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Abstract

Limited access to safe and proximate water remains a defining constraint in Haiti, where access to piped water remains limited and school enrollment is not universal. Using a pseudo-panel constructed from four rounds of the Haiti Demographic and Health Surveys (DHS), we estimate the causal impact of water hauling time on children's school enrollment. Our findings reveal a strong and statistically significant, each additional minute spent fetching water reduces the likelihood of enrollment by about 1.3 percentage points,with substantially larger effects in rural areas where hauling time is highest. Gender-specific estimates reveal that the burden of distance is not symmetric. While girls more often perform water collection overall, boys disproportionately undertake long-distance trips, and simulated enrollment probabilities indicate a widening gender gap once collection times exceed 30–40 minutes, with boys experiencing steeper enrollment losses. These findings demonstrate how deficient water infrastructure depresses educational participation, underscoring the potential of investments in improved and more proximate water access to generate meaningful school enrollment gains.

JEL Codes: C36, H31, I24, Q25.

Keywords: hauling water; children; school enrollment; education; water; Haiti; Demographic and Health Surveys (DHS).

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1 Introduction

Water hauling, the manual transport of water from an external source to the point of use in the absence of piped supply, imposes substantial time and physical burdens on households and can significantly reduce children's school enrollment. When children are responsible for fetching water, they reallocate time away from study and regular school participation, lowering their likelihood of sustained engagement in education (Komarulzaman et al., 2019). These constraints can compound over time, as reduced educational attainment limits future economic opportunities and contributes to the intergenerational persistence of poverty.

While a growing literature examines how water infrastructure improvements affect schooling outcomes, most existing work has focused on water quality, leaving the effects of interventions that expand access to water sources or reduce collection time relatively understudied. As noted by Andres et al. (2018), some studies document substantial reductions in absenteeism following improvements that ease access and shorten water collection times; yet the evidence remains too limited to yield robust statistical conclusions. Moreover, prior research has concentrated primarily on school attendance, a dynamic measure of short-term participation that is highly sensitive to transitory shocks such as extreme weather or political instability. In contrast, school enrollment reflects formal registration and thus provides a more stable indicator of educational access. The smaller body of work that examines enrollment finds that water collection responsibilities are associated with lower enrollment rates, often with disproportionately larger effects on girls (Koolwal, 2013; Gebru and Bezu, 2014; Levison et al., 2017; Komarulzaman et al., 2019; Agesa and Agesa, 2019).

Most existing research on water fetching and its implications has concentrated on Asia (Jadhav et al., 2016) and Africa (Komarulzaman et al., 2019; Agesa and Agesa, 2019; Nauges and Strand, 2017), while studies in Latin America and the Caribbean (LAC) remain scarce (Levison and Moe, 1998; Ilahi and Grimard, 2000). Although evidence on the educational impacts of water collection responsibilities in LAC is limited, household surveys reveal significant gender differences in water-fetching tasks between men and women, as well as by country (Libra, 2025).

In our study, we focus on the case of Haiti, where both water access and school enrollment remain critical (Chapman et al., 2020; Zanotti et al., 2016). For instance, 16% of children are not enrolled in primary school, with rates even higher for boys than for girls. The situation worsens in lower secondary, where 65% of girls and 77% of boys do not attend school (UNICEF, 2022). Access to piped water is limited, only 19% of households have piped water, while 67% have basic access, defined as water from an improved source not on premises, with a round-trip collection time of up to 30 minutes (WHO/UNICEF, 2025).

We focus on enrollment rather than attendance for two reasons. First, the Demographic and Health Surveys (DHS), our primary data source, report enrollment status rather than daily attendance. Second, enrollment provides a more stable measure of educational access, less vulnerable to short-term shocks such as extreme weather events or political instability, which can temporarily affect attendance without reflecting structural barriers to education. This distinction is crucial in the Haitian context, where persistent infrastructure deficits and household time constraints, such as those imposed by water hauling, are likely to influence whether children are enrolled in school at all.

Our empirical strategy addresses two sources of potential endogeneity: household-level heterogeneity (e.g., parental preferences regarding education) and community-level characteristics correlated with infrastructure investments. Following Nauges and Strand (2017), we estimate enrollment at the community level to mitigate household-level bias and exploit the pseudo-panel structure of DHS data to control for time-invariant unobserved effects. We complement this with a control function approach using instrumental variables to address time-varying endogeneity. To identify the causal effect of water hauling time on school enrollment, we use as our main instrument the exogenous variation in lagged annual rainfall for water collection time. The rationale is that rainfall directly governs local water availability. For example, drier conditions reduce water levels in nearby springs, rivers, and shallow wells, forcing households to travel greater distances, thereby increasing hauling time. By using the previous year's rainfall, the instrument is orthogonal to contemporaneous schooling decisions, conditional on cluster-level controls and regional and time fixed effects. Consistent with this mechanism, first-stage estimates confirm that higher lagged rainfall significantly reduces average water collection time at the cluster level, supporting the instrument's relevance. This strategy isolates the effect of water access on school enrollment while accounting for both household and community-level confounders.

Our main finding reveals a strong and statistically significant negative relationship between the time spent fetching water and children's school enrollment in Haiti. Each additional minute devoted to water collection reduces a child's likelihood of enrollment by 1.31 percentage points. Given that households without water on premises spend an average of 28 minutes per day on water collection, this time burden constitutes a substantial barrier to education. The effect is even more pronounced in rural areas and in households with young children. A plausible explanation for the latter is that, because women are typically responsible for water collection in Haiti, when mothers remain at home to care for younger children, older children assume the task of hauling water—thereby limiting their ability to enroll in school. Furthermore, when simulating predicted probabilities of school enrollment by gender, we find that after the 20-minute threshold, boys experience a sharper decline than girls, with enrollment probabilities dropping by an additional 2–3 percentage points.

This paper is structured as follows. Section 2 reviews the existing literature on the relationship between water access and educational outcomes, with a focus on gender disparities in LAC countries. Section 3 outlines the empirical strategy, including data sources, variable construction, and the econometric model based on a pseudo-panel approach using DHS data from Haiti. Section 4 presents descriptive statistics, main results of our estimations, simulation analysis, and includes the robustness checks. Section 5 discusses the implications of the findings, policy recommendations and directions for future research.

2 Literature Review

In many developing regions, the absence of piped water within the dwelling or yard forces households to fetch water from external sources. This task, while essential, imposes significant time costs that are unevenly distributed within households. Empirical studies on intrahousehold time allocation consistently document that the burden of water collection falls disproportionately on women and children (Ilahi, 2000; Levison et al., 2017; Agesa and Agesa, 2019; Dhital et al., 2022). The implications of this activity extend beyond the household, notably affecting the educational outcomes of the children tasked with collecting water[1].

A growing body of evidence establishes a negative association between water hauling responsibilities and educational outputs, including enrollment, attendance, and academic performance. Time spent collecting water consistently reduces school attendance, with girls bearing a disproportionate burden, although boys are also adversely affected when water is unavailable on household premises (Ilahi, 2000; Hasan and Alam, 2020; Hamlet et al., 2021). For example, in Kenya, Agesa and Agesa (2019) estimates that each additional minute spent fetching water reduces the likelihood of school attendance by about 32% for girls compared to 18% for boys. Similarly, Koolwal (2013) finds that improved water infrastructure in rural areas across nine countries correlates with higher school attendance, suggesting that the time and physical demands of water collection crowd out educational activities. Regarding academic performance, Hamlet et al. (2021) reports declines in math, reading, and writing scores as water collection time increases, with the effect particularly pronounced among girls.

Evidence on school enrollment reinforces these patterns but reveals a more nuanced picture: boys and girls are affected differently, and in some cases, boys experience greater adverse impacts. Komarulzaman et al. (2019) shows that districts with greater access to private water facilities exhibit higher enrollment and reduced absenteeism, underscoring

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[1] See the Literature Review Overview in the Appendix F for a comprehensive synthesis of findings on the impact of water collection responsibilities on children's educational outcomes.

water access as a critical determinant of educational participation. However, these impacts vary considerably across countries, shaped by cultural and social norms that assign responsibility for water collection (Koolwal, 2013). In Nepal, Dhital et al. (2022) finds gender-specific responses to increased water collection time: girls are more likely to drop out of school, whereas boys tend to repeat grades rather than withdraw. Similarly, Koolwal (2013) reports that, in most countries, the magnitude of these effects is slightly smaller for boys than for girls, with the notable exception of Morocco, where boys appear to benefit more. These findings highlight that while girls often bear the heaviest burden, the educational consequences of water collection are not uniform and can, under certain conditions, be more severe for boys.

Although most existing research focuses on African and Asian contexts, evidence from LAC remains limited, with studies focused on Peru (Levison and Moe, 1998; Ilahi and Grimard, 2000). A recent descriptive analysis by Libra (2025), drawing on census and household data across LAC countries, reveals that women perform an average of 41% of water-fetching tasks among households lacking on-premises water. Notable regional disparities emerge, with women assuming this responsibility in 60% of such households in Honduras and 56% in Suriname. Despite these contributions, the study does not examine the allocation of water-fetching duties among children, particularly the gendered differences between girls and boys.

Qualitative and ethnographic research in Haiti underscores that women and children bear the primary responsibility for water collection (Sheller et al., 2017). This task often entails waiting in lengthy queues and transporting heavy containers, typically carried on the head. Access to piped water is not only scarce and unreliable but has further deteriorated due to recurrent natural disasters and persistent political instability. Consequently, community taps and private connections operate only intermittently because of lack of maintenance and investments (Chapman et al., 2020). These infrastructure failures have been compounded by the withdrawal of external support. According to JMP (2024), the proportion of households with piped water has declined from 42% in 2000 to 26% in 2024. This time-intensive responsibility are shared between household members and imposes significant domestic labor demands and constrains educational opportunities for children.

To the best of our knowledge, this study provides the first causal evidence on the impact of water hauling on educational outcomes in Haiti. Given the limited availability of data-driven research on this topic in LAC, empirical studies are needed to shed light on how inadequate water infrastructure influences children's school enrollment. Moreover, such evidence is critical for informing targeted policy interventions and guiding resource allocation, particularly in contexts where access to safe, on-premises water, such as, piped connections, has declined over time in Haiti.

3 Empirical Strategy

3.1 Data and Variables

To measure the impact of improvements in water infrastructure on childrens' school enrollment, this study uses data from the DHS. The DHS database comprises data collected through nationally representative household surveys and covers a wide range of topics from fertility to family planning, but we mainly focus on data concerning household characteristics.

Clusters correspond to census enumeration areas (typically villages in rural areas or urban neighborhoods) and serve as primary sampling units in the two-stage stratified design. Our use of cluster-level averages to build a pseudo-panel follows the approach of Nauges and Strand (2017) and exploits within-community variation over time[2]. Therefore, to construct a pseudo-panel by spatially linking clusters across survey rounds, we used data from four rounds of Haiti's DHS household surveys conducted in 2000, 2005–2006, 2012, and 2016–2017. Specifically, using the GPS coordinates provided by DHS, we identify for each cluster in the 2016–2017 round the geographically nearest cluster, within the same admin-

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[2] DHS surveys are designed to be representative at the national and regional levels, not at the cluster level, a distinction that does not affect our identification strategy, which requires only that clusters constitute geographically stable units over time.

istrative region, from each of the three earlier rounds (Haiti's administrative regions shown in Appendix B, Figure B.1)[3]. Figure B.1 visually summarizes the matching procedure, illustrating the sequential steps used to link clusters across survey years.

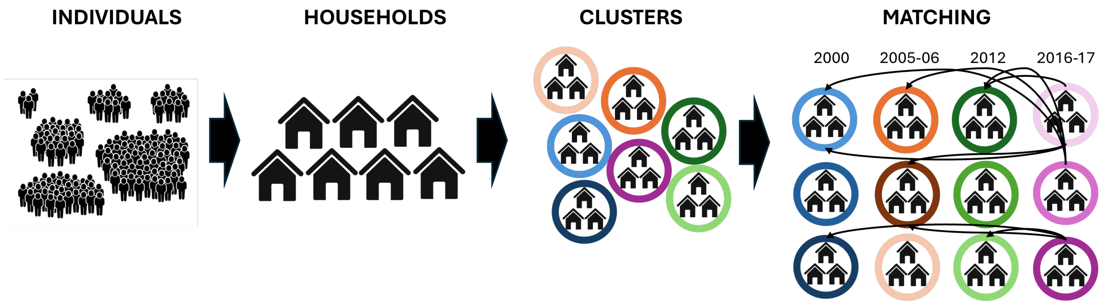

Figure 1: Spatial matching process to link clusters across DHS rounds

Table 1 reports the number of clusters in each region and the average distance between the clusters matched in each round and the 2016-2017 clusters. The overall average distance between the matched clusters is 2.29 miles. After matching the cluster by proximity, cluster averages were estimated for the households within these clusters, creating community averages calculated for our variables of interest. Community averages are calculated using data from households with at least one child aged 6–16. If no child in that age range is present in the household, the proportion is recorded as zero.[4]

Our main outcome variable is the proportion of children aged 6–16 enrolled in school within each cluster. This variable captures the share of school-enrolled children in each primary sampling unit, serving as a proxy for educational participation in the community. To control for household and contextual characteristics potentially correlated with school enrollment, we include explanatory variables such as average household size, average number of children below 6 years of age, average number of children aged 6–16, average number of

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[3] To protect respondent confidentiality, the DHS displaces cluster GPS coordinates. For example, urban clusters are randomly displaced by up to 2 km, while rural clusters are displaced by up to 5 km, with approximately 1% of rural clusters displaced by up to 10 km (Burgert-Brucker et al., 2016). Because our pseudo-panel is constructed by matching clusters across survey rounds based on geographic proximity, this displacement introduces potential measurement error in identifying the nearest clusters across waves. However, recent simulation evidence suggests that the impact of DHS coordinate displacement on estimated relationships is limited, as socioeconomic and demographic effects remain stable when cluster locations are jittered (Massoda Tonye et al., 2024).

[4] This study uses the 6–16 age range to adjust the DHS survey structure, where school enrollment refers to the previous year rather than the current survey year.

Table 1: Average distance (in miles) between matched clusters

Region	2016-2000 cluster match	2016-2006 cluster match	2016-2012 cluster match	# of clusters in 2016
Artibonite	3.13	3.23	2.48	57
Center	2.78	2.95	2.81	38
Grand-Anse	3.07	2.40	1.92	34
Metropolitan area/West	1.75	1.68	1.66	102
North-West	2.21	2.48	1.92	43
North	2.13	2.18	1.99	39
North-East	2.45	1.62	1.69	31
Nippes	3.82	2.11	2.00	32
South	3.13	2.49	1.84	38
South-East	2.69	2.31	2.26	36

women aged 17–65, average number of men aged 17–65, proportion of male household heads, average education of the household head (0 for no education or preschool only, 1 for those who have primary education, and 2 for those who have secondary education), average wealth quintile, regional dummies, and dummies to control for month of interview.

We include a covariate capturing the proportion of women in each cluster who report having experienced violence, both within and outside the household, since exposure to violence can undermine household stability, caregiving responsibilities, and constrain children's ability to enroll in school. Haiti faces some of the highest rates of violence globally (Faintuch and Chafetz, 2025), with far-reaching consequences for daily life. The pervasive threat of violence undermines socio-economic indicators by restricting mobility and disrupting access to essential services, including education. Unsafe commutes and school closures due to conflict particularly hinder school enrollment among children(Gage, 2005).

Two sources of endogeneity motivate our instrument set. First, time to haul water may covary with unobserved household or community traits that also affect enrollment. We therefore use lagged annual rainfall—matched to DHS clusters from standard gridded climate data—as an exogenous shifter of local water availability and thus collection time; by construction, previous-year rainfall is plausibly orthogonal to contemporaneous schooling decisions after conditioning on rich cluster-level controls and time effects (details in the

Section 3.2). Rainfall data are sourced from the Climatic Research Unit (University of East Anglia, 2025). Second, the average number of children aged 6–16 may be endogenous if unobservables influence both household composition and schooling; to address this, we use the cluster-average age of the household head as a demographic shifter correlated with household size but unlikely to affect enrollment directly once common controls are included. Following Nauges and Strand (2017), all instruments are constructed at the cluster level; aggregation, together with the aforementioned controls, limits non-water channels (e.g., idiosyncratic income shocks) and absorbs slow-moving socioeconomic differences. Variable definitions, sources, and units appear in Table 2.

Table 2: Description of Variables

Type	**Variable**	**Source**	**Description**
Outcome Variable	Children aged 6–16 enrolled in school	DHS	Proportion of children aged 6–16 enrolled in school in the cluster
Endogenous Variables	Children aged 6–16	DHS	Average total number of children aged 6–16 in the cluster
	Time to water	DHS	Average time required to fetch water per household in the cluster (minutes)
IVs	Household head age	DHS	Average head of household age (years)
	Rainfall	East Anglia University	Previous year's annual rainfall precipitation on a $0.5^{\circ}\times0.5^{\circ}$ grid (millimeters)
Exogenous Variables	Household size	DHS	Average number of household members per household in the cluster
	Children under 6	DHS	Average number of children aged 0–5 per household in the cluster
	Children aged 6-16	DHS	Average number of children aged 6-16 per household in the cluster
	Women aged 17–65	DHS	Average number of women aged 17–65 per household in the cluster
	Men aged 17–65	DHS	Average number of men aged 17–65 per household in the cluster
	Household head male	DHS	Proportion of households with a male head in the cluster
	Household head education	DHS	Average household head education score across households in the cluster (0 = no education or preschool only; 1 = primary education; 2 = secondary education)
	Wealth index	DHS	Average wealth quintile score across households in the cluster
	Women Violence	DHS	Proportion of households with women reporting violence (inside or outside household) in the cluster

Table 3 reports descriptive statistics for the main variables used in the analysis, based on 1,785 observations. On average, about 79% of children aged 6 to 16 are enrolled in school, though the relatively large standard deviation indicates that school enrollment was far from universal. The mean time required to reach a household's primary water source was 26 minutes, with considerable variation, with some households spending far more than an hour to reach a water source. The average household size was 5.73 members, including, on average, roughly 1 child under 6 (six) and 2 children between ages 6 and 16. The typical household also includes, on average, around 1 woman and 1 man aged 17–65. Approximately 55% of household heads were male, and the head of the household has an average age of 47 years. The educational level of household heads averaged 0.54, indicating a low level of education. The wealth index had a mean of 2.84, between the second and third quintiles, leaning slightly toward the middle of the distribution, implying that the sample is moderately poor. Finally, average annual rainfall indicates substantial pluviometric variation across regions.

Table 3: Descriptive Statistics

Variable	**N**	**Mean**	**Std. Dev.**	**Min**	**Max**
Children aged 6–16 enrolled in school	1,785	0.791	0.210	0.03	1.00
Time to water	1,785	26.015	23.625	0.00	192.50
Household size	1,785	5.730	0.769	3.43	9.22
Children under 6	1,785	1.035	0.357	0.11	2.40
Children aged 6–16	1,785	2.069	0.363	1.11	4.00
Women aged 17–65	1,785	1.428	0.204	0.99	2.21
Men aged 17–65	1,785	1.168	0.158	0.78	1.93
Household head male	1,785	0.549	0.109	0.22	0.82
Household head age	1,785	47.112	5.190	29.25	62.71
Household head education	1,785	0.543	0.216	0.14	1.31
Wealth index	1,785	2.837	1.110	1.00	5.00
Rainfall	1,785	1,527.27	505.33	306.90	2,891.80
Women Violence	1,785	0.293	0.201	0.00	1.00

3.2 Estimation Strategy

As detailed in the previous section, our dependent variable is the proportion of children aged 6–16 enrolled in school within a given cluster and DHS round. This variable is expressed as a fraction bounded between 0 and 1. To estimate the effect of reductions in water hauling time on school enrollment, we employ a panel data approach for fractional response models, following the methodology introduced by Papke and Wooldridge (1996) and applied in Nauges and Strand (2017). This framework accommodates the bounded nature of the dependent variable and allows us to model cluster-level unobserved heterogeneity through a Mundlak–Chamberlain specification.

Specifically, we model the expected value of childrens' school enrollment in cluster i and t, where $t = 1$ to 4, corresponding to the years 2000, 2005-2006, 2012, and 2016-2017, using a fractional probit model, where the expected value of s_{it} is linked to covariates through the standard normal cumulative distribution function $\Phi(\cdot)$. The model accounts for observed covariates $\mathbf{x}_{it}$, unobserved cluster-specific heterogeneity c_i, and an idiosyncratic error v_{it}, as follows:

$$\mathbb{E}(s_{it} \mid \mathbf{x}_{it}, c_i, v_{it}) = \Phi(\mathbf{x}_{it}\boldsymbol{\beta} + c_i + v_{it}) \tag{1}$$

We assume that the unobserved cluster-specific effects are normally distributed conditional on the time-averaged covariates $\bar{\mathbf{x}}_i$ (Papke and Wooldridge, 1996), and $\bar{\mathbf{x}}_i = \frac{1}{4}\sum_{t=1}^{4} \mathbf{x}_{it}$ denotes the vector of cluster-level means of the time-varying covariates, computed over the four survey periods. The residual component a_i, conditional on $\mathbf{x}_{it}$, is assumed to follow a normal distribution[5].

$$c_i = \psi + \bar{\mathbf{x}}_i\boldsymbol{\xi} + a_i \tag{2}$$

Substituting this into the original model, we obtain the modified estimating equation:

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[5] To relax the assumption that the unobserved effect c_i is uncorrelated with the regressors, we follow the Mundlak-Chamberlain device (Chamberlain, 1980; Mundlak, 1978) and specify c_i as a linear function of the time-averaged covariates, plus an idiosyncratic component a_i

$$\mathbb{E}(s_{it} \mid \mathbf{x}_i, a_i, v_{it}) = \Phi(\mathbf{x}_{it}\boldsymbol{\beta} + \psi + \bar{\mathbf{x}}_i\boldsymbol{\xi} + a_i + v_{it}) \tag{3}$$

In which the cluster-specific term, a_i, is assumed here to be independent of $\mathbf{x}_i$. In nonlinear models like the Probit, the coefficients themselves do not directly represent marginal effects. Instead, the partial effects (i.e., the effect of a one-unit change in a covariate on the expected value of the dependent variable) depend on the distribution of the unobserved heterogeneity, and population-averaged partial effects are computed after estimation. To address potential endogeneity of certain regressors, such as time to water source or the number of children aged 6–16, we use a control function approach. Addressing endogeneity in a nonlinear model like the probit requires a different approach than in the linear case. A natural but incorrect solution would be to replace the endogenous variables with its predicted value from the first stage. While this works in linear models, it fails in nonlinear ones because the probit applies a transformation to the entire index, and averaging before versus after that transformation produces different results, leading to inconsistent estimates. Instead, we follow (Terza et al., 2008) and include the residuals from the first-stage regression directly as additional regressors in the second stage. By controlling for them explicitly, the remaining variation in hauling time is free of that contamination, allowing the probit model to be estimated consistently without altering its functional form. Formally, for each potentially endogenous regressor y_{it}, we estimate a linear first-stage equation by OLS using both contemporaneous and time-averaged instruments $\mathbf{z}_{it}$ and $\bar{\mathbf{z}}_i$, as well as the other exogenous variables.

$$y_{it} = \psi_2 + \mathbf{x}_{it}\boldsymbol{\delta}_1 + \mathbf{z}_{it}\boldsymbol{\delta}_2 + \bar{\mathbf{x}}_i\boldsymbol{\eta}_1 + \bar{\mathbf{z}}_i\boldsymbol{\eta}_2 + u_{it} \tag{4}$$

Assuming that the structural error v_{it} depends linearly on the first-stage residual u_{it}, we write:

$$v_{it} = \rho u_{it} + \varepsilon_{it}, \quad \varepsilon_{it} \sim \mathcal{N}(0, \sigma_\varepsilon^2). \tag{5}$$

Substituting into the main equation, the final model of the second-stage estimation is the following:

$$\mathbb{E}(s_{it} \mid \mathbf{x}_{it}, u_{it}, v_{it}) = \Phi(\mathbf{x}_{it}\boldsymbol{\beta} + \psi + \bar{\mathbf{x}}_i\boldsymbol{\xi} + \rho u_{it} + v_{it}). \tag{6}$$

This model is estimated in two stages. In the first stage, the endogenous regressors are regressed on all instruments to retrieve residuals $\hat{u}_{it}$ by Ordinary Least Squares (OLS). In the second stage, the main equation is estimated by pooled quasi-maximum likelihood with a Probit link, using the residuals as additional regressors. We also correct for potential bias on the standard error of the second-stage regression by using a bootstrap. Instrument strength and relevance are evaluated using conventional first-stage diagnostics, including the Kleibergen–Paap rk LM statistic, the Kleibergen–Paap rk Wald F-statistic, and Wald tests of joint significance of the instruments. To interpret the results, we calculate average partial effects (APEs) of the explanatory variables, which provide consistent estimates of the marginal impacts of time to water source and other covariates on children's school enrollment.

4 Results

4.1 Descriptive Statistics

We begin our analysis with a descriptive examination of the intrahousehold dynamics related to water collection, current access to water infrastructure, and average hauling times across survey years. Although data on water-fetching responsibilities were not consistently collected in all DHS rounds, the 2005–2006 household survey provides valuable insights (Figure 2). According to the data, adult women are overwhelmingly responsible for water collection, accounting for 52.7% of cases, followed by girls (19.5%), adult men (14.2%), and boys (8.0%). This pattern highlights a significant gender and age disparity, where women and girls bear the greatest burden. Interestingly, the average time spent fetching water varies by group, women and girls typically handle shorter trips, averaging around 24–25 minutes, while men and boys are more often responsible for longer distances, with averages near 28–29 minutes.

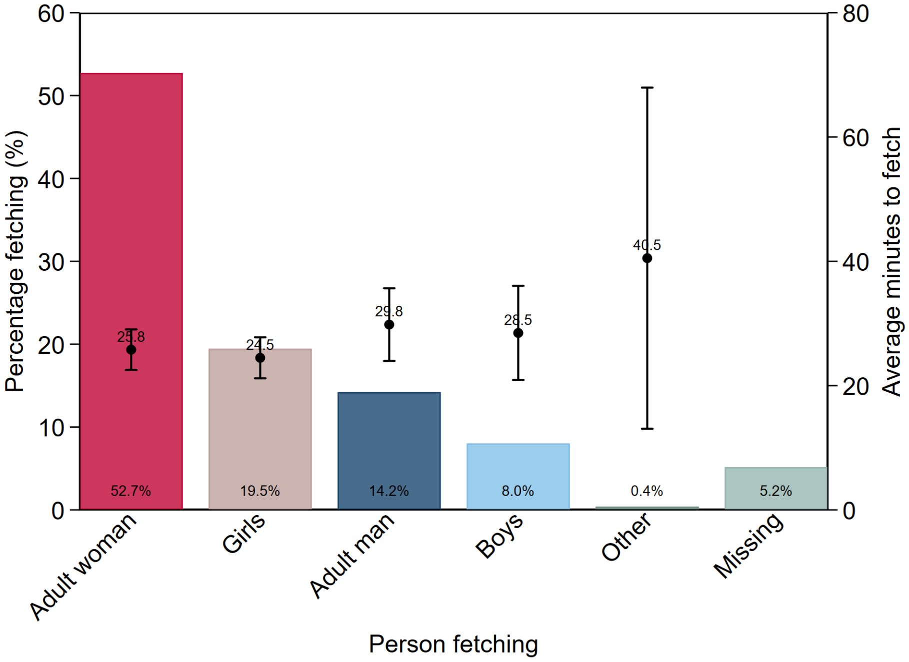

Figure 2: Person in the Household responsible for Fetching Water and average time to fetch in the household (2005-2006)

Regarding access to water infrastructure, only 6.9% of households across all DHS rounds reported having water on their premises (inside the residence or the yard), either through piped access or well[6]. For households without on-premises access, the average round-trip time to the source ranged from 25 to 33 minutes, depending on the survey year (Figure 3). Appendix C also provides more details on average times in the different survey rounds by water sources. Public taps were the most commonly used source (18–34%), followed by unprotected springs (25–34%). By 2016–2017, water kiosks had emerged as a significant source, serving 31% of households with relatively short hauling times (14 minutes) and high school enrollment rates (97%).

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[6] To calculate this percentage were taken into account the following categories from the all the DHS surveys: Piped Into Dwelling, Piped Into Yard/Plot, Piped To Yard/Plot and Protected Well To Yard.

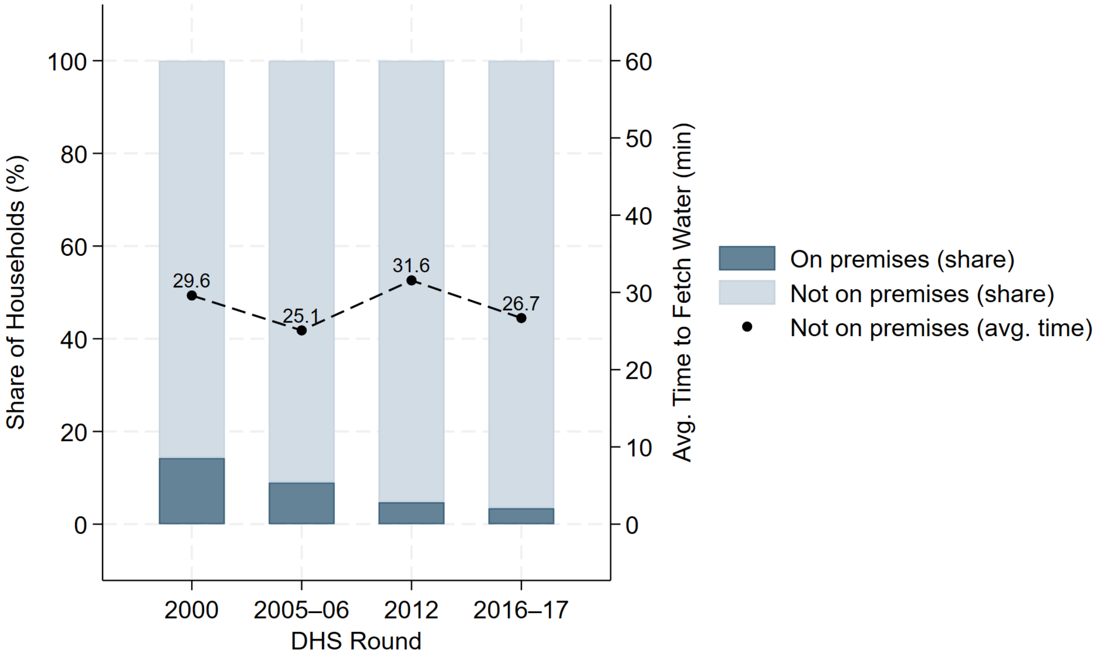

Figure 3: Share of households with water sources on the premises by year

Water access and hauling times varied significantly across Haiti's ten departments. Figure 4 shows that administrative regions, such as Nippes, North and Grand-Anse consistently reported the longest water collection times across all survey rounds, with times ranging from 35 to over 60 minutes in 2000, and decreasing to 35-40 minutes in 2016-2017. In contrast, other regions demonstrate a minimal change in average time to haul water over the years. Appendix D provides further detail, demonstrating that in 2000, access to water within the residence was very limited, with most departments reporting less than 10% of households with such access. At the same time, school enrollment for children aged 6–16 was generally low, ranging from 41% in South-East to 60% in South. By 2005–2006, both water access and school enrollment had a notable improvement. Average hauling times decreased in many regions and children's school enrollment increased to between 60 to 84%.

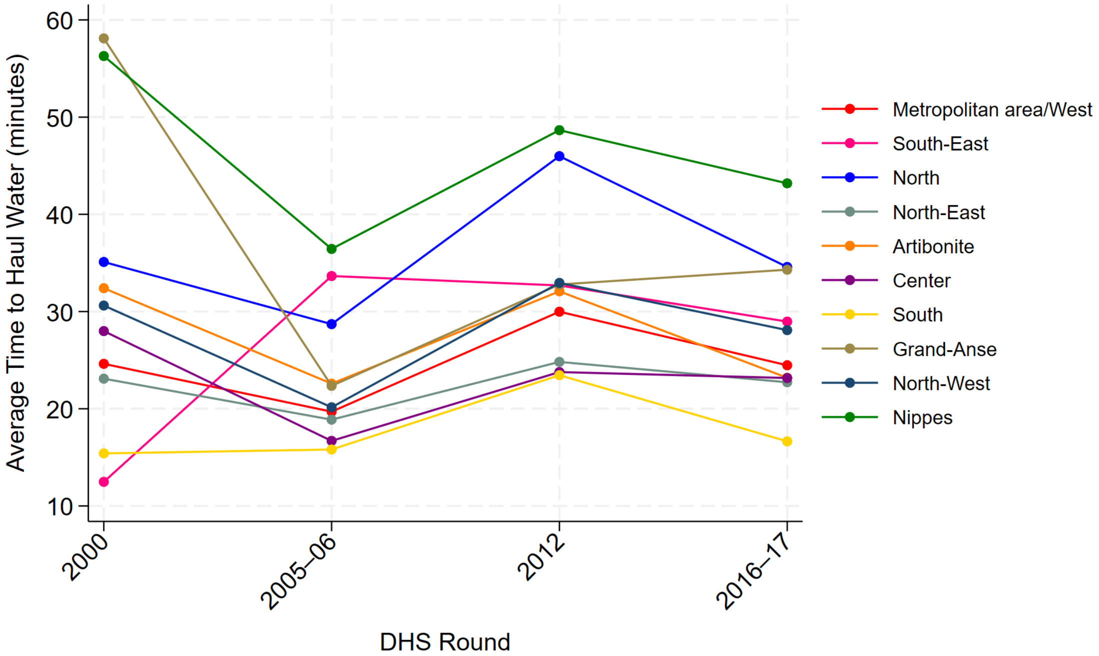

Figure 4: Average time to Haul Water by Region and DHS round

After 2005–2006, progress in reducing water hauling time was minimal. The share of households with water available inside the residence remained very low, around 1% in the North and South, reflecting a broader decline in access to water on premises nationwide. In contrast, school enrollment improved across the departments, reaching 85% or higher in areas such as the Metropolitan region and the West. Despite these educational gains, water hauling times stayed high in some regions, notably Nippes (49 minutes) and the North (47 minutes), underscoring limited investment in water infrastructure. By 2016–2017, school enrollment reached 88–96% in most regions. Hauling times generally decreased, with the South reporting the shortest average (17 minutes), while Nippes continued to face long delays at 42 minutes.

While educational enrollment is influenced by multiple factors, Figure 5 reveals a descriptive correlation between time spent hauling water and school enrollment. Children living in households farther from water sources tend to exhibit lower school enrollment rates, particularly in earlier years. This pattern suggests that limited water access may impose time constraints that disproportionately hinder educational outcomes.

At the same time, the figure highlights a steady increase in school enrollment since 2000. This upward trend is likely associated with the implementation of major tuition waiver initiatives. The Tuition Waiver Program (Programme de Subvention), launched in 2007 and co-financed by the Haitian government and multilateral development partners, including the IDB, World Bank, and Global Partnership for Education (Inter American Development Bank (IDB), 2012), helped reduce financial barriers to schooling. This intervention was particularly significant given that over 90% of primary schools in Haiti were non-public and charged tuition fees (Adelman et al., 2017)[7].

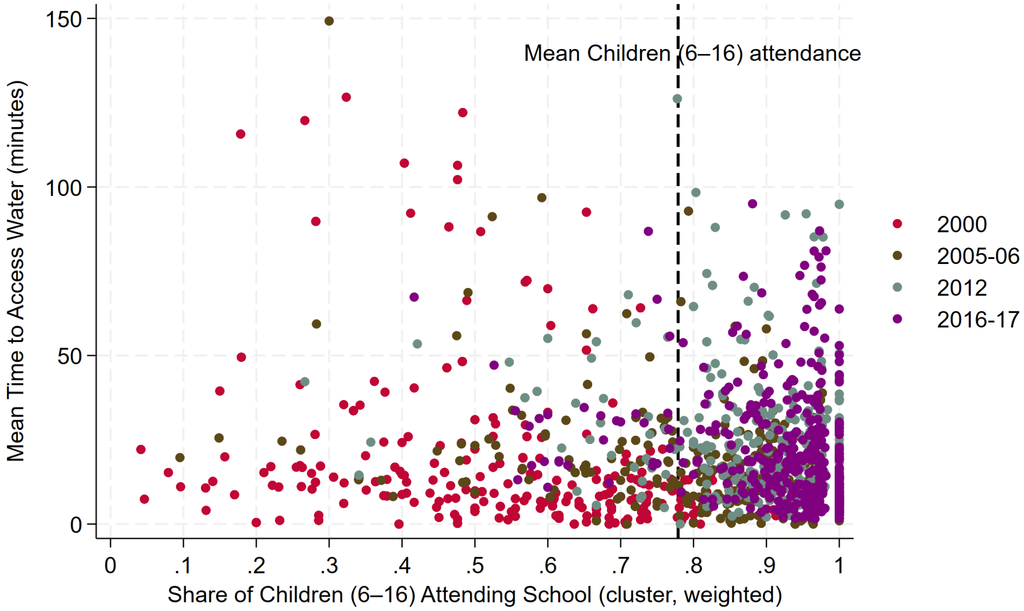

Figure 5: Water Hauling Time and School Enrollment Among Children Aged 6–16, by Year

Figure 5 is further supported by evidence provided in Appendix C. For instance, in 2000, most households relied on public taps (40%) and unprotected sources[8] (21%), which had

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[7] It is important to mention that our enrollment rates in our descriptive statistics appear higher than the national figures cited in the introduction for two reasons: (i) the UNICEF indicator is a *total net attendance rate*, which requires children to attend the age-appropriate education level, whereas our DHS-based variable captures enrollment at any school-level; (ii) our data predate the severe post-2017 deterioration of Haiti's education system—by 2024, UNICEF reported 919 school closures due to armed violence (UNICEF, 2024).

[8] The unprotected sources considered comprise: Lake, Pond, Canal, River, and Source Not Protected.

high average hauling times 18-42 minutes and relatively low school enrollment for children (55%-37%). In contrast, households with access to piped water into the dwelling (10%) or wells in the residence (3%), reported significantly higher enrollment rates (68% and 69%, respectively). By 2012, water access began to diversify, with more households using piped water, protected wells, and water sales companies. Children's school enrollment reached 97% in households with piped water on the premises (piped into dwelling and piped into yard/plot). In 2016-2017, water kiosks emerged as a major source (30% of households), with relatively short hauling times (14 minutes) and high school enrollment (98%). Households using surface water or unprotected springs still faced long hauling times (43–44 minutes) and lower enrollment rates (86–91%), though better than in prior years.

Overall, the data indicate a correlation between access to improved water sources, reduced water collection times, and increased school enrollment among children. However, this relationship should not be interpreted as causal. Households with better access to water are also more likely to be wealthier, more educated, and to place a higher value on education, all of which may independently influence school enrollment.

4.2 Estimation Results

As discussed in Section 3.1, both time to water and number of children aged 6–16 may be endogenous. To address potential endogeneity, we implement a control function approach using instrumental variables. Specifically, we instrument time to water with lagged rainfall and the number of children with the age of the household head, as detailed in Section 3.1. Various tests suggest that our instruments are relevant and that the model is well identified. Because each endogenous regressor is instrumented with a single instrument, the model is exactly identified, and formal overidentification tests are not applicable. To assess identification, we use the Kleibergen-Paap rk LM statistic, which yielded a p-value below 0.05, rejecting the null of underidentification and confirming that the instruments are sufficiently correlated with the endogenous regressors. For weak instrument diagnostics, the Kleibergen-Paap rk Wald F-statistic was 8.614, exceeding the Stock-Yogo critical value of

7.03, indicating that the instruments are not weak and provide adequate explanatory power in the first stage (Stock and Yogo, 2002). Finally, exogeneity was tested using a nonlinear Wald test, which produced a chi-squared statistic of 89.26 (p-value = 0.0000), leading us to reject the null of exogeneity. This confirms the presence of endogeneity and justifies the use of instrumental variables. In addition, to test whether rainfall affects school attendance through agricultural income rather than water collection, we estimate the model separately for urban and rural (Table I.1 in Appendix I). Rainfall significantly predicts water collection time in urban areas but not in rural areas, suggesting that rainfall primarily captures variation in water supply conditions rather than agricultural productivity. Importantly, the estimated impact of water collection time on school attendance remains negative and statistically significant in both subsamples. Moreover, Table J.1 in Appendix J, reports that the instruments have no statistically significant direct effect on the the share of children enrolled in school, providing empirical support for the exclusion restriction (Cameron and Trivedi, 2005, p. 551)(Pérez-Urdiales et al., 2024).

With the estimation strategy validated, we proceed to examine the determinants of children's school enrollment. Table 4 presents our results, as the coefficients in nonlinear models are not directly interpretable, we calculated the average partial effects (APEs) (Table 5). The results indicate that longer water collection times are associated with lower school enrollment among children. Our estimates suggest that each additional minute spent fetching water corresponds to a 1.31 percentage point decrease in the probability of school enrollment, on average. In practical terms, even modest increases in water collection time can substantially reduce enrollment rates, holding other factors constant. Importantly, including the squared term for Time to water in the regression reveals a nonlinear relationship, where the negative effect on enrollment becomes slightly larger for children living farther from the water source, although the overall impact remains modest. These results underscore the educational opportunity cost of water insecurity, in which, when basic necessities like water require significant time investments, children's education suffers.

Table 4: Regression: School Enrollment of Children Aged 6–16 (Cluster-Level Analysis)

	Children 6–16		
	First Stage	First Stage	Second Stage
	Children 6–16	*Time to water*	*Children 6–16 enrolled in school*
Time to water	–	–	-0.0524***
			(0.00656)
Time to water (squared)	–	–	-0.0000560***
			(0.0000105)
Children aged 6–16	–	–	-1.759***
			(0.237)
Residuals (Children aged 6–16)	–	–	1.727***
			(0.254)
Residuals (Time to water)	–	–	0.0626***
			(0.00636)
Household head age	-0.0159***	0.0772	–
	(0.000907)	(0.123)	
Rainfall	0.0000155*	-0.00531***	–
	(0.00000761)	(0.00123)	
Household size	0.883***	-0.0210	1.391***
	(0.0130)	(1.747)	(0.210)
Children under 6	-0.713***	-2.430	-1.951***
	(0.0195)	(2.817)	(0.166)
Women aged 17–65	-0.0360	-0.972	-0.930***
	(0.0418)	(6.930)	(0.163)
Men aged 17–65	0.0557	-2.405	-0.381*
	(0.0411)	(6.869)	(0.153)
Household head male	-0.0512	-7.039	-0.665**
	(0.0563)	(8.792)	(0.225)
Household head education	0.0408	8.959	0.128
	(0.0307)	(4.580)	(0.149)
Wealth index	-0.0175	-1.379	0.120**
	(0.00950)	(1.833)	(0.0390)
Women Violence	-0.0557**	-4.467	-0.603***
	(0.0202)	(2.472)	(0.0865)
Household size—mean	-0.00274	-2.496	0.0567
	(0.0231)	(3.894)	(0.0914)
Children under 6—mean	-0.0152	8.902	0.665***
	(0.0348)	(5.835)	(0.139)
Women aged 17–65—mean	-0.875***	0.882	-0.944***
	(0.0209)	(2.720)	(0.220)
Men aged 17–65—mean	-0.872***	1.280	-1.269***
	(0.0204)	(2.681)	(0.220)
Household head male—mean	0.0596*	10.16**	0.280*
	(0.0269)	(3.859)	(0.137)
Household head education—mean	-0.0659***	-5.521*	0.761***
	(0.0164)	(2.170)	(0.101)
Wealth index—mean	0.00456	-6.576***	-0.434***
	(0.00515)	(0.788)	(0.0483)
Women Violence—mean	0.0381	-1.706	0.315*
	(0.0425)	(5.688)	(0.154)
Constant	0.819***	56.14***	4.479***
	(0.0807)	(13.28)	(0.446)
Observations	1792	1785	1785
R-squared	0.877	0.299	
Pseudo R-squared (McFadden)			0.170
F-statistic	317.7	23.79	

Notes: Bootstrap standard errors in parentheses. All regressions include region and month fixed effects. Standard errors are clustered at the cluster level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: Average Partial Effects (APE) on School Enrollment of Children (Probit 2nd Stage, 500 reps, clustered)

Variable	**APE**	**P-value**
Time to water	-0.0131*** (0.0016)	0.000
Children under 6	-0.4880*** (0.0424)	0.000
Household size	0.3480*** (0.0530)	0.000
Women aged 17–65	-0.2361*** (0.0551)	0.000
Men aged 17–65	-0.3175*** (0.0555)	0.000
Household head male	0.0701* (0.0342)	0.041
Household head education	0.1904*** (0.0254)	0.000
Wealth index	-0.1086*** (0.0121)	0.000
Women Violence	-0.1508*** (0.0216)	0.000

Notes: Average partial effects (APE) are derived from Probit second-stage regressions that include the variable Time to water and its squared term. Bootstrap standard errors are based on 500 replications and clustered at the cluster level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The results also suggest that certain household characteristics may help offset this burden. For example, a larger household size is modestly associated with an increased likelihood of children's school enrollment. One possible explanation is that in bigger households, the burden of chores and income-generating activities might be distributed among more members, potentially freeing up time for the child to enroll at school. However, the presence of very young siblings dramatically alters this dynamic. We find that if there is a child under the age of 6 in the household, the probability of a school-age child enrolls drops by approximately 50 percentage points on average. This extremely large negative effect suggests that children often take on caregiving responsibilities for their younger siblings, which can severely limit their ability to go to school. In other words, in households with infants or toddlers, older children may remain at home to babysit or help their mother, thereby foregoing schooling.

The analysis also reveals a counterintuitive result regarding the number of adult members in the household. An increase in the number of adult women and men aged 17–65 is associated with a lower probability of children's school enrollment, holding other factors constant. In contrast to Nauges and Strand (2017), who did not report a significant negative effect of additional adult members, our results show a statistically significant negative association. This finding may indicate intra-household trade-offs in role allocation: even when there are more adult women or men present, it does not necessarily ease the children's domestic workload. In some contexts, it might even indicate that adults engage in external work while leaving the child to handle home chores and sibling care, thereby increasing the likelihood that children stay at home instead of enrolling in school.

Head of household characteristics are also associated with children's enrollment. Children are significantly more likely to enroll in school when the household head is female or more educated. This aligns with Nauges and Strand (2017)'s interpretation that female heads may place greater value on education and prioritize their children's enrollment. Similarly, we find that a higher level of education among the household head is strongly associated with an increased likelihood of children enrolling in school.

We also find a strong and statistically significant negative effect of women's reported experiences of violence within and outside the household on children's school enrollment. This may be indicative of both direct and indirect associations between experiences of violence (domestic and external) and children's well-being. The potential endogeneity of the variable "women violence" is not considered in the paper, since we are not trying to make any type of causal inference about the impact of this type of violence on children's school enrollment. Following Angrist and Pischke (2009), we consider this variable as a proxy control variables, in the sense that it is included in the regression in order to serve as a measure of the observed reported violence experienced by women and in order to avoid omitted variable bias. While the inclusion of this variable does not yield a coefficient of direct interest, it may represent an improvement over omitting the control altogether.

Lastly, the negative effect of the wealth index should be interpreted with caution due to the correlation between this variable and the variable measuring the education level of the household head.

4.3 Simulation Analysis

In addition, we assess the magnitude of the effect of time to haul water on children's school enrollment by calculating hypothetical increases in school enrollment in response to 50% reductions in hauling times, relative to the actual conditions observed in 2016-2017.

On average, reducing hauling water by half leads to a 9.0 percentage point increase in children's school enrollment (Figure 6). The median partial effect is 7.1 percentage points, indicating that half of the communities would experience an increase below this level. This effect is slightly higher than in the African context Nauges and Strand (2017), who found average and median increases of 6.9 and 4.2 percentage points, respectively.

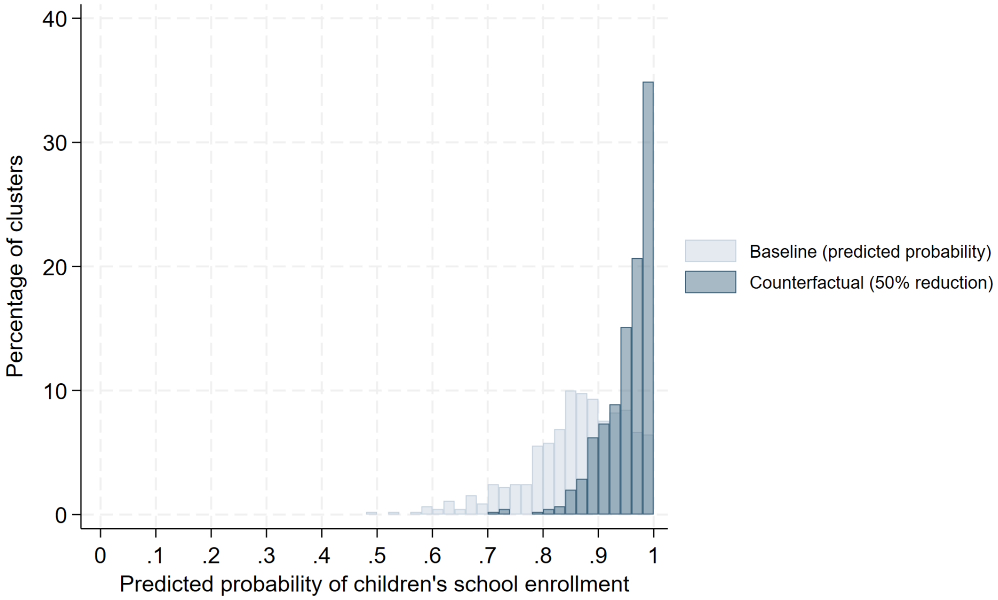

Figure 6: Distribution of estimated increase in the proportion of children's school enrollment following a 50 % reduction in hauling time

We also analyzed the effects of the 50% reduction in the time to haul water on children's school enrollment, disaggregated by rural and urban areas (Figure 7). The increase in school enrollment is generally larger in clusters where the initial hauling time is longer, suggesting that the marginal benefits of reducing hauling time are greater when the burden is higher. Rural communities exhibit both longer baseline hauling times and substantially greater improvements in enrollment, with an average increase of 11.7 percentage points, compared to 3.7 percentage points in urban areas. Urban clusters, which typically start with shorter hauling times, experience smaller gains. These findings suggest that investments in improving water access can yield significantly stronger educational benefits for children in rural settings. Our estimated effects are somewhat larger than those reported in Nauges and Strand (2017), the study most comparable to ours in terms of empirical strategy and outcomes examined. In their analysis, a 50% reduction in water hauling time increases girls' school enrollment by 9.6 percentage points in rural areas and 3.5 percentage points in urban areas, with similar magnitudes for boys. A useful distinction, however, lies in the substantially different baseline hauling times across settings. In Haiti, the average round-trip collection time in our data is 26.7 minutes, compared with roughly 19 minutes in the Ghana sample analyzed by Nauges and Strand (2017). As a result, a proportional (50 %) reduction in hauling time represents a considerably larger absolute time savings in our context. Given the nonlinear nature of fractional response models, and the well-documented convex relationship between time burdens and schooling outcomes, larger baseline hauling times naturally generate larger predicted improvements in enrollment when those burdens are reduced. Our somewhat larger estimates are therefore consistent with differences in underlying time costs across settings.

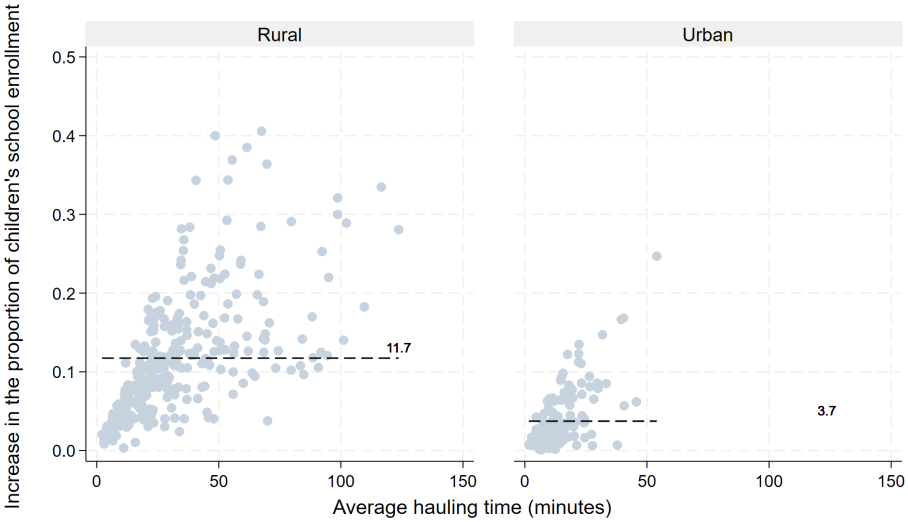

Figure 7: Estimated increase in the proportion of children's school enrollment in the cluster following a 50% reduction in the time to haul water, for rural and urban communities

4.4 Analysis by Gender

We also estimate the model separately for girls and boys to explore gender-specific determinants of school enrollment (Table 6). The average partial effects indicate comparable magnitudes: 1.25 percentage points for girls and 1.34 for boys (Table 7). Although the specification includes a quadratic term in time to water, the average marginal effects remain close to linear. However, simulated predicted probabilities by gender indicate that the gap widens at longer hauling times.

Table 6: Regression: School Enrollment of Girls and Boys Aged 6–16 (Cluster-Level Analysis)

	Girls 6–16			Boys 6–16		
	First Stage	First Stage	Second Stage	First Stage	First Stage	Second Stage
	Children 6–16	*Time to water*	*Girls 6–16 enrolled in school*	*Children 6–16*	*Time to water*	*Boys 6–16 enrolled in school*
Time to water	–	–	-0.0514***	–	–	-0.0540***
			(0.00734)			(0.00716)
Time to water (squared)	–	–	-0.0000576***	–	–	-0.0000523***
			(0.0000115)			(0.0000115)
Children aged 6–16	–	–	-1.960***	–	–	-1.386***
			(0.248)			(0.271)
Residuals (Children aged 6–16)	–	–	1.855***	–	–	1.388***
			(0.272)			(0.288)
Residuals (Time to water)	–	–	0.0618***	–	–	0.0636***
			(0.00716)			(0.00697)
Household head age	-0.0159***	0.0772	–	-0.0159***	0.0772	–
	(0.000907)	(0.123)		(0.000907)	(0.123)	
Rainfall	0.0000155*	-0.00531***	–	0.0000155*	-0.00531***	–
	(0.00000761)	(0.00123)		(0.00000761)	(0.00123)	
Household size	0.883***	-0.0210	1.533***	0.883***	-0.0210	1.143***
	(0.0130)	(1.747)	(0.226)	(0.0130)	(1.747)	(0.239)
Children under 6	-0.713***	-2.430	-2.097***	-0.713***	-2.430	-1.803***
	(0.0195)	(2.817)	(0.182)	(0.0195)	(2.817)	(0.191)
Women aged 17–65	-0.0360	-0.972	-1.117***	-0.0360	-0.972	-0.578***
	(0.0418)	(6.930)	(0.197)	(0.0418)	(6.930)	(0.174)
Men aged 17–65	0.0557	-2.405	-0.457**	0.0557	-2.405	-0.400*
	(0.0411)	(6.869)	(0.171)	(0.0411)	(6.869)	(0.167)
Household head male	-0.0512	-7.039	-0.658*	-0.0512	-7.039	-0.605*
	(0.0563)	(8.792)	(0.266)	(0.0563)	(8.792)	(0.247)
Household head education	0.0408	8.959	0.0550	0.0408	8.959	0.181
	(0.0307)	(4.580)	(0.168)	(0.0307)	(4.580)	(0.168)
Wealth index	-0.0175	-1.379	0.148***	-0.0175	-1.379	0.0851*
	(0.00950)	(1.833)	(0.0439)	(0.00950)	(1.833)	(0.0416)
Women Violence	-0.0557**	-4.467	-0.541***	-0.0557**	-4.467	-0.643***
	(0.0202)	(2.472)	(0.103)	(0.0202)	(2.472)	(0.0926)
Household size—mean	-0.00274	-2.496	0.109	-0.00274	-2.496	-0.0106
	(0.0231)	(3.894)	(0.107)	(0.0231)	(3.894)	(0.0937)
Children under 6—mean	-0.0152	8.902	0.608***	-0.0152	8.902	0.733***
	(0.0348)	(5.835)	(0.163)	(0.0348)	(5.835)	(0.155)
Women aged 17–65—mean	-0.875***	0.882	-1.083***	-0.875***	0.882	-0.819**
	(0.0209)	(2.720)	(0.241)	(0.0209)	(2.720)	(0.255)
Men aged 17–65—mean	-0.872***	1.280	-1.400***	-0.872***	1.280	-1.077***
	(0.0204)	(2.681)	(0.234)	(0.0204)	(2.681)	(0.252)
Household head male—mean	0.0596*	10.16**	0.398**	0.0596*	10.16**	0.285
	(0.0269)	(3.859)	(0.153)	(0.0269)	(3.859)	(0.150)
Household head education—mean	-0.0659***	-5.521*	0.724***	-0.0659***	-5.521*	0.821***
	(0.0164)	(2.170)	(0.105)	(0.0164)	(2.170)	(0.126)
Wealth index—mean	0.00456	-6.576***	-0.435***	0.00456	-6.576***	-0.432***
	(0.00515)	(0.788)	(0.0533)	(0.00515)	(0.788)	(0.0540)
Women Violence—mean	0.0381	-1.706	0.311	0.0381	-1.706	0.359*
	(0.0425)	(5.688)	(0.190)	(0.0425)	(5.688)	(0.163)
Constant	0.819***	56.14***	4.589***	0.819***	56.14***	4.452***
	(0.0807)	(13.28)	(0.518)	(0.0807)	(13.28)	(0.462)
Observations	1792	1785	1785	1792	1785	1785
R-squared	0.877	0.299		0.877	0.299	
Pseudo R-squared (McFadden)			0.170			0.174
F-statistic	317.7	23.79		317.7	23.79	

Notes: Bootstrap standard errors in parentheses. All regressions include region and month fixed effects. Standard errors are clustered at the cluster level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: Average Partial Effects (APE) on School Enrollment of Girls and Boys (Probit 2nd Stage, 500 reps, clustered)

Variable	**Girls 6–16**		**Boys 6–16**	
	APE	**P-value**	**APE**	**P-value**
Time to water	-0.0125^{***} (0.0018)	0.000	-0.0134^{***} (0.0018)	0.000
Children under 6	-0.5112^{***} (0.0456)	0.000	-0.4471^{***} (0.0476)	0.000
Household size	0.3736^{***} (0.0559)	0.000	0.2835^{***} (0.0592)	0.000
Women aged 17–65	-0.2640^{***} (0.0592)	0.000	-0.2030^{**} (0.0630)	0.001
Men aged 17–65	-0.3411^{***} (0.0577)	0.000	-0.2672^{***} (0.0626)	0.000
Household head male	0.0971^{**} (0.0371)	0.009	0.0706 (0.0369)	0.056
Household head education	0.1764^{***} (0.0257)	0.000	0.2035^{***} (0.0313)	0.000
Wealth index	-0.1059^{***} (0.0129)	0.000	-0.1070^{***} (0.0133)	0.000
Women Violence	-0.1319^{***} (0.0251)	0.000	-0.1594^{***} (0.0228)	0.000

Notes: Average partial effects (APE) are derived from Probit second-stage regressions that include the variable Time to water and its squared term. Bootstrap standard errors are based on 500 replications and clustered at the cluster level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

To understand these differences, we simulated probabilities by gender. As time to water increases from 10 to 60 minutes, enrollment declines for both genders, but with differences (Figure 8). Girls and boys school's enrollment show nearly identical rates when collection time is below 20 minutes, but by 40–60 minutes, girls retain a 2–3 percentage point advantage (Figure 9).Enrollment among boys declines more when water sources are farther from the home, plausibly reflecting their more frequent participation in longer water-collection trips.This pattern aligns with the descriptive evidence in Figure 2, where girls are more commonly responsible for water collection overall, but boys disproportionately take on the chore when the source is farther away.

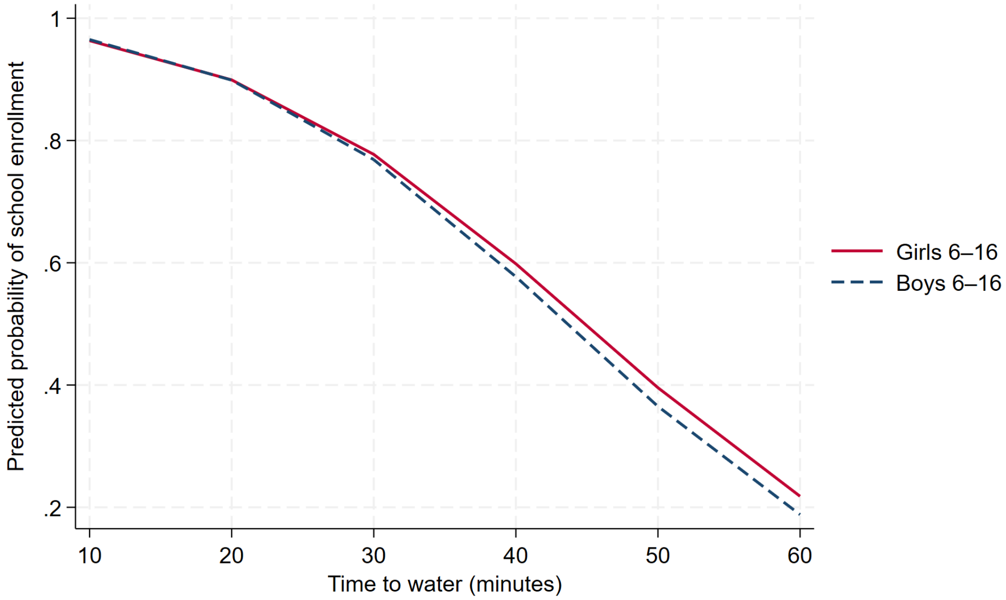

Figure 8: Predicted school enrollment by time to water (all DHS rounds)

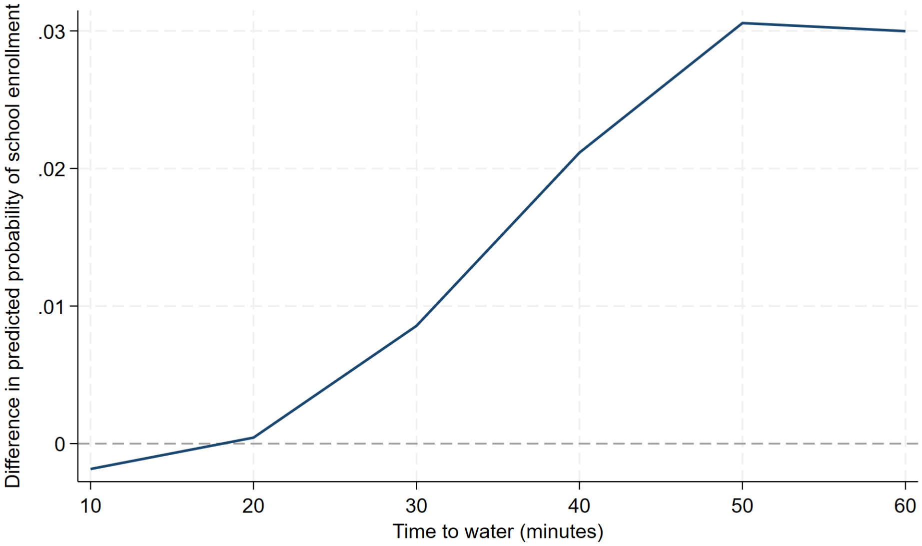

Figure 9: Gap in predicted school enrollment between girls and boys

Household composition also influences school enrollment for both genders, though boys appear less sensitive than girls to the number of children under six and overall household size. Interestingly, having a male household head increases the likelihood of girls enrolling in school, while the effect is not significant for boys. Finally, exposure to violence is negatively correlated with enrollment for both genders, but the association is stronger for boys.

4.5 Robustness Checks

Several robustness checks were conducted to validate the consistency of our main findings. First, we re-estimate the model using household-level data rather than aggregated cluster-level data. Given the cross-sectional nature of the household surveys and the absence of panel tracking, we are unable to control for unobserved household-specific heterogeneity. Nevertheless, we include a comprehensive set of observable household characteristics. The estimation results, presented in Table E.1 in Appendix E, show that the key coefficient on hauling time remains negative and statistically significant, with a magnitude closely aligned with the cluster-level estimates. This consistency suggests that our findings are not driven by the level of data aggregation.

Second, we test the sensitivity of our results to the treatment of households without children aged 6–16 in the computation of cluster-level enrollment rates. As described in Section 3.1, our baseline specification computes cluster averages across all households, assigning an enrollment value of zero to those without children in this age range. As an alternative, we recompute cluster-level averages using only households with at least one child aged 6–16, excluding childless households from the denominator. The results, presented in Appendix F (Tables F.1 and F.2), are virtually identical to the baseline: the APE of time to water is -0.0130, compared to -0.0131 in the main specification, and all other coefficients remain unchanged in magnitude, sign, and statistical significance. This confirms that the choice of denominator in the cluster-level aggregation does not affect our conclusions.

Third, to test the sensitivity of our matching procedure, we impose a stricter geographic constraint by limiting the maximum allowable distance between matched clusters to 2 (two) miles. This restriction reduces the sample size but increases the comparability of matched pairs. As shown in Appendix G, while the regional composition of the sample shifts slightly (Tables G.3 and G.4), the estimated effects of hauling time on school enrollment remain robust (Table G.1). Although some coefficients lose statistical significance due to reduced variability and sample size, the direction and magnitude of the main effects are preserved. Notably, when restricting the sample to clusters matched within 2 miles, the quadratic term in time to water remains negative but becomes statistically insignificant (Table G.1). This attenuation is consistent with a contraction in the support of the treatment variable, with the average hauling time declining from 25.9 to 23.5 minutes, and the upper tail is substantially reduced (Table G.4). In addition, the geographic composition of the matched sample shifts in a way that lowers exposure to extreme collection costs. Regions with the longest travel times, such as North-West and Nippes, decline in sample share. At the same time, North-East, one of the areas with systematically shorter hauling durations, increases from 22.4 to 27.2 percent of observations (Table G.3). Because nonlinear effects are primarily identified at higher values of time to water, the reduced presence of the longest-distance clusters mechanically weakens the curvature signal, leaving the linear term robust and significant while rendering the squared term imprecisely estimated.

Finally, we exclude the last round of observations (2016–2017). This step is motivated by a notable increase in school enrollment observed in that round, during which children's school enrollment surpassed 70% across all regions. The results, presented in Appendix H (Tables H.1 and H.2) confirm that the core findings are not driven by this temporal variation. The effect of water hauling time on children's school enrollment continues to be negative and statistically significant. The estimated average partial effect is slightly larger in magnitude when the final year is excluded (-0.0221 compared to -0.0147), but the direction and significance of the effect are robust. Other coefficients also remain broadly similar, with minor variations. For instance, exposure to violence continues to show strong negative associations with school enrollment, while the education level of the household head remains positively associated.

5 Conclusion

Our findings provide robust empirical evidence that longer water collection times significantly reduce children's school enrollment in Haiti. On average, each additional minute spent fetching water is associated with a 1.31 percentage point decline in the likelihood of enrollment. Importantly, this relationship is not fully linear: the penalty intensifies at higher hauling durations, indicating that children living in more remote areas face disproportionately larger educational losses. Simulated counterfactuals suggest that in rural communities, where travel times are longest, a 50 percent reduction in water fetching time could increase school enrollment by as much as 9 percentage points. These results highlight that improving access to water, particularly in underserved rural regions, is not only a matter of service provision but also an educational intervention with measurable returns in human capital.

In addition, our analysis reveals distinct patterns for girls and boys. Gender disaggregated simulations reveal that the effect of water hauling time on school participation is similar in magnitude for girls and boys at short distances, but diverges as collection time increases. When access is relatively close (below 20 minutes), school enrollment is nearly identical for both genders. However, at 40–60 minutes, girls maintain a 2–3 percentage point enrollment advantage, indicating that the educational penalty of distance becomes disproportionately larger for boys at longer hauling times. This pattern mirrors descriptive evidence: girls are primarily responsible for water collection overall, but boys increasingly assume the task when the source is farther away, which likely explains their steeper enrollment decline under high time burdens.

For girls, school enrollment is negatively associated with the presence of children under six in the household, suggesting that older girls may assume caregiving responsibilities. Interestingly, a higher number of adult household members does not offset this effect and is instead linked to lower enrollment, possibly reflecting intrahousehold labor dynamics. Girls are more likely to enroll in school in households headed by men and where the head has attained higher education levels. For boys, household composition also matters, but boys are less sensitive than girls to the number of young children and overall household size. Exposure to violence is associated with a more pronounced negative impact on boys' enrollment compared to girls, highlighting gendered vulnerabilities to household and community safety conditions.

Future research could expand this analysis to other LAC countries, where evidence on the relationship between water hauling time and school enrollment remains limited. Another important area for exploration is the impact of water collection responsibilities on academic performance, such as grades or learning outcomes, dimensions that could not be assessed in this study due to data limitations. Finally, exploring intrahousehold dynamics around chores allocation could offer valuable insights into who benefits most from improved water access, shedding light on gendered patterns of time use and educational investment.

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A Appendix: Literature Review on Water Collection and Educational Outcomes

Title	Author(s)	Year	Country	Period	Method	Results: Children	Results: Girls	Results: Boys
Household Work as a Deterrent to Schooling: An Analysis of Adolescent Girls in Peru	Levison & Moe	1998	Peru	1985–1986	Sample: Girls aged 10–19 from 5,024 households in Lima and rural Peru. Method: Generalized Tobit (Heckman selection model)	Running water reduces chores by ≈1.5 h/week and increases school hours by ≈1.3 h/week. Mother's presence raises attendance but reduces school hours by 10 h/week.	More chores when more males or children present; fewer chores when more adult women present.	—
Children's Work and Schooling: Does Gender Matter?	Ilahi	2001	Peru	1994–1997	Sample: 898 households, 1961 children (6–18). Probit regressions.	—	Urban girls without in-house water have 16.9 p.p. lower grade-for-age. Rural girls: no significant effect.	Impacts small though significant; boys less penalized by lack of water.
Natural Resource-Collection Work and Children's Schooling in Malawi	Nankhuni & Findeis	2004	Malawi	1997–1998	Sample: Children 6–14. Bivariate probit; 2SCML IV (fuelwood/water scarcity).	Each extra hour collecting reduces schooling by 0.8 p.p.; own-piped water saves ≈5 hours/week in rural areas.	Girls are 12 p.p. more likely to collect; work ≈2.4 hours more than boys.	Boys' attendance slightly lower in poor households, but gap smaller.
Household Water Supply Choice and Time Allocated to Water Collection	Boone, Glick & Sahn	2011	Madagascar	2004–2005	Sample: 2,190 households. Conditional logit with time-use models, instrumented.	Piped access associated with school attendance and less collection work.	Gender schooling effects largely consistent with higher female fetching time.	Results referenced from Ethiopia: longer fetching time reduces boys' schooling.
Access to Water, Women's Work, and Child Outcomes	Koolwal & van de Walle	2013	Multiple Countries	1991–2006	Sample: Boys/girls 5–14 rural. Aggregated regressions with placement controls.	Reducing time/distance to water ↑ enrollment by 10–15 p.p. on average.	Effects larger for girls; up to +35–40 p.p. in some South Asian cases.	Positive but smaller gains; Morocco exception where boys benefit more.
Environmental Resource Collection: Implications for Schooling	Gebru & Bezu	2014	Ethiopia	2010–2011	Sample: 120 rural households (7–18). Bivariate probit; IV.	50% ↑ in collection intensity ↓ reduce children's enrolment in school by 11 per cent ≈11%.	No significant gender difference.	Same as girls—no significant gender difference.
Implications of Environmental Chores for Schooling	Levison et al.	2017	Tanzania	2011	Cross-sectional (57 HH, 114 children). Descriptive and qualitative.	Chores negatively associated with enrollment; time conflicts noted.	Girls not in school fetch more; fatigue/time conflict reported.	Mixed; some positive homework-time associations.
Household Access to Water and Education for Girls	Dhital et al.	2018	Nepal	2014–2015	Sample: 2,641 rural households. OLS & IV using neighbors' water access.	—	+1h fetching → 24.1 p.p. primary completion; girls more likely to drop out.	+1h fetching → +0.10 years of grade repetition.
Effects of Water and Health on Primary School Enrolment and Absenteeism	Komarulzaman, de Jong & Smits	2019	Indonesia	1994–2014	Panel regressions with fixed effects.	Private water access ↑ enrollment (+0.025), ↓ absenteeism (0.027).	—	—
Time Spent on Household Chores and the Alternatives Forgone	Agesa & Agesa	2019	Kenya	2004–2005	Cross-section (807k youth 14–23). Probit IV (electricity).	Time fetching water negatively affects enrollment.	Each minute fetching ↓ enrollment by ≈32% vs. boys.	—
Inequality in Access to Improved Drinking Water and Childhood Diarrhoea	Hasan & Alam	2020	Multiple Countries	2010–present	Cross-sectional (1.63m HH).	Improved water access ↓ diarrhoea; no schooling outcomes.	—	—
Reduced Water Collection Time Improves Learning Achievement	Hamlet, Chakrabarti & Kaminsky	2021	India	2004–2005 & 2011–2012	2SLS/IV (instrument: rainfall).	Higher fetching times ↓ math (1.23 SD), reading (1.13 SD), writing (1.21 SD).	Girls' scores improve more when fetching time ↓.	Boys' scores 0.26–0.27 points higher than girls'.
Water Hauling and Girls' School Attendance: New Evidence from Ghana	Nauges & Strand	2017	Ghana	1993–2008 (4 DHS rounds)	Pseudo-panel DHS clusters; 2SLS (rainfall, lagged hauling time, age of head).	—	Each extra minute fetching ↓ attendance by 0.9 p.p.; 50% reduction ↑ by 6.9 p.p. rural (median 4.2 p.p.).	Similar but slightly smaller effect (≈ 0.009 marginal).

B Appendix: Map of Haiti

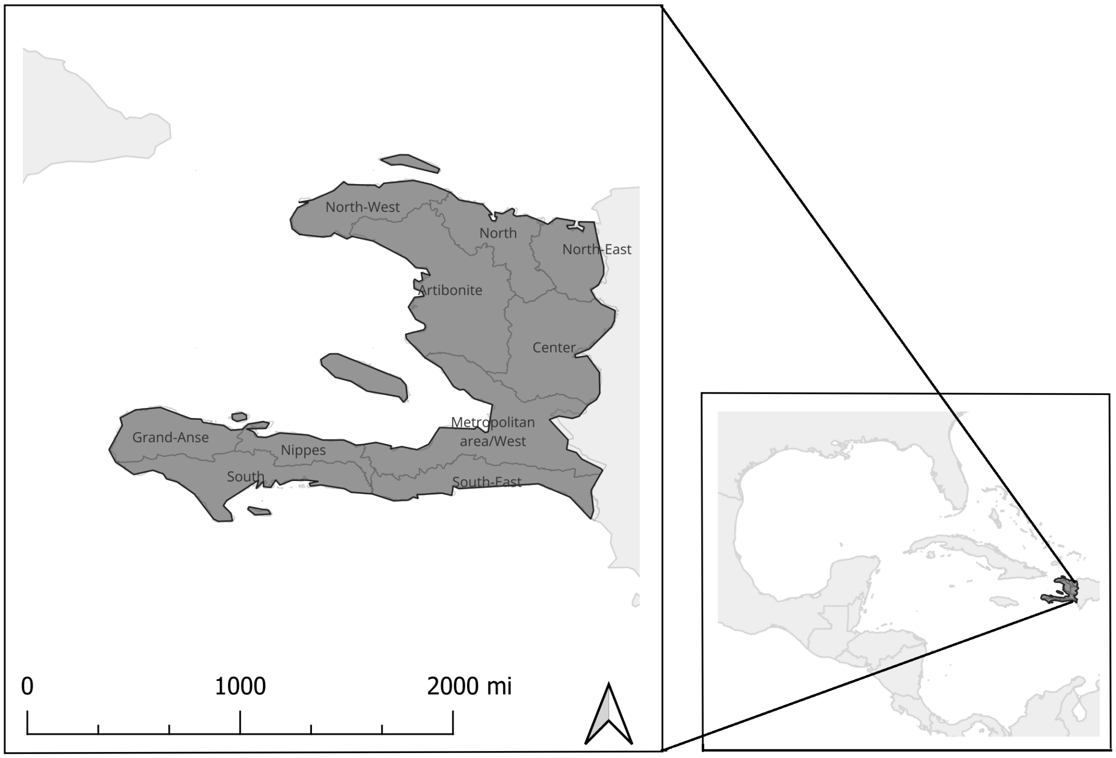

Figure B.1: Map of Haiti by Administrative Region (Source: DHS Report on Haiti)

C Appendix. Time to Haul Water and School Enrollment, by Source of Drinking Water

Table C.1: Time to Haul Water and School Enrollment by Water Source (2000)

Source of drinking water	Number of households	% of households	Time to haul water (min)	Children 6–16 in school (%)
Bottled Water	18	0%	–	65%
Canal	114	3%	38	42%
Lake, Pond	8	0%	34	64%
NA	1	0%	130	37%
Piped Into Dwelling	390	10%	–	68%
Protected Source	326	8%	56	51%
Public Tap	1,661	40%	18	55%
Public Well	351	9%	21	51%
Rainwater	74	2%	–	29%
River	139	3%	45	43%
Source Not Protected	865	21%	42	37%
Tanker Truck	10	0%	0	70%
Water Vendor	17	0%	–	60%
Well In Dwelling	133	3%	–	69%

Table C.2: Time to Haul Water and School Enrollment by Water Source (2005–2006)

Source of drinking water	Number of households	% of households	Time to haul water (min)	Children 6–16 in school (%)
Bottled Water	171	3%	8	91%
Cart With Small Tank	8	0%	12	90%
Dug – Well Unprotected	205	4%	29	78%
Dug Well – Protected	256	5%	17	86%
Other	7	0%	14	92%
Piped – Public	1,327	27%	21	82%
Piped Into Dwelling	77	2%	0	91%
Piped Into Yard/Plot	361	7%	0	87%
Rainwater	117	2%	0	74%
Spring Water Protected	261	5%	38	75%
Spring Water Unprotected	1,261	25%	38	66%
Surface Water (River/Dam)	291	6%	25	74%
Tanker Truck	84	2%	13	88%
Tube Well Or Borehole	332	7%	17	86%
Water Sale By Company	196	4%	8	90%

Table C.3: Time to Haul Water and School Enrollment by Water Source (2012)

Source of drinking water	Number of households	% of households	Time to haul water (min)	Children 6–16 in school (%)
Bottled Water	214	4%	17	93%
Cart With Small Tank	77	1%	12	92%
NA	6	0%	18	72%
Other	22	0%	36	94%
Others Protected Well	272	5%	26	89%
Piped From The Neighbor	246	5%	16	94%
Piped Into Dwelling	61	1%	0	99%
Piped To Yard/Plot	137	3%	0	96%
Protected Spring	284	5%	39	90%
Protected Well To Yard	43	1%	0	92%
Unprotected Well	277	5%	24	86%
Public Tap/Standpipe	1,131	21%	30	93%
Rainwater	89	2%	0	82%
Surface Water	114	2%	55	86%
Sales Company Of Water	692	13%	16	95%
Tanker Truck	50	1%	20	78%
Unprotected Spring	1,502	29%	48	80%
Unprotected Well To Yard	48	1%	0	92%

Note: The category “River/Dam/Lake/Ponds/Stream/Canal/Irrigation Channel” was renamed “Surface Water”.

Table C.4: Time to Haul Water and School Enrollment by Water Source (2016–2017)

Source of drinking water	Number of households	% of households	Time to haul water (min)	Children 6–16 in school (%)
Bottled Water	126	2%	16	98%
Cart With Small Tank	16	0%	14	97%
Other	2	0%	5	100%
Piped Into Dwelling	98	1%	0	95%
Piped To Neighbor	304	4%	0	97%
Piped To Yard/Plot	198	2%	0	95%
Protected Spring	550	7%	47	86%
Protected Well	543	7%	21	97%
Public Tap/Standpipe	1,524	19%	31	95%
Rainwater	146	2%	13	86%
Surface Water	111	1%	43	86%
Tanker Truck	68	1%	16	94%
Unprotected Spring	1,640	21%	44	85%
Unprotected Well	277	3%	18	91%
Water Selling Kiosk	2,361	30%	14	98%

Note: The category “River/Dam/Lake/Ponds/Stream/Canal/Irrigation Channel” was renamed “Surface Water”.

D Appendix. Time to Haul Water and School Enrollment, by Region

Table D.1: Time to Haul Water and School Enrollment, by Source of Drinking Water (2000)

Region	Time to haul water (min)	Source in residence (#)	Source in residence (%)	Children 6–16 in school(%)
Artibonite	26	2	3%	49%
Center	27	17	7%	58%
Grand-Anse	63	18	8%	51%
Metropolitan area/West	25	167	18%	46%
Nippes	64	8	3%	45%
North	36	30	15%	59%
North-East	27	186	15%	58%
North-West	30	39	11%	46%
South	15	13	9%	60%
South-East	14	43	9%	41%

Table D.2: Time to Haul Water and School Enrollment, by Source of Drinking Water (2005-2006)

Region	Time to haul water (min)	Source in residence (#)	Source in residence (%)	Children 6–16 in school(%)
Artibonite	24	7	5%	80%
Center	16	51	9%	77%
Grand-Anse	21	37	13%	75%
Metropolitan area/West	21	40	4%	78%
Nippes	38	7	2%	75%
North	29	3	2%	72%
North-East	19	216	14%	84%
North-West	21	52	13%	83%
South	16	5	3%	80%
South-East	43	20	5%	60%

Table D.3: Time to Haul Water and School Enrollment, by Source of Drinking Water (2012)

Region	Time to haul water (min)	Source in residence (#)	Source in residence (%)	Children 6–16 in school(%)
Artibonite	31	14	7%	94%
Center	23	17	3%	92%
Grand-Anse	34	9	3%	89%
Metropolitan area/West	30	35	3%	87%
Nippes	49	10	4%	88%
North	47	3	1%	86%
North-East	26	104	7%	88%
North-West	33	32	8%	89%
South	24	2	1%	85%
South-East	30	18	4%	90%

Table D.4: Time to Haul Water and School Enrollment, by Source of Drinking Water (2016-2017)

Region	Time to haul water (min)	Source in residence (#)	Source in residence (%)	Children 6–16 in school(%)
Artibonite	23	18	7%	96%
Center	23	26	3%	94%
Grand-Anse	34	19	4%	94%
Metropolitan area/West	24	58	5%	91%
Nippes	42	27	6%	92%
North	34	13	4%	91%
North-East	22	53	2%	94%
North-West	28	39	7%	93%
South	17	5	2%	93%
South-East	28	37	6%	88%

E Appendix. Robustness Checks: Pooled Household-Level Regression

Table E.1: Regression: School Enrollment of Children Aged 6–16 (Pooled Household-Level Analysis)

	First Stage	First Stage	Second Stage
	Children aged 6–16	*Time to water*	*Children 6–16 enrolled in school*
Time to water	–	–	-0.0814*** (0.00921)
Time to water (squared)	–	–	-0.0000138*** (0.00000390)
Children aged 6–16	–	–	-0.364*** (0.0638)
Residuals (Children aged 6–16)	–	–	0.345*** (0.0673)
Residuals (Time to water)	–	–	0.0838*** (0.00905)
Household head age	-0.0173*** (0.000460)	0.00655 (0.0274)	–
Rainfall	0.0000311** (0.0000106)	-0.00511** (0.00158)	–
Household size	0.875*** (0.00444)	-0.0407 (0.247)	0.372*** (0.0558)
Children under 6	-0.721*** (0.00616)	0.205 (0.341)	-0.514*** (0.0452)
Women aged 17–65	-0.842*** (0.00726)	-0.121 (0.448)	-0.261*** (0.0601)
Men aged 17–65	-0.826*** (0.00677)	-0.344 (0.405)	-0.364*** (0.0556)
Household head male	0.0617*** (0.0100)	2.812*** (0.672)	0.204*** (0.0342)
Household head education	-0.0222* (0.00946)	-0.423 (0.690)	0.382*** (0.0249)
Wealth index	-0.0144*** (0.00410)	-7.316*** (0.462)	-0.445*** (0.0702)
Women Violence	-0.00127 (0.00945)	-1.088 (0.827)	-0.111*** (0.0282)
Constant	0.816*** (0.0352)	51.87*** (4.413)	4.523*** (0.450)
Observations	14,176	13,775	13,724
R-squared	0.820	0.127	
Pseudo R-squared (McFadden)			0.138
F-statistic	1623.2	25.58	

Notes: Bootstrap standard errors in parentheses. All regressions include region and month fixed effects. Standard errors are clustered at the community/cluster level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

F Appendix. Robustness Checks: Only Households with Children Aged 6–16

Table F.1: Regression: School Enrollment of Children Aged 6–16 (Cluster-Level Analysis), excluding households without children aged 6–16

	First Stage *Children aged 6–16*	First Stage *Time to water*	Second Stage *Children 6–16 enrolled in school*
Time to water	–	–	-0.0518***
			(0.00647)
Time to water (squared)	–	–	-0.0000561***
			(0.0000105)
Children aged 6–16	–	–	-1.740***
			(0.236)
Residuals (Children aged 6–16)	–	–	1.708***
			(0.253)
Residuals (Time to water)	–	–	0.0621***
			(0.00628)
Household head age	-0.0159***	0.0715	–
	(0.000907)	(0.123)	
Rainfall	0.0000157*	-0.00536***	–
	(0.00000762)	(0.00123)	
Household size	0.884***	-0.0180	1.375***
	(0.0130)	(1.753)	(0.209)
Children under 6	-0.713***	-2.507	-1.940***
	(0.0195)	(2.813)	(0.166)
Women aged 17–65	-0.0362	-0.785	-0.919***
	(0.0418)	(6.939)	(0.163)
Men aged 17–65	0.0554	-2.537	-0.390*
	(0.0411)	(6.882)	(0.153)
Household head male	-0.0508	-6.603	-0.629**
	(0.0563)	(8.790)	(0.224)
Household head education	0.0412	9.317*	0.145
	(0.0307)	(4.565)	(0.149)
Wealth index	-0.0174	-1.394	0.120**
	(0.00948)	(1.836)	(0.0389)
Women Violence	-0.0557**	-4.317	-0.595***
	(0.0202)	(2.471)	(0.0860)
Household size—mean	-0.00285	-2.528	0.0556
	(0.0232)	(3.899)	(0.0913)
Children under 6—mean	-0.0152	8.870	0.662***
	(0.0348)	(5.839)	(0.139)
Women aged 17–65—mean	-0.875***	0.792	-0.934***
	(0.0209)	(2.730)	(0.220)
Men aged 17–65—mean	-0.872***	1.257	-1.254***
	(0.0204)	(2.678)	(0.220)
Household head male—mean	0.0598*	9.990**	0.261
	(0.0269)	(3.851)	(0.137)
Household head education—mean	-0.0657***	-5.704**	0.756***
	(0.0164)	(2.153)	(0.101)
Wealth index—mean	0.00465	-6.547***	-0.429***
	(0.00515)	(0.785)	(0.0477)
Women Violence—mean	0.0384	-1.451	0.334*
	(0.0425)	(5.691)	(0.153)
Constant	0.820***	56.31***	4.426***
	(0.0806)	(13.27)	(0.440)
Observations	1792	1785	1785
R-squared	0.877	0.301	
Pseudo R-squared (McFadden)			0.170
F-statistic	316.7	23.58	

Notes: Bootstrap standard errors in parentheses. All regressions include region and month fixed effects. Standard errors clustered at the cluster level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table F.2: Average Partial Effects (APE) on Children's School Enrollment (500 reps, clustered), excluding households without children aged 6–16

Variable	**APE**	**P-value**
Time to water	-0.0130*** (0.0016)	0.000
Children under 6	-0.4852*** (0.0422)	0.000
Household size	0.3440*** (0.0528)	0.000
Women aged 17–65	-0.2336*** (0.0549)	0.000
Men aged 17–65	-0.3137*** (0.0553)	0.000
Household head male	0.0654 (0.0340)	0.054
Household head education	0.1890*** (0.0255)	0.000
Wealth index	-0.1072*** (0.0119)	0.000
Women Violence	-0.1487*** (0.0215)	0.000

Notes: Average partial effects (APE) are derived from Probit second-stage regressions that include the variable Time to water and its squared term. Bootstrap standard errors are based on 500 replications and clustered at the cluster level. This specification computes cluster-level enrollment averages using only households with at least one child aged 6–16, excluding childless households from the denominator.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

G Appendix. Robustness Checks: Cluster matching within 2 (two) miles distance

Table G.1: Regression: School Enrollment of Children Aged 6–16 (Cluster-Level Analysis), cluster matching within 2 miles

	First Stage	First Stage	Second Stage
	Children aged 6–16	*Time to water*	*Children 6–16 enrolled in school*
Time to water	–	–	-0.0337***
			(0.00938)
Time to water (squared)	–	–	-0.0000381
			(0.0000199)
Children aged 6–16	–	–	-1.479***
			(0.342)
Residuals (Children aged 6–16)	–	–	1.548***
			(0.347)
Residuals (Time to water)	–	–	0.0412***
			(0.00894)
Household head age	-0.0145***	0.0460	–
	(0.00110)	(0.117)	
Rainfall	0.0000184	-0.00512**	–
	(0.0000102)	(0.00166)	
Household size	0.873***	3.422*	1.258***
	(0.0175)	(1.689)	(0.301)
Children under 6	-0.692***	-3.559	-1.752***
	(0.0291)	(2.567)	(0.229)
Women aged 17–65	-0.854***	-7.851**	-1.167***
	(0.0255)	(2.689)	(0.339)
Men aged 17–65	-0.879***	0.0937	-1.099***
	(0.0273)	(2.929)	(0.314)
Household head male	0.0830*	7.440	0.0922
	(0.0383)	(4.390)	(0.189)
Household head education	-0.0806***	-2.368	0.649***
	(0.0196)	(2.133)	(0.115)
Wealth index	0.00423	-5.099***	-0.179**
	(0.00752)	(1.201)	(0.0593)
Women Violence	-0.0572*	-0.552	-0.510***
	(0.0263)	(2.769)	(0.115)
Household size—mean	0.00303	-3.257	0.0280
	(0.0243)	(3.589)	(0.108)
Children under 6—mean	0.0275	10.10	0.632***
	(0.0370)	(5.529)	(0.182)
Women aged 17–65—mean	-0.0506	6.644	-0.166
	(0.0429)	(6.362)	(0.187)
Men aged 17–65—mean	0.0258	-0.00687	-0.284
	(0.0399)	(5.922)	(0.182)
Household head male—mean	-0.0864	1.586	-0.00518
	(0.0578)	(8.693)	(0.263)
Household head education—mean	0.0687*	3.948	0.337*
	(0.0323)	(3.930)	(0.168)
Wealth index—mean	-0.00394	-1.944	-0.0804
	(0.0104)	(1.739)	(0.0527)
Women Violence—mean	0.0580	-5.964	0.374
	(0.0475)	(5.286)	(0.207)
Constant	0.691***	36.47**	2.657***
	(0.0815)	(12.04)	(0.434)
Observations	1166	1163	1163
R-squared	0.872	0.351	
Pseudo R-squared (McFadden)			0.138
F-statistic	198.4	15.64	

Notes: Bootstrap standard errors in parentheses. All regressions include region and month fixed effects. Standard errors clustered at the cluster level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table G.2: Average Partial Effects (APE) on Children's School Enrollment (450 clusters, 500 reps, clustered), cluster matching within 2 miles

Variable	**APE**	**P-value**
Time to water	-0.0073*** (0.0020)	0.000
Children under 6	-0.3794*** (0.0497)	0.000
Household size	0.2724*** (0.0650)	0.000
Women aged 17–65	-0.2529*** (0.0730)	0.001
Men aged 17–65	-0.2380*** (0.0678)	0.000
Household head male	0.0200 (0.0407)	0.624
Household head education	0.1406*** (0.0251)	0.000
Wealth index	-0.0387** (0.0128)	0.003
Women Violence	-0.1105*** (0.0248)	0.000

Notes: Average partial effects (APE) are derived from Probit second-stage regressions that include the variable Time to water and its squared term. Bootstrap standard errors are based on 500 replications and clustered at the cluster level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table G.3: Weight of each region in the full and restricted samples

Region	**Full sample**		**Restricted sample**	
	Freq.	Percent	Freq.	Percent
Metropolitan Area / West	228	12.8	130	11.2
South-East	152	8.5	84	7.2
North	133	7.5	85	7.3
North-East	400	22.4	316	27.2
Artibonite	124	7.0	71	6.1
Center	156	8.7	103	8.9
South	124	7.0	91	7.8
Grand-Anse	172	9.6	115	9.9
North-West	152	8.5	82	7.1
Nippes	144	8.1	86	7.4
Total	1,785	100.0	1,163	100.0

Table G.4: Distribution of the variable ‘time to the source’ in the full and restricted samples

Sample	**First quartile**	**Median**	**Third quartile**	**Mean**
Full sample	11.3	18.4	33.1	25.9
Restricted sample	10.0	16.8	29.1	23.5

H Appendix. Robustness Checks: Excluding last survey round (2016-2017)

Table H.1: Regression: School Enrollment of Children Aged 6–16 (Cluster-Level Analysis), excluding last survey round (2016–2017)

	First Stage	First Stage	Second Stage
	Children aged 6–16	*Time to water*	*Children 6–16 enrolled in school*
Time to water	–	–	-0.0685***
			(0.00523)
Time to water (squared)	–	–	-0.0000622***
			(0.0000104)
Children aged 6–16	–	–	-1.095***
			(0.240)
Residuals (Children aged 6–16)	–	–	1.187***
			(0.250)
Residuals (Time to water)	–	–	0.0803***
			(0.00487)
Household head age	-0.0157***	-0.0282	–
	(0.000977)	(0.144)	
Rainfall	0.00000460	-0.00805***	–
	(0.00000971)	(0.00172)	
Household size	0.886***	-2.213	0.805***
	(0.0143)	(2.028)	(0.215)
Children under 6	-0.723***	-4.253	-1.635***
	(0.0222)	(3.154)	(0.165)
Women aged 17–65	-0.870***	6.466	-0.124
	(0.0238)	(3.298)	(0.221)
Men aged 17–65	-0.880***	3.502	-0.671**
	(0.0256)	(3.234)	(0.229)
Household head male	0.0555	9.718*	0.535***
	(0.0306)	(4.704)	(0.139)
Household head education	-0.0634**	-4.773	0.421***
	(0.0202)	(2.793)	(0.105)
Wealth index	-0.00134	-7.638***	-0.534***
	(0.00609)	(0.953)	(0.0398)
Women Violence	-0.0700**	-6.954*	-0.665***
	(0.0242)	(3.059)	(0.0865)
Household size—mean	0.0283	0.538	0.0883
	(0.0266)	(4.350)	(0.107)
Children under 6—mean	-0.0572	8.807	0.683***
	(0.0389)	(6.352)	(0.158)
Women aged 17–65—mean	-0.0815	-6.580	-1.135***
	(0.0489)	(7.581)	(0.194)
Men aged 17–65—mean	0.0474	-7.327	-0.716***
	(0.0481)	(7.571)	(0.175)
Household head male—mean	-0.0284	-4.802	-0.770**
	(0.0616)	(10.02)	(0.252)
Household head education—mean	0.0282	4.753	0.339*
	(0.0369)	(5.125)	(0.152)
Wealth index—mean	-0.0112	0.105	0.114**
	(0.0106)	(2.031)	(0.0425)
Women Violence—mean	0.0409	-2.685	0.0625
	(0.0485)	(6.600)	(0.178)
Constant	0.766***	70.30***	5.428***
	(0.0909)	(15.72)	(0.419)
Observations	1342	1335	1335
R-squared	0.879	0.301	
Pseudo R-squared (McFadden)			0.163
F-statistic	254.4	17.51	

Notes: Bootstrap standard errors in parentheses. All regressions include region and month fixed effects. Standard errors are clustered at the community/cluster level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table H.2: Average Partial Effects (APE) on Children's School Enrollment (450 clusters, 500 reps, clustered), excluding last survey round (2016–2017)

Variable	APE	P-value
Time to water	-0.0192*** (0.0015)	0.000
Children under 6	-0.4588*** (0.0466)	0.000
Household size	0.2259*** (0.0604)	0.000
Women aged 17–65	-0.0348 (0.0619)	0.574
Men aged 17–65	-0.1882** (0.0643)	0.003
Household head male	0.1502*** (0.0389)	0.000
Household head education	0.1183*** (0.0296)	0.000
Wealth index	-0.1498*** (0.0111)	0.000
Women Violence	-0.1865*** (0.0241)	0.000

Notes: Average partial effects (APE) are derived from Probit second-stage regressions that include the variable Time to water and its squared term. Bootstrap standard errors are based on 500 replications and clustered at the cluster level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

I Appendix. Robustness Checks: Urban and Rural

Table I.1: Regression: School Enrollment of Urban and Rural Children Aged 6–16

	Urban Sample			**Rural Sample**		
	First Stage	First Stage	Second Stage	First Stage	First Stage	Second Stage
	Children aged 6–16	*Time to water*	*Children 6–16 enrolled in school*	*Children aged 6–16*	*Time to water*	*Children 6–16 enrolled in school*
Time to water	–	–	-0.0508***	–	–	-0.406***
			(0.00695)			(0.114)
Time to water (squared)	–	–	-0.0000555***	–	–	-0.0000472
			(0.0000104)			(0.0000633)
Children aged 6–16	–	–	-1.675***	–	–	4.340**
			(0.283)			(1.507)
Residuals (Children aged 6–16)	–	–	1.540***	–	–	-4.275**
			(0.304)			(1.524)
Residuals (Time to water)	–	–	0.0615***	–	–	0.416***
			(0.00691)			(0.114)
Household head age	-0.0188***	-0.0351	–	-0.0118***	-0.156	–
	(0.00131)	(0.225)		(0.00122)	(0.0941)	
Rainfall	0.0000182	-0.00613***	–	0.00000893	-0.000372	–
	(0.00000978)	(0.00181)		(0.0000145)	(0.000911)	
Household size	0.881***	-0.826	1.275***	0.879***	1.816	-3.201**
	(0.0173)	(2.665)	(0.248)	(0.0190)	(1.430)	(1.135)
Children under 6	-0.732***	-3.838	-2.072***	-0.684***	-2.248	1.738*
	(0.0243)	(4.499)	(0.200)	(0.0306)	(2.222)	(0.794)
Women aged 17–65	0.0610	-11.64	-1.139***	-0.131*	8.158	3.394**
	(0.0550)	(10.52)	(0.233)	(0.0641)	(5.236)	(1.123)
Men aged 17–65	0.0989	-5.401	-0.222	-0.0248	-0.765	-0.570*
	(0.0547)	(10.23)	(0.207)	(0.0552)	(4.666)	(0.235)
Household head male	-0.0356	-6.507	-0.709*	-0.0765	-1.946	-0.0995
	(0.0759)	(13.04)	(0.279)	(0.0768)	(6.074)	(0.383)
Household head education	0.0847	18.42*	0.280	0.0382	0.208	-0.147
	(0.0519)	(9.043)	(0.249)	(0.0360)	(2.979)	(0.176)
Wealth index	-0.0304*	-1.412	0.148**	0.000908	0.646	0.420***
	(0.0129)	(2.748)	(0.0491)	(0.0125)	(1.178)	(0.0940)
Women Violence	-0.0207	-6.909	-0.563***	-0.103***	3.239	1.222*
	(0.0293)	(4.291)	(0.122)	(0.0263)	(1.910)	(0.582)
Household size—mean	-0.0443	-4.514	-0.267*	0.0567	-2.918	-1.286**
	(0.0293)	(5.382)	(0.119)	(0.0347)	(2.903)	(0.438)
Children under 6—mean	0.0179	11.34	0.828***	-0.0798	13.49**	6.010***
	(0.0425)	(8.389)	(0.183)	(0.0517)	(4.849)	(1.655)
Women aged 17–65—mean	-0.846***	1.322	-0.643*	-0.892***	-0.170	4.087**
	(0.0320)	(4.755)	(0.264)	(0.0303)	(2.384)	(1.357)
Men aged 17–65—mean	-0.839***	1.262	-1.254***	-0.888***	0.808	4.431**
	(0.0276)	(4.377)	(0.259)	(0.0299)	(2.768)	(1.442)
Household head male—mean	0.0488	13.61*	0.178	0.0954*	7.318*	2.385**
	(0.0372)	(6.563)	(0.173)	(0.0414)	(2.962)	(0.756)
Household head education—mean	-0.0854**	-11.10*	1.244***	-0.0572**	-4.110*	-0.876*
	(0.0261)	(4.921)	(0.132)	(0.0212)	(1.668)	(0.379)
Wealth index—mean	-0.00319	-7.074***	-0.518***	-0.0140	-3.965***	-1.582***
	(0.00703)	(1.346)	(0.0525)	(0.00966)	(0.765)	(0.434)
Women Violence—mean	0.0256	-1.811	0.184	0.0340	-3.021	-0.918
	(0.0547)	(9.602)	(0.216)	(0.0628)	(3.894)	(0.475)
Constant	0.955***	91.90***	6.407***	0.693***	17.58	4.257***
	(0.105)	(19.34)	(0.673)	(0.129)	(10.36)	(1.061)
Observations	1089	1086	1086	703	699	699
R-squared	0.865	0.213		0.897	0.276	
Pseudo R-squared (McFadden)			0.196			0.139
F-statistic	214.43	11.76		202.70	5.98	

Notes: Standard errors in parentheses. All regressions include region and month fixed effects. Standard errors are clustered at the community/cluster level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

J Appendix. Robustness Checks: Exclusion Restriction

Table J.1: Instruments Added Directly to the Second Stage

	Children 6–16 enrolled in school (mean)
Children 6–16 enrolled in school (mean)	-12.72
	(20.40)
Water source (minutes)	0.248
	(0.220)
Water source (minutes, squared)	-0.0000560***
	(0.0000105)
Household size	11.08
	(18.02)
Children under 6	-9.035
	(14.01)
Women aged 17–65	-10.80
	(18.04)
Men aged 17–65	-11.21
	(18.06)
Household head male	-2.118*
	(1.044)
Household head education	1.697***
	(0.202)
Wealth index (median)	1.590
	(1.541)
Women experienced violence (mean)	0.127
	(0.200)
Household size—DHS mean	0.776
	(0.503)
Children under 6—DHS mean	-2.174
	(2.279)
Women aged 17–65—DHS mean	-1.033
	(0.537)
Men aged 17–65—DHS mean	0.951
	(1.650)
Household head male—DHS mean	0.887
	(0.573)
Household head education—DHS mean	-2.116
	(1.181)
Wealth index (median)—DHS mean	0.343***
	(0.0714)
Women experienced violence—DHS mean	1.245
	(1.164)
Residuals (First stage: Children 6–16)	12.68
	(20.39)
Residuals (First stage: Time to water)	-0.238
	(0.220)
Rainfall	0.00176
	(0.00149)
Household head age	-0.197
	(0.341)
Constant	-3.400
	(4.582)
Observations	1785
R-squared	(R-squared from your output)

Notes: Bootstrap standard errors in parentheses (500 reps), clustered at the cluster level. This test directly adds the instrumental variables (rainfall, household head age) to the second-stage regression alongside the residuals from the first-stage regressions.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$