Precipitation and Women's/Children's Domestic Work: Evidence from Ugandan Panel Time-Use for Fetching Water

Akito Kamei*

In a society without infrastructure, climate conditions affect daily activities. This paper documents how one activity, fetching water, changes depending on the precipitation. Using satellite-collected, daily precipitation data, this study finds that a decrease in rainfall increases the time spent fetching water, especially for children and women. Analysis by gender revealed that, while girls spend more time fetching water, the change in time fetching water in response to rainfall is larger for boys. The impact is the largest for adult women. A decrease in daily rainfall from the 75th percentile to the 25th percentile increases the labor hours of women by 0.54 hours per week (13.3% from the average). Further analysis shows that severe weather (a dry spell lasting more than 20 days) increases the distance between the main water source and the dwellings. The effect of the severe weather on the choice of the water source was not observed in this study.

Keywords: Climate, Rainfall, Time Allocation and Labor Supply, Child Labor, Domestic Labor, Uganda

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*Department of Agricultural and Consumer Economics, University of Illinois at Urbana-Champaign, PhD Student in Agricultural and Applied Economics, 326 Mumford Hall, MC-710, 1301 West Gregory Drive, Urbana, IL 61801-3605, E-mail: kamei.akito@gmail.com

1 Introduction

While climate change has a global impact, it affects vulnerable populations more (Flatø, Muttarak, & Pelser, 2017). Even within the same household, women and children are more likely to suffer the climate-related shocks in societies with male dominance (WorldBank, 2010). In those societies, preparing food and enough water for all household members is mostly the responsibility of women and children. Volatility in weather conditions affects their labor supply, because people in communities without well-managed water infrastructure are vulnerable to weather conditions.

However, little is known about how extrinsic factors such as precipitation affect labor supply. Using data from the American Time Use Survey, Connolly (2008) shows that people spend 30 mins more at the office on rainy days in the United States. This is because workers value leisure outside less on rainy days. However, no empirical evidence shows the behavioral change in labor supply due to contemporary precipitation from developing countries.[1]

This paper documents how the labor supply of water collection is affected by precipitation in developing countries. While it takes a large portion of all domestic work, fetching water has attracted relatively small attention in labor economics. In Sub-Saharan Africa, 71 percent of water collection is carried out by women and girls. In total, people in Sub-Saharan African spend about 200 million hours per day collecting water (Farley, 2018; UN, 2012). Another estimates from Graham, Hirai, and Kim (2016) using the Demographic Health Survey (DHS) and the Multiple Indicator Cluster Survey (MICS) revealed that 3.36 million children and 13.54 million adult females were responsible for water collection greater than 30 minutes for twenty four sub-Saharan Africa countries studied.

Furthermore, this paper investigates if the severe weather affects the choice for water source and the distance to the water source from the household. UNICEF (2015) points out that children have to walk long distances to fetch water during droughts, since many water sources dry up. However, there is no quantitative evidence to support the argument.

This research matches daily satellite precipitation information with a household survey that

[1] Graff Zivin and Neidell (2014); Seppanen, Fisk, and Lei (2006) investigate the effect of weather (temperature) on labor supply in the similar framework. For the literature of climate change and natural disaster on social outcomes, see Carleton and Hsiang (2016); Dell, Jones, and Olken (2014); Maccini and Yang (2009). Other studies on the effect of mid-term (seasonal/annual) rainfall on agriculture labor supply include Jayachandran (2006); Shah and Steinberg (2017).

has information on domestic labor supply. The identification assumption relies on the exogeneity of the rainfall and the panel structure of the survey.

The empirical results suggest that a decrease in rainfall increases the time used for fetching water, especially for children and women. A one millimeter (0.039 inches) decrease in daily average rainfall in the past two weeks increases labor hours used to fetch water by 0.123 and 0.079 hours per week for boys and girls (Age 5-14) respectively. Given that the decrease in daily rainfall from the 75th percentile to the 25the percentile is 3.43 mm (=5.13-1.7), the decrease in rainfall increases the labor hours for boys by 0.42 hours per week. This is an increase of 14.4% from the average. The same statistics is 13.3% for adult women.

Further analysis on distance to the water source shows that a severe weather (dry spell lasting more than 20 days) increases the distance to the main water source from the dwellings by 19.7%. The satellite precipitation data used in this study suggests that the experience in severe weather (dry spell lasting more than 20 days) in Uganda is increasing over the years (Appendix A). The results emphasize the importance of policies on mitigation of effect in weather, especially for a vulnerable population. Since households with lower standards of living do not have access to water preserving technologies, their labor of domestic work are significantly affected by external factors. The study argues the importance of policy intervention for water security especially around the time of drought.

The remainder of the paper is organized into seven sections. Section 2 presents the prior literature on fetching water in developing countries. Sections 3 presents the labor survey data and satellite rainfall data used in this study. Section 4 discusses the empirical strategy and the identification for estimation. Section 5 provides descriptive statistics on household characteristics and time use by gender and age. In Section 6, the paper first presents the effect of rainfall on labor supply and later investigates the effect of rainfall on the distance to water source and Section 7 concludes with discussions.

2 Background

In communities lacking water infrastructure, fetching water is one of the activities that take a large portion of domestic work. In Uganda, the country of the study in this paper, only 34 percent of households reported that there is no issue with accessing a safe water source (Figure 1). More than 50% of households reported that long distance and the quality of the water source is their primary issue related to accessing a safe water source.

In the theoretical framework, household time use is classified into four categories: work at home, market work, leisure and time allocated to human capital investment (DeGraff & Bilsborrow, 2003; Skoufias, 1993). For women with a high burden of domestic work, an increase in domestic labor means less time for economic activities. An increase in time for domestic activities means less time for other activities. Devoto, Duflo, Dupas, Parienté, and Pons (2012) find that the private connection to water in Moroco increases the time for leisure (e.g. watching television) and leisure (e.g. visit or receive the visits of family or friends). It consequently increases the quality of life and welfare of the treated households. However, the study does not find the impact on time for income generating activity.

For small children, domestic labor burden takes time away from playtime and leisure. Significant workload deter their educational investment as well (Arends-Kuenning & Amin, 2001; Assaad, Levison, & Zibani, 2010; King & Hill, 1993; Levison, 1998).

The previous set of studies specifically investigates the effect of fetching water (and firewood collection) on time use and child schooling outcomes.[2] Those studies concluded that the distance to the water source is associated with higher labor demand for children to work, and lower performance at school. Koolwal and Van de Walle (2013) provides the meta-analysis of relationship between water access and female labor outcomes and child outcomes from rural areas of nine countries. The study finds positive impacts on access to water on children's schooling for both boys' and girls', while strong claims cannot be made about causal impacts as the authors discussed in the paper.

Gross, Günther, and Schipper (2018) study the impact of distance to water source by utilizing the construction of new water sources. They find that improved water access via a public pump reduced daily labor hours by 41 minutes per household in rural Benin. (However, the study did not find an increase in labor supply even thought women save time for fetching water.)

More and more studies reveal the effects of climate change and associated behavioral changes. However, none of the previous empirical studies investigate the effect of weather on domestic labor

[2] Akabayashi and Psacharopoulos (1999); Cockburn and Dostie (2007); Cooke (1998); Gebru and Bezu (2014); Ilahi (2001); Ilahi and Grimard (2000); Nankhuni and Findeis (2004); Ndiritu and Nyangena (2011).

activity in developing countries. To fill the gap in the literature, this paper studies how the labor supply of each household member changes by precipitation.

3 Data

The data in this paper comes from three rounds of the Living Standard Measurement Survey (LSMS) conducted between 2009 and 2012 in Uganda. The respondents reported the number of hours spent on fetching water for all household members above age 5.[3] The data is collected by asking the question "In the last 7 days, how much time in hours did [NAME] spend fetching water for the household, including travel time?"

Figure 2 shows a map of Uganda with sub-counties where samples were collected highlighted in gray. The sample sub-counties are sparsely located nationwide. This is particularly important for the study, since it gives a large variation in rainfall patterns. The final analytical sample is 13,888 individuals from 2481 households.[4]

The precipitation data is obtained by Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS): a database developed by the U.S. Geological Survey (USGS) and the Climate Hazards Group at the University of California, Santa Barbara.[5] A nice feature of the dataset is the availability of daily rainfall for high grid granularity. It has daily rainfall information at 0.05° spatial resolution, which is approximately 5.3 km by 5.3 km. The daily rainfall data allowed to create flexible rainfall variables 7 days prior to the interview date. By overlaying the sub-county border map, the sub-county level average rainfall for 7 days prior to the interview is calculated. This precipitation information is matched up with labor information as the LSMS contains sub-county information.[6]

[3]Another round of LSMS was collected in 2014. However, this paper does not use the LSMS 2014 since the minimum age for domestic work was raised to ten years and above, from five years and above.

[4]Since the analysis in this paper includes individual fixed effect, a sample that only appear once in the data is dropped from the analysis (See Section 7.3). Sixty-four percent of the individuals appear all three rounds, and the rest appears twice in the data.

[5]The rainfall data is calculated by remote precipitation climatology, quasi-global geostationary TIR satellite observations from the CPC and the National Climatic Data Center (NCDC), atmospheric model rainfall fields from the National Oceanic and Atmospheric Administration (NOAA) Climate Forecast System version 2 (CFSv2), and in situ precipitation observations. (Toté et al., 2015)

[6]The average area of sub-counties in Uganda is 249 km^2 (approximately 16 km×16 km). This means, on average, there are nine grid points in each sub-county.

4 Estimation Strategy

4.1 Time for Fetching Water

This paper utilizes panel data structure (individual fixed effects) and rainfall exogeneity as the identification strategy.

$$y_{ist} = \alpha + \beta_0 \text{Rainfall}_{0st} + \beta_1 \text{Rainfall}_{1st} + \beta_2 \text{Rainfall}_{2st} + \xi_i + \theta_{1year} + \theta_{2month} + \epsilon_{ist} \quad (1)$$

where y_{ist} is the number of hours that the respondent "i" residing in sub-county "s" spent on fetching water in the last 7 days prior to the day of the interview "t".[7]

Using the panel nature of the data, individual fixed effects (ξ_i) is included to control for time-invariant characteristics such as household wealth, household/community infrastructure and household demography.

The estimation includes year and month fixed effects separately. The monthly fixed effects control for the seasonality of social activities. For school attending children, they are expected to work more during the off school months. Monthly fixed effects control for the seasonality in the academic calendar.

The coefficient of 7 days of rainfall (β) is the parameter of interest in this study. "Rainfall$_{0st}$" is the average 7 days of rainfall prior to the interview date. Since the labor hours are collected as an aggregate of 7 days, the variable reveals the household response to rainfall during the data collection week. "Rainfall$_{1st}$" is the average rainfall 8-14 days (2 weeks) before the interview date. The past rainfall variables are included to investigate the effect of the past rainfall on the present labor supply.

The next specification includes past ten years average rainfall to explicitly control rainfall seasonality from the concurrent rainfall (β_0-β_2).

$$\begin{aligned} y_{ist} = \alpha &+ \beta_0 \text{Rainfall}_{0st} + \beta_1 \text{Rainfall}_{1st} + \beta_2 \text{Rainfall}_{2st} \\ &+ \delta_7 \textbf{Past Rainfall (10 Years)}_{0st} + \delta_8 \textbf{Past Rainfall}_{1st} + \delta_9 \textbf{Past Rainfall}_{2st} \\ &+ \xi_i + \theta_{1year} + \theta_{2month} + \epsilon_{ist} \end{aligned} \quad (2)$$

[7] The robust standard errors is used to deal with heteroskedasticity and autocorrelation in the error term. Denote the composite error term as $u(i) + e(i,t)$. When the mode is estimated with individual fixed effect, u(i) is absorbed in fixed effect. To deal with possible heteroskedasticity and autocorrelation, the standard error for e(i,t) is calculated using robust standard error.

Since the trend in monthly labor supply and trend of rainfall of the interview week is controlled by monthly fixed effects and rainfall of the past ten years, the contemporaneous rainfall variable (β_0-β_2) captures the labor supply response to rainfall regardless of seasonality.

Given that domestic work is incurred mostly by women and children, it is predicted that they are affected more than men who traditionally do not perform domestic chores. To see the effect of rainfall by demographic characteristics, the further estimation provides heterogeneous analysis by dividing the sample by age and sex. Children are divided into 5-14, and 15-19 years old.[8] Men and women are defined as adult aged 20-59, and senior is defined as above age 60 years old.[9]

4.2 Distance to Main Water Source

To investigate rainfall scarcity and the distance to water sources, further, the following estimation is conducted using the household level sample.

$$\text{Distance}_{hst} = \alpha + \beta_1 \text{Dry Spell}_{st} + \xi_h + \theta_{1year} + \theta_{2month} + \epsilon_{hst} \tag{3}$$

where $Distance_{hst}$ is the distance to the main water source from the dwelling for household "h" residing in the sub-county "s" at the time of the interview "t". To focus on the severe rainfall scarcity, the dry spell is calculated as the number of consecutive days prior to the interview when there was no rainfall.

While the data on distance could be noisy due to assessment error, the household fixed effects absorb the reporting bias. Therefore, the dry spell coefficient captures changes in distance reported by the same household due to the dry spell.

5 Descriptive Statistics

Table 1a shows the summary statistics of rainfall variables.[10] The average daily rainfall of the past 7 days is 3 millimeters. The maximum daily rainfall is around 15-18 millimeters for all rainfall variables.

[8] Boys and girls age 15-19 both has no impact of rainfall. Therefore the estimation does not separate this age group by gender.

[9] The maximum age for the senior is 98'

[10] Table 1b shows the correlation between each rainfall variable.

Figure 3 shows the average number of hours (including 0) that households spent fetching water in the last seven days by gender. The task is highly concentrated on women and children. The labor hours are always higher for females above age 10.

The labor participation rate (proportion of sample with a positive labor hour) and number of their labor hours, and the number of sample from the first round of the data collection are shown in Table 2.[11] The labor participation is the highest among girls age 5-14, and 62% of girls spend at least one hour fetching water. Females age 20-59 participating in the activity spend, on average, 7.28 hours fetching water in the last 7 days.

For the water source, only five percent have a private-tap. Most of the households have a water source outside of their home. While 80% of the households in this data set reside in the urban areas, the prevalence of the private tap is low.

The average distance to the main water source from the dwelling is 0.65 km. The maximum distance to the water source is 120 km, and a few other observations take extreme values. Since 48.2% of the households reported that the distance to the main water source is zero, this paper applies IHS transformation (instead of log transformation) to distances to the water source to deal with large value of distance variable.[12]

Figure 5 shows the average rainfall and average distance to the water source by month of the interview. In Uganda, the end of December to February is the first dry season, and July is the second dry season, which is milder than the first one. The distance to the water source increases in January, which is the severe dry season.

6 Empirical Results

Labor Hours for Fetching Water

Table 3 shows the estimation results for the time spent fetching water.[13] The results show that the time fetching water 7 days prior to the interview is related to the contemporaneous rainfall (Column (1)-(2)). The rainfall of 7-14 days prior to the interview day has lingering effects with respect to time spent fetching water during the interview week (Column (3)). While the significance

[11] The household characteristics are similar over three rounds of data collection.

[12] Figure 4 shows natural log and IHS transformation of distance to the main water source (km). The 120 km (maximum distance) is transformed to 5.48 and takes a similar value with other next large numbers.

[13] Appendix B shows coefficients of all control variables (month and year fixed effects).

level differs, coefficients on the rainfall of the interview week and one week before are negative in all specification.

Given that the rainfall of the past two weeks affects the time spent fetching water, a sub-sample analysis presented in Table 4 provides the coefficients of average rainfall in the past two weeks combined (1-14 Days). The result shows that women and children adjust their labor supply to buffer the rainfall conditions. An increase in time fetching water due to little rain is observed children (Age 5-14) for both boys and girls. A similar increase is observed for women (Age 20-59), but not for children age 15-19, adult males, nor seniors. When children age 5-14 are divided by gender, an increase in time fetching water due to little rain is larger for boys than girls. While girls spend more time for fetching water on average, boys are more likely to respond due to change in rainfall.

A one millimeter (0.039 inches) decrease in daily average rainfall in the past two weeks increases labor hours used to fetch water by 0.123 and 0.079 hours per week for boys and girls (Age 5-14) respectively. A decrease from the 75th percentile to the 25th percentile (3 mm) increases the labor hours for boys by 0.42 hours per week. This is an increase of 14.4% from average. The same statistics is 13.3% for adult women.

The result shows that rainfall saves time spent fetching water, and scarcity of rainfall increases the time spent fetching water. It is easy to imagine that the rainfall during the data collection week is related to saving time fetching water. The household can obtain rainwater just by putting a water pot outside of the house. This reduces the household labor need for fetching water.

Another mechanism for the increase is the case where the water source dries up or household change water source because of the bad water quality during the rainfall scarcity. In this case, the household has to walking longer distance in search of a new water source.

Distance to Main Water Source and Severe Weather

Table 5 shows the regression result of a dry spell and distance to the main water source. Columns (1) & (3) show the regression result with dry spell specified as a linear relationship. In the IHS specification, an increasing the dry spell by one day increases the distance to the water source by 0.45%.

Columns (2) & (4) control the dry spell non-linearly. The base of the categorical dummy in the estimation is a dry spell less than seven days. This means that it rained at least once in the past seven days of the data collection. The maximum dry spell in the data set is 50 days. The quintile dry spell categorical dummy variables are created between 7 to 50 days to make equal numbers of samples fall into each category. Those are 7-8 days, 9 days, 10-13 days, 14-19 days, and 20 -25 days. There is around 100 samples in each category.

In the non-linear specification, compared to the dry spell of 0-7 days (base), dry spells up to 19 days do not show any statistically significant difference. Only dry spells more than 20 days show a relatively large coefficient. It is significant at 5% for distance transformed by IHS. The result suggests that a dry spell of 20-50 days increases the distance by 17% on average. However, the dry spell variables with the same specification did not show any effect on time spent fetching water. For more discussion on the effect of severe weather on time and choice of water source, see Section 7.4.

7 Robustness

7.1 Reporting Bias

One common issue for time use data is reporting bias. This may be especially large for child labor information since parents have an incentive to underreport the child labor (Dammert & Galdo, 2013; Janzen, 2017). However, reporting anaccuracy may also come from the difference in the sense of time between children and adults, especially in the absence of clock (Levison, DeGraff, & Dungumaro, 2017).

For the data used in this study, the guardian reports the child's information: especially if he or she is under seven years old. Figure 6 shows how much respondents reported their own labor hours. The figure reveals that the likelihood of self-reporting increases with age.

However, the self-reporting variable should not be included in the estimation. This is because who is available in the household at the time of the interview can be affected by the rainfall. To investigate the relationship between precipitation and self-reporting, a simple regression of self-reporting and rainfall of the interview week is performed (Table 6). The coefficient does not show any relationship between rainfall and self-reporting. Therefore, the paper excludes the possibility that reporting bias skew the findings in the main analysis.

7.2 Inverse Hyperbolic Sin Transformation

To deal with large rainfall values and the possible non-linear relationship between rainfall and time spent fetching water, this section presents the estimation results with rainfall variables transformed with Inverse Hyperbolic Sin (IHS). Almost 10 percent of the rainfall variables are zero (no rain in the last 7 days).

Figure 7 shows the rainfall variable transformed into IHS. The IHS transformation is an alternative to natural log transformation (Burbidge, Magee, & Robb, 1988). One nice feature of the IHS is that it is defined at zero. IHS transformation has a similar form with the natural log transformation (except around zero). Therefore, the coefficient is interpreted in the same way as a standard logarithmic transformation.

Table 7 shows the estimation results. The interpretation of the coefficient change to an increase in percentage. While the significance changes depending on the results, the argument from the main analysis is robust with IHS specification.

7.3 Attrition

If the attrition pattern is affected by rainfall, it creates an attrition bias in the estimator. For both the second and third round, around 8% of the households were not followed in subsequent rounds. Figure 8 (a) and (c) show the distribution of those households.

The figures show a different rate of attrition by regions. This could be due to different rainfall patterns affecting respondents, but there are other factors to consider unrelated to rainfall. People in the big cities like Kampala (Central), Entebbe (Central), and Mbarara (West) are more mobile than people living in the rural areas. Another reason why Central and West regions, which have big cities, have higher attrition is that none of the household members were available for the interview since they were outside working. Figure 8 (b) and (d) show attrition for an individual while household itself was interviewed. Similar to household attrition, the attrition rate for individual is higher for the Central and Western regions.

Ideally, the attrition pattern should be checked by regressing the exit pattern with rainfall data. However, the data does not allow such regression since the intended day of the interview is not recorded when the interview was not conducted. Therefore, the exit pattern due to rainfall is not investigated.

If households relocate themselves to another sub-county to mitigate the effect of rainfall, it can create overestimation bias. While it is not clear if the migration pattern is related to the variation of rainfall variables used in this research, the external validity of the results is limited to non-migrated households, which is not uncommon in Uganda.[14]

7.4 Effect of Weather on Choice of Water Source

The further estimation does not find any evidence of an increase in time fetching water due to severe weather.[15] Time for fetching water is complex since it is not simply affected by its distance alone. The household may decide to reduce consumption of water, start obtaining water by paying for it, or reduce the number of trips by increasing the amount of water that they carry for each trip (Boone, Glick, & Sahn, 2011)

This section investigates the effect of severe weather on the water source choice. Table 8 shows the regression result of each water source as binary outcome. Given that the estimation includes household fixed effects, the coefficients are considered as switch from one source to another.

A dry spell more than 20 days decrease the household to use private tap as water source. On the other hand, severe weather increases the probability for household to obtain water through vender or Tanker truck. However, the result from other water source are largely insignificant. Even thought we do not see changes in the type of water source, it is possible that they change the water source within the same type.

8 Conclusion

This paper studies the causal impact of rainfall on household domestic labor supply by age and gender. While fetching water takes a significant portion of domestic labor activity, it is not studied widely in labor economics. The failure to include domestic activity in studies and leave the burden of domestic work unrecognized leads to a lack of policies that benefit household members who are responsible for such tasks (Guarcello, Lyon, Rosati, Valdivia, et al., 2005).

[14]Several studies show that rainfall shock induces more labor out-migration. In Uganda, Strobl and Valfort (2013) shows a region with a historical rainfall shock (average of 5 years prior) is related to net out-migration using the census data in 2002.

[15]The result is available upon request.

The empirical results show that women and children (especially for boys) buffer an increased burden of fetching water due to a change in rainfall. The findings add to the literature on other evidence of how rainfall patterns affect the daily life of people. For women who are responsible for both domestic work and economic activities, the increased burden of domestic work implies less time for economic activity or leisure (Arora & Rada, 2017). However, it is not easy to provide robust evidence of this using rainfall because rainfall could also affect economic activity directly.

Another finding of this paper is an increase in the distance to a water source from the dwelling due to severe weather. There is no empirical research documenting the relationship in the previous literature. The adverse effect of an increase in burden of fetching water due to scarcity is not limited to an increase in time for work itself. Qualitative studies revealed that women and children are a target of assault when they walk to the water source (Levison et al., 2017). Asaba, Fagan, Kabonesa, and Mugumya (2013) documents a negative health effect of work such as prolonged fatigue, chest pain, and headache as a result of carrying water. Similarly, not only does severe weather affect the distance to a water source, switching to another water source may affect the quality of water that households consume as well. Future research should investigate the relationship and the outcomes on health due to the severe weather.

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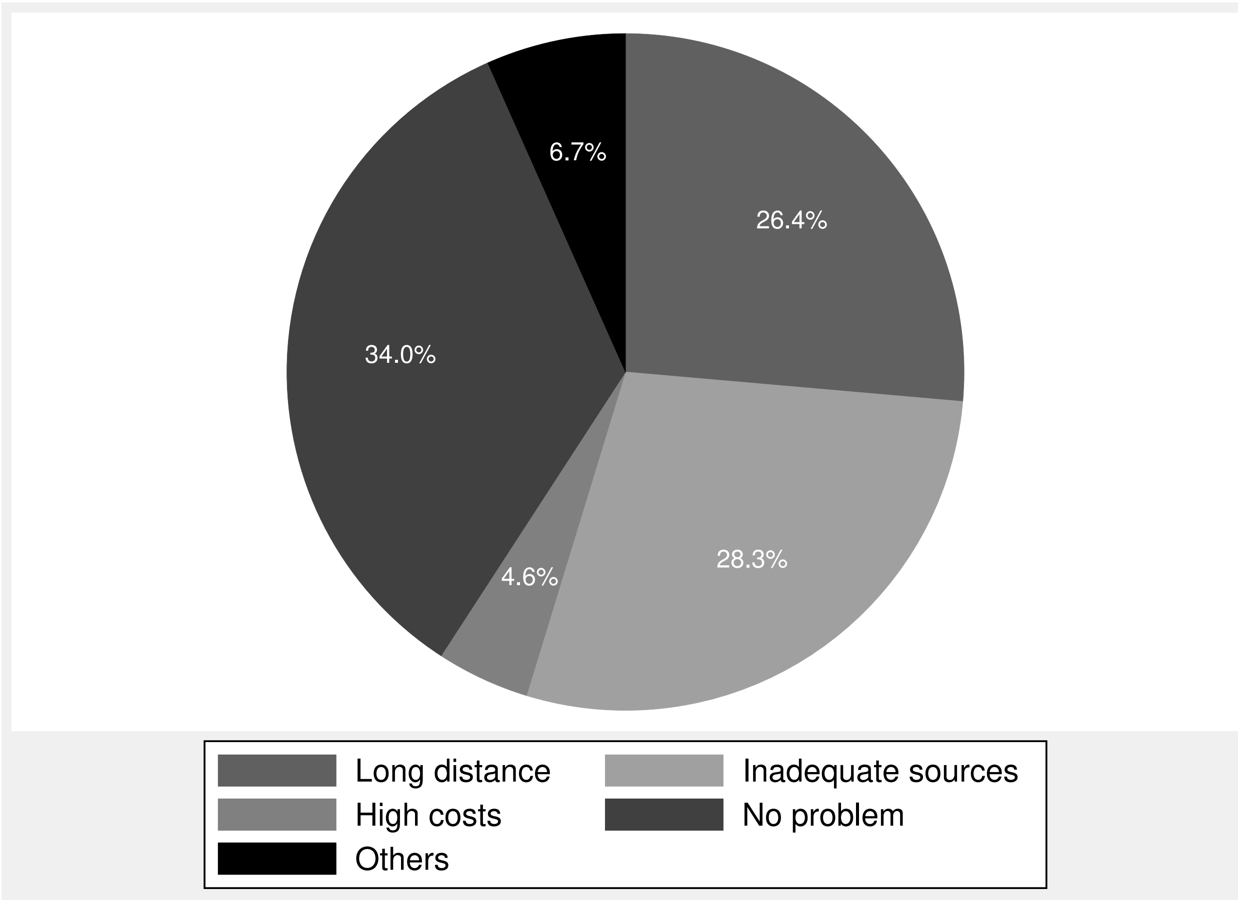
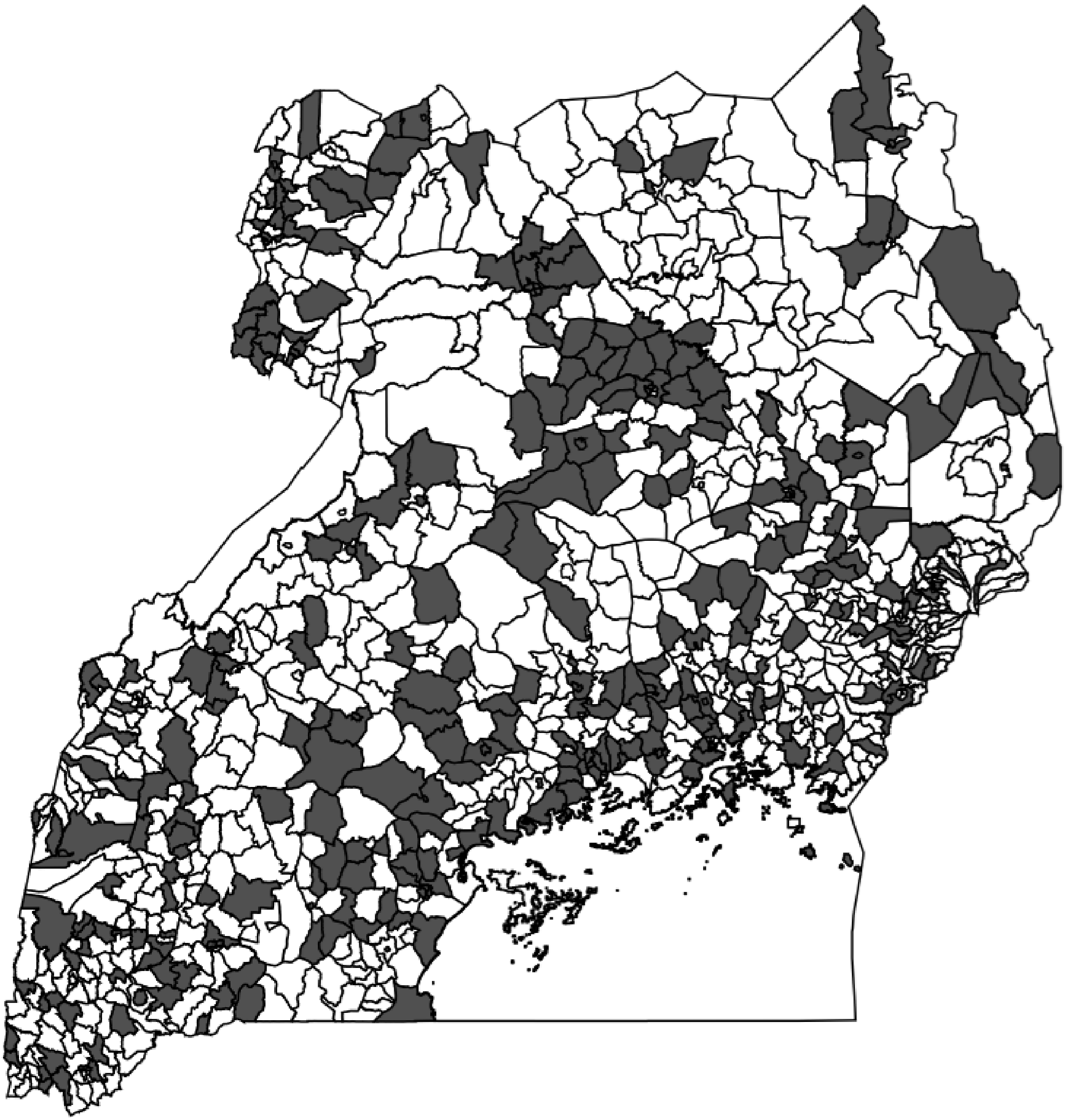
Figure 1: Constraints that Household Faces in Accessing Safe Water Source



Source: The Living Standard Measurement Survey (LSMS) 2009/2012. The case of "Insecurity" is included in others because of the small cases.

Figure 2: Sample Area: 2009-2012 Panel



Notes: The map shows 326 sub-counties where the samples have been collected. Reported land area for Uganda is 200,520 square kilometres, and there are 967 sub-counties in the map.

Figure 3: Number of Hours per Week on Fetching Water by Age and Gender

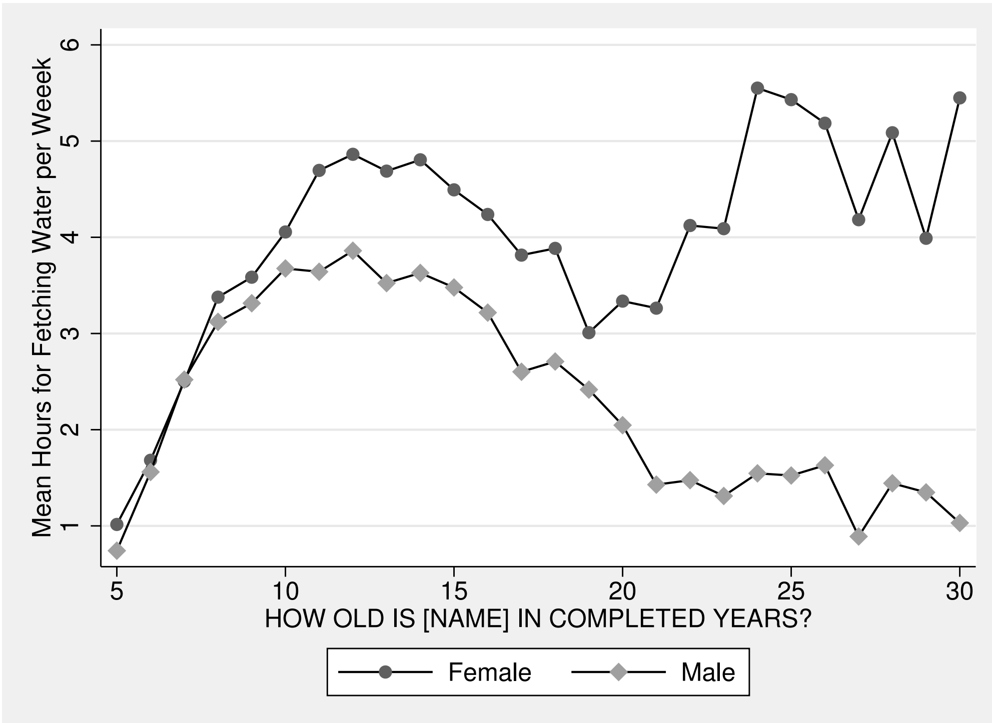


Figure 4: IHS and Natural Log Transformation for Distance to Water Source (km)

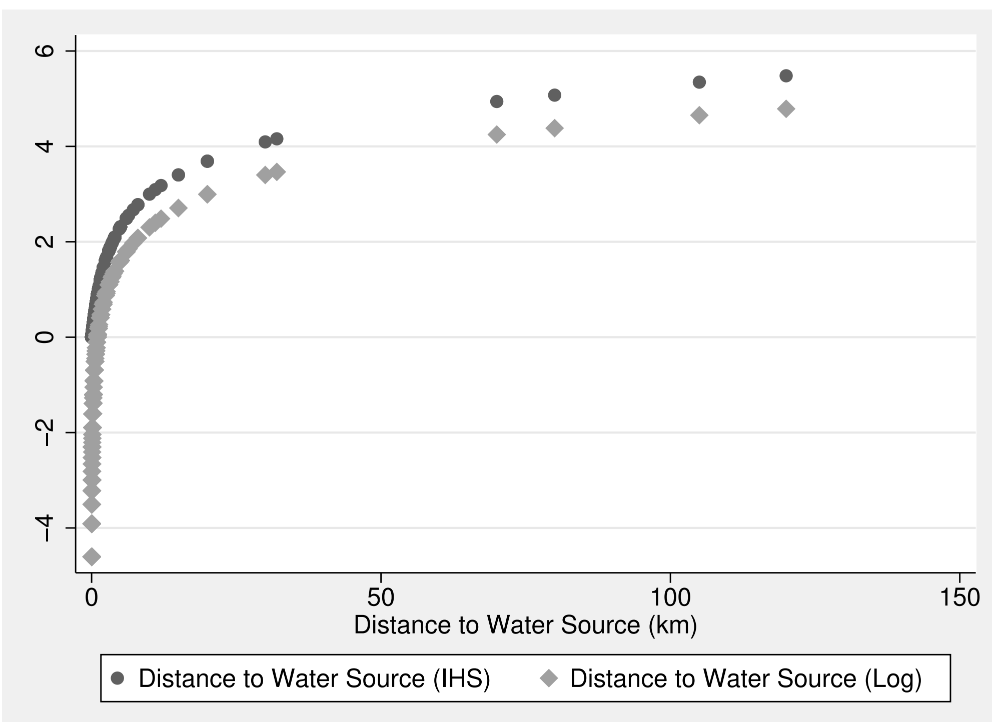
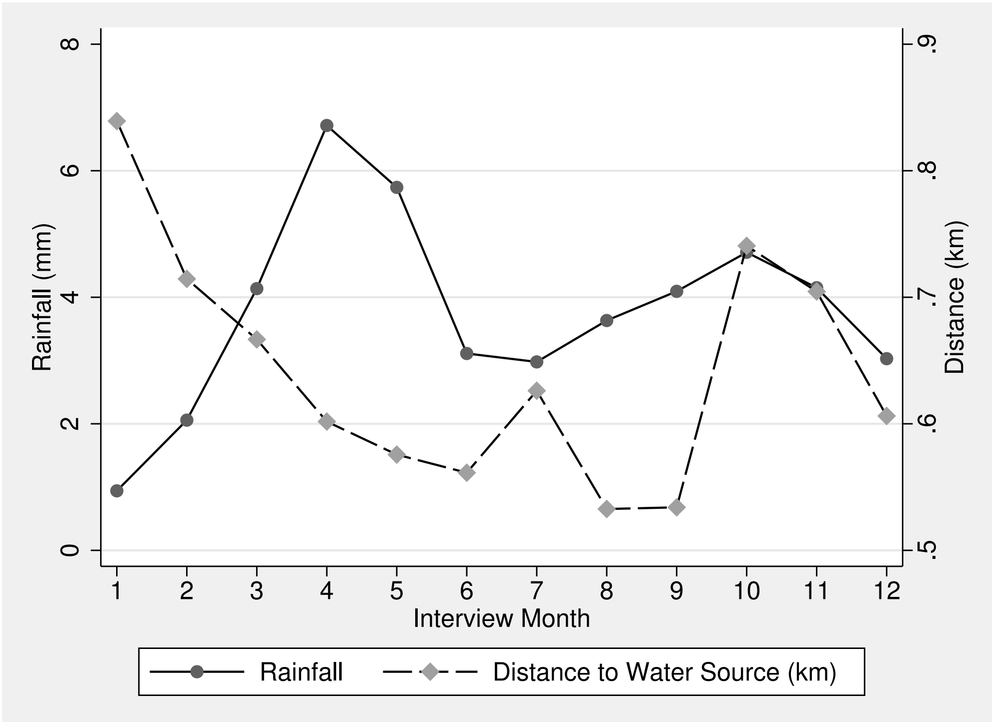


Figure 5: Average Daily Rainfall and Distance to Water Source by Month



Notes: N=6,886 (Households). The distance to main water source by the month of interview and average daily rainfall of the past 7 days from the interview date.

Figure 6: Respondents who Self-reported Their Labor Hours

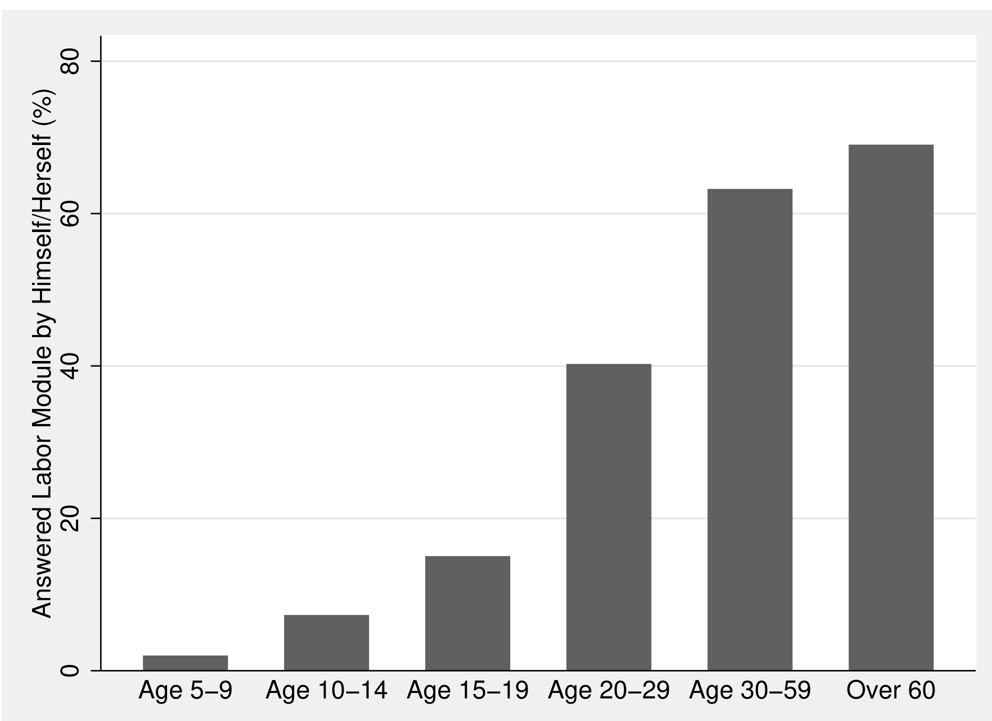


Figure 7: IHS and Natural Log Transformation for 7 Days Rainfall Variable (mm)

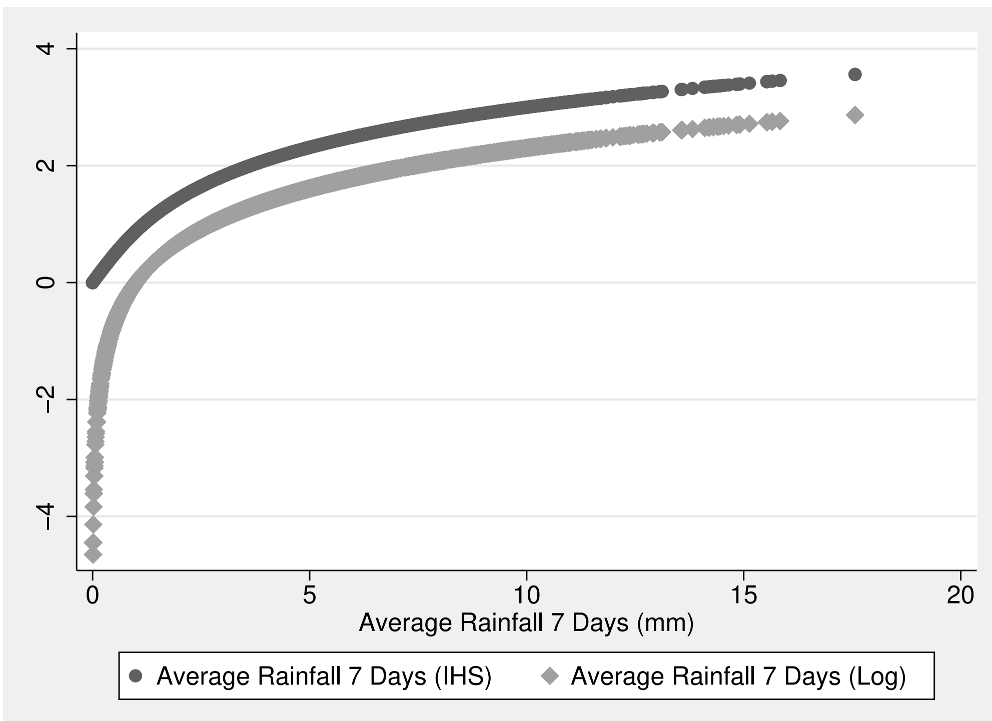
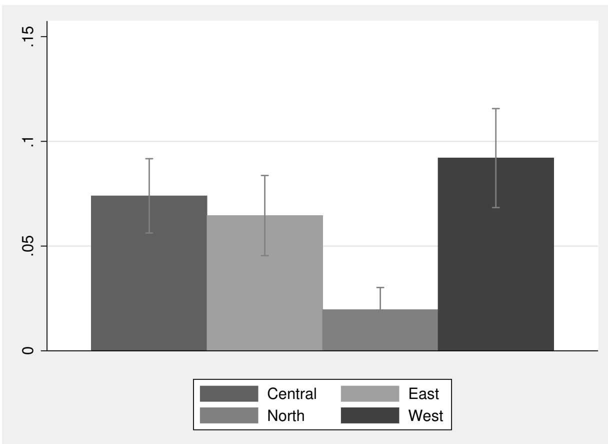
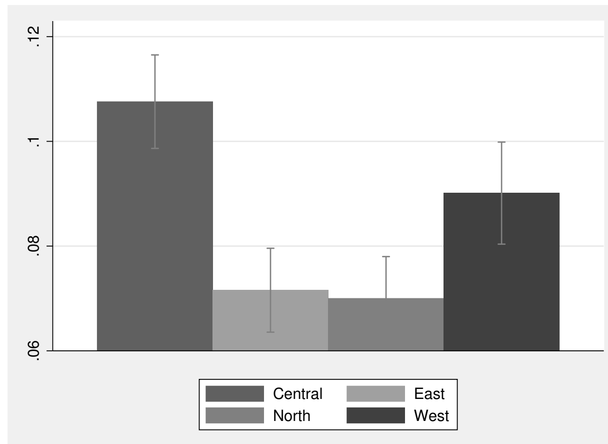


Figure 8: Attrition Rate for Round Two and Three by Regions

(a) Household Level: Round Two

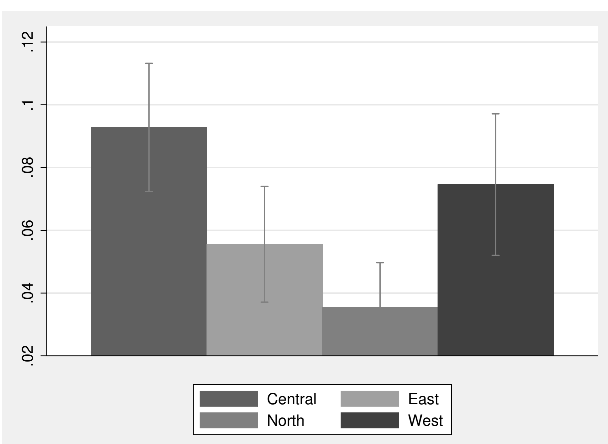


(b) Individual Level: Round Two

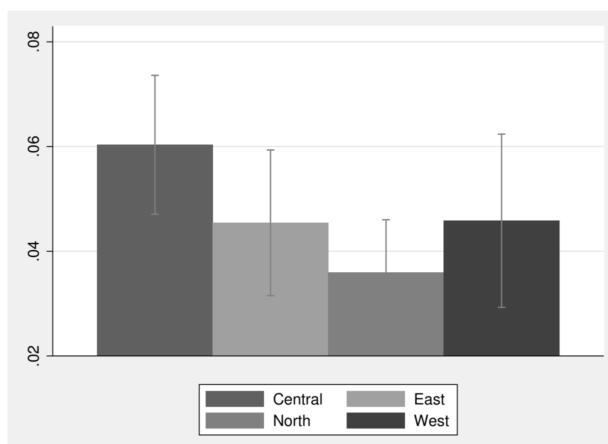


Note: Sample with attrition is defined as respondents who appeared in the first round but did not appear at the rest of the survey.

(c) Household Level: Round Three



(d) Individual Level: Round Three



Note: Sample with attrition is defined as respondents who do not appear in the third round but appeared in the second round.

Table 1: Summary Statistics of Rainfall Variables

(a) Rainfall Variables

Variable	Obs	Mean	Std. Dev.	Min	Max	P25	P50	P75
1-7 Days	6886	3.76	3.04	0	17.56	1.38	3.24	5.43
8-14 Days	6886	3.55	2.92	0	18.41	1.23	3.05	5.21
15-21 Days	6886	3.54	2.88	0	18.75	1.18	3.14	5.26
1-14 Days	6886	3.65	2.45	0	14.46	1.7	3.44	5.13
1-7 (Past 10 Years)	6886	3.44	1.68	.03	12.2	2.2	3.36	4.55
8-14 (Past 10 Years)	6886	3.37	1.74	0	10.69	2.04	3.31	4.55
15-21 (Past 10 Years)	6886	3.43	1.72	0	10.41	2.13	3.49	4.57

Note: The decrease of rainfall from 75 percentile to 25% for 1-14 days average daily rainfall is 3.43mm (=5.13-1.7).

(b) Cross-Correlation between Rainfall Variables

Variables	1-7 Days	8-14 Days	15-21 Days
1-7 Days	1		
8-14 Days	0.353	1	
15-21 Days	0.278	0.369	1

Table 2: Individual Labor Supply for Fetching Water and Household Characteristics

	Mean	SD	Min	Max	Observation
Panel A: Time for Fetching Water (at first round, N=11632)					
Whole Sample	2.35	4.76	0	63	11632
Participation 42%	5.63	5.98			
Boy Age 5-14	2.86	4.71	0	63	2062
Participation 57%	4.93	5.30			
Girl Age 5-14	3.35	5.00	0	49	1924
Participation 62%	5.31	5.41			
Children Age 15-19	3.25	5.02	0	45	1343
Participation 60%	5.36	5.50			
Male (20-59)	0.99	3.09	0	40	1675
Participation 22%	4.54	5.27			
Female (20-59)	4.17	6.64	0	56	2008
Participation 57%	7.28	7.37			
Senior (Over 60)	1.19	3.26	0	28	590
Participation 22%	5.32	5.07			
Panel B: Household Characteristics					
Household Size	5.89	3.00	1	23	
Age less than 5	0.16	0.18	0	1	
Age 5-19 (Boy)	0.21	0.18	0	1	
Age 5-19 (Girl)	0.20	0.18	0	1	
Age 20-59 (Men)	0.17	0.19	0	1	
Age 20-59 (Women)	0.19	0.16	0	1	
Senior (Age over 60)	0.08	0.19	0	1	
Region					
Central Urban	0.19	0.40	0	1	
Central Rural	0.10	0.30	0	1	
East Urban	0.21	0.41	0	1	
East Rural	0.03	0.16	0	1	
North Urban	0.22	0.41	0	1	
North Rural	0.04	0.19	0	1	
West Urban	0.18	0.38	0	1	
West Rural	0.03	0.18	0	1	
Water					
Private Tap	0.05	0.22	0	1	
Public taps	0.11	0.31	0	1	
Bore-hole	0.37	0.48	0	1	
Protected well/spring	0.22	0.41	0	1	
Unprotected well/spring	0.16	0.36	0	1	
River, stream, lake, pond	0.06	0.23	0	1	
Vendor/Tanker truck	0.01	0.09	0	1	
Gravity flow scheme	0.01	0.11	0	1	
Rain water	0.01	0.12	0	1	
Distance to Water Source (km)	0.65	2.59	0	120	

Table 3: Number of Hours Spent Fetching Water (Whole Sample)

	(1)	(2)	(3)	(4)	(5)
1-7 Days	-0.0310***	-0.0343***	-0.0302***	-0.0292***	-0.0231**
	(0.00850)	(0.00969)	(0.00963)	(0.00972)	(0.00999)
8-14 Days			-0.0431***	-0.0416***	-0.0334***
			(0.00931)	(0.00937)	(0.0100)
15-21 Days				-0.0166	-0.00923
				(0.0102)	(0.0107)
1-7 (Past 10 Years)					-0.0254
					(0.0300)
8-14 (Past 10 Years)					-0.0430
					(0.0283)
15-21 (Past 10 Years)					-0.0287
					(0.0320)
Individual FE	Yes	Yes	Yes	Yes	Yes
Year & Month	No	Yes	Yes	Yes	Yes
Observations	36566	36566	36566	36566	36566
Adjusted R^2	0.325	0.326	0.327	0.327	0.327

Standard errors in parentheses, $^{*}p < .10,^{**}p < .05,^{***}p < .01$

Table 4: Number of Hours Spent Fetching Water (Whole Sample and Sub-Sample)

	Whole	Boy (5-14)	Girl (5-14)	Child (15-19)	Man	Woman	Senior
1-14 Days	-0.0564***	-0.123***	-0.0798*	0.0225	-0.0260	-0.156***	-0.0182
	(0.0148)	(0.0454)	(0.0446)	(0.0526)	(0.0255)	(0.0519)	(0.0459)
15-21 Days	-0.00921	-0.0411	0.0169	-0.0196	0.00897	-0.0281	-0.0164
	(0.0107)	(0.0334)	(0.0354)	(0.0447)	(0.0177)	(0.0343)	(0.0305)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year & Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Past Rainfall	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation	36566	6363	6171	4458	5356	6315	1927
Adjusted R^2	.327	.132	.227	.278	.192	.305	.418
Mean	2.4	2.9	3.43	3.4	.956	4.06	1.15

Standard errors in parentheses, $^{*}p < .10,^{**}p < .05,^{***}p < .01$

Table 5: Distance to the Main Water Source and Dry Spell: HH Unit

	Distance (km)		Distance (IHS)	
	(1)	(2)	(3)	(4)
Dry Spell	0.0454		0.00453*	
	(0.0328)		(0.00238)	
7-8 Days		0.0798		0.00223
		(0.164)		(0.0518)
9 Days		-0.0740		-0.0724
		(0.206)		(0.0787)
10-13 Days		0.191		0.0337
		(0.131)		(0.0619)
14-20 Days		0.0678		-0.00417
		(0.115)		(0.0613)
>20 Days		1.865		0.197**
		(1.400)		(0.0930)
Household FE	Yes	Yes	Yes	Yes
Year & Month	Yes	Yes	Yes	Yes
Observation	6741	6741	6741	6741
Adjusted R^2	.105	.106	.364	.364
Mean	.647	.647	.437	.437

Standard errors in parentheses, $^{*}p < .10,^{**} p < .05,^{***} p < .01$.

March and 0-7 Days are the base for categorical variables.

Table 6: Self Reporting and Rainfall

	Self Report	Self Report
1-7 Days	-0.00102	-0.000659
	(0.00103)	(0.00106)
8-14 Days		0.000866
		(0.00105)
15-21 Days		0.000880
		(0.00108)
1-7 (Past 10 Years)		-0.00252
		(0.00304)
8-14 (Past 10 Years)		-0.00215
		(0.00291)
15-21 (Past 10 Years)		-0.00216
		(0.00315)
Individual FE	Yes	Yes
Year & Month	Yes	Yes
Observations	30569	30569
Adjusted R^2	0.508	0.508

Standard errors in parentheses, $^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$

Table 7: Number of Hours Spent Fetching Water (IHS)

	(1)	(2)	(3)	(4)	(5)
1-7 Days (IHS)	-0.0759***	-0.0904***	-0.0757**	-0.0631*	-0.0373
	(0.0288)	(0.0345)	(0.0344)	(0.0351)	(0.0368)
8-14 Days (IHS)			-0.126***	-0.122***	-0.0893**
			(0.0324)	(0.0325)	(0.0350)
15-21 Days (IHS)				-0.0924***	-0.0582
				(0.0350)	(0.0378)
1-7 Days (IHS: 10 Years)					-0.0457
					(0.100)
8-14 Days (IHS: 10 Years)					-0.0976
					(0.0997)
15-21 Days (IHS: 10 Years)					-0.190*
					(0.101)
Individual FE	Yes	Yes	Yes	Yes	Yes
Year & Month	No	Yes	Yes	Yes	Yes
Observations	36566	36566	36566	36566	36566
Adjusted R^2	0.325	0.326	0.326	0.327	0.327

Standard errors in parentheses, $^{*}p < .10,^{**} p < .05,^{***} p < .01$

Table 8: The Main Water Source and Dry Spell: HH Unit Analysis

	(1) Private Taps	(2) Public Taps	(3) Bore-hole	(4) Protected Well	(5) Unprotected Well	(6) River/Lake	(7) Vendor
7-8 Days	-0.0128	0.0324	-0.0196	0.00537	0.0135	-0.0189	0.00204
	(0.0138)	(0.0234)	(0.0287)	(0.0280)	(0.0320)	(0.0224)	(0.00828)
9 Days	-0.0310	0.0339	0.00750	0.0237	-0.0698	0.0709**	-0.000180
	(0.0188)	(0.0255)	(0.0410)	(0.0459)	(0.0481)	(0.0296)	(0.00264)
10-13 Days	-0.000891	-0.0258	0.0306	0.0171	-0.0138	-0.0353	0.00488
	(0.0188)	(0.0280)	(0.0363)	(0.0349)	(0.0404)	(0.0282)	(0.0125)
14-20 Days	-0.0145	0.0195	-0.0564*	0.0112	0.0309	0.0290	-0.00185
	(0.0165)	(0.0200)	(0.0342)	(0.0334)	(0.0337)	(0.0251)	(0.00667)
>20 Days	-0.0381**	0.0184	0.0687	0.0252	-0.0505	-0.00540	0.00589*
	(0.0174)	(0.0273)	(0.0432)	(0.0406)	(0.0380)	(0.0269)	(0.00351)
Household FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year & Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation	6841	6841	6841	6841	6841	6841	6841
Adjusted R^2	.627	.577	.686	.595	.439	.333	.128
Mean	.0501	.107	.374	.216	.156	.0583	.0077

Standard errors in parentheses, $^{*}p < .10,^{**} p < .05,^{***} p < .01$.
0-7 Days of dry spell (=rained at least onece in the interview week) is the base for categorical variables.

Appendices

A Experience of Dry Spell in Uganda

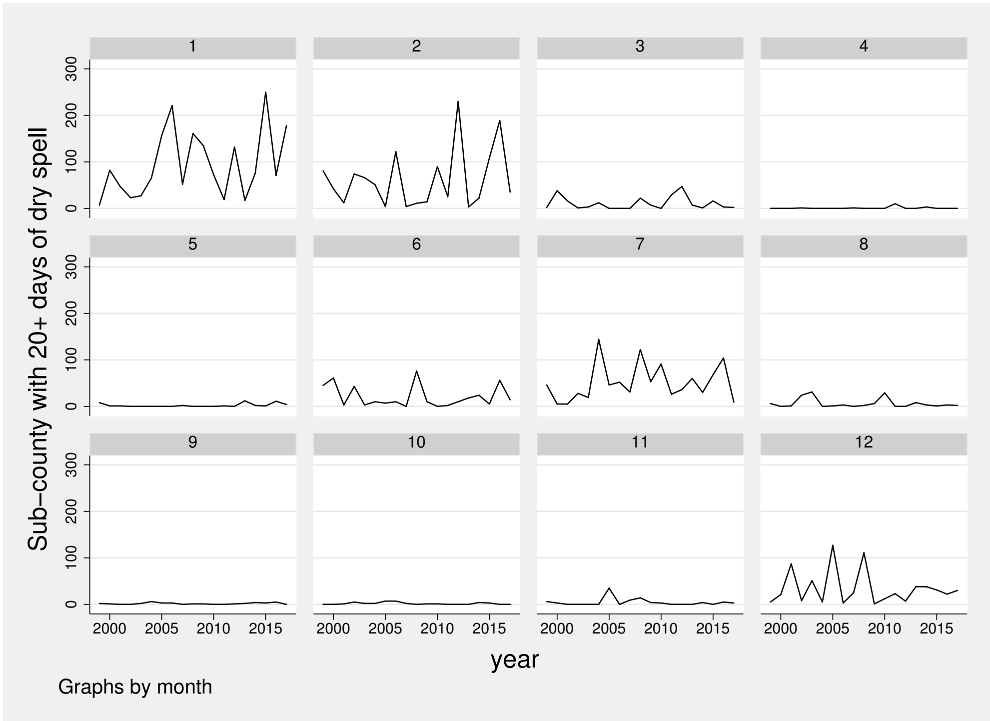
Rainfall data suggests that the number of sub-counties in Uganda that face dry spell more than 20 days is increasing in recent years. Figure 9a shows the number of sub-counties that experienced a dry spell more than 20 days out of 326 sub-counties in Uganda. The frequency of dry spells is higher during the dry season.

Figure 9b sums up the count in Figure 9a by year. The y-axis shows

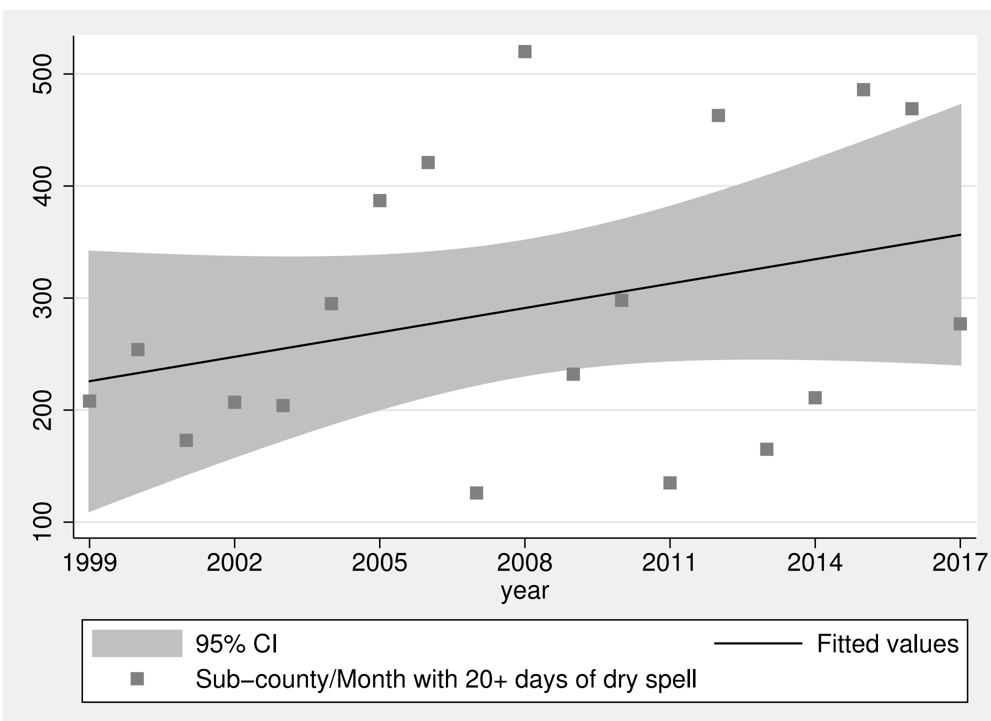
$$\sum_{s=1}^{326} \sum_{m=1}^{12} x_{sm}$$

where x is the binary variable of 1 if the sub-county s experienced dry spell more than 20 days in the month m, and 0 otherwise. Following the calculation method from Osbahr, Dorward, Stern, and Cooper (2011), if the preceding month finished with a dry spell, the dry spell of the next month 'inherit' the number from the previous month. It shows increasing trend over the year. The sloop of the fitted line is 7.25.

Figure 9: Experience of dry spell more than 20 days in Uganda



(a) Number of sub-county that faces more than 20 days of dry spell by month



(b) Number of sub-county/month that faces more than 20 days of dry spell

B With Control Variables

Table 9 shows coefficients of year and month variables that is not shown in the main text.

Table 9: Household Labor Supply and Rainfall: Individual Unit

	Fetch Water
1-7 Days	-0.0231**
	(0.00999)
8-14 Days	-0.0334***
	(0.0100)
15-21 Days	-0.00923
	(0.0107)
1-7 (Past 10 Years)	-0.0254
	(0.0300)
8-14 (Past 10 Years)	-0.0430
	(0.0283)
15-21 (Past 10 Years)	-0.0287
	(0.0320)
Year of Full Administration of HH Questionnaire=2010	0.0203
	(0.102)
Year of Full Administration of HH Questionnaire=2011	0.235**
	(0.101)
Year of Full Administration of HH Questionnaire=2012	0.191**
	(0.0938)
Month of Full Administration of HH Questionnaire=2	0.0104
	(0.122)
Month of Full Administration of HH Questionnaire=3	0.330**
	(0.144)
Month of Full Administration of HH Questionnaire=4	0.510***
	(0.176)
Month of Full Administration of HH Questionnaire=5	0.899***
	(0.192)
Month of Full Administration of HH Questionnaire=6	0.522***
	(0.166)
Month of Full Administration of HH Questionnaire=7	0.324**
	(0.152)
Month of Full Administration of HH Questionnaire=8	0.733***
	(0.166)
Month of Full Administration of HH Questionnaire=9	0.814***
	(0.191)
Month of Full Administration of HH Questionnaire=10	0.423**
	(0.182)
Month of Full Administration of HH Questionnaire=11	0.347**
	(0.172)
Month of Full Administration of HH Questionnaire=12	0.311**
	(0.135)
Individual FE	Yes
Observations	36566
Adjusted R^2	0.327

Standard errors in parentheses, $^{*}p < .10,^{**} p < .05,^{***} p < .01$