs of each alternative. We then discount the net benefits from each alternative for the duration of the Sawyer filter potential life to obtain the net present value (NPV) for each alternative.

We value our alternatives relative to BWM's current policy. The current policy is the present method of distributing the Sawyer filters to 1,435 households across seven communities (labelled in the dataset 1-7). Therefore, our alternatives are the additional benefits and costs associated with distributing the filters to the remaining households in La Moskitia, which we approximate as 18,500 households.

Under our first alternative, BWM would increase the distribution of filters to the remaining households within La Moskitia using current distribution methods. Under second alternative, alongside current distribution methods, BWM would replace the buckets with the rigid, narrow-mouth containers. Finally, under the education alternative, more resources would be allocated to volunteering within schools to advocate for the proper use of filters, alongside the distribution of the Sawyer filters. This would require volunteers to visit schools to lead workshops for teachers and to lead in-classroom activities that encourage children to use filters properly and foster good hygiene practices.



Background

Geographical Context

La Moskitia is a sparse underdeveloped region in northeastern Honduras. This area has remote settlements and dense jungles. Its residents engage in small-scale cocoa production, fishing, and subsistence farming. La Moskitia has significant infrastructure and public health issues, especially concerning access to clean drinking water. Residents often rely on untreated water sources, including wells, rivers, and lagoons that are frequently contaminated by bathing, laundry, and other household tasks. Older adults and children are especially vulnerable to waterborne diseases. These illnesses cause significant disruptions to daily life.

Current Water Management

The divide in water management between urban and rural areas in Honduras is significant. As the region of La Moskitia is primarily rural, households rely on untreated water sources such as rivers, lagoons, and wells. These untreated sources — frequently contaminated by natural contaminants, agricultural wastewater, and human activity — cause numerous waterborne illnesses. Environmental degradation, such as soil erosion and deforestation, contaminates important water sources like the Patuca River and further reduces water quality. Climate-related events like hurricanes and storms worsen these issues by polluting freshwater supplies and causing flooding. In La Moskitia, efforts to increase access to water primarily depend on community initiatives and foreign assistance. The regional situation further highlights the importance of this intervention. The Patuca River is becoming more polluted in places like Kuhrpa due to deforestation and soil erosion. At the same time, the settlement of Río Plátano is affected by storm surges and beach erosion. Therefore, providing water filtration is essential for the health of communities within La Moskitia.

Sawyer Filter

The Sawyer filter uses hollow-fiber membrane technology to treat water while remaining relatively lightweight and compact. With proper use, a Sawyer filter can last up to 10 years. Its micro-tubes with pores can capture contaminants larger than 0.1 microns (Sawyer Products 2015). Under perfect laboratory conditions, the Sawyer filter can remove more than 99.9 percent of bacteria — including *E. coli* and protozoa — from water, although improper use in the field lowers its efficacy (Sawyer Products 2015). Additionally, Sawyer filters can remove turbidity from water, but they are ineffective at removing viruses or chemicals.

Effective use of the Sawyer filter requires proper maintenance. After use, dirt and contaminants can clog the hollow fiber membrane, obstructing flow. Therefore, the Sawyer filter must be backflushed, which can be done with clean bottled or other filtered water (“Section Hiker” 2024). The filtration efficiency is significant if maintenance is done correctly alongside properly storing filtered water. Issues of storing water improperly, not practicing proper hygiene, using unfiltered water for cooking, and not properly maintaining the Sawyer filter can lead to lower levels of efficacy in reducing waterborne diseases.

Methodology

We transform the benefits into monetary terms to determine the value of the Sawyer filters across the three alternatives. Cost-benefit analysis monetizes valued impacts into a single metric of NPV, allowing straightforward comparisons between alternatives with varying outcomes. As the principal decision criterion for this analysis, NPV represents the discounted sum of net social benefits (the difference between social benefits and costs). We determine the NPV for each alternative relative to the current policy.

The reduction in the risk of waterborne diseases is the primary social benefit of water filters. As data is unavailable for the exact waterborne diseases prevalent in each community, we use diarrhea symptoms as a proxy to identify waterborne diseases. Other symptoms, including presence of worms on dysentery or vomit, could indicate severity; however, insufficient data prevents such an analysis. We assess risk reduction for diarrhea of household members with four indicators: general risk reduction per household, risk reduction for children under five, reduction in workdays missed due to diarrhea, and reduction in school days missed due to diarrhea.

We expect the second source of social benefits to be time saved in water collection, with a comparison of the amount of time each households spent collecting water before and after receiving a filter calculated in minutes. Our data analysis finds that the average time spent collecting water increased for households with filters, indicating post-distribution water collection is a net cost rather than a benefit of the filters (see Appendix A).

VSL

Value of Statistical Life (VSL) is a crucial metric in our research. To obtain our VSL, we adjusted the estimate from Viscusi and Masterman (2017) of \$392,000 to the baseline income from La Moskitia, which, adjusted for inflation, becomes \$483,000 (Viscusi and Masterman 2017). At the time of the Viscusi and Masterman article, Honduras's GNI was \$2,300; adjusted for inflation, this value becomes \$2,900. We then found the average income from the Gracias a Dios Department dataset to be \$2,400 in 2022 and \$2,600 in 2023 (Universidad Nacional Autónoma de Honduras 2022). We used the area-adjusted VSL equation from Hammitt and Robinson (2011) to estimate the VSL of this specific region of Honduras (Hammitt and Robinson 2011).

$$VSL_{\text{area}} = VSL_{\text{Honduras}} * (\text{Income}_{\text{area}} / \text{Income}_{\text{Honduras}})$$

We used Viscusi and Materman's income elasticity of 1 in the area-adjusted VSL. This assumes that the VSL is proportional to income. We estimate the VSL in 2023 for La Moskitia to be \$434,000. Additionally, because the VSL focuses on monetizing the possible reduction in mortality for children under five after the Sawyer filters are distributed, we adjust the metric for children. As parents often value their children's lives higher than their own, we multiply the average VSL by a factor of 1.5 for a value of \$651,000 (OCED 2012).

Data

We received data for households during the distribution of Sawyer filter via survey through BWM partners including Aquora Research and One Atta Time. This data included information regarding household demographics, water sources, medical costs, and symptoms related to different waterborne diseases. The data included some follow-up surveys for households that received the filter, which we then used to complete a before-and-after risk reduction analysis from filter usage. We used this information to inform our analysis of the region's baseline characteristics and estimate average waterborne disease costs.

Additionally, we used data from peer-reviewed studies to estimate the reduction in diarrhea rates for alternatives that alter the distribution methods. We also obtained data on child mortality from diarrhea symptoms in low-income countries from existing scholarship.

The most significant variable in evaluating the benefits of each alternative is the change in diarrhea rates. The cost of each alternative is affected primarily by the number of households receiving filters. Still, increased volunteering costs due to varying levels of education also produce differing costs across alternatives. The benefits derived from each alternative are driven significantly by reduced mortality for children under five. The remaining benefit parameters yield modest results.

Discount Rate

According to the World Bank, the social discount rate for development projects in Honduras is around 3 to 4 percent for low growth and 5 to 7 percent for high growth (Lopez 2008). Considering currently low investment levels, high poverty, and high inequality, a social discount rate of 3 to 4 percent may be justified. However, Honduras has several properties that justify a higher discount rate, including moderately high growth in exports, higher payoffs from investment, and high vulnerability to natural disasters. The U.S. Federal Reserve suggested Honduras' yield-to-maturity was 8.75 percent, which implies an approximate real discount rate of 5 percent when adjusting for U.S. inflation, if we consider the sovereign borrowing rate as a benchmark. However, considering Gracias a Dios Department has disproportionately less economic activity and with sustainable social service projects expecting medium-long-term returns, we believe the appropriate social discount rate to be 4 percent.

Objective

Our objective is to determine the NPV for each of the three alternatives. This is calculated as the discounted sum of net benefits for each alternative compared to the current policy over the lifetime of a Sawyer filter.

Standing

Due to the significant challenges of waterborne diseases, we prioritize the communities of La Moskitia and the broader Gracias a Dios Department. These illnesses impact entire households. Adults face increased healthcare expenses and lost workdays, burdening family well-being. Children are frequently absent from school, sometimes for extended periods, disrupting their education and limiting their long-term opportunities. Young children, particularly those under five years of age, face the highest risk of mortality. Additionally, with limited access to reliable drinking water, households often spend hours searching for safer sources, incurring a significant time cost.

We consider also parties invested in filter distribution, including BWM, One Atta Time, and groups investing time volunteering including Yamnika Laya and other local stakeholders such as the local Moravian church leadership. The scope of this analysis is limited to the direct impact of the Sawyer filter's distribution and usage.

Current Policy & Alternatives

Current Policy

BWM's Blessings Flow program provides Sawyer filters with a three-phase strategy. Initially, the team visited the communities to inform it of the Sawyer filters and determine how many would be needed based on the village census. In the second phase, the organization recruited volunteers to distribute, train, and educate households about proper filter use. Volunteers typically took one day to distribute filters to households in communities, with around 30 minutes to an hour spent providing education. In the final step, BWM conducted follow-up visits to assess the impact of the filters, get user feedback, and resolve any problems. Currently, the Blessings Flow project has distributed filters to 1,435 households in La Moskitia.

Alternative 1: Distribute Sawyer Filters to All Households

In this proposed alternative, our client would distribute the Sawyer filters to the remaining households in La Moskitia that currently do not have a filter, which is approximately 18,500 households. This alternative emphasizes equitable access to clean water by providing the Sawyer filtration systems to all households, regardless of their geographic or demographic characteristics. The implementation strategy for this alternative involves maintaining the client's existing distribution methods alongside the current education and training provided to recipients on the proper use and maintenance of the Sawyer filters.

This alternative would have social benefits associated with reduced health care costs, reduced mortality to children younger than five, and reduced costs from lost work and school days. The costs associated with this alternative are extrapolated from the current policy based on the additional number of households served. These costs include acquisition, volunteering, and administration.

Alternative 2: Rigid, Narrow-Mouth Containers

In this alternative, each Sawyer filter would be distributed with rigid, narrow-mouthed containers for safe water storage. We assume that part of the reason for prevailing symptoms is the possibility of storage contamination, which can occur when using wide vessels (such as buckets) or when the same bucket is used to collect untreated water and store filtered water. These rigid containers with narrow-mouthed vessels — including lids, spouts, and food-grade plastic — can be easily cleaned. According to studies from the National Library of Medicine, rigid, narrow-mouthed vessels may provide a 75 percent reduction in the transmission of pathogens when used with point-of-use water filtration like the Sawyer filter (Mintz et al. 2005; see Appendix I for details of costs). The containers we chose for our analysis would cost \$19.88 each, replacing the gallon-size buckets included in the acquisition cost (around \$4 each). The following table displays the additional costs associated with this alternative.

Table 1: Cost for Rigid, Narrow-Mouth Containers

Container Alternative Cost (at \$19.88 per Container)	1,435 Households	18,500 Households
Container Acquisition Cost	\$28,500	\$369,000
Subtracted Cost of Buckets	-\$5,700	-\$74,300
Total Acquisition Cost	\$166,300	\$2,200,000

The narrow, rigid-mouth containers have a greater effect on filtration effectiveness and contaminant removal than the Sawyer filters alone. Therefore, this alternative directly affects the rates of waterborne-related symptoms while indirectly affecting the benefits associated with missed school and workdays.

Alternative 3: Distribute to All Households with Expanded Education

Our third alternative proposes a comprehensive approach involving the distribution of the Sawyer filters to all households within seven communities while maintaining the current household education and supplementing it with a Water, Sanitation, and Hygiene program (WASH) for children attending the schools within the communities. A WASH program is a public health initiative with three aspects that must be observed to eliminate waterborne illnesses by reducing disease risk and improving health. These components are: clean water, proper sanitation, and hygiene practices. The emphases of school WASH programs underscore the comprehensive nature of our proposal, ensuring that children are sensitized to proper water safety, hygiene, and sanitation practices.

Children are known to be great agents of change in families and communities. Teaching children the knowledge and skills for proper filter usage and hygiene practices can benefit the broader community. Studies show that incorporating school visits in hygiene campaigns significantly raises the success rates of projects. According to the National Library of Medicine, “hand washing promotion among communities in LMICs probably prevents around one-quarter of diarrhea episodes (rate ratio 0.72, 95% CI 0.62 to 0.83)” (Ejemot-Nwadiaro et al. 2015).

We propose a school WASH program that would be conducted alongside the distribution of Sawyer filters within the seven communities in the La Moskitia region. The program is modeled after a similar intervention conducted in the Nyanza region of Kenya that significantly reduced disease incidence among children under five and improved hygiene practices. The intervention significantly reduced diarrhea and gastrointestinal-related clinic visits among children under five years old whose siblings attended the schools. In water-scarce areas, the odds of diarrhea were reduced overall by 56 percent, and specifically to children over five by 66 percent.

The alternative would include two phases: (1) volunteers educating teachers on proper Sawyer filter usage and hygiene practices that they can convey to their students, and (2) volunteers/educators leading educational workshops for students once a week in a central venue per school. See Appendix O for a comprehensive description of the model for this alternative.

Table 2: Estimated Cost for the WASH Intervention Program

	Teachers (per School)	Schools (per Community)	Hours	Duration	Total Costs*
Hygiene Education Sessions	1	1	3	52	\$909
Annualized Hygiene Education Costs					\$10,800
Educator Training	1	1	8	1	\$448
Monitoring and Evaluation	2	3	8	3	\$1,900
WASH Intervention Program Total Cost					\$12,700
*Valuated between 0.5 - 1.5 of average wage (\$1.22).					



Socioeconomic Parameters

Health Benefits

This category consists of avoiding the cost of waterborne diseases. We used the distribution data on diarrhea treatment and medical costs to estimate costs and converted them to USD 2023 from the local currency, the lempira. We estimated the average cost of medical treatment to households in two weeks from the distribution data, which we extrapolated to an average annual cost for the number of households distributed. We estimated the annual average of \$31.64 per household before distributing filters.

We estimated reduced costs of households seeking treatment after the filter by using the average cost of medical treatments per household from the follow-up data. We compared the average cost to households annually before and after treatment from the follow-up data, finding a reduction of \$13.78 (see Appendix E for calculations on medical costs). For the remaining alternatives, we estimated the reduction in medical costs from peer-reviewed literature on field studies conducted in conditions similar to La Moskitia.

Additionally, we include the reduced cost of reducing mortality in children under five within the health benefits estimates. We monetize this effect using the estimate of childhood VSL of \$651,000. The mortality rate of diarrhea in low- and middle-income countries for children under five once they have diarrhea is 0.5 percent (Hartman et al. 2023). Therefore, to estimate the reduced costs from childhood mortality, we calculated the proportion of young children within the population with diarrhea. The estimate is based on reducing young children with diarrhea by comparing the communities with follow-up data to act as a before and after benchmark (Appendix G).

Water Accessibility

Our analysis of La Moskitia's water accessibility included calculating water collection opportunity and time costs. We calculated the overall time spent on water collection using community data by multiplying the average duration of each trip (30 to 45 minutes) by the total number of trips over two weeks. To assign these times a monetary value, we used the local average wage of \$0.0196 per minute to account for the unpaid nature of water collection (see Appendix D for wage details).

Table 3: Cost of Collecting Water with Filter

Total Number of Minutes of Water Collection (Two Weeks)	Cost of Water Collection (20-80% Valuation)	Increasing Costs at 21.38%	Annual Increased Cost
14,966	\$294 (\$58.66 - \$235)	\$62.78 (\$12.55-\$55.22)	\$1,600 (\$326-\$1,400)

This 21.4-percent increase reflects the additional time spent collecting water after obtaining a filter. The increasing costs at 21.4 percent represent 20 to 80 percent of the total increased cost value, demonstrating the range for opportunity cost estimates. In contrast, annual values are obtained by multiplying these costs by 26 weeks.

Productivity

Productivity is measured as the reduced costs of fewer workdays missed when using Sawyer filters. This is based on the opportunity cost of the average wage in the Gracias a Dios Department, around \$1.22 per hour (Universidad Nacional Autónoma de Honduras 2022). See Appendix K for details on how the productivity benefits were calculated and Appendix A for limitations regarding the data. Table 4 details the before and after of workdays missed.

Table 4: Work Absences Reduction

Workdays C7	Total Work Missed/Workers (Two Weeks)	Work Missed Value/Total Earnings	Worker Earnings Lost
Distribution	56/84	\$547/\$8,200	0.07
Follow-Up	84/186	\$1050/\$18,200	0.06

“Work Missed Value” calculates the “Total Work Missed” value by multiplying the average wage by an 8-hour workday. At the same time, the “Total Earnings” reflects 10 full workdays over two weeks for each worker, calculated as $(\text{Workers} * ((\$1.22 * 8 \text{ hours}) * 10))$. Worker earnings loss shows the community loss in potential earnings due to work absences (for example, $\$546.56$ out of $\$8,198.40 = 0.0666$). We derive our treatment effect from the difference in “Work Lost Earnings.” In this case, 0.0666 and 0.058 have a difference of 12.91 percent.

Our figure for the total cost of workdays missed is derived from the total number of missed days and daily earnings. This will give us a potential reduced cost of \$4,600. See the following table for details on workdays missed.

Table 5: Benefits from Reduced Cost of Workdays

Total Number of Workdays Missed in Distribution Survey (Two Weeks)	Cost of Workdays Missed	Reduced Costs at 12.91%	Annual Reduced Cost 12.91%
368	\$35,900	\$4,600	\$120,600

School Absenteeism

We estimate the benefits from the reduced cost of children missing school days based on the shadow price of school absences multiplied by the number of school days missed. We measure Honduras's chronic absenteeism threshold (H-CAT) as 10 to 20 percent of the school year (UNESCO 2021). Honduran national policy sets the target number of school days at 200, but the average number is 125 (Arcia and Gargiulo 2010). The dropout risk for chronic absenteeism is 20 to 25 percent (Castro et al. 2019; see Appendix J for details on calculations). We found the adjusted shadow price of school absenteeism to be \$0.132.

Table 6: Before-and-After School Days Missed

School days C7	Number of School Attendees	Two-Week Absences (Adjusted)	Cost of Absences (Dollars)	Treatment Effect (Percent)
Distribution	272	188	24.82	-21.42
Follow-Up	197	(148)	19.50	

Table 7: Benefits from Reduced Cost of School Absenteeism

Total Number of School Days Missed in Distribution Survey (Two Weeks)	Adjusted Shadow Cost of School Days Missed	Reduced Costs at 21.42%	Annual Reduced Cost
416	\$54.91	\$11.76	\$306



Administrative Costs

Acquisition Costs

The acquisition costs represent the total costs of supplying Sawyer filters to homes, which is approximately \$100 per household. This \$100 includes the Sawyer filter and the supplementary components and services necessary for distributing the filters to the end users. The Sawyer filter is \$20 to \$22 of the overall expense, while \$3 to \$4 is for the buckets. The remaining \$73 is allocated for transportation costs, including fuel and labor associated with the distribution process.

Volunteering Costs

Volunteering costs are associated with the time spent training households in proper filter use and maintenance, as well as distributing filters to households within the community. Eight volunteers from the Yamnika Laya spend an entire day (approximately eight hours) volunteering per community served. The total hours worked by the volunteers is then multiplied by the average wage in the region of \$1.22 and by a wage randomizer (between 0 to 1) to account for our uncertainty in the region's average wage (Universidad Nacional Autónoma de Honduras 2022). See Appendix D for details on wage calculation.

Administrative Costs/Data Follow-Up

Administrative costs include the \$5 to \$7 involved in distributing surveys to the communities to assess the impacts of the water filters. Our client wants to conduct three surveys: the distribution survey and two follow-up surveys on a population sample. Therefore, we use an average cost of \$6 per survey. We assume our client wants to survey 10 percent of the population receiving a filter to represent said population adequately, and the surveys will occur throughout the filter's lifetime. Therefore, this is the only cost annualized in our analysis.



Benefit and Cost Summary Tables

The tables below show the benefits and cost categories discussed above.

Table 8: Cost and Benefits Summary — Incremental Costs Compared to Current Policy

Costs			
	Current Policy	Alternative 2	Alternative 3
Acquisition	\$143,500	\$166,300	\$143,500
Volunteering	\$234	\$234	\$234
Overhead	\$7,700*	\$7,700*	\$7,700*
Additional Education Costs	NA	NA	\$1,400*
Total Costs (10 Years Annualized)	\$150,000	\$170,000	\$160,000
Benefits			
Healthcare Costs Reduced	\$86,900*	\$86,900*	\$86,900*
Young Children's Diarrhea Cases Reduced	\$492,381*	\$581,000*	\$702,700*
Change in Water Collection	-\$816*	-\$816*	-\$816*
Reduction in Workdays Missed	\$6,024*	\$17,200*	\$6,000*
Reduction in School Days Missed	\$617	\$2,465*	\$1,066*
Total Benefits (1 Year)	\$585,100	\$686,800	\$795,900
Total Benefits (10 Years Annualized)	\$1.25 million	\$1.5 million	\$1.7 million
Net Benefits (10 Years Annualized)	\$1.1 million	\$1.3 million	\$1.5 million
*Annualized Values			

Table 9: Cost and Benefits Summary — Alternatives

Costs			
	Alternative 1	Alternative 2	Alternative 3
Acquisition	\$1,800,000	\$2,200,000	\$1,800,000
Volunteering	\$3,000	\$3,000	\$3,000
Overhead	\$100,300*	\$100,300*	\$100,300*
Additional Education Costs	NA	NA	\$17,600*
Total Costs (10 Years Annualized)	\$1,900,000	\$2,300,000	\$2,100,000
Benefits			
Healthcare Costs Reduced	\$1,100,000*	\$1,100,000*	\$3,400,000*
Young Children's Diarrhea Cases Reduced	\$7,600,00*	\$9,000,000*	\$8,800,000*
Change in Water Collection	-\$10,500*	-\$42,100*	\$3,700*
Reduction in Workdays Missed	\$77,900*	\$223,000*	\$45,200*
Reduction in School Days Missed	\$7,988*	\$8,000*	\$13,800*
Total Benefits (1 yYar)	\$8,800,000	\$10.3 million	\$12 million
Total Benefits (10 Years Annualized)	\$18.8 million	\$22.6 million	\$27 million
Net Benefits (10 Years Annualized)	\$16.9 million	\$20.3 million	\$24.9 million
*Annualized values			

Results

Alternative 1: Distribute the Sawyer Filter to All Households

In this alternative, BWM would distribute water filters to the remaining 18,500 households using current methods. The following table breaks down the costs and benefits of this alternative.

Table 10: Present Value of Net Benefits, Distribution to All Households La Moskitia

	Alternative 1
Benefits (\$)	\$18,800,000
Costs (\$)	\$1,900,000
NPV (\$)	\$16,900,000

Under this alternative, the NPV is positive, indicating that the expected benefits within the 10-year lifetime of the Sawyer filter exceed costs. This alternative does not have an NPV associated with these interventions on a scale less than the total, so the NPV is larger than all other alternatives on a reduced scale. However, when the other alternatives are scaled up, this alternative's costs are the lowest, but the benefits are also the lowest.

Alternative 2: Rigid, Narrow-Mouth Containers

In this alternative, BWM would distribute the Sawyer filters in rigid, narrow-mouth containers rather than buckets. This introduces an additional cost in the direct acquisition category. We assume that further risk reduction of diarrhea symptoms is increased proportionally to the values from existing literature. As a result, the benefits are larger than the previous alternative. Furthermore, we found the NPV if the rigid, narrow-mouth containers were given only to the 1,435 households that already have the filters (Alternative 2) and distributed to 18,000 households in the region along with a set of Sawyer filters (Alternative 2 Expanded), as listed in the table below.

Table 11: Present Value of Net Benefits, Rigid, Narrow-Mouth Containers

	Alternative 2	Alternative 2 Expanded
Benefits (\$)	\$1,500,000	\$22,600,000
Costs (\$)	\$170,000	\$2,300,000
NPV (\$)	\$1,300,000	\$20,300,000

Under this alternative, all the NPVs are positive, indicating the benefits of rigid, narrow-mouth containers combined with the Sawyer filters. One reason the NPV for this alternative is higher than the total distribution alternative is that the additional cost of the containers is lower than the benefits of reduced diarrhea risk that the containers provide.

Alternative 3: Distribute to All Households with Expanded Education

In this alternative, BWM would increase education about water filters and hygiene within schools. This alternative introduces additional costs related to volunteering, but the most significant benefit is the reduction of symptoms. Therefore, this alternative has the most significant benefits. We evaluate the NPV of this alternative with expanded education considering the 1,435 households that already have a filter and distributed to 18,000 households in the region in the expanded version as listed in Table 12.

Table 12: Present Value of Net Benefits, Distribution with Expanded Education

	Alternative 3	Alternative 3 Expanded
Benefits (\$)	\$1,700,000	\$27,000,000
Costs (\$)	\$160,000	\$2,100,000
NPV (\$)	\$1,500,000	\$24,900,000

Under this alternative, the NPVs are positive, indicating that the benefits exceed the costs. This alternative significantly reduces the risk of waterborne diseases and has the largest NPV.



Sensitivity Analysis

We adjusted our model's values of uncertain parameters and variables to explore their impact. The NPVs for all alternatives were closely aligned, prompting us to include all three in our Monte Carlo analysis. To address uncertainty, we varied multiple parameter estimates in our assessment. In this section, we explain the rationale for selecting these parameters, ensuring our NPV estimates are robust and comprehensive by conducting 100,000 simulations.

Filter Attrition

We considered filter attrition, or the decay in filtration effectiveness, in the sensitivity analysis. Although 10 years is commonly cited as the standard duration for which a sSwyer filter retains its filtration effectiveness, we will be accounting for the possibility of damages and poor maintenance practices (Murray et al. 2017). Filtration durability decreases to around three years, accounting for poor maintenance practices. Therefore, the sensitivity analysis will consider an attrition rate between 10 and 33 percent each year, meaning the progressive efficiency loss would increase and result in diminishing benefits at a faster rate.

Valuing Volunteer Time

The sensitivity analysis accounts for the uncertainties. Volunteering valuation may vary depending on the opportunity cost of volunteers and the volunteers' preferences; its value may be between 0 and 100 percent of the local wage. There is also uncertainty about the volunteering locations, estimated to be between five and seven communities.

Medical Expenses Reduction Uncertainty

Overall, the uncertainty of the reduction risk per household falls within the standard error of 20.3 percent. The possible reduction, according to the literature, comes to 83.2 percent (Tintle et al. 2021). Accounting for this uncertainty in the Monte Carlo should address the possibility of misreporting or possible non-use.

Health Care Expenses Average Cost

Existing literature suggests that the data overestimates the effect of Sawyer filters on severe diarrhea. Therefore, we set a 50-percent likelihood between risk reduction according to the literature and the reduction according to the data. According to the distribution data, the average cost of health care expenses is \$1.23 (standard error: 10.55) and \$0.53 (standard error: 1.72) in the follow-up. The standard error accounts for the uncertainty of treatment costs.

Children VSL

The VSL for children is set at \$651,000. Still, to account for overestimation, we conducted a uniform distribution using the VSL for the general population without adjusting for age. We also used an alternative that estimates the VSL for Honduras to be set at 0.06 million; the adjusted value for children is \$90,000 (Mardones and Riquelme 2018). This uniform distribution accounts for the validity of calculations of the VSL for children and overvaluation in our calculations. These ranges were modified between (60,000 to 90,000) and (434,000 to 651,000) with the standard VSL on the lower end and the child VSL on the high end.

To address the uncertainty in the reduction of diarrhea cases for young children, we triangulated risk reduction in our alternatives by accounting for standard error on the low end, which equals 0 (no effect from filters), and we account for enhancement in risk reduction at the upper limit by conducting a uniform distribution between our risk reduction and the enhanced rate (Mardones and Riquelme 2018). To provide a more conservative estimate

and prevent overestimation of these values, we peaked probabilities at 15.70 percent for each alternative (see Appendix N for details on triangulation). In the third alternative, risk reduction increases to 56 percent in the second alternative, risk reduction increases to 27 percent.

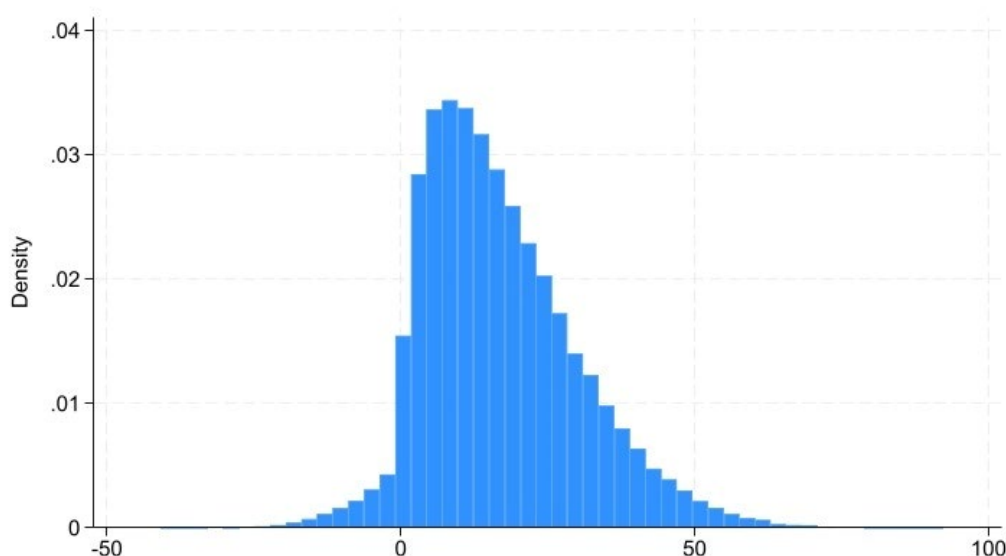
Valuing Water Collection

The value of the water-accessible wage (excluding children) would depend on a value between 20 and 80 percent of the minimum wage in the region. Water collection is laborious and can take several hours, justifying a high opportunity cost. This also accounts for members of the household who collect water but would only be work in the household or under specific circumstances (self-employed and homemakers).

Workdays Missed and School Day Absenteeism

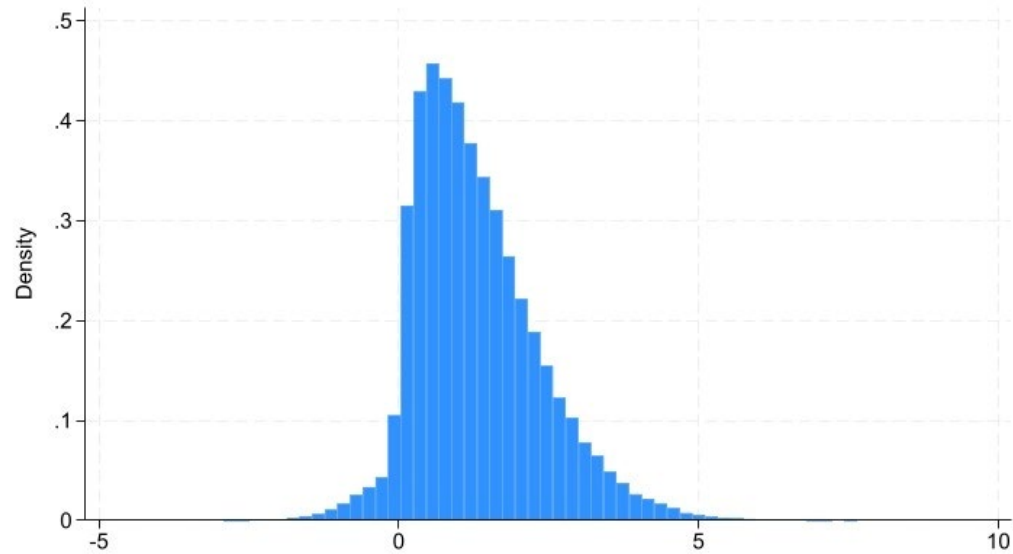
Due to the uncertainty about workdays and missed school days, we adjusted the impact of filters on workdays to account for the standard error in the reduction rate. Uncertainty in the percentage of chronic absenteeism (10 to 20 percent) and the percentage of dropout likelihood (20 to 25 percent) are also accounted for. It's also quite challenging to predict the opportunity cost of lifetime earnings on secondary education, as we don't know which students will drop out before completing primary school and which will drop out before secondary school. Therefore, we set a Monte Carlo between the opportunity cost of both outcomes.

Figure 1: Total Distribution, Monte Carlo



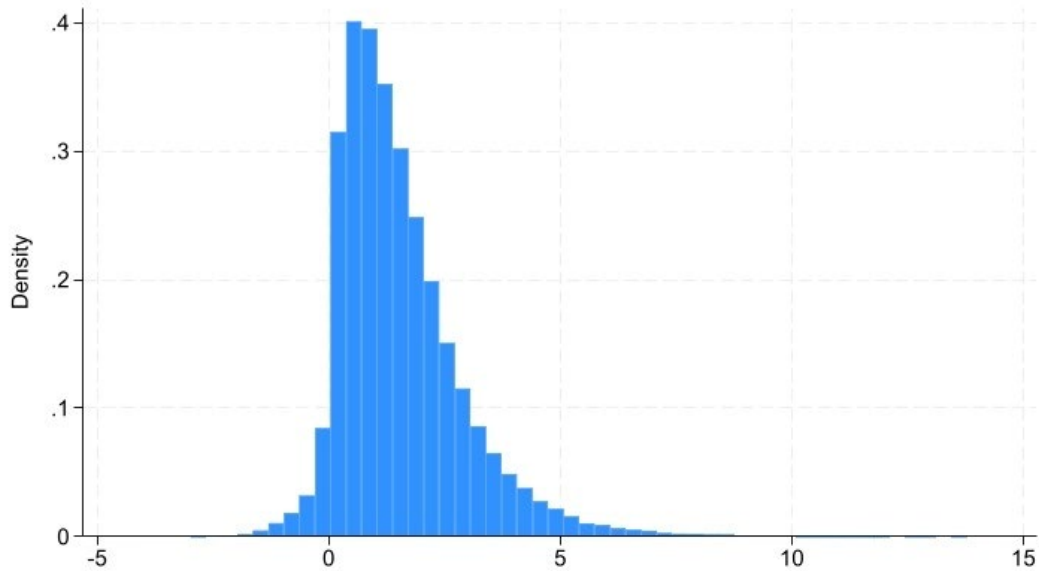
Alternative 1's average is 16.9 million, with a standard deviation of 13.3 million. The scenario with the highest number of benefits shows around 92.2 million, while the worst-case scenario is around a cost of 40.9 million. In 100,000 observations, 95.39 percent resulted in positive outcomes.

Figure 2: Rigid, Narrow-Mouth Containers, Monte Carlo



Alternative 2 average net benefits total around 1.29 million, with a standard deviation of 1.04 million. The best-case scenario results in 7.65 million net benefits, while the worst-case scenario results in -2.92 million net cost. Similar to Alternative 1, 95.39 percent of cases have positive net benefits.

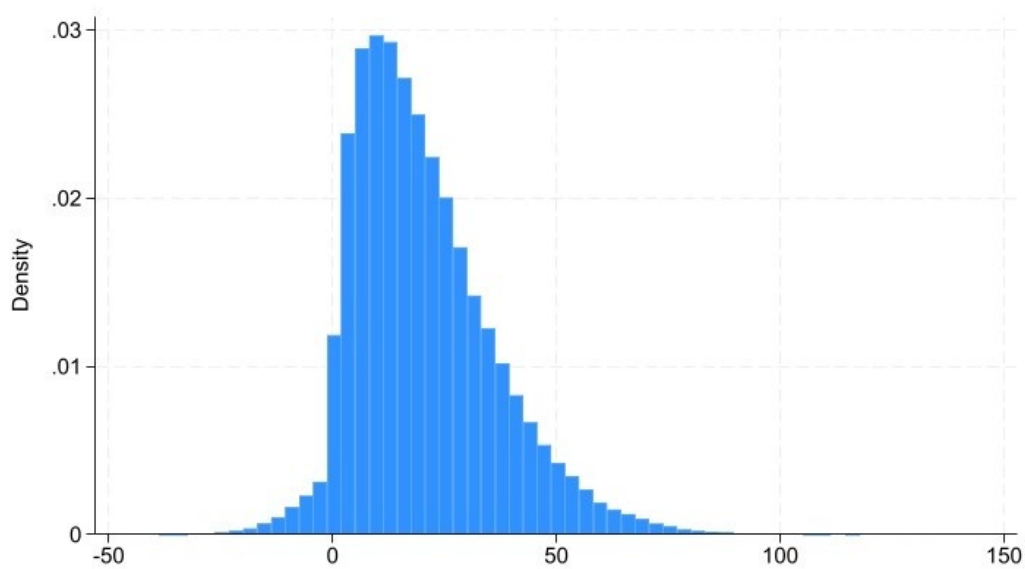
Figure 3: Education, Monte Carlo



On average, Alternative 3 has net benefits of 1.34 million, with a standard deviation of 1.35 million. In the best-case scenario, net benefits would be around 13.8 million; in the worst-case scenario, the alternative would equal a cost of 2.97 million. Compared to Alternative 2, this alternative introduces a broader range of positive outcomes, 95.65 percent of which would result in net benefits.

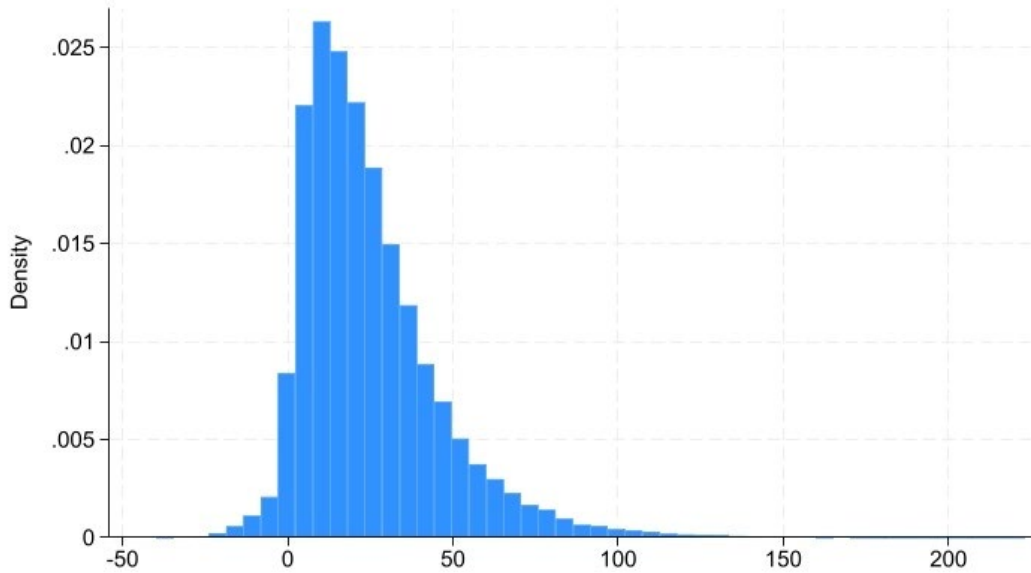


Figure 4: Rigid, Narrow-Mouth Containers Expanded



A combination of Alternative 1 and 2 has an average net benefit of around 20.3 million, with a standard deviation of 15.8 million. The highest possible benefits equal 118 million net benefits, while the worst-case scenario results in -38.7 million net cost. 96.11 percent of outcomes result in positive net benefits.

Figure 5: Expanded Education with Total Distribution



The combination of Alternative 1 and 3 equals net benefits of 24.9 million, with a standard deviation of 21.2 million. The range of outcomes is wide but far unlikely to exceed 50 million. The best-case scenario equals 223 million, while the worst-case scenario costs 39.7 million, with 96.59 percent of outcomes resulting in positive net benefits. Comparing the performance of Alternative 2 and Alternative 3 shows the latter carries more consistent net benefits despite the difference in spread between both graphs.

Conclusion and Recommendations

Our report considers the different benefits and cost categories associated with the different alternatives related to water filtration systems. Our findings reveal that the NPV associated with increased school education for all households within the region is the largest. Still, we note in our sensitivity analysis that our findings are sensitive to variations in specific parameters.

Table 13: Results

	Alternatives				
NPV (\$US million)	Total Distribution	Rigid-Mouth Filter	Rigid-Mouth Filters + Total Distribution	Expanded Education	Expanded Education + Total Distribution
	\$17 million	\$1.3 million	\$20 million	\$1.5 million	\$25 million

We recommend that BWM consider expanding education to households with the filters or expand distribution to the rest of the region with increased education. The NPV in this alternative can be scaled based on the number of households distributed.



Appendices

Appendix A: Limitations

Distribution-Follow-Up Community Survey

This survey version analyzes distribution and follow-up survey data from communities 7 and 5 to assess the impact on missed school days, workdays, and water accessibility.

We analyzed and compared the distribution and follow-up survey data for Communities 5 and 7, as they are the only locations with nearly complete data from both sources. We subsequently extrapolated the findings from this analysis to the other communities represented in the distribution survey for evaluation. Due to the limitations of the dataset, we modified the dataset to get a more precise estimate for different impact categories.

Standing

We recognize that other parties may have standing, including the local healthcare facilities affected by waterborne disease cases. Future analysis should consider assessing the impact in this area.

Assumptions

We assume that the data recorded is representative of a yearlong survey of Honduras if multiplied by 26 weeks.

We estimated the treatment effect on Community 7 by comparing the foregone labor value from workdays missed before and after the filters. In the Monte Carlo section, we used a regression coefficient to account for uncertainty. We then derived our estimate for the change in workdays missed value by applying the calculated treatment effect to the total number of workdays missed as reported in the distribution data.

Water Collection Costs in Follow-up Data

A notable issue in this analysis is the increasing cost of water collection according to our shadow cost calculations using the amount of time to collect as a measurement. We expected a decrease due to the filters, not an increase in minutes. Our model has difficulty explaining this pattern; however, we suspect that this might be due to confounding variables affecting local water sources (contamination of local source in Community 7) or changes in preferred locations for water collection. Evidence for these possibilities is seen through changes in the sources of water. These changes can be found by matching the barcodes in the distribution and follow-up data, as shown in Figure 6.

Figure 6: Changes in Sources of Water

Summary statistics: Sum, Mean, SD, Variance

Group variable: communityid (CommunityID)

communityid	WSou~ped	WSourc~W	WSourc~p	W~nwater	W~_water	WSourc~l	WSou~ted
Community5	0	61	0	30	1	0	76
	0	.480315	0	.2362205	.007874	0	.5984252
	0	.501591	0	.4264414	.0887357	0	.4921582
	0	.2515936	0	.1818523	.007874	0	.2422197
Community5Follow	0	0	0	0	0	0	28
	0	0	0	0	0	0	1
	0	0	0	0	0	0	0
	0	0	0	0	0	0	0
Community7	0	8	0	62	70	6	102
	0	.0540541	0	.4189189	.472973	.0405405	.6891892
	0	.2268922	0	.4950574	.5009643	.1978929	.4643971
	0	.0514801	0	.2450818	.2509653	.0391616	.2156646
Community7Follow	1	14	0	63	59	11	50
	.0095238	.1333333	0	.6	.5619048	.1047619	.4761905
	.09759	.341565	0	.4922476	.4985326	.3077152	.5018282
	.0095238	.1166667	0	.2423077	.2485348	.0946886	.2518315

(Water sources in order: piped, protected well, public tap, rainwater, surface, tubewell/borehole, unprotected well)

Inconsistencies

The data shows inconsistencies with the expected results, which leads us to suggest the following:

- The data is not fully representative of the household with filters or the populations using the sample of the population.
- The population sample did not follow appropriate protocol for filter maintenance.
- A confounding variable impacted the population sample (possibly non-use of filters or changes in water collection patterns).



Appendix B: Case Studies

Rigid Containers in India

Evidence for rigid containers comes from previous studies regarding reductions in cholera infections cases using narrow-necked containers in India. In this intervention study, families were given “sorais,” narrow-necked earthenware pitchers designed for safe water storage. The results showed that families using these vessels had a cholera infection rate of 4.4 percent, compared to 17.3 percent in families using traditional buckets, indicating a significant reduction in cholera transmission (Mintz 1995).

Point-of-Use Water Treatment in Kenya

A case study on the role of school children in promoting point-of-use water treatment and handwashing in schools and households showed a statistically significant increase in water treatment and handwashing knowledge among the 17 schools in Kenya (Blanton et al. 2007). The knowledge could be traced to their households.



Appendix C: Regression Analysis

Workdays Missed

We estimated the treatment effect on Community 7 by comparing the foregone labor value from workdays missed before and after the filters. In the Monte Carlo section, we used a regression coefficient to account for uncertainty. Then, our estimate for the change in workdays missed value will be derived by applying the calculated treatment effect to the total number of workdays missed as reported in the distribution data.

Figure 6: Workdays Missed Regression (P-Value is Too High)

```
. regress workmissed Has_filter
```

Source	SS	df	MS	Number of obs	=	85
Model	34.2209889	1	34.2209889	F(1, 83)	=	2.95
Residual	963.355482	83	11.6066926	Prob > F	=	0.0897
				R-squared	=	0.0343
				Adj R-squared	=	0.0227
Total	997.576471	84	11.8759104	Root MSE	=	3.4069

workmissed	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
Has_filter	1.269103	.7391028	1.72	0.090	-.2009427	2.739149
_cons	1.302326	.5195412	2.51	0.014	.268979	2.335672

A notable issue with this calculation is that the regression coefficient indicates the opposite interaction, suggesting the number of workdays missed increased after introducing the filters. Follow-up data shows that households report many workers and absences, resulting in a disproportionate influence coefficient estimate. Even when accounting for outliers and non-responders, the follow-up survey has over twice the worker population of the distribution; therefore, this regression has unequal weighting. However, in the sensitivity section we considered the possibility of not affecting the missed workdays.

School Days Missed

Following a similar approach to calculating workdays missed, we conducted a pre-post analysis for Community 7. This community was a better fit for the analysis due to its more extensive data in this area than the limited follow-up information available for Community 5. However, Community 7 still has disproportionately different school attendance-to-school absence ratios. The follow-up survey data has more school attendees and, therefore, more absences. To address this, we adjusted the proportion of absences in the distribution survey data.

Figure 7: School Days Missed Regression (P Value is Too High)

. regress schoolmissed Has_filter

Source	SS	df	MS	Number of obs	=	135
Model	.030906769	1	.030906769	F(1, 133)	=	0.00
Residual	8125.18391	133	61.0916083	Prob > F	=	0.9821
				R-squared	=	0.0000
				Adj R-squared	=	-0.0075
Total	8125.21481	134	60.6359315	Root MSE	=	7.8161

schoolmissed	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
Has_filter	-.0316092	1.405327	-0.02	0.982	-2.811292	2.748073
_cons	2.448276	.8379752	2.92	0.004	.7907934	4.105758



Appendix D: Wage Calculations

We used socioeconomic data from the Universidad Nacional Autónoma de Honduras to obtain the average wage. This data consisted of four municipalities: Ahuas, Puerto Lempira, Ramon Villeda Morales, and Wampusiripi. At least four of the locations in the survey are located in these municipalities.

Table 14: 2023 Income per Capita in Communities

Municipalities	Village	Income_per_Capita
Ahuas	<u>Warunta</u>	\$2,417
Puerto Lempira	Tumtum Tara	\$3,021
Ramon Villeda Morales	Pakwi	\$2,234
Wampusiripi	Kurhpa	\$2,117

Avg =\$2,447

All values from the report were converted into 2023 USD. By aggregating the income per capita (2,447), we calculated the average wage to be \$1.176 per hour in 2022. After being adjusted for 2023 inflation, this figure increases to \$1.22.

Wage Ranges

From our conversation with Rick Nelson (Missionary for the Moravian church) via email, we accounted for the volunteering costs of the eight individuals who contributed to the distribution of filters. We accounted for the shadow price of this in the Monte Carlo to be somewhere between 0 and 100 percent (0 to 1) of the average wage. We assumed these ranges because of unclear volunteering circumstances; perhaps community obligations or expectations resulted in the volunteering participation (0 percent), or perhaps volunteers are proactive about volunteering and they choose this activity over the next best alternative, perhaps working or volunteering elsewhere or for different projects (100 percent).

For water collection, we excluded children from our calculation due to complexities. We can make an argument that this is part of their house chores and that there's no need to find a value for water collection in their case. However, because this activity has an opportunity cost for adults — such as spending more time working rather than collecting water — we can justify using a minute wage.

Alternative 3

In Alternative 3, we estimate the wage between 0.5 to 1.5 * the value of the average wage for teachers. Expecting teachers to fill out these duties, we went with this assumption under the premise that teachers would require at least some secondary education to teach in secondary schools. This could put them above average in earnings according to our socioeconomic statistics. However, this assumption may overestimate teacher earnings — some teachers may potentially be volunteers — so we decided to counter that with 0.5.

Appendix E: Estimating Medical Costs from the Dataset

Step	Description	Formula/Calculation	Result
1	Calculate the average medical costs for two weeks before filters from survey data	Average from survey data	\$1.21 (two-week average cost)
2	Extrapolate two-week cost to the region (18,565 households)	$\$1.21 * 18,565$	\$22,464
3	Calculate the annual cost for the region before the filters	$\$22,464 * 26$	\$584,055
4	Calculate the average medical costs for two weeks after filters from survey data	Average from survey data	\$0.53
5	Extrapolate the two-week post-filter cost to the region	$\$0.53 * 18,565$	\$9,839
6	Calculate the annual cost for the region after filters	$\$9,839 * 26$	\$255,826

We dropped an outlier that paid \$81.034 from the after-data. This value was between 10 and 11 standard deviations above the mean and significantly increased the average. We assume that if a household did not answer whether it had received diarrhea treatment in the distribution and follow-up data, it did not receive treatment. The values and reductions presented as an example are for the total distribution alternative and vary based on the additional risk reductions of the other alternatives.

Appendix F: Estimating Medical Costs from the Dataset with Stata Code

- 1) Find baseline medical costs for households before the filter.
 - a) drop if formtype == "Follow Up"
 - i) 1431 Households, after dropping the first four observations that are missing all data/wrongly inputted
 - b) replace DiarrheaMedCost_\$23 = 0 if missing(diarrheatreatment)
 - c) count if missing(DiarrheaMedCost_\$23) | DiarrheaMedCost_\$23 > 0
 - i) 291 households with severe diarrhea (treatment), 20.34% of households
 - d) summarize DiarrheaMedCost_\$23
 - i) \$1.21 per household per two-week period (standard deviation 10.55)
 - ii) $\$1.21 * 26 = 31.46 * 18,565 = \$584,055$ in medical costs per year to the region
- 2) Find reduction in medical costs after treatment (filters) from the dataset.
 - a) drop if formtype == "Distribution"
 - i) 133 Households
 - b) drop if trim(communityid) == ""
 - c) replace DiarrheaMedCost_\$23 = 0 if missing(diarrheatreatment)
 - d) count if missing(DiarrheaMedCost_\$23) | DiarrheaMedCost_\$23 > 0
 - e) 32 households with severe diarrhea (treatment) 24.06% of households
 - f) \$0.53 per household per two-week period (sd 1.72)
 - g) $.53 * 26 = 13.78 * 18,565 = \$255,826$
 - i) Decrease \$328,229 from baseline
- 3) We dropped an outlier that paid \$81.034 from the after data. This value was between 10 and 11 standard deviations above the mean and significantly increased the average.
- 4) We assume that if a household did not answer whether it had received diarrhea treatment in the distribution and follow-up data, it did not receive treatment.
- 5) The values and reductions presented as an example are for the total distribution alternative and vary based on the additional risk reductions of the other alternatives.

Appendix G: Estimating Reduced Costs from Young Child Mortality Through VSL

Step	Description	Formula/Calculation	Result
1	Calculate the proportion of young children in the distribution data.	Number of young children/total individuals	18.95%
2	Find the approximate number of people per household	Total individuals in survey/total households	5.12
3	Calculate the proportion of young children with diarrhea in the before data	Young children with diarrhea/young children	14.98%
4	Find the proportion of young children with diarrhea before filters	Young children with diarrhea/young children	26.82%
5	Find the proportion of young children with diarrhea after filters	Young children with diarrhea/young children	22.62%
6	Calculate the risk reduction	$(26.82 - 22.62) / 26.82$	15.66%
7	Estimate the new percentage of children with diarrhea in the population	$14.98 * (1 - (15.66/100))$	12.63%



Appendix H: Estimating Reduced Costs from Young Child Mortality Through VSL with Stata Code

- 1) Original Mortality and Diarrhea Incidence in Young Children.
 - a) Estimate from literature \$651,331 for children under 5
 - b) Drop if formtype == "Follow Up"
 - c) Drop if trim(communitid) == ""
 - d) Summarize youngchilddiarrhea
 - e) Display r(sum)
 - f) 175 young children with diarrhea
 - g) Summarize youngchildren
 - h) Display r(sum)
 - i) 1168 young children
 - j) Summarize children
 - k) Display r(sum)
 - l) 2674 children
 - m) Summarize adults
 - n) Display r(sum)
 - o) 3489 adults
 - p) Young children are 18.95% of the population. Total population of the sample is 7,331 for 1,431 households, approximately 5.12 people per household.
 - q) Currently, 14.98% of children have diarrhea in the distribution which would be around 2,907 total children in the region.
 - r) Once a young child has diarrhea there is a 0.5% chance that they will die in low and middle-income countries
- 2) Reduced Mortality from Risk Reduction of Filters.
 - a) Before and after of young child diarrhea
 - b) drop if formtype == "Follow Up"
 - c) drop if communityid == "Community 1, 2, 3, 4, and 6)
 - d) drop if trim(communitid) == ""
 - e) summarize youngchilddiarrhea
 - f) display r(sum)
 - g) 70 young children with diarrhea



- h) summarize youngchildren
- i) display r(sum)
- j) 261 young children
 - i) 26.82% of young children with diarrhea
- k) drop if formtype == "Distribution"
- l) summarize youngchilddiarrhea
- m) display r(sum)
- n) 38 young children with diarrhea
- o) summarize youngchildren
- p) display r(sum)
- q) 168 young children
 - i) 22.62% of young children with diarrhea after the filters
- r) Percent reduction before and after from the filters $((26.82 - 22.62) / 26.82) = 15.66\%$
- s) New value = $14.98\% * (1 - (15.66/100)) = 12.63\%$ of young children have diarrhea after the filters



Appendix I: Container Costs

Step 1: Container Logistics for Appendix

1. **Unit Price:** \$19.88 per container (from Walmart listing).
2. **Number of Containers:** 1,435 households.
3. **Total Purchase Cost:** $\text{Unit Price} \times \text{Number of Containers} = 19.88 \times 1,435 = 28,529.80$ $\text{\$}$
 $\text{Unit Price} \times \text{Number of Containers} = 19.88 \times 1,435 = 28,529.80$ $\text{\$}$

Step 2: Calculate Shipping Weight and Volume

1. **Weight per Container:** ~2 pounds (0.91 kg).
 - a. **Total Weight:** $2 \text{ lbs} \times 1,435 = 2,870 \text{ lbs}$ (1,302 kg).
 $2 \text{ lbs} \times 1,435 = 2,870 \text{ lbs}$ (1,302 kg).
2. **Volume per Container:** ~0.11 cubic meters (CBM).
 - a. **Total Volume:** $0.11 \text{ CBM} \times 1,435 = 157.85 \text{ CBM}$.
 $0.11 \text{ CBM} \times 1,435 = 157.85 \text{ CBM}$.

Step 3: Calculate Shipping Costs

Air Freight

1. **Cost per Kilogram:** ~\$3.50 per kg.
2. **Total Cost:** $1,302 \text{ kg} \times 3.50 = 4,557$ $\text{\$}$.
 $1,302 \text{ kg} \times 3.50 = 4,557$ $\text{\$}$.

Sea Freight

1. **Cost per CBM:** ~\$69.30 per CBM.
2. **Total Cost:** $157.85 \text{ CBM} \times 69.30 = 10,937.81$ $\text{\$}$.
 $157.85 \text{ CBM} \times 69.30 = 10,937.81$ $\text{\$}$.



Step 4: Add It Up

Air Freight Total Cost

- **Purchase Cost:** \$28,529.80.
- **Shipping Cost:** \$4,557.
- **Total:** $28,529.80 + 4,557 = 33,086.80$ $\text{\$}28,529.80 + 4,557 = 33,086.80 \text{ \textbackslash,}$
 $\text{\textbackslashtext{\$}}.28,529.80 + 4,557 = 33,086.80 \text{\$}.$

Sea Freight Total Cost

- **Purchase Cost:** \$28,529.80.
- **Shipping Cost:** \$10,937.81.
- **Total:** $28,529.80 + 10,937.81 = 39,467.61$ $\text{\$}28,529.80 + 10,937.81 = 39,467.61 \text{ \textbackslash,}$
 $\text{\textbackslashtext{\$}}.28,529.80 + 10,937.81 = 39,467.61 \text{\$}.$



Appendix J: School Absences Formula

Lifetime Opportunity Cost

A couple of things to consider when calculating the shadow price of school days missed is the opportunity cost in earnings throughout a person's lifetime.

- No primary education income = \$1,464
- Primary education income = \$2,213
- Secondary education income = \$3,335

As you can see, the opportunity cost varies depending on when a student drops out of school. Dropping out early before finishing primary school results in an opportunity cost of \$1,871, while dropping out before finishing secondary education is \$1,122. Assuming a lifetime in the workforce consists of 40 years, at a discount rate of 4 percent, these would be the annualized values:

- No primary education income = \$28,977
- Primary education income = \$43,801
- Secondary education income = \$66,008

$$\text{Lifetime Income}_{\text{Education Level}} = \text{Monthly Income}_{\text{Education Level}} \times \left(1 - \frac{1}{(1 + \text{Discount Rate})^{40}} \right) \div \text{Discount Rate}$$

Using these values, we get our minimum and maximum opportunity cost:

- No primary education opportunity cost = \$37,031
- Only Primary education income = \$22,207

Education Level

{No Education, Primary Education, Secondary Education}

$$\text{Lifetime Opportunity Cost}_{\text{Max/Min}} = \text{Lifetime Income}_{\text{Secondary}} - \text{Lifetime Income}_{\text{No Education/Primary}}$$

Chronic Absenteeism Threshold (HCAT)

In Honduras, the chronic absenteeism threshold (H-CAT) is between 10 and 20 percent of the school year, which consists of 125 school days. Using the average between 10 and 20 percent (15 percent) would give us 18.75 days. This range is accounted for in our sensitivity analysis. The daily probability of dropping out is derived by dividing the 1 by the H-CAT and multiplying by drop-out probability for chronically absent students (20 to 25 percent).

$$\text{HCAT} = \text{Total School Days} \times \text{Chronic Absenteeism Threshold}$$

$$\text{HCAT}_{\text{Daily}} = \frac{1}{\text{HCAT}}$$

$$\text{HCAT}_{\text{Daily Dropout Risk}} = \text{HCAT}_{\text{Daily}} \times \text{Dropout Probability}$$

Base Absence Shadow Cost

$$\text{Base Absence Shadow Cost} = \frac{\text{HCAT}_{\text{Daily Dropout Risk}} \times \frac{(\text{Lifetime Opportunity Cost}_{\text{Min}} + \text{Lifetime Opportunity Cost}_{\text{Max}})}{2}}{\text{Total School Days} \times \text{Years of School Attendance}}$$

Dropout Risk Adjustment (DRA):

$$\text{DRA} = \frac{0.7 \times \text{Total School Days}}{\text{Years of School Attendance}}$$

$$\text{Proportional DRA to HCAT} = \frac{\text{DRA}}{\text{HCAT}}$$

To adjust for populations that would've continued their education if it wasn't for waterborne illness concerns, we used a figure from previous studies suggesting the absences of waterborne illness concerns would result in an additional 0.7 years of school.

Drop out risk adjustment (DRA) is used to account for said at risk population, here equal to 7.95. Dividing by H-CAT will give us the proportional DRA, and we can derive its contribution to the dropout rate by multiplying by the dropout probability.

$$\text{Proportional DRA to Dropout Contribution} = \text{Proportional DRA to HCAT} \times \text{Dropout Probability}$$

Adjusted Absence Shadow Cost

At-risk population = Below Secondary Education Population x Proportional DRA to Dropout Contributions

Using the population shares, for those with secondary education equal to 17.16 percent and 82.83 percent for those without secondary education, we used the formulas below to find the adjusted shadow cost for each population.

Multiplying the proportional DRA to dropout contributions by the below secondary population provided the at-risk population.

The shadow cost formula for both populations is below.

- Below Secondary Education (At-Risk Population):

$$\text{Adj Absence Shadow Cost}_{\text{Below Secondary}} = \text{At-Risk population} \times \text{Base Absence Shadow Cost}$$

- Secondary Education:

$$\text{Adj Absence Shadow Cost}_{\text{Secondary}} = \text{Secondary Education Pop} \times \text{Base Absence Shadow Cost}$$

- Weighted

Weighted Shadow Cost of Absence = Adj Absence Shadow Cost_{Below Secondary} + Adj Absence Shadow Cost_{Secondary}

Adding both these populations provides our weighted shadow cost for the populations affected by waterborne illness.

Impact of Treatment on School Attendance (Two Weeks):

School Attendance Benefit/Cost (Two Weeks) = $-1 \times \text{Weighted Shadow Cost of Absence} \times \text{Treatment Effect (Two Weeks)}$

Overall School Attendance Benefits:

School Attendance Benefits (Yearly) = School Attendance Benefit/Cost (Two Weeks) $\times$ Number of Absences Per Two Weeks $\times$ 26



Appendix K: Workdays Missed Formula

$$\text{workdays_missed_reduction} = 0.1291 \times \text{RandomUniform}()$$

- Assumption: Random uniform value simulates variability in reduction.

$$\text{workmissed_per_day_person} = 9.76$$

- Definition: Estimated wage loss per person per workday missed.

$$\text{wages_lost_twoweeks} = \text{total_workdays_missed_dis} \times \text{workmissed_per_day_person}$$

- Definition: Total wages lost due to missed workdays over a two-week period.

$$\text{workdays_missed_cost_reduction} = \text{wages_lost_twoweeks} \times \text{workdays_missed_reduction}$$

- Definition: Reduction in wage losses due to the intervention.

$$\text{yearly_workloss_benefits} = \text{workdays_missed_cost_reduction} \times 26$$

- Definition: Annual benefit derived from reduced wage losses, assuming 26 two-week periods in a year.

Full Formula:

$$\text{yearly_workloss_benefits} = [(\text{total_workdays_missed_dis} \times 9.76) \times (0.1291 \times \text{RandomUniform}())] \times 26$$



Appendix L: Water Collection Cost Formula

Determine Minute Wage:

$$\text{Minute Wage} = 0.0196$$

Calculate Change in Water Access (Mean Difference):

$$\text{Water Access Increase} = -0.2138$$

Total Minutes for Water Collection:

$$\text{Total Water Collection (minutes)} = \text{Total Adults Collecting Water} \times \text{Average Minutes per Person}$$

Substituting the given constant:

$$\text{Total Water Collection (minutes)} = 14966$$

Adjusted Wage for Water Access Post-Intervention:

$$\text{Adjusted Wage} = 0.20 + 0.60 \times \text{Random Variable (0 to 1)}$$

Total Opportunity Cost of Water Collection (Post-Intervention):

$$\text{Total Water Collection Cost (Post)} = \text{Total Water Collection Cost (Pre)} \times \text{Adjusted Wage}$$

Adjusted Total Water Collection Cost (Benefit Adjustment):

$$\text{Adjusted Total Water Collection Cost} = \text{Total Water Collection Cost (Post)} \times \text{Water Access Increase}$$

(Assumes benefits are calculated over 26 biweekly periods in a year.)

Full Formula for Annualized Benefits:

$$\text{Total Benefits (Annualized)} = 26 \times ((14966 \times 0.0196) \times (0.20 + 0.60 \times \text{Uniform}()) \times -0.2138)$$

Appendix M: Alternative 2 and 3 Benefits Calculations

Alternative 2: Rigid, Narrow-Mouth Containers

Risk Reduction for Young Children

This alternative improves risk reduction by 74.57 percent across the population, which directly and indirectly impacts socioeconomic parameters. To be clear, this is a 74.57 percent improvement on reduction risk of point-of-use filtration.

1. Risk reduction = 15.70%
 2. $15.70 * 1.7457$
- = **0.27% New risk reduction.**

School Days Missed Reduction

1. Initial Child diarrhea risk: 21.42%
 2. Regression coefficient = for every decrease in cases of child diarrhea, , there is a decrease of 2.8934 days absent.
 3. Distribution data: 108 diarrhea cases/ 438 children = **0.1085**
 4. Follow Up data: 28 diarrhea cases/ 258 children
 5. $(47.5 \text{ diarrhea cases} / 438 \text{ children}) = \mathbf{0.2465}$
 6. 0.2465 to 0.1085 is a **56% difference in diarrhea cases.**
 7. New risk reduction: 74.57% improvement in reduction from literature:
 8. New risk reduction $56\% * 1.7457 = 97.75\%$ New risk reduction.
 9. $47.5 * .9775 = \mathbf{45.08 \text{ change in number of cases (less cases)}}$
 10. $47.5 - 45.08 = \mathbf{2.42 \text{ diarrhea cases total with container}}$
 11. $45.08 * -2.894 \text{ (regression coefficient)}$
- = **-128 days absent (128 less days absent) in two weeks**

Now we need to calculate the impact this will have on the current number of school days missed due to waterborne symptoms in proportion to the number of school children (Community 7).

1. 188 school days missed and 197 school children
2. 107 school days missed and 272 school children
3. $188/272 = \mathbf{0.69}$
4. $107/197$
5. (equal to $147/272$) = **0.54**
6. $128 \text{ days} - 147 \text{ days} = 19 \text{ days absent after treatment effect}$
7. $19/272 = 0.10$

8. (distribution to treatment) 0.69 to 0.10 = 85.5%

- (School days) Risk reduction in absences= **85.5 %**

Work Days Missed Reduction

Adult diarrhea risk reduction:

1. 162 adults with diarrhea /629 adults with diarrhea= 0.257 (distribution)
2. 80 adults with diarrhea /332 adults with diarrhea
3. $(152/629) = 0.242$
4. 0.257 to 0.2409 = 6.27% reduction
5. $6.27\% * 1.7457$ (new risk reduction) = 10.945%
6. 0.257 reduced by 10.945% = 0.228
7. $0.228 * 629$ adults =144 adult diarrhea after treatment
8. New proportion adults with diarrhea to adults total = $144/629$
9. $162 - 144 = 18$ less sick adults
10. Regression coefficient = for every decrease in cases of adult diarrhea, there is a decrease of 0.29 days absent from work.
11. $18 \text{ days} * 0.29 = \mathbf{2.32 \text{ days reduced in two weeks}}$

Work absences:

1. Workdays missed/Workers = 56 workdays missed /84 workers = **.6666** (Distribution Community 7)

Workdays missed/workers:

2. 84 workdays missed/186 workers (Follow up Community 7)
3. $(37.8 \text{ workdays missed} /84 \text{ workers}) = .45$
4. $37.8 - 2.32 \text{ days reduced} = \mathbf{35.48 \text{ total days absent after treatment}}$
5. $35.48/84 = \mathbf{.42}$
6. .45 to .42 is a 6.667% decrease
7. Two week earnings = $((1.22 * 8) * 10)$, Cost of absences = $(1.22 * 8)$
8. $35.48 (* \text{ Cost of absences}) / 84 (* \text{ Two week earnings})$
9. $346/8198.40 = \mathbf{0.042}$
10. 0.0666 to 0.042 = 36.94%

Workdays missed reduction = 36.94%

Alternative 3: Distribute to all Households with Expanded Education

Risk Reduction for Young Children

This effect is supported by various studies regarding the relationship of water treatment, education, and risk reduction. Meta-analysis studies regarding water quality improvements (e.g., filtration or point-of-use treatment) without extensive sanitation components were associated with a 17 percent reduction in diarrheal disease, while Sanitation improvements yielded a 36 percent reduction without accounting for behavior change (Marmot et al. 2010).

Another study evaluating the effects of improved sanitation and drinking water on diarrhea occurrence among children under five in rural low and middle-income countries suggests a similar impact. The findings indicated that access to improved sanitation was associated with a 16.6 percent reduction in the probability of developing diarrhea among under-five children but when combined with improved water sources, the reduction increased to 24.5 percent (Rehman et al. 2020).

Other analyses suggest the effects of various WASH interventions, including sanitation improvements and education, showed diarrhea risk reductions between 27% and 56%, depending on the intervention type and combinations (Chaudhary et al. 2017).

Academic consensus seems to indicate somewhere between 10-20% risk reduction in diarrhea if solely relying on water filtration without a rigorous sanitation intervention.

Although OTA and BWM's intervention did have instructional and educational elements, we suggest these interventions, although beneficial, could be improved upon to yield a higher risk reduction rate. The current educational component of this intervention is 30 minutes to an hour of instructional information about filter usage and sanitation. We are assuming there that there is no other sanitation initiative besides this one (Nelson email to author 2024).

The intervention that is Alternative 3, which is based on targeted interventions on schools suggesting a 56 percent reduction in diarrhea cases, which although the rate is on the higher end of general consensus, its plausible, specially accounting for uncertainties (Dreibelbis et al. 2014).

Risk reduction is adjusted to from 15.70 percent to 56 percent as upper limit.

School Days Missed Reduction

Distribution:

1. 108 Diarrhea/438 children (.2465)

Follow-up:

2. 28 Diarrhea cases/258 children (.1085)
3. (47.5 Diarrhea cases/438 children)
4. .2465 to .1085 = 56% decrease
5. 56% current reduction rate
6. 66% new risk reduction
7. 56% - 66% an increase of 17.86% in risk reduction

8. $108 \text{ diarrhea cases} * 66\% = 71.28$
9. $108 - 71.28 = 36.72$
10. $36.72 \text{ diarrhea cases} / 438 \text{ children}$
11. $36.72 \text{ diarrhea cases} - 47.5 \text{ diarrhea cases} = \text{difference of } 10.8 \text{ cases}$
12. Regression coefficient = for each decrease in child diarrhea reduction, there is a 2.8934 days absent
- $10.8 * 2.2894 = \mathbf{24.726 \text{ change in absences (24.726 less absences)}}$

School days missed

Distribution:

11. $188 \text{ school days missed} / 272 \text{ school children} = 0.69$

Follow-up:

12. $107 \text{ school days missed} / 197 \text{ school children} = 0.54$
(Converted to $147 / 272$)

Change in absences

13. $147 - 24.726 = 122.24 \text{ school days}$
14. $122.24 \text{ school days missed} / 272 \text{ school children}$
 $122.24 / 272 = 0.45$

(Distribution to treatment) 0.69 to 0.45 = 34.78% reduction in absences



Appendix N: Triangulation

When accounting for risk reduction with young children, we place additional uncertainty to properly assess the filter's impact. Compared to the other age groups, children under the age of five experiencing diarrhea symptoms can experience direct lethal consequences. Due to the severity of this impact category and young children's lives being the largest contributor of net benefits, we took additional steps to ensure accuracy of the filter's effect.

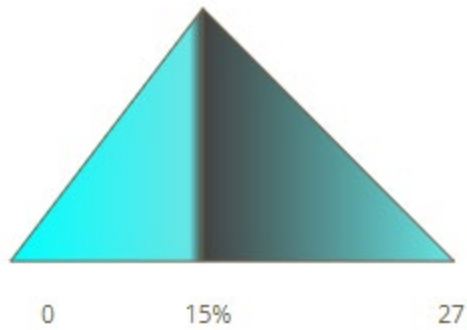
In our model, risk reduction uncertainty is accounted for by placing a maximum of 15.70 percent and a minimum of 0 percent (derived from pre-test post-test on Community 7 and 5, as well as regression analysis). We decided to keep the upper limit at 15.70 percent to prevent overestimating the impact. Literature on sawyer filters often prescribes a risk reduction of 61 to 95 percent, which is a far cry from our figures. This discrepancy suggests possible non-use, poor maintenance, or errors with the sample. We originally planned to use risk reduction figures from the literature as the upper limit to account for these factors while peaking probabilities at 15.70 percent, but the results appeared to be overly optimistic and potentially misleading. Therefore, we decided to peak probabilities at 15.70 percent and keep it as the higher limit.



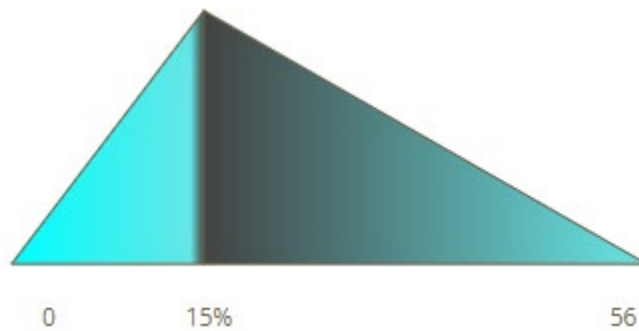
Current policy's risk reduction.

Our two alternatives directly impact young children's diarrhea risk: Alternative 2 increases reduction up to 27 percent, and Alternative 3 increases reduction up to 56 percent. We did not haste in concluding this was a definite replacement of our risk reduction calculations; instead, we created a uniform function to randomize the upper limit of risk reduction to a value between 15.70 percent and the new risk reduction rate. We made sure peak probability remained at 15.70 percent across each alternative. Although both these alternatives will have a positive impact on the young children population, uncertainties include possible implementation issues, geographical considerations, differences in infrastructure, cultural diversity amongst communities, and possible unknown confounding variables. Therefore, we decided that the best way to align our assumptions with these obstacles is to randomize the impact while keeping it constant with our original calculations.





Alternative 2's risk reduction. Probabilities peak at 15.70 percent, and a uniform distribution between 15.70 and 27 percent results in a different upper limit for each observation. Darker shades represent the areas of risk reduction is likely to be in each observation.



Alternative 3 has a wider range of probabilities for the upper limit, but this range is unlikely to distort the results, as the area closer 15.70 has a higher probability compared to the upper limit of 56 percent.

Each Monte Carlo simulation will have not only a randomized risk reduction rate (with a higher likelihood placed closer to 15.70 percent), but also a randomized risk reduction upper limit. For example, Alternative 2 in Simulation A will have a risk reduction between 0 and 17 percent while Simulation B will have one between 0 and 23 percent.

Appendix O: Comprehensive WASH Intervention Program Plan

The program targets school-going students in schools within the seven selected communities. The program aims at:

1. Reducing diarrhea cases and health costs for children under five, schoolgoing children, and adults.
2. Reducing the number of school days missed for students and missed days of work for adults.
3. Increasing the knowledge of proper usage of filters and adequate hygiene practices.
4. Cultivating a sustainable, hygienic culture in the population in days to come.

It consists of two components. First, a half-day workshop will be organized for one teacher/educator per school, who will be trained on proper Sawyer water filter usage and the proper washing of hands by the volunteers at the beginning of the school term. The teachers will be encouraged to go back to their schools, educate their fellow teachers and students about these methods, and invite clubs among students to promote safe water use and hygiene. Teachers additional roles will be to monitor the students' hand-washing behaviors and patronize the formation and activities of a hygiene club that would champion safe water use and hygiene behaviors among students.

Second, Blessings Flow project educators will lead a one-hour classroom activity at all grade levels to introduce the Sawyer water filters, explain the importance of proper use, and illustrate how to use them properly. The following activities are recommended:

1. Clubs should hold weekly forums with practical demonstrations to reinforce knowledge of handwashing and safe water use.
2. Children will create posters with hygiene messages to display around the school.
3. Selected schools will receive Sawyer water filters and handwashing stations.
4. Clubs will hold weekly forums with practical demonstrations to reinforce hygiene and safe water practices.
5. Volunteers will visit schools monthly to observe, remind students of lessons, and encourage practice.



Appendix P: Current Policy

Costs	
Current Policy	
Acquisition	-\$143,500
Volunteering	-\$234
Overhead	-\$7,749*
Total Costs	-\$151,483
Benefits	
Health Care Costs Reduced	\$86,940*
Young Children Diarrhea Cases Reduced	\$492,381*
Change in Water Collection	-\$816*
Reduction in Workdays Missed	\$6,024*
Reduction in School Days Missed	\$617*
Total Benefits (1 Year)	\$585,148
Net Benefits (1 Year)	\$433,665
Net Benefits (10 Years Annualized)	\$1,103,165
*Annualized Values	



Appendix Q: Monte Carlo PVTN STATA Code Current Policy

```
set obs 100000
set seed 100

gen discount_rate_Honduras = 0.04
gen acquisition_cost = 143500
gen distribution_cost = 0 //104682
gen overhead_cost = (77490 * .1) //((1435 * 18)*3) * .1
gen vol_range_selector = (uniform() > 0.5)
gen volunteering = . //between 0 to (390.40 to 546.56)
replace volunteering = 390.40 * uniform() if vol_range_selector == 0
replace volunteering = 546.56 * uniform() if vol_range_selector == 1

gen net_costs = acquisition_cost + distribution_cost + volunteering

gen pv_overhead = overhead / (1 + discount_rate_Honduras)^10

gen population = 7731
gen working_pop = 1808
gen hourwage = 1.22
gen total_workdays_missed_dis = 368
gen households_distribution = 1435
gen dia_reporting_households_dis = 644
gen households_follow_up = 133
gen dia_reporting_households_FU = 84
gen number_of_school_years = 11

gen honduras_schooldays = 125
gen honduras_schoolyears = 11

gen school_attend_treatment_twoweek = -0.2142 //45% reduction on absences to 15% increase on absences. Pretty
sure its 21% reduction. So possibel -0.45 + 0.60 * uniform()
gen secondary_ed_pop = 0.1716
```



```

gen below_secondary_ed_pop = 0.8283
gen No_ed_income = 1464
gen Primary_ed_income = 2213
gen Secondary_ed_income = 3335
gen lifetime_No_ed_income = No_ed_income * (1 - (1 + discount_rate_Honduras)^(-40)) / discount_rate_Honduras
gen lifetime_Primary_ed_income = Primary_ed_income * (1 - (1 + discount_rate_Honduras)^(-40)) / discount_rate_Honduras
gen lifetime_Secondary_ed_income = Secondary_ed_income * (1 - (1 + discount_rate_Honduras)^(-40)) / discount_rate_Honduras
gen lifetime_Oppostunity_Cost_max = lifetime_Secondary_ed_income - lifetime_No_ed_income
gen lifetime_Oppostunity_Cost_min = lifetime_Secondary_ed_income - lifetime_Primary_ed_income
gen chronic_absent_threshold = .10 + .10 * uniform() //10% - 20%
gen dropout_prob_chronic_absent = .20 + .5 * uniform() // 20%-25%
gen HCAT = honduras_schooldays*chronic_absent_threshold
gen HCAT_daily = 1/HCAT
gen HCAT_daily_dropout_risk = HCAT_daily * dropout_prob_chronic_absent
gen base_absence_shadow_cost = (HCAT_daily_dropout_risk * (lifetime_Oppostunity_Cost_min + lifetime_Oppostunity_Cost_max * uniform())) / (honduras_schooldays * number_of_school_years)
//(lifetime_Oppostunity_Cost_min or lifetime_Oppostunity_Cost_max/(honduras_schooldays * number of school years))
gen DRA = (0.7 * honduras_schooldays)/honduras_schoolyears
gen proportional_DRA_HCAT = DRA/HCAT
gen proportional_DRAHCAT_DropoutCont = proportional_DRA_HCAT * dropout_prob_chronic_absent
gen At_Risk_student_pop = below_secondary_ed_pop * proportional_DRAHCAT_DropoutCont
gen adj_absence_shadow_cost_below_SE = At_Risk_student_pop * base_absence_shadow_cost
gen adj_absence_shadow_cost_SE= secondary_ed_pop * base_absence_shadow_cost
gen weighted_shadow_cost_absence = adj_absence_shadow_cost_SE + adj_absence_shadow_cost_below_SE
gen school_attendance_BorC_twoweek = (-1*weighted_shadow_cost_absence) * school_attend_treatment_twoweek
gen num_absences = 416
gen school_att_benefits = school_attendance_BorC_twoweek * num_absences
gen yearly_SchoolAtt_benefits = school_att_benefits * 26

```

```
gen diarrhea_Risk_Reduction = 0.182 + 0.428 * uniform() //diarrhea2 and Has_filter (MAIN)
```

```
gen pop_Risk_Reduction = 0.05 //totaldiarrhea and Has_filter
```

```
gen dis_avg_treatent = rnormal(1.21, 10.55)
```

```
replace dis_avg_treatent = rnormal(1.21, 10.55) if dis_avg_treatent < 0
```

```
gen dis_Dtreatment_HH = dis_avg_treatent * households_distribution
```

```
gen followup_avg_treatment = rnormal(.53, 1.722)
```

```
replace followup_avg_treatment = rnormal(.53, 1.722) if followup_avg_treatment < 0
```

```
gen followup_Dtreatment_HH = followup_avg_treatment * households_distribution
```

```
gen difference_Dtreatment = dis_Dtreatment_HH - followup_Dtreatment_HH
```

```
// (1004.50)
```

```
gen dis_severe_diarrhea = .2034
```

```
gen literature_reduction = .8317
```

```
gen post_rate_SevereDia = dis_severe_diarrhea * (1 - literature_reduction)
```

```
gen post_hh_SevereDia = households_distribution * post_rate_SevereDia
```

```
gen severetreatment_avg = 11.68
```

```
gen lit_Dtreat_HH = post_hh_SevereDia * severetreatment_avg
```

```
//(554.78)
```

```
gen annual_lit_Dtreamt = difference_Dtreatment * 26
```

```
gen annual_differenceD = lit_Dtreat_HH * 26
```

```
gen chloe_selector = (uniform() > 0.5)
```

```
gen chloe_method_treat = .
```

```
replace chloe_method_treat = annual_lit_Dtreamt if chloe_selector == 0
```

```
replace chloe_method_treat = annual_differenceD if chloe_selector == 1
```



```

//gen avg_medical_range_selector = (uniform() > 0.5)
//gen avg_medical_cost= . //between 1.91 (SE:tba) and 6.38 (SE:tba)

//replace dis_avg_treatent = rnormal(1.21, 10.55) if avg_medical_range_selector == 0
//replace avg_medical_cost = rnormal(6.3, 25.03) if avg_medical_range_selector == 1
// Replace negatives with new random values iteratively
//replace avg_medical_cost = rnormal(1.91, 14.02) if avg_medical_range_selector == 0 & avg_medical_cost < 0
//replace avg_medical_cost = rnormal(6.3, 25.03) if avg_medical_range_selector == 1 & avg_medical_cost < 0

gen avg_medical_range_selector = (uniform() > 0.5)
gen avg_medical_cost= . //between 1.91 (SE:tba) and 6.38 (SE:tba)

replace avg_medical_cost = rnormal(1.91, 14.02) if avg_medical_range_selector == 0
replace avg_medical_cost = rnormal(6.3, 25.03) if avg_medical_range_selector == 1
// Replace negatives with new random values iteratively
replace avg_medical_cost = rnormal(1.91, 14.02) if avg_medical_range_selector == 0 & avg_medical_cost < 0
replace avg_medical_cost = rnormal(6.3, 25.03) if avg_medical_range_selector == 1 & avg_medical_cost < 0

gen dia_prevalance_FU = households_follow_up *
((dia_reporting_households_dis/households_distribution)*diarrhea_Risk_Reduction)
gen dia_prevalance_overall_estimate = (dia_prevalance_FU/households_distribution) * households_distribution
gen medical_cost_reduction_two_weeks = dia_prevalance_overall_estimate * avg_medical_cost
gen yearly_med_cost_benefits = medical_cost_reduction_two_weeks * 26

gen workdays_missed_reduction = 0 + 0.1291 * uniform() //Comm7 compared to Comm7FU. Barcode doesn't have
enough data. Not StatSig but we are using it
gen workmissed_per_day_person = 9.76

```

```

gen wages_lost_twoweeks = total_workdays_missed_dis * workmissed_per_day_person
gen workdays_missed_cost_reduction = wages_lost_twoweeks * workdays_missed_reduction
gen yearly_workloss_benefits = workdays_missed_cost_reduction * 26

gen DiaReduce_lower_limit = 0
gen DiaReduce_peak = .1570 //new peak
gen DiaReduce_upper_limit = .1570
gen u = runiform()
gen DiaReduce_random = cond(u <= (DiaReduce_peak - DiaReduce_lower_limit) / (DiaReduce_upper_limit -
DiaReduce_lower_limit), DiaReduce_lower_limit + sqrt(u * (DiaReduce_peak - DiaReduce_lower_limit) *
(DiaReduce_upper_limit - DiaReduce_lower_limit)), DiaReduce_upper_limit - sqrt((1 - u) * (DiaReduce_upper_limit -
DiaReduce_peak) * (DiaReduce_upper_limit - DiaReduce_lower_limit)))

// Young children risk reduction randomizer.
gen youngchildren_pop_Risk_Reduction = 0.105 //Not statistically significant

gen VSL1 = 434220 + (651331 - 434220) * runiform()
gen VSL2 = 60000 + (90000 - 60000) * runiform()
gen VSL_Childern_Honduras = VSL1 + (VSL2 - VSL1) * runiform()

//gen VSL_Childern_Honduras = 60000 + 591331 * uniform()
gen youngchildren_diarrhea_total = 175
gen childerns_without_diseases = youngchildren_diarrhea_total * DiaReduce_random
gen youngchild_mortality_dia = 0.001677 + 0.003323 * uniform()

gen lower_limit = 0.01677
gen peak = 0.01677
gen upper_limit = 0.03323
gen u2 = runiform()

//gen youngchild_mortality_dia = cond(u2 <= (peak - lower_limit) / (upper_limit - lower_limit), lower_limit + sqrt(u *
(peak - lower_limit) * (upper_limit - lower_limit)), upper_limit - sqrt((1 - u) * (upper_limit - peak) * (upper_limit -
lower_limit)))

```

```

gen childrens_life_saved = childrens_without_diseases * youngchild_mortality_dia
gen VSL_benefits = childrens_life_saved * VSL_Childern_Honduras
gen yearly_VSL_benefits = VSL_benefits * 26

gen minute_wage = 0.0196
gen water_access_increase = -0.2138 //This the difference in mean
gen total_water_collect = 14966 //not counting children
gen total_water_collect_min = total_water_collect * minute_wage
gen water_access_cost_adj_wage = .20 + .60 * uniform() // (0.2 to 0.8 * minute_wage)
gen water_access_min_post = total_water_collect_min * water_access_cost_adj_wage
gen water_cost_adj_total = water_access_min_post * water_access_increase
gen water_access_total_benefits = water_cost_adj_total * 26

gen net_benefits = yearly_SchoolAtt_benefits + chloe_method_treat + yearly_workloss_benefits +
water_access_total_benefits + yearly_VSL_benefits

//chloe_method_treat instead of yearly_med_cost_benefits

gen year1_net_benefits = net_benefits

gen year2_net_benefits = year1_net_benefits * 0.6666 + 0.2333 * uniform()
gen year3_net_benefits = year2_net_benefits * 0.50 + 0.3889 * uniform()
gen year4_net_benefits = year3_net_benefits * 0.01 + 0.875 * uniform()
gen year5_net_benefits = year4_net_benefits * 0.01 + 0.8525 * uniform()
gen year6_net_benefits = year5_net_benefits * 0.01 + 0.834 * uniform()
gen year7_net_benefits = year6_net_benefits * 0.01 + 0.8 * uniform()

gen year8_net_benefits = year7_net_benefits * 0.01 + 0.75 * uniform()
gen year9_net_benefits = year8_net_benefits * 0.01 + 0.70 * uniform()
gen year10_net_benefits = year9_net_benefits * 0 + 0.5 * uniform()

```

```
gen annualized_benefits = year1_net_benefits * (1 + discount_rate_Honduras)^1 + year2_net_benefits * (1 + discount_rate_Honduras)^2 + year3_net_benefits * (1 + discount_rate_Honduras)^3 + year4_net_benefits * (1 + discount_rate_Honduras)^4 + year5_net_benefits * (1 + discount_rate_Honduras)^5 + year6_net_benefits * (1 + discount_rate_Honduras)^6 + year7_net_benefits * (1 + discount_rate_Honduras)^7 + year8_net_benefits * (1 + discount_rate_Honduras)^8 + year9_net_benefits * (1 + discount_rate_Honduras)^9 + year10_net_benefits * (1 + discount_rate_Honduras)^10
```

```
gen all_benefits = annualized_benefits
```

```
gen all_costs = net_costs + pv_overhead
```

```
gen PVNB = all_benefits - all_costs
```

```
hist PVNB
```

```
gen proportionBenefitsCosts = 0 if PVNB < 0
```

```
replace proportionBenefitsCosts = 1 if proportionBenefitsCosts == .
```

```
tab proportionBenefitsCosts
```

```
sum PVNB
```



Appendix R: Monte Carlo PVBN STATA Code Alternative 1

```
set obs 100000
set seed 100

gen multiplier_alt1 = 18565/1435
//change 20000 to whatever population number

gen discount_rate_Honduras = 0.04
gen acquisition_cost = 143500 * multiplier_alt1
gen distribution_cost = 0 //104682 * multiplier_alt1
gen overhead_cost = (77490 * .1) * multiplier_alt1
gen vol_range_selector = (uniform() > 0.5)
gen volunteering = . //between 0 to (390.40 to 546.56)
replace volunteering = (390.40 * uniform() * multiplier_alt1) if vol_range_selector == 0
replace volunteering = (546.56 * uniform() * multiplier_alt1) if vol_range_selector == 1

gen net_costs = acquisition_cost + distribution_cost + volunteering

gen pv_overhead = overhead / (1 + discount_rate_Honduras)^10

gen population = 7331 * multiplier_alt1
gen working_pop = 1808 * multiplier_alt1
gen hourwage = 1.22
gen total_workdays_missed_dis = 368 * multiplier_alt1
gen households_distribution = 1435 * multiplier_alt1
gen dia_reporting_households_dis = 644
gen households_follow_up = 133 * multiplier_alt1
gen dia_reporting_households_FU = 84 * multiplier_alt1
gen number_of_school_years = 11

gen honduras_schooldays = 125
```

```

gen honduras_schoolyears = 11

gen school_attend_treatment_twoweek = -0.2142 //45% reduction on absences to 15% increase on absences. Pretty
sure its 21% reduction. So possibel -0.45 + 0.60 * uniform()

gen secondary_ed_pop = 0.1716

gen below_secondary_ed_pop = 0.8283

gen No_ed_income = 1464

gen Primary_ed_income = 2213

gen Secondary_ed_income = 3335

gen lifetime_No_ed_income = No_ed_income * (1 - (1 + discount_rate_Honduras)^(-40)) / discount_rate_Honduras

gen lifetime_Primary_ed_income = Primary_ed_income * (1 - (1 + discount_rate_Honduras)^(-40)) /
discount_rate_Honduras

gen lifetime_Secondary_ed_income = Secondary_ed_income * (1 - (1 + discount_rate_Honduras)^(-40)) /
discount_rate_Honduras

gen lifetime_Oppostunity_Cost_max = lifetime_Secondary_ed_income - lifetime_No_ed_income

gen lifetime_Oppostunity_Cost_min = lifetime_Secondary_ed_income - lifetime_Primary_ed_income

gen chronic_absent_threshold = .10 + .10 * uniform() //10% - 20%

gen dropout_prob_chronic_absent = .20 + .5 * uniform() // 20%-25%

gen HCAT = honduras_schooldays*chronic_absent_threshold

gen HCAT_daily = 1/HCAT

gen HCAT_daily_dropout_risk = HCAT_daily * dropout_prob_chronic_absent

gen base_absence_shadow_cost = (HCAT_daily_dropout_risk * (lifetime_Oppostunity_Cost_min +
lifetime_Oppostunity_Cost_max * uniform())) / (honduras_schooldays * number_of_school_years)

//(lifetime_Oppostunity_Cost_min or lifetime_Oppostunity_Cost_max/(honduras_schooldays * number of school
years))

gen DRA = (0.7 * honduras_schooldays)/honduras_schoolyears

gen proportional_DRA_HCAT = DRA/HCAT

gen proportional_DRAHCAT_DropoutCont = proportional_DRA_HCAT * dropout_prob_chronic_absent

gen At_Risk_student_pop = below_secondary_ed_pop * proportional_DRAHCAT_DropoutCont

gen adj_absence_shadow_cost_below_SE = At_Risk_student_pop * base_absence_shadow_cost

gen adj_absence_shadow_cost_SE= secondary_ed_pop * base_absence_shadow_cost

gen weighted_shadow_cost_absence = adj_absence_shadow_cost_SE + adj_absence_shadow_cost_below_SE

gen school_attendence_BorC_twoweek = (-1*weighted_shadow_cost_absence) * school_attend_treatment_twoweek

gen num_absences = 416 * multiplier_alt1

```

```

gen school_att_benefits = school_attendance_BorC_twoweek * num_absences
gen yearly_SchoolAtt_benefits = school_att_benefits * 26

```

```

gen diarrhea_Risk_Reduction = 0.182 + 0.428 * uniform() //diarrhea2 and Has_filter (MAIN)

```

```

gen pop_Risk_Reduction = 0.05 //totaldiarrhea and Has_filter

```

```

gen dis_avg_treatent = rnormal(1.21, 10.55)
replace dis_avg_treatent = rnormal(1.21, 10.55) if dis_avg_treatent < 0
gen dis_Dtreatment_HH = dis_avg_treatent * households_distribution
gen followup_avg_treatment = rnormal(.53, 1.722)
replace followup_avg_treatment = rnormal(.53, 1.722) if followup_avg_treatment < 0
gen followup_Dtreatment_HH = followup_avg_treatment * households_distribution
gen difference_Dtreatment = dis_Dtreatment_HH - followup_Dtreatment_HH
// (1004.50)

```

```

gen dis_severe_diarrhea = .2034
gen literature_reduction = .8317
gen post_rate_SevereDia = dis_severe_diarrhea * (1 - literature_reduction)
gen post_hh_SevereDia = households_distribution * post_rate_SevereDia
gen severetreatment_avg = 11.68
gen lit_Dtreat_HH = post_hh_SevereDia * severetreatment_avg
//(554.78)
gen annual_lit_Dtreatmt = difference_Dtreatment * 26
gen annual_differenceD = lit_Dtreat_HH * 26

```

```

gen chloe_selector = (uniform() > 0.5)
gen chloe_method_treat = .

```

```
replace chloe_method_treat = annual_lit_Dtreamt if chloe_selector == 0
```

```
replace chloe_method_treat = annual_differenceD if chloe_selector == 1
```

```
//gen avg_medical_range_selector = (uniform() > 0.5)
```

```
//gen avg_medical_cost= . //between 1.91 (SE:tba) and 6.38 (SE:tba)
```

```
//replace dis_avg_treatent = rnormal(1.21, 10.55) if avg_medical_range_selector == 0
```

```
//replace avg_medical_cost = rnormal(6.3, 25.03) if avg_medical_range_selector == 1
```

```
// Replace negatives with new random values iteratively
```

```
//replace avg_medical_cost = rnormal(1.91, 14.02) if avg_medical_range_selector == 0 & avg_medical_cost < 0
```

```
//replace avg_medical_cost = rnormal(6.3, 25.03) if avg_medical_range_selector == 1 & avg_medical_cost < 0
```

```
gen avg_medical_range_selector = (uniform() > 0.5)
```

```
gen avg_medical_cost= . //between 1.91 (SE:tba) and 6.38 (SE:tba)
```

```
replace avg_medical_cost = rnormal(1.91, 14.02) if avg_medical_range_selector == 0
```

```
replace avg_medical_cost = rnormal(6.3, 25.03) if avg_medical_range_selector == 1
```

```
// Replace negatives with new random values iteratively
```

```
replace avg_medical_cost = rnormal(1.91, 14.02) if avg_medical_range_selector == 0 & avg_medical_cost < 0
```

```
replace avg_medical_cost = rnormal(6.3, 25.03) if avg_medical_range_selector == 1 & avg_medical_cost < 0
```

```
gen dia_prevalance_FU = households_follow_up *
```

```
((dia_reporting_households_dis/households_distribution)*diarrhea_Risk_Reduction)
```

```
gen dia_prevalance_overall_estimate = (dia_prevalance_FU/households_distribution) * households_distribution
```

```
gen medical_cost_reduction_two_weeks = dia_prevalance_overall_estimate * avg_medical_cost
```

```
gen yearly_med_cost_benefits = medical_cost_reduction_two_weeks * 26
```



```

gen workdays_missed_reduction = 0 + 0.1291 * uniform() //Comm7 compared to Comm7FU. Barcode doesn't have
enough data. Not StatSig but we are using it

gen workmissed_per_day_person = 9.76

gen wages_lost_twoweeks = total_workdays_missed_dis * workmissed_per_day_person

gen workdays_missed_cost_reduction = wages_lost_twoweeks * workdays_missed_reduction

gen yearly_workloss_benefits = workdays_missed_cost_reduction * 26


gen DiaReduce_lower_limit = 0
gen DiaReduce_peak = .1570 //New peak
gen DiaReduce_upper_limit = .1570
gen u = runiform()

gen DiaReduce_random = cond(u <= (DiaReduce_peak - DiaReduce_lower_limit) / (DiaReduce_upper_limit -
DiaReduce_lower_limit), DiaReduce_lower_limit + sqrt(u * (DiaReduce_peak - DiaReduce_lower_limit) *
(DiaReduce_upper_limit - DiaReduce_lower_limit)), DiaReduce_upper_limit - sqrt((1 - u) * (DiaReduce_upper_limit -
DiaReduce_peak) * (DiaReduce_upper_limit - DiaReduce_lower_limit)))

// Young children risk reduction randomizer.

gen youngchildren_pop_Risk_Reduction = 0.105 //Not statistically significant


gen VSL1 = 434220 + (651331 - 434220) * runiform()
gen VSL2 = 60000 + (90000 - 60000) * runiform()
gen VSL_Childern_Honduras = VSL1 + (VSL2 - VSL1) * runiform()


gen young_pop_multitplier = 15.42
gen youngchildren_diarrhea_total = 175 * young_pop_multitplier
gen childerns_without_diseases = youngchildren_diarrhea_total * DiaReduce_random
gen youngchild_mortality_dia = 0.001677 + 0.003323 * uniform()


//gen lower_limit = 0.01677
//gen peak = 0.01677
//gen upper_limit = 0.03323
//gen u2 = runiform()

```

```
//gen youngchild_mortality_dia = cond(u2 <= (peak - lower_limit) / (upper_limit - lower_limit), lower_limit + sqrt(u *
(peak - lower_limit) * (upper_limit - lower_limit)), upper_limit - sqrt((1 - u) * (upper_limit - peak) * (upper_limit -
lower_limit)))
```

```
gen childerns_life_saved = childerns_without_diseases * youngchild_mortality_dia
```

```
gen VSL_benefits = childerns_life_saved * VSL_Childern_Honduras
```

```
gen yearly_VSL_benefits = VSL_benefits * 26
```

```
gen minute_wage = 0.0196
```

```
gen water_access_increase = -0.2138 //This the difference in mean
```

```
gen total_water_collect = 14966 * multiplier_alt1 //not counting children
```

```
gen total_water_collect_min = total_water_collect * minute_wage
```

```
gen water_access_cost_adj_wage = .20 + .60 * uniform() // (0.2 to 0.8 * minute_wage)
```

```
gen water_access_min_post = total_water_collect_min * water_access_cost_adj_wage
```

```
gen water_cost_adj_total = water_access_min_post * water_access_increase
```

```
gen water_access_total_benefits = water_cost_adj_total * 26
```

```
gen net_benefits = yearly_SchoolAtt_benefits + chloe_method_treat + yearly_workloss_benefits +
water_access_total_benefits + yearly_VSL_benefits
```

```
//chloe_method_treat instead of yearly_med_cost_benefits
```

```
gen year1_net_benefits = net_benefits
```

```
gen year2_net_benefits = year1_net_benefits * 0.6666 + 0.2333 * uniform()
```

```
gen year3_net_benefits = year2_net_benefits * 0.50 + 0.3889 * uniform()
```

```
gen year4_net_benefits = year3_net_benefits * 0.01 + 0.875 * uniform()
```

```
gen year5_net_benefits = year4_net_benefits * 0.01 + 0.8525 * uniform()
```

```
gen year6_net_benefits = year5_net_benefits * 0.01 + 0.834 * uniform()
```

```
gen year7_net_benefits = year6_net_benefits * 0.01 + 0.8 * uniform()
```



```

gen year8_net_benefits = year7_net_benefits * 0.01 + 0.75 * uniform()
gen year9_net_benefits = year8_net_benefits * 0.01 + 0.70 * uniform()
gen year10_net_benefits = year9_net_benefits * 0 + 0.5 * uniform()

gen annualized_benefits = year1_net_benefits * (1 + discount_rate_Honduras)^1 + year2_net_benefits * (1 +
discount_rate_Honduras)^2 + year3_net_benefits * (1 + discount_rate_Honduras)^3 + year4_net_benefits * (1 +
discount_rate_Honduras)^4 + year5_net_benefits * (1 + discount_rate_Honduras)^5 + year6_net_benefits * (1 +
discount_rate_Honduras)^6 + year7_net_benefits * (1 + discount_rate_Honduras)^7 + year8_net_benefits * (1 +
discount_rate_Honduras)^8 + year9_net_benefits * (1 + discount_rate_Honduras)^9 + year10_net_benefits * (1 +
discount_rate_Honduras)^10

gen all_benefits = annualized_benefits

gen all_costs = net_costs + pv_overhead

gen PVNB = all_benefits - all_costs

hist PVNB

gen proportionBenefitsCosts = 0 if PVNB < 0
replace proportionBenefitsCosts = 1 if proportionBenefitsCosts == .
tab proportionBenefitsCosts

sum PVNB

```

Appendix S: Monte Carlo PVTN STATA Code Alternative 2

```
set obs 100000
set seed 100

gen discount_rate_Honduras = 0.04
gen acquisition_cost = (143500 - (4 * 1435)) + 28529
gen distribution_cost = 0 //104682
gen overhead_cost = (77490 * .1)
gen vol_range_selector = (uniform() > 0.5)
gen volunteering = . //between 0 to (390.40 to 546.56)
replace volunteering = 390.40 * uniform() if vol_range_selector == 0
replace volunteering = 546.56 * uniform() if vol_range_selector == 1

gen net_costs = acquisition_cost + distribution_cost + volunteering

gen pv_overhead = overhead / (1 + discount_rate_Honduras)^10

gen population = 7731
gen working_pop = 1808
gen hourwage = 1.22
gen total_workdays_missed_dis = 368
gen households_distribution = 1435
gen dia_reporting_households_dis = 644
gen households_follow_up = 133
gen dia_reporting_households_FU = 84
gen number_of_school_years = 11

gen honduras_schooldays = 125
gen honduras_schoolyears = 11
gen school_attend_treatment_twoweek = -0.855 //New value
```



```

gen secondary_ed_pop = 0.1716
gen below_secondary_ed_pop = 0.8283
gen No_ed_income = 1464
gen Primary_ed_income = 2213
gen Secondary_ed_income = 3335
gen lifetime_No_ed_income = No_ed_income * (1 - (1 + discount_rate_Honduras)^(-40)) / discount_rate_Honduras
gen lifetime_Primary_ed_income = Primary_ed_income * (1 - (1 + discount_rate_Honduras)^(-40)) / discount_rate_Honduras
gen lifetime_Secondary_ed_income = Secondary_ed_income * (1 - (1 + discount_rate_Honduras)^(-40)) / discount_rate_Honduras
gen lifetime_Oppostunity_Cost_max = lifetime_Secondary_ed_income - lifetime_No_ed_income
gen lifetime_Oppostunity_Cost_min = lifetime_Secondary_ed_income - lifetime_Primary_ed_income
gen chronic_absent_threshold = .10 + .10 * uniform() //10% - 20%
gen dropout_prob_chronic_absent = .20 + .5 * uniform() // 20%-25%
gen HCAT = honduras_schooldays*chronic_absent_threshold
gen HCAT_daily = 1/HCAT
gen HCAT_daily_dropout_risk = HCAT_daily * dropout_prob_chronic_absent
gen base_absence_shadow_cost = (HCAT_daily_dropout_risk * (lifetime_Oppostunity_Cost_min + lifetime_Oppostunity_Cost_max * uniform())) / (honduras_schooldays * number_of_school_years)
//(lifetime_Oppostunity_Cost_min or lifetime_Oppostunity_Cost_max/(honduras_schooldays * number of school years))
gen DRA = (0.7 * honduras_schooldays)/honduras_schoolyears
gen proportional_DRA_HCAT = DRA/HCAT
gen proportional_DRAHCAT_DropoutCont = proportional_DRA_HCAT * dropout_prob_chronic_absent
gen At_Risk_student_pop = below_secondary_ed_pop * proportional_DRAHCAT_DropoutCont
gen adj_absence_shadow_cost_below_SE = At_Risk_student_pop * base_absence_shadow_cost
gen adj_absence_shadow_cost_SE= secondary_ed_pop * base_absence_shadow_cost
gen weighted_shadow_cost_absence = adj_absence_shadow_cost_SE + adj_absence_shadow_cost_below_SE
gen school_attendance_BorC_twoweek = (-1*weighted_shadow_cost_absence) * school_attend_treatment_twoweek
gen num_absences = 416
gen school_att_benefits = school_attendance_BorC_twoweek * num_absences
gen yearly_SchoolAtt_benefits = school_att_benefits * 26

```

```
gen diarrhea_Risk_Reduction = 0.182 + 0.428 * uniform() //diarrhea2 and Has_filter (MAIN)
```

```
gen pop_Risk_Reduction = 0.05 //totaldiarrhea and Has_filter
```

```
gen dis_avg_treatent = rnormal(1.21, 10.55)
```

```
replace dis_avg_treatent = rnormal(1.21, 10.55) if dis_avg_treatent < 0
```

```
gen dis_Dtreatment_HH = dis_avg_treatent * households_distribution
```

```
gen followup_avg_treatment = rnormal(.53, 1.722)
```

```
replace followup_avg_treatment = rnormal(.53, 1.722) if followup_avg_treatment < 0
```

```
gen followup_Dtreatment_HH = followup_avg_treatment * households_distribution
```

```
gen difference_Dtreatment = dis_Dtreatment_HH - followup_Dtreatment_HH
```

```
// (1004.50)
```

```
gen dis_severe_diarrhea = .2034
```

```
gen literature_reduction = .8317
```

```
gen post_rate_SevereDia = dis_severe_diarrhea * (1 - literature_reduction)
```

```
gen post_hh_SevereDia = households_distribution * post_rate_SevereDia
```

```
gen severetreatment_avg = 11.68
```

```
gen lit_Dtreat_HH = post_hh_SevereDia * severetreatment_avg
```

```
//(554.78)
```

```
gen annual_lit_Dtreamt = difference_Dtreatment * 26
```

```
gen annual_differenceD = lit_Dtreat_HH * 26
```

```
gen chloe_selector = (uniform() > 0.5)
```

```
gen chloe_method_treat = .
```

```
replace chloe_method_treat = annual_lit_Dtreamt if chloe_selector == 0
```

```
replace chloe_method_treat = annual_differenceD if chloe_selector == 1
```



```
//gen avg_medical_range_selector = (uniform() > 0.5)
//gen avg_medical_cost= . //between 1.91 (SE:tba) and 6.38 (SE:tba)

//replace dis_avg_treatent = rnormal(1.21, 10.55) if avg_medical_range_selector == 0
//replace avg_medical_cost = rnormal(6.3, 25.03) if avg_medical_range_selector == 1
// Replace negatives with new random values iteratively
//replace avg_medical_cost = rnormal(1.91, 14.02) if avg_medical_range_selector == 0 & avg_medical_cost < 0
//replace avg_medical_cost = rnormal(6.3, 25.03) if avg_medical_range_selector == 1 & avg_medical_cost < 0
```

```
gen avg_medical_range_selector = (uniform() > 0.5)
gen avg_medical_cost= . //between 1.91 (SE:tba) and 6.38 (SE:tba)
```

```
replace avg_medical_cost = rnormal(1.91, 14.02) if avg_medical_range_selector == 0
replace avg_medical_cost = rnormal(6.3, 25.03) if avg_medical_range_selector == 1
// Replace negatives with new random values iteratively
replace avg_medical_cost = rnormal(1.91, 14.02) if avg_medical_range_selector == 0 & avg_medical_cost < 0
replace avg_medical_cost = rnormal(6.3, 25.03) if avg_medical_range_selector == 1 & avg_medical_cost < 0
```

```
gen dia_prevalance_FU = households_follow_up *
((dia_reporting_households_dis/households_distribution)*diarrhea_Risk_Reduction)
gen dia_prevalance_overall_estimate = (dia_prevalance_FU/households_distribution) * households_distribution
gen medical_cost_reduction_two_weeks = dia_prevalance_overall_estimate * avg_medical_cost
gen yearly_med_cost_benefits = medical_cost_reduction_two_weeks * 26
```

```
gen workdays_missed_reduction = 0 + 0.3694 * uniform() //New value
```

```
gen workmissed_per_day_person = 9.76
```

```

gen wages_lost_twoweeks = total_workdays_missed_dis * workmissed_per_day_person
gen workdays_missed_cost_reduction = wages_lost_twoweeks * workdays_missed_reduction
gen yearly_workloss_benefits = workdays_missed_cost_reduction * 26

gen DiaReduce_lower_limit = 0
gen DiaReduce_peak = .1570 // New value
gen DiaReduce_upper_limit = 0.157 + .117 * uniform() //.2740
gen u = runiform()

gen DiaReduce_random = cond(u <= (DiaReduce_peak - DiaReduce_lower_limit) / (DiaReduce_upper_limit -
DiaReduce_lower_limit), DiaReduce_lower_limit + sqrt(u * (DiaReduce_peak - DiaReduce_lower_limit) *
(DiaReduce_upper_limit - DiaReduce_lower_limit)), DiaReduce_upper_limit - sqrt((1 - u) * (DiaReduce_upper_limit -
DiaReduce_peak) * (DiaReduce_upper_limit - DiaReduce_lower_limit)))

// Young children risk reduction randomizer.
gen youngchildren_pop_Risk_Reduction = 0.105 //Not statistically significant

gen VSL1 = 434220 + (651331 - 434220) * runiform()
gen VSL2 = 60000 + (90000 - 60000) * runiform()
gen VSL_Childern_Honduras = VSL1 + (VSL2 - VSL1) * runiform()

//gen VSL_Childern_Honduras = 90000 + 561331 * uniform()
gen youngchildren_diarrhea_total = 175
gen childrens_without_diseases = youngchildren_diarrhea_total * DiaReduce_random
gen youngchild_mortality_dia = 0.001677 + 0.003323 * uniform()

gen lower_limit = 0.01677
gen peak = 0.01677
gen upper_limit = 0.03323
gen u2 = runiform()

//gen youngchild_mortality_dia = cond(u2 <= (peak - lower_limit) / (upper_limit - lower_limit), lower_limit + sqrt(u *
(peak - lower_limit) * (upper_limit - lower_limit)), upper_limit - sqrt((1 - u) * (upper_limit - peak) * (upper_limit -
lower_limit)))

gen childrens_life_saved = childrens_without_diseases * youngchild_mortality_dia

```

```

gen VSL_benefits = childrens_life_saved * VSL_Childern_Honduras
gen yearly_VSL_benefits = VSL_benefits * 26

gen minute_wage = 0.0196
gen water_access_increase = -0.2138 //This the difference in mean
gen total_water_collect = 14966 //not counting children
gen total_water_collect_min = total_water_collect * minute_wage
gen water_access_cost_adj_wage = .20 + .60 * uniform() // (0.2 to 0.8 * minute_wage)
gen water_access_min_post = total_water_collect_min * water_access_cost_adj_wage
gen water_cost_adj_total = water_access_min_post * water_access_increase
gen water_access_total_benefits = water_cost_adj_total * 26

gen net_benefits = yearly_SchoolAtt_benefits + chloe_method_treat + yearly_workloss_benefits +
water_access_total_benefits + yearly_VSL_benefits

//chloe_method_treat instead of yearly_med_cost_benefits

gen year1_net_benefits = net_benefits

gen year2_net_benefits = year1_net_benefits * 0.6666 + 0.2333 * uniform()
gen year3_net_benefits = year2_net_benefits * 0.50 + 0.3889 * uniform()
gen year4_net_benefits = year3_net_benefits * 0.01 + 0.875 * uniform()
gen year5_net_benefits = year4_net_benefits * 0.01 + 0.8525 * uniform()
gen year6_net_benefits = year5_net_benefits * 0.01 + 0.834 * uniform()
gen year7_net_benefits = year6_net_benefits * 0.01 + 0.8 * uniform()
gen year8_net_benefits = year7_net_benefits * 0.01 + 0.75 * uniform()
gen year9_net_benefits = year8_net_benefits * 0.01 + 0.70 * uniform()
gen year10_net_benefits = year9_net_benefits * 0 + 0.5 * uniform()

gen annualized_benefits = year1_net_benefits * (1 + discount_rate_Honduras)^1 + year2_net_benefits * (1 +
discount_rate_Honduras)^2 + year3_net_benefits * (1 + discount_rate_Honduras)^3 + year4_net_benefits * (1 +

```

```
discount_rate_Honduras)^4 + year5_net_benefits * (1 + discount_rate_Honduras)^5 + year6_net_benefits * (1 +  
discount_rate_Honduras)^6 + year7_net_benefits * (1 + discount_rate_Honduras)^7 + year8_net_benefits * (1 +  
discount_rate_Honduras)^8 + year9_net_benefits * (1 + discount_rate_Honduras)^9 + year10_net_benefits * (1 +  
discount_rate_Honduras)^10
```

```
gen all_benefits = annualized_benefits
```

```
gen all_costs = net_costs + pv_overhead
```

```
gen PVNB = all_benefits - all_costs
```

```
hist PVNB
```

```
gen proportionBenefitsCosts = 0 if PVNB < 0
```

```
replace proportionBenefitsCosts = 1 if proportionBenefitsCosts == .
```

```
tab proportionBenefitsCosts
```

```
sum PVNB
```

```
gen PVNB_graph = PVNB/1000000
```

```
hist PVNB_graph
```



Appendix T: Monte Carlo PVBN STATA Code Alternative 3

```
set obs 100000
set seed 100

gen discount_rate_Honduras = 0.04
gen acquisition_cost = 143500
gen distribution_cost = 0 //104682
gen overhead_cost = (77490 * .1)
gen vol_range_selector = (uniform() > 0.5)
gen volunteering = . //between 0 to (390.40 to 546.56)
replace volunteering = 390.40 * uniform() if vol_range_selector == 0
replace volunteering = 546.56 * uniform() if vol_range_selector == 1

gen net_costs = acquisition_cost + distribution_cost + volunteering

gen pv_overhead = overhead / (1 + discount_rate_Honduras)^10

gen population = 7731
gen working_pop = 1808
gen hourwage = 1.22
gen total_workdays_missed_dis = 368
gen households_distribution = 1435
gen dia_reporting_households_dis = 644
gen households_follow_up = 133
gen dia_reporting_households_FU = 84
gen number_of_school_years = 11

gen honduras_schooldays = 125
gen honduras_schoolyears = 11
gen school_attend_treatment_twoweek = -0.37 //45% reduction on absences to 15% increase on absences. Pretty sure
its 21% reduction. So possibel -0.45 + 0.60 * uniform()
gen secondary_ed_pop = 0.1716
```



```

gen below_secondary_ed_pop = 0.8283
gen No_ed_income = 1464
gen Primary_ed_income = 2213
gen Secondary_ed_income = 3335
gen lifetime_No_ed_income = No_ed_income * (1 - (1 + discount_rate_Honduras)^(-40)) / discount_rate_Honduras
gen lifetime_Primary_ed_income = Primary_ed_income * (1 - (1 + discount_rate_Honduras)^(-40)) / discount_rate_Honduras
gen lifetime_Secondary_ed_income = Secondary_ed_income * (1 - (1 + discount_rate_Honduras)^(-40)) / discount_rate_Honduras
gen lifetime_Oppostunity_Cost_max = lifetime_Secondary_ed_income - lifetime_No_ed_income
gen lifetime_Oppostunity_Cost_min = lifetime_Secondary_ed_income - lifetime_Primary_ed_income
gen chronic_absent_threshold = .10 + .10 * uniform() //10% - 20%
gen dropout_prob_chronic_absent = .20 + .5 * uniform() // 20%-25%
gen HCAT = honduras_schooldays*chronic_absent_threshold
gen HCAT_daily = 1/HCAT
gen HCAT_daily_dropout_risk = HCAT_daily * dropout_prob_chronic_absent
gen base_absence_shadow_cost = (HCAT_daily_dropout_risk * (lifetime_Oppostunity_Cost_min + lifetime_Oppostunity_Cost_max * uniform())) / (honduras_schooldays * number_of_school_years)
//(lifetime_Oppostunity_Cost_min or lifetime_Oppostunity_Cost_max/(honduras_schooldays * number of school years))
gen DRA = (0.7 * honduras_schooldays)/honduras_schoolyears
gen proportional_DRA_HCAT = DRA/HCAT
gen proportional_DRAHCAT_DropoutCont = proportional_DRA_HCAT * dropout_prob_chronic_absent
gen At_Risk_student_pop = below_secondary_ed_pop * proportional_DRAHCAT_DropoutCont
gen adj_absence_shadow_cost_below_SE = At_Risk_student_pop * base_absence_shadow_cost
gen adj_absence_shadow_cost_SE= secondary_ed_pop * base_absence_shadow_cost
gen weighted_shadow_cost_absence = adj_absence_shadow_cost_SE + adj_absence_shadow_cost_below_SE
gen school_attendance_BorC_twoweek = (-1*weighted_shadow_cost_absence) * school_attend_treatment_twoweek
gen num_absences = 416
gen school_att_benefits = school_attendance_BorC_twoweek * num_absences
gen yearly_SchoolAtt_benefits = school_att_benefits * 26

```

```
gen diarrhea_Risk_Reduction = 0.182 + 0.428 * uniform() //diarrhea2 and Has_filter (MAIN)
```

```
gen pop_Risk_Reduction = 0.05 //totaldiarrhea and Has_filter
```

```
gen dis_avg_treatent = rnormal(1.21, 10.55)
```

```
replace dis_avg_treatent = rnormal(1.21, 10.55) if dis_avg_treatent < 0
```

```
gen dis_Dtreatment_HH = dis_avg_treatent * households_distribution
```

```
gen followup_avg_treatment = rnormal(.53, 1.722)
```

```
replace followup_avg_treatment = rnormal(.53, 1.722) if followup_avg_treatment < 0
```

```
gen followup_Dtreatment_HH = followup_avg_treatment * households_distribution
```

```
gen difference_Dtreatment = dis_Dtreatment_HH - followup_Dtreatment_HH
```

```
// (1004.50)
```

```
gen dis_severe_diarrhea = .2034
```

```
gen literature_reduction = .8317
```

```
gen post_rate_SevereDia = dis_severe_diarrhea * (1 - literature_reduction)
```

```
gen post_hh_SevereDia = households_distribution * post_rate_SevereDia
```

```
gen severetreatment_avg = 11.68
```

```
gen lit_Dtreat_HH = post_hh_SevereDia * severetreatment_avg
```

```
//(554.78)
```

```
gen annual_lit_Dtreamt = difference_Dtreatment * 26
```

```
gen annual_differenceD = lit_Dtreat_HH * 26
```

```
gen chloe_selector = (uniform() > 0.5)
```

```
gen chloe_method_treat = .
```

```
replace chloe_method_treat = annual_lit_Dtreamt if chloe_selector == 0
```

```
replace chloe_method_treat = annual_differenceD if chloe_selector == 1
```



```

//gen avg_medical_range_selector = (uniform() > 0.5)
//gen avg_medical_cost= . //between 1.91 (SE:tba) and 6.38 (SE:tba)

//replace dis_avg_treatent = rnormal(1.21, 10.55) if avg_medical_range_selector == 0
//replace avg_medical_cost = rnormal(6.3, 25.03) if avg_medical_range_selector == 1
// Replace negatives with new random values iteratively
//replace avg_medical_cost = rnormal(1.91, 14.02) if avg_medical_range_selector == 0 & avg_medical_cost < 0
//replace avg_medical_cost = rnormal(6.3, 25.03) if avg_medical_range_selector == 1 & avg_medical_cost < 0

gen avg_medical_range_selector = (uniform() > 0.5)
gen avg_medical_cost= . //between 1.91 (SE:tba) and 6.38 (SE:tba)

replace avg_medical_cost = rnormal(1.91, 14.02) if avg_medical_range_selector == 0
replace avg_medical_cost = rnormal(6.3, 25.03) if avg_medical_range_selector == 1
// Replace negatives with new random values iteratively
replace avg_medical_cost = rnormal(1.91, 14.02) if avg_medical_range_selector == 0 & avg_medical_cost < 0
replace avg_medical_cost = rnormal(6.3, 25.03) if avg_medical_range_selector == 1 & avg_medical_cost < 0

gen dia_prevalance_FU = households_follow_up *
((dia_reporting_households_dis/households_distribution)*diarrhea_Risk_Reduction)
gen dia_prevalance_overall_estimate = (dia_prevalance_FU/households_distribution) * households_distribution
gen medical_cost_reduction_two_weeks = dia_prevalance_overall_estimate * avg_medical_cost
gen yearly_med_cost_benefits = medical_cost_reduction_two_weeks * 26

gen workdays_missed_reduction = 0 + 0.1291 * uniform() //Comm7 compared to Comm7FU. Barcode doesn't have
enough data. Not StatSig but we are using it
gen workmissed_per_day_person = 9.76

```

```

gen wages_lost_twoweeks = total_workdays_missed_dis * workmissed_per_day_person
gen workdays_missed_cost_reduction = wages_lost_twoweeks * workdays_missed_reduction
gen yearly_workloss_benefits = workdays_missed_cost_reduction * 26

gen DiaReduce_lower_limit = 0
gen DiaReduce_peak = .157
gen EdEffectRR = .157 + .403 * uniform()
gen DiaReduce_upper_limit = .113 + EdEffectRR * uniform()
gen u = runiform()
gen DiaReduce_random = cond(u <= (DiaReduce_peak - DiaReduce_lower_limit) / (DiaReduce_upper_limit -
DiaReduce_lower_limit), DiaReduce_lower_limit + sqrt(u * (DiaReduce_peak - DiaReduce_lower_limit) *
(DiaReduce_upper_limit - DiaReduce_lower_limit)), DiaReduce_upper_limit - sqrt((1 - u) * (DiaReduce_upper_limit -
DiaReduce_peak) * (DiaReduce_upper_limit - DiaReduce_lower_limit)))
// Young children risk reduction randomizer.
gen youngchildren_pop_Risk_Reduction = 0.105 //Not statistically significant

gen VSL1 = 434220 + (651331 - 434220) * runiform()
gen VSL2 = 60000 + (90000 - 60000) * runiform()
gen VSL_Childern_Honduras = VSL1 + (VSL2 - VSL1) * runiform()

//gen VSL_Childern_Honduras = 90000 + 561331 * uniform()
gen youngchildren_diarrhea_total = 175
gen childerns_without_diseases = youngchildren_diarrhea_total * DiaReduce_random
gen youngchild_mortality_dia = 0.001677 + 0.003323 * uniform()

gen lower_limit = 0.01677
gen peak = 0.01677
gen upper_limit = 0.03323
gen u2 = runiform()

//gen youngchild_mortality_dia = cond(u2 <= (peak - lower_limit) / (upper_limit - lower_limit), lower_limit + sqrt(u *
(peak - lower_limit) * (upper_limit - lower_limit)), upper_limit - sqrt((1 - u) * (upper_limit - peak) * (upper_limit -
lower_limit)))

```

```

gen childrens_life_saved = childrens_without_diseases * youngchild_mortality_dia
gen VSL_benefits = childrens_life_saved * VSL_Childern_Honduras
gen yearly_VSL_benefits = VSL_benefits * 26

gen minute_wage = 0.0196
gen water_access_increase = -0.2138 //This the difference in mean
gen total_water_collect = 14966 //not counting children
gen total_water_collect_min = total_water_collect * minute_wage
gen water_access_cost_adj_wage = .20 + .60 * uniform() // (0.2 to 0.8 * minute_wage)
gen water_access_min_post = total_water_collect_min * water_access_cost_adj_wage
gen water_cost_adj_total = water_access_min_post * water_access_increase
gen water_access_total_benefits = water_cost_adj_total * 26

gen net_benefits = yearly_SchoolAtt_benefits + chloe_method_treat + yearly_workloss_benefits +
water_access_total_benefits + yearly_VSL_benefits

//chloe_method_treat instead of yearly_med_cost_benefits

gen year1_net_benefits = net_benefits

gen year2_net_benefits = year1_net_benefits * 0.6666 + 0.2333 * uniform()
gen year3_net_benefits = year2_net_benefits * 0.50 + 0.3889 * uniform()
gen year4_net_benefits = year3_net_benefits * 0.01 + 0.875 * uniform()
gen year5_net_benefits = year4_net_benefits * 0.01 + 0.8525 * uniform()
gen year6_net_benefits = year5_net_benefits * 0.01 + 0.834 * uniform()
gen year7_net_benefits = year6_net_benefits * 0.01 + 0.8 * uniform()
gen year8_net_benefits = year7_net_benefits * 0.01 + 0.75 * uniform()

gen year9_net_benefits = year8_net_benefits * 0.01 + 0.70 * uniform()
gen year10_net_benefits = year9_net_benefits * 0 + 0.5 * uniform()

gen hourwage_ed = 0.5 + 1 * uniform()

```

```

gen schoolnum = 1 + 3 * uniform()
gen comnum = 7
gen hoursed = 8
gen weeksed = 52
gen Education_cost = (hourwage_ed * (comnum * schoolnum) * weeksed)

gen annualized_benefits = year1_net_benefits * (1 + discount_rate_Honduras)^1 + year2_net_benefits * (1 +
discount_rate_Honduras)^2 + year3_net_benefits * (1 + discount_rate_Honduras)^3 + year4_net_benefits * (1 +
discount_rate_Honduras)^4 + year5_net_benefits * (1 + discount_rate_Honduras)^5 + year6_net_benefits * (1 +
discount_rate_Honduras)^6 + year7_net_benefits * (1 + discount_rate_Honduras)^7 + year8_net_benefits * (1 +
discount_rate_Honduras)^8 + year9_net_benefits * (1 + discount_rate_Honduras)^9 + year10_net_benefits * (1 +
discount_rate_Honduras)^10

gen annualized_education_cost = Education_cost * (1 + discount_rate_Honduras)^1 + Education_cost * (1 +
discount_rate_Honduras)^2 + Education_cost * (1 + discount_rate_Honduras)^3 + Education_cost * (1 +
discount_rate_Honduras)^4 + Education_cost * (1 + discount_rate_Honduras)^5 + Education_cost * (1 +
discount_rate_Honduras)^6 + Education_cost * (1 + discount_rate_Honduras)^7 + Education_cost * (1 +
discount_rate_Honduras)^8 + Education_cost * (1 + discount_rate_Honduras)^9 + Education_cost * (1 +
discount_rate_Honduras)^10

gen annualized_education_tot = annualized_education_cost + ((hoursed * hoursed) * (comnum * schoolnum)) +
((hoursed * 8) * 3)

gen all_benefits = annualized_benefits

gen all_costs = (net_costs + pv_overhead + annualized_education_tot)

gen PVNB = all_benefits - all_costs

hist PVNB

gen proportionBenefitsCosts = 0 if PVNB < 0
replace proportionBenefitsCosts = 1 if proportionBenefitsCosts == .
tab proportionBenefitsCosts

```

```
sum PVNB
```

```
gen PVNB_graph = PVNB/1000000
```

```
hist PVNB_graph
```



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