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Too poor to migrate? Weather shocks reduce temporary migration among small-scale farmers in Uganda

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Abstract

In the absence of reliable and timely weather information, unprecedented weather shocks can influence farmers' decision-making. We take the case of Uganda to investigate the relationship between weather shocks and temporary migration among smallholders. Using longitudinal data from a nationally representative survey – Living Standard Measurement Study-Integrated Survey in Agriculture (LSMS-ISA) –, we examine if household-level weather shocks affect temporary migration. Using panel data estimators, we show that weather shocks reduce temporary migration among poor households, and the relationship is more pronounced for smallholders. We also find that the relationship differs by the type of migration. Weather shocks reduce temporary labor migration and migration for educational purposes, but migration for other reasons is not affected. These results are confirmed by focused group interviews with 24 rural farmers from all four regions of Uganda. We identify reduced agricultural productivity and low farm revenue as potential channels for the negative relationship between weather shocks and migration.

Keywords: Weather shocks, small-scale agriculture, temporary migration, Uganda

JEL Codes: Q12, Q54, O15

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Abstract

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1. Introduction

People migrate for various reasons[1] but climate/weather anomalies are a leading cause of the movement of millions of people every year (Benonnier 2019, Call and Gray 2020, KacZan 2020, Marotzke 2020, Marchiori 2012; Clement et al. 2021; FAO 2016). Extreme weather events are an important determinant of both internal and international migration (Kniveton et al. 2008; Perch-Nielsen, Bättig and Imboden 2008). For example, drought can displace people by decreasing agricultural productivity and reducing livelihood diversification (Call, Gray and Jagger 2019). Likewise, frequent and intense floods, high temperatures, and irregular precipitation can affect migration by reducing agricultural productivity and damaging crops, livestock, or farmland (Challinor et al. 2010; Gornall et al. 2010; Knox et al. 2012). In addition to the direct effects on crop failure and low agricultural productivity, weather shocks can also affect migration by increasing poverty and food insecurity in the origin (Gentle and Maraseni 2012). How do household-level weather shocks affect temporary migration among resource-poor agricultural households? Despite significant importance, whether and how intermittent household-level weather shocks affect temporary migration among poor households is understudied.

The study of extreme weather events and migration is not a new topic. However, existing evidence on the weather-migration relationship is mixed and inconclusive. One strand of literature has documented a positive relationship between weather shocks and migration (Call and Gray 2020; Kubik and Maurel 2016; Reuveny 2007; Deschenes and Moretti 2007; Pajaron and Vasquez 2020). In contrast, another strand of literature has demonstrated a negative relationship between the two (Mueller, Gray and Hopping 2020; Marotzke, Semmann and Milinski 2020; Mueller, Sheriff, et al. 2020; Cattaneo and Peri

[1] Push factors in the origin such as lack of employment, poverty, relative deprivation, crop failure, and drought (Czaika and Haas 2011; Mehlum 2002; Flippen 2013; Stark 2006; Nguyen, Raabe and Grote 2015) and pull factors in the destination such as higher expected wage, better access to services (Quinn 2006; Massey et al. 1993) can induce migration.

2016). For example, in Kenya and Burkina Faso, abnormal temperature is found to be negatively associated with migration rates, but the relationship is opposite in the case of Uganda (Gray and Wise 2016). Others have argued that weather shocks tend to increase migration in middle-income countries but decrease migration in poor countries (Gray and Wise 2016; Bertoli et al. 2022).[2]

There are some significant voids in the existing literature. First, much of the existing literature examines the relationship between migration and objective measures of weather shocks such as rainfall and temperatures, usually at 60 km radius (0.5 x 0.5 degree) grid (Cattaneo and Peri 2016; Call et al. 2019; Deschenes and Moretti 2007; Marchiori, Maystadt and Schumacher 2012). This overlooks the effects of localized household-level weather shocks[3], inadvertently. Second, much of the literature uses cross-sectional data or data from a specific part of the country resulting in poor internal and external validity. Third, some studies estimate the weather-migration relationship at much broader levels (regional or country levels), even though the decision-making units for migration are almost always households. In addition, a vast majority of empirical studies have examined the relationship between climate change and migration, with less focus on intermittent weather shocks.

While persistent weather shocks (and climate change) may displace people, short-run weather shocks can reduce migration by reducing smallholders' capability to migrate temporarily. Farmers who can afford migration may migrate elsewhere for employment but, resource poor farmers who primarily depend on agriculture may delay or forfeit migration in response to the weather-induced decline in household income. We test this hypothesis by

[2] Considering the complex relationship between weather shocks and migration, more recent papers have called for extreme caution in generalizing the relationship because it varies greatly by countries and context (Bertoli et al. 2022).

[3] Objective weather data are available at a much higher resolution (usually a 60 km radius) and researchers are forced to assume that all households in the area received the same degree of weather shocks, which is not realistic. Household-level objective weather data are rarely available and household-level analysis almost always involves self-reported weather shocks.

using longitudinal data from a nationally representative integrated household and agriculture survey – Living Standard Measurement Study Integrated Survey in Agriculture (LSMS-ISA) – in Uganda. Considering the potential heterogeneous relationship between weather shocks and migration, we estimate the relationship for different types of migration (migration for labor, education, or other reasons), as well as for different sub-samples (female-headed vs. male-headed, rural vs. urban, and ethnic minority vs non-minority households).

Understanding the weather-migration relationship has significant policy importance. Policymakers in developing countries aim to attract new job seekers into agriculture and keep the rates of rural-urban migration at a natural rate (Clement et al. 2021; African Union 2020; FAO 2016; African Union 2014; Mercandalli et al. 2019). This is especially true in Uganda where the government aims to address the country's growing poverty and food insecurity by revitalizing the agricultural sector and attracting the new job seekers into agriculture (Ministry of Agriculture, Animal Industry and Fisheries 2013). The country has a long history of extreme weather events which have affected rural livelihood primarily through its effects on agriculture (Berman, Quinn and Paavola 2015; Gray and Wise 2016; Call et al. 2019; Call and Gray 2020). Since policymakers want to use agriculture as a vehicle for rural economic development and to check the unprecedented flow of rural-to-urban migration, it is important and timely to understand how weather shocks affect migration among smallholders.

This analysis fills the knowledge gap in the literature on weather/climate migration by offering insights on how household level weather-shocks affect temporary migration among small-scale farmers in a developing country setting. We estimate the weather-migration relationship using both self-reported household-level weather shocks and meteorological weather data - daily records of precipitation and temperatures at 0.1 x 0.1-degree grids. We use nationally representative longitudinal household data which allows us to estimate the relationship between weather shocks and migration with panel data estimators. We use the two-way fixed effect (TWFE) estimator. Our approach estimates the weather-migration relationship at household level by removing household-specific time-invariant confounders which may influence the migration decisions. As our estimates come from observational data and there are no ways to identify potential *selection bias* (if households and individuals *self-selected* into migration), we do not claim causal relationship. Nonetheless, our TWFE results are robust to multiple alternative panel data specifications as well as to the generalized synthetic control which provides us robust correlations if not causal relationships.

We show empirically that weather shocks reduce temporary migration among poor farming households by reducing agricultural productivity, but the negative relationship vanishes for wealthier households. We also find that the negative relationship between weather shocks and migration is more pronounced for male-headed, urban, and ethnic non-minority households than for female-headed, rural, and ethnic minority households. The weather-migration relationship is primarily driven by the negative relationship between drought and migration for education. Empirical findings are confirmed by qualitative accounts of local farmers we interviewed during two focused group interviews in Uganda.

The rest of the paper proceeds as follows. Section 2 describes a conceptual framework. Section 3 describes the data and explains migration and weather shock variables. Econometric methods and identification strategy are discussed in section 4. Section 5 provides results and discussion. Section 6 concludes.

2. Conceptual framework

Weather shocks can decrease households' disposable income by reducing agricultural productivity. The weather-induced decrease in disposable income reduces the household capability to migrate. Following Kaczan and Orgill-Meyer (2020), who summarizes literature on long-term climate change and migration, we argue that short-run weather shocks also reduce migration by 1) reducing smallholders' capability to migrate and 2) increasing their vulnerability in staying. This is illustrated in Figure 1.

--Figure 1 here--

First, extreme weather events can reduce agricultural productivity (and farm revenue) by making agricultural production less suitable or more susceptible to pests and diseases. Lower agricultural productivity (and revenue) can affect migration, but the direction of effect likely depends on household socioeconomic status. For credit constrained households, a reduced cash flow means that they can no longer support migration of their household members, even though staying behind makes them worse off. As such, small-scale farmers who rely on agriculture for day-to-day living may not be able to afford migration. For farming households that are not credit constrained, weather shocks can induce migration as they may be better off looking for opportunities outside of agriculture elsewhere. Second, weather shocks can increase householders' vulnerability in staying in the origin by damaging homestead, agricultural land, or other assets. In this case weather shocks may contribute to migration.

It is also important to note that reduction in agricultural productivity can also increase household vulnerability in staying and property/asset damage can also decrease household capability to migrate. In cases where households experience both effects, the net effect on migration depends on which of these effects dominates. In the context of Uganda, both extreme weather shocks and migration are commonly observed, and both channels may be at play. However, we have no data on property damage due to weather events. Hence, we focus on the first channel – intermittent weather shocks reduce smallholders' capability to migrate.

3. Data

Data come from LSMS-ISA surveys and two focused group discussions (FGDs) in Uganda. The LSMS-ISA surveys are conducted by Uganda Bureau of Statistics (UBOS) with technical and financial support from the World Bank. FGDs are conducted by the authors with help from local collaborators.

The LSMS-ISA surveys are nationally representative panel surveys and collect data on various topics including but not limited to migration, weather shocks, household demographics, and agricultural activities. Data are available for seven different time periods between 2005/06 and 2019/20. The LSMS-ISA survey is a longitudinal survey but the data from the first three periods do not overlap with the data from the last four periods. In the fourth survey period, 2013/14, a significant number of old households were replaced with new households. As a result, we work with an unbalanced panel. Table 1 presents the sample size for each survey period.

--Table 1 here—

The survey collects data on various topics; we use data on migration, household demographics, weather shocks, and agricultural production in this analysis. Information about migration and demographics is available at the individual level but most of the other information is available at the household level. Therefore, household is the primary unit of analysis. Next, we describe the creation of migration and weather shock variables.

For FGD, we interviewed 12 farmers (seven women, five men) from six different villages and six different producer groups in Kabale district[4] and 12 students (six women, six men) from the Mbarara University of Science and Technology (MUST).[5] Students came from seven different districts and represented all four regions of the country. The plan was to conduct multiple FGDs with farmers across the country, but we interviewed students from different regions instead due to resource limitations; this allowed us to capture heterogeneity across regions in the most cost-effective way. To be consistent with the FGDs with farmers, students were asked to respond on behalf of their family back home.

3.1. Migration

The outcome variable, migration, is measured in three different ways: 1) *migrant household*, 1 if household has at least one migrant and 0 otherwise, 2) *proportion of migrants,* number of migrants per household divided by household size, and 3) *migrant months*, the average number of months household members lived away from the household in the last 12 months. Following the recent literature on this topic, an individual is considered a migrant if they lived away from the household for at least one month in the last 12 months (Kafle, Benfica and Winters 2020; Brewer, Larsen and Noack 2022). Anyone who did not spend one or more months in the household in the last 12 months due to death or new birth is excluded. A household that has at least one migrant member is considered a 'migrant household'.

The second outcome variable, proportion of migrants, is used to account for the intensity of migration at the household level. Considering the heterogeneities in the number of months migrants lived away from the household, we use the number of migrant months as

[4] Kabale district is located in the South-Western region of Uganda, approximately between 30^0 0'E and 1^0 15'S. Kabale's long history of extreme weather events and migration makes it good site for the case study.
[5] All 12 students were fourth year students pursuing a Bachelor of Science in Agriculture and Livelihoods at MUST.

our third outcome variable. The number of migrant months is the average number of months household members lived away from the household in the last 12 months.

We also categorize migrant households according to the average number of migration months (1-3 months, 4-6 months, 7-9 months, and 10-12 months) and estimate the relationship between weather shocks and migration for these four categories. Finally, we categorize migration into three different types based on the purpose of migration – migration for education, labor, and other economic reasons – and assess how weather shocks affect different types of migration.

3.2.Weather shocks

Household level weather shocks reported by the respondents are the primary variable of interest. Weather shock data consist of experiences of drought, flood, and irregular rainfall at the household level. Each weather shock type is recorded as a binary variable. For example, *drought* equals 1 if a household experienced drought at some point in the 12 months preceding the survey and 0 otherwise. The same is true for *floods* and *irregular rainfall*.

Weather shocks reported by the householders are used as the primary variables of interest instead of meteorological weather shocks for two reasons. First, farmers in developing countries have different abilities to adapt to weather shocks and the same level of meteorological condition is realized differently by different types of farmers. This heterogeneity can't be captured in meteorological data. Second, meteorological data are not always available and when available they don't vary at the household level (Michler et al. 2022). As argued by Michler et al. (2022), using gridded meteorological data to match with household level geocodes involves a high degree of measurement error. Most meteorological data are available as gridded data at 0.5 x 0.5-degree resolution. A 0.5 x 0.5-degree grid is equivalent to an area of 60-mile radius near the equator. Therefore, meteorological data are more susceptible to measurement error in locations near the equator, including several sub-Sahara African countries. Nevertheless, we use meteorological weather data (precipitation and temperature) to complement the household level weather shock data.

3.3.Precipitation and temperature data

We use precipitation and temperature data to complement the household level weather shock variables. Records of daily precipitation and temperature were obtained from the European Centre for Medium-Range Weather Forecasts (ECMWF).[6] The data were collected and archived by the Copernicus Climate Change Service in ECMWF. Unlike most other databases which record monthly data at 0.5 x 0.5-degree grids, ECMWF precipitation and temperature data are available in daily frequency at 0.1 x 0.1-degree grids. These records of precipitation and temperature are available between 1959 and 2022, but we use the data between 2009 to 2020 to be consistent with the LSMS survey years. Before matching the gridded weather data with LSMS household data, we create seasonal averages of daily precipitation and temperature in each grid.

The gridded weather data are matched with LSMS household data using geocodes in ArcGIS. LSMS geocodes are available at the enumeration area (EA) level only. Household geocodes were recorded during the survey, but the publicly available dataset uses EA level modified geocodes for privacy reasons. Modified geocodes are created by LSMS team post-survey based on the actual household geocodes. The modified geocode for an EA represents all households in that EA but it does not provide the actual household locations. Since LSMS geocodes are available at EA level only, gridded weather data and LSMS data are matched at EA levels. Consequently, all households within an EA are assigned the same value for

[6] The ECMWF data are accessible in this link https://www.ecmwf.int/en/forecasts/dataset/ecmwf-reanalysis-v5

average precipitation and temperature. The matched weather data and the modified location of LSMS-ISA household are presented in Figure 2.

--Figure 2 here--

After the weather data are matched with LSMS data, we create rainfall and temperature shocks using the seasonal averages of daily precipitation and temperature. This is done to be consistent with household level weather shocks. The LSMS-ISA survey collects data for two cropping seasons (first season between January and June and the second season between July and December). Therefore, we use the same categorization of seasons to construct seasonal rainfall and temperature averages. Since the precipitation and temperature data are averaged at the EA level, precipitation and temperature shocks are defined at the EA level too. An EA is considered to have rainfall (temperature) shock, if the average daily rainfall (temperature) for a particular season in that EA is greater than 2 SD or lower than 2 SD of the regional average daily rainfall (temperature) for the same season.

4. Econometric method

We estimate the relationship between weather shocks and migration using the two-way fixed effects (TWFE) estimator with household and year fixed effects. Let *i* indicate a household and *t* indicate survey year. Let M_{it} denote migrant household *i* at time *t*, S_{it} denote the indicator of weather shock reported by household *i* at time *t*, X_{it} denote the vector of control covariates, μ_i denote household fixed effects, and $Year_t$ denote year fixed effects. Equation 1 provides an econometric relationship between weather shocks and migration.

$$M_{it} = \alpha_0 + \alpha_1 S_{it} + \Theta X_{it} + \mu_i + Year_t + \varepsilon_{it} \tag{1}$$

Estimating equation 1 with the TWFE estimator provides the estimated relationship between weather shocks and migration, $\hat{\alpha}_1$. The null hypothesis for the analysis is that migration has no significant association with weather shocks, i.e. $\hat{\alpha}_1 = 0$.

4.1. Identification

In equation 1, α_1 may not be identified if there are unobserved factors that affect both weather shocks and migration. The potential endogeneity of household level weather shocks can be a threat to identification. We assume that the unobserved endogenous factors that affect both household level weather shocks and migration do not vary across time. This is a reasonable assumption because individual traits that are correlated with migration and perception of weather shocks such as ability, consciousness, self-reliance do not vary over time. Since the TWFE estimator purges the effects of time-invariant factors, α_1 is free of the effects of time-invariant endogenous variables on migration.

Another concern for identification of $\alpha_1$is that some *treated* households (household that report weather shocks) may become *control* households (household that do not report weather shocks) over time. For example, households that experienced weather shocks in baseline might not have experienced weather shocks in the subsequent years and vice versa. We address this problem by running a separate analysis on the sub-sample of households that did not report weather shocks in the baseline (2009/10) survey year). In this setting, no household received the treatment (weather shocks) in baseline. Household that reported weather shocks in the subsequent periods form the treatment group and the households that did not report weather shocks in either period form the control group. We then estimate equation (2) using the difference-in-difference estimator. The coefficient estimate, β_1, in equation (2) is the effect of weather shocks on migration.

$$M_{it} = \beta_0 + \beta_1 S_{it} + \Delta X_{it} + \mu_i + Year_t + u_{it} \tag{2}$$

4.2. Heterogeneity analysis

Different types of farmers have different incentives to migrate and their abilities to cope with weather shocks also vary. To account for these heterogeneities, we estimate the relationship between weather shocks and migration for three different categories of household socioeconomic status – the bottom 40%, middle 40%, and top 20% in the distribution of consumption expenditure. We also run separate analysis for male-headed and female-headed households, ethnic minority and majority households, and rural and urban households. Another source of heterogeneous effects is the reasons for migration. We estimate the relationship between weather shocks and migration for different types of migration including migration for employment, education, and other economic reasons. To account for the effects of the duration of migration, we estimate the weather-migration relationship for four different lengths of migration: 1-3 months, 4-6 months, 7-9 months, and 10-12 months. All regressions of heterogeneity analysis estimate equation (1) with the TWFE estimator.

5. Results

5.1. Descriptive statistics

Table 2 presents summary statistics for migration variables for four different survey years – 2009/10, 2011/12, 2013/14, 2019/20. We skip summary statistics for three survey years (2010/11, 2012/13, and 2015/16) for brevity. Summary statistics for all seven survey periods are available in appendix table B1. The first row in Table 2 shows that temporary migration is a common phenomenon in Uganda. In 2009/10, 50% of households have at least one migrant member (referred to as migrant households). The share of migrant households increased to 71% in 2011/12, but it fell to 43.5% in 2015/16, and 34.8% in 2019/20. Among the migrant households, the average number of migrants is between two and three persons per household. Most of the migrant members are migrated for education followed by migration for employment and other unspecified economics reasons – the survey instrument does not specify the other reasons. The number of migrant months (averaged for all migrants in a household) is also presented. On average, a migrant member is away from the household for about two to three months in the last 12 months of the survey. Again, those who migrate for education are away from the household the most.

--Table 2 here—

Figure 3 demonstrates the distribution of migrant households for four different durations of migration – 1-3 months, 4-6 months, 7-9 months, and 10-12 months. The first panel shows the distribution of migration for the full sample and the second panel shows the distribution for agricultural households. Figure 3 shows that, among the people who migrated, most of them were away from the household for four to nine months in the last 12 months; 25% of them were away for four to six months and 45% for seven to nine months. About 20% of migrants were away for less than three months and 10-20% of them were away for more than 10 months. Statistics in Table 2 and Figure 3 indicate that most migration in this setting is temporary and seasonal migration. This observation in the data is confirmed with qualitative evidence; FGDs respondents reported that many villagers who migrate to seek better opportunities elsewhere return after some time.

--Figure 3 here--

Summary statistics for explanatory variables are presented in Table 3. Weather shocks are presented on the first panel. Weather shock is a binary indicator of the incidence of drought, floods, irregular rainfall, landslides, and other unspecified weather shocks, reported by the respondents. In 2009/10, 47% of sample households reported weather shocks. The share of households reporting weather shocks declined over time to 24% in 2011/12, 19% in 2015/16, and 20% in 2019/20. Drought is the most commonly reported weather shock with about 46% of sample households reporting drought in 2009/10. The share of drought-affected households deceased over time reaching 20% in 2011/12, 16% in 2015/16, and 12% in 2019/20. Flood is less commonly reported than drought, only between 2% and 5% households reported flood.

The last two rows in the first panel present average daily rainfall (meter) and average daily temperature (Kelvin) in the respective years. On average, the country received between 4.7 millimeters and 5.33 millimeters of rainfall per day. The average daily temperature remained about 295 Kelvin in each of the survey periods.

The second panel in Table 3 presents summary statistics for agricultural variables. More than 75% of sample households are agricultural households (cultivate crops or keep livestock). Most households have ownership or user rights to land but a significant majority of them possess no ownership or user right certificate. Possession of land ownership certificate is below 20% except in 2019/20 when 26% of households reported having land ownership/user right certificate. The average land-holding size is less than two acres – it was about two acres in 2009/10 and 2011/12 but declined to about an acre in 2015/16 and 2019/20.

Next panel in Table 3 presents household wellbeing indicators – assets and monthly per-capita consumption expenditures. The aggregated asset index is constructed employing principal component analysis of 26 different assets. The index is averaged around zero by construction. Consumption expenditures are presented in ten thousand Ugandan shillings per adult-equivalent per year. The values are deflated with 2009/2010 prices. The value of monthly per-capita consumption expenditure first increases from 1,08,110 shilling (53.87 USD) in 2009/10 to 1,65,120 shilling (82.27 USD) in 2011/12, but it decreases after that reaching 1,17,080 shilling (58.34 USD) in 2015/16 and 1,15,800 shilling (57.69 USD) in 2019/20.

--Table 3 here—

The last panel in Table 3 presents the household head's characteristics and household demographics. The average age of household head is between 45 and 48 years and about one third of the sample households are headed by a female. Female headship increases over time from 28% in 2009/10 to 36% in 2019/20. More than 70% of household heads are married and about 15% of them have completed secondary school or a higher level of education. Close to two-thirds of sample households reside in rural areas. On average a sample household had about 6 members in 2009/10, seven members in 2011/12 but the household size decreased to about five members after that. Sample households are young in that the population age structure is highly skewed to children and youth. In our sample, children between the age of zero and 14 years are the largest demographic groups (two to three children per household) followed by youth between the age of 15 and 34 years (about two youth per household), and adults between the age of 35 and 64 (one adult per household).

5.2. Econometric results

Table 4 presents the effects of household level weather shocks on temporary migration. Point estimates in the tables are the coefficient estimates from the regression of weather shocks on migration variables using the two-way fixed effects estimator. The first three columns provide the relationship for all households and the next three columns provide the relationship for agricultural households. Columns 1 and 4 present the effects on binary indicator of migration, columns 2 and 5 present the effects on the number of migrants per household, and columns 3 and 6 present the effects on migrant months.

--Table 4 here--

Results show that weather shock is negatively correlated with migration and the negative relationship holds for household level binary migration, the number of migrants per household, and the number of migrant months. Experiencing weather shocks at some point in the last 12 months reduces the probability of migration by 2.2%, the number of migrants by 0.10 persons, and the number of migrant months by 0.10 months. Disaggregating weather shocks into drought and flood shows that drought is the primary driver of the negative relationship between weather shocks and migration. The migration-weather relationship holds for agricultural households as well in that both the direction and magnitude of the effects for agricultural households are similar to that of full sample.

Table 5 presents the relationship between objective measures of weather shocks (daily average rainfall and temperatures for the survey year) and migration variables for both full sample and the sample of agricultural households separately. To account for weather variability across seasons, we estimate the relationship for the first cropping season (January to June) and the second cropping season (July to December) separately.[7] To be consistent with the household level weather shocks, we also aggregate the rainfall shocks and temperature shocks into weather shocks, as described in section 3.3. We use the two-way fixed effects estimator to estimate the weather-migration relationship.

--Table 5 here—

Results in Table 5 show that objective measures of weather shocks (daily averages of rainfall and temperate at 0.1 x 0.1 degree grids) also decrease migration. We find that weather shocks during the second cropping season have stronger effects on migration than in the first cropping season. In the first cropping season, temperature shocks reduce the probability of migration by 6%, with a stronger 7.8% reduction among agricultural households. Rainfall

[7] Uganda has two rainy seasons. The long rainy season (January to June) is the primary cropping season, and the short rainy season (July to December) is the second cropping season.

shocks also reduce migration, but the relationship is not statistically significant. In the second cropping season, while rainfall shocks reduce the number of migrant months by 0.2 months and temperature shock is also negatively correlated with migration (though statistically insignificant), the combined weather shocks reduce the probability of migration by 4.7%. For agricultural households, weather shocks in the second cropping season reduce the probability of migration by 5.1%, primarily driven by temperate shocks which reduce the probability of migration by 6.5%.

Table 6 presents the effects of weather shocks on different types of migration – labor migration, education migration, and migration of other economics reasons. Results show that households that experienced weather shocks in the last 12 months are less likely to migrate for employment, education, and other economic reasons, even though the coefficient estimates are statistically significant for education migration only. Experiencing weather shocks at least once in the past 12 months decreases the number of education migrants by 0.05, for both agricultural and non-agricultural households.

--Table 6 here---

Figure 4 presents weather-migration relationship for the number of months people migrated for different reasons. The figure presents estimated coefficients with 90% confidence intervals. Point estimates are not statistically different from zero if the confident interval crosses the vertical line at zero. Results how that weather shocks reduce the number of migrant months for education only. Weather shocks have no effect on the number of months household members migrated for labor or other economic reasons.

--Figure 4 here—

5.3. Weather shocks' effects on the duration of migration

The weather-migration relationship so far does not distinguish between short-term temporary migration and longer-term migration. We address this concern by estimating the effects of weather shocks on household-level migration for different lengths of migration: 1-3 months, 4-6 months, 7-9 months, and 10-12 months. Results are presented in Table 7.

--Table 7 here—

Results in Table 7 show that weather shocks reduce both short-term migration and longer-term migration across the board. Experiencing weather shocks at least once in the last 12 months reduces the probability of migrating for one to three months by 1.5 percent. Similarly, weather shocks also reduce the probability of migrating for seven to nine months by 2.5%, and more than 10 months by ~1% but the latter is not statistically significant. The relationship between weather shocks and migration duration is similar for agricultural households too but it is statistically significant for migration between 7 to 9 months only. Results indicate that weather shocks negatively affect migration for a short period of time (less than 6 months) as well as migration for longer periods of time (more than 6 months).

5.4.Channels

Weather shocks are negatively correlated with both the occurrence and intensity of migration. The results may look counterintuitive, but we dig deeper to identify potential channels that explain the negative relationship. As stated in the conceptual framework, weather shocks can reduce migration by reducing household's capability to migrate. We test this hypothesis by estimating the relationship between weather shocks and migration along the distribution of consumption expenditure. Practically, we estimate equation (1) for three different sub-samples: the bottom 40% of consumption distribution, middle 40% of consumption distribution, and the top 20% of consumption distribution, separately. Results are presented in Table 8.

--Table 8 here—

Results in Table 8 show that the negative relationship between weather shocks and migration holds primarily for poor households. Experiencing weather shocks at least once in the last 12 months reduces the number of migrants per household and the number of migrant months among households in the bottom 40% and middle 40% of consumption distribution. The relationship is not significant for households in the top 20% of consumption distribution. This indicates that weather shock' effects on migration are mediated by its effects on agricultural revenue. Weather shocks reduce household capability to migrate by reducing agricultural revenue.

Next, we demonstrate that weather shocks reduce household capability to migrate by estimating the effects of weather shocks on agricultural productivity and agricultural revenue. A significant negative relationship between weather shocks and agricultural revenue shows that weather shocks reduce household capability to migrate by reducing disposable income. We use the TWFE estimator to estimate this relationship. Equation (3) shows the estimating equation where Rev_{it} is agricultural revenue of household *i* at year *t*.

$$Rev_{it} = \delta_0 + \delta_1 Weather\ Shocks_{it} + \Pi X_{it} + \mu_i + Year_t + \eta_{it} \tag{3}$$

Results presented in Table 9 show that household level weather shocks reduce the value of agricultural production and agricultural revenue for poor households. Among the households in the bottom 40% of consumption distribution, experiencing weather shocks at least once in the last 12 months reduces the value of agricultural production by 20% and the agricultural revenue by 27%. Neither of these relationships is statistically significant for households in the middle 40%. For the households in the top 20% of the consumption distribution, weather shocks increase the value of agricultural revenue by 51%. This indicates that while poor farmers suffer the most from weather shocks, richer farmers may benefit, perhaps by selling more agricultural goods at higher prices, but testing this hypothesis is out of the scope of this paper.

--Table 9 here—

Our empirical finding that weather shocks reduce agricultural revenue forcing farmers to delay or defer their migration plan is consistent with qualitative accounts of FGD respondents. A young farmer in Kabale district in Uganda said "yes, several of us have given up our plans to go elsewhere to look for better opportunities due to bad weather reducing our crop harvest. We wait for a good harvest to come so that we can make some money to support the transportation cost."

5.5.Heterogeneity Analysis

The relationship between weather shocks and migration may be different for different groups of households. We estimate the relationship separately for male-headed vs. female-headed households, rural vs. urban households, and for ethnic minority[8] and non-minority households. Results are presented in Table 10.

--Table 10 here—

Results show that weather shocks reduce migration among both female-headed households (1.3% reduction) and male-headed households (2.5% reduction), but the relationship is statistically significant for male-headed households only. Weather shocks

[8] Uganda has more 65 ethnic groups there is no consensus on which of them are ethnic minority. We follow the Minority Rights Group International's classification of ethnicity in Uganda which defines ethnic minority and indigenous people as individuals who belong to the following tribes: *Baganda, Banyankore, Basoga, Bakiga, Iteso, Langi, Banyarwanda, Acholi, Bagisu, Lugbara, Batoro, Bunyoro, Alur, Bagwere, Bakonzo, Jopadhola, Karamojong, Barundi, Basongora, and Batwa*.

reduce migration in both rural and urban households, but the relationship is stronger for urban households (6.8% reduction) than for rural households (1.8% reduction). In the case of ethnic minority and non-minority households, weather shocks negatively affect migration for both groups, but the relationship is statistically significant for ethnic non-minority households only (3.9% reduction). In all cases, the negative relationship between weather shocks and migration is driven by drought effects.

5.6.Effects of persistent weather shocks

Even though temporary weather shocks reduce migration by reducing smallholder's capability to migrate, experiencing weather shocks persistently for a long period of time can displace smallholders. We test this empirically by estimating the relationship between the number of times a household experienced weather shocks across seven survey periods between 2009 and 2020 and migration outcomes. Specifically, we regress the number of times a household has had migrants over the seven survey periods (ranges between 0 and 7) on the number of years the household experienced weather shocks (ranges between 0 and 7). Results are presented in Appendix Table A1. We find that persistent weather shocks are positively associated with migration, in contrast to the negative relationship between weather shocks and temporary migration. Households experiencing an additional year of weather shocks have had at least one migrant for 0.2 more years in the last seven years.

5.7. Robustness checks

Our results are robust to different model specifications and estimators. First, we use the difference-in-difference (DID) estimator to estimate the average treatment effect (ATT)[9]

[9] We estimate ATT by assuming that weather shocks are exogenous. While the objective weather shocks are exogenous, subjective measures of weather shocks may not be endogenous. We assume the

of weather shocks on migration variables. Second, we use the two-way Mundlak (TWM) estimator proposed by Wooldridge (2021). TWM estimator is equivalent to DID estimator, but it avoids the requirement of parallel trend assumption and allows us to estimate the effects of time-invariant variables. Third, we use the synthetic control method to estimate the causal effects of weather shocks on migration variables. Finally, we use placebo regression to demonstrate that the negative effect of weather shocks on migration does not hold for randomly created fake weather variables. Robustness results show that the negative relationship between weather shocks and migration is robust to alternative specification and the relationship did not emerge by chance.

Difference-in-Difference (DID) estimator

Our goal here is to estimate the average treatment effects on the treated (ATT) of weather shocks on migration. The *treatment* in this case is the experience of weather shocks, but we need a base period where neither the treatment units nor the control units are exposed to the *treatment*. Since there is no clear baseline period, we create a baseline period by dropping all households that reported weather shocks in 2013/14. Considering a significant change in the panel sample in the fourth survey period, 2013/14, we exclude the data from the first three survey periods for this analysis. This ensures that no household receives the *treatment* in the baseline. We then run the DID regression of migration variables on weather shocks controlling for the same set of covariates we controlled for in the main analysis. Results are presented in Table A2.

--Table A2 here--

confoundedness of subjective weather shocks is time-invariant and hence purged by the diff-in-diff estimator.

Results show that weather shocks reduce migration, and the relationship holds for agricultural households as well. Households that experience weather shocks at some point in the last 12 months are 2.4% less likely to migrate, have 0.12 less migrants, and migrate for 0.11 fewer months than those who do not experience weather shocks. Among agricultural households, weather shocks reduce the probability of migration by 2% and the number of migrants by 0.11 person, though the former is not statistically significant at 10% level.

Two-way Mundlak (TWM) estimator

The TWFE estimator is unbiased but not efficient. The loss of efficiency in TWFE can be recovered by using a GLS estimator. Following Wooldridge (2021), we use the two-way Mundlak estimator (TWM) which is both unbiased and efficient. Wooldridge (2021) provides the mathematical proof establishing the equivalence between TWFE and TWM estimators. TWM estimator is an extension of Chamberlin-Mundlak estimator, and it estimates the effects of S_{it} on M_{it} by using a pooled regression. Panel fixed effects and time fixed effects are accounted for by including time-constant means and panel-constant means of all explanatory variables, as shows in equation 2.

$$M_{it} = \beta_0 + \beta_1 S_{it} + \Pi X_{it} + \beta_2 Si. + \beta_3 S.t + \Pi_1 Xi. + \Pi_2 X.t + u_{it} \qquad (3)$$

In practice, equation 3 is estimated with a pooled OLS estimator. Where $S_{i.}$ is time constant mean of self-reported weather shocks and $S_{.t}$ is time-varying means of self-reported shock of all the households. Similarly, $X_{i.}$ is the vector of time-constant means of all control covariates and $X_{.t}$ is time-varying means of all control covariates. TWM results are presented in Table A3. Results confirm the negative relationship between weather shocks and temporary migration.

Synthetic control

We estimate the average treatment effect by using the Generalized Synthetic Control method for multiple treated units. We choose the fourth survey wave (2013/14 survey year) as the treatment period and use the data from the first three survey periods (2009/10, 2011/12, and 2012/13) as the pretreatment data following Xu (2017). By assigning weights to each treated unit with a control group, the treatment-control relationship in the pre-treatment period is optimized to zero while the relationship in post-treatment periods can provide the average treatment effects. The generalized synthetic control estimation proceeds as follows: First, we estimate the coefficients from the control periods (first three survey waves in this case) by minimizing the mean squared error. Second, we obtain the estimated optimal factor loadings by adjusting factor loadings for each treated unit from the pre-treatment periods. Finally, we apply the estimated factor loadings to the treated units to estimate the average treatment effects. Synthetic control results are presented in Figure 5. Results confirm our main finding that weather shocks negatively affect migration.

--Figure 5 here—

One limitation of this method is that it requires a balanced panel. In our case, the size of the balanced panel is small because, in 2013/14, the data collectors (Uganda Bureau of Statics and the World Bank) dropped the majority of households and replaced them with new households. Only 1271 households are surveyed in all seven waves.

Placebo regression

Finally, we use placebo regression to demonstrate that the negative relationship between weather shocks and migration does not hold for randomly created weather shocks. We create fake weather shock variable using a random number generator (*runiform* function in STATA). For comparability, the sample mean of the fake weather shock variable is forced to be the same as the mean of the true weather shock variable. We regress migration variables on the fake weather shock variable; we find no significant effects of the fake weather shock on migration. Results are available in Appendix Table A4.

6. Conclusion

We investigate the relationship between household level weather shocks and temporary migration among smallholders in Uganda. We use longitudinal household and agriculture data from the World Bank's LSMS-ISA database and employ the two-way fixed effects estimator to estimate the relationship between weather shocks and migration. Migration is measured with household level binary indicator of migration as well as the number of migrants per household and number of migrant months. The weather-migration relationship is estimated for different types of migration (labor, education etc.) and for the different lengths of migration. We use the difference-in-difference estimator, two-way Mundlak estimator (TWM), and synthetic control method for robustness check. We corroborate the empirical findings with two focused group studies (FGD) with farmers and university students (representing their families) representing all four regions of Uganda.

Results show that households that experienced (and reported) weather shocks in the past 12 months of the survey are less likely to migrate. Specifically, households that experienced weather shocks are 2.2% less likely to have at least one migrant member, have 0.1 fewer migrant members, and migrate 0.1 less months than households that do not experience weather shocks. These relationships are consistent for agricultural households as well. The negative relationship between weather shocks and migration is primarily driven by drought’s effects on migration for education. We perform series of robustness checks, and our primary result is robust to alternative specifications. The empirical findings are also confirmed by FGD participants as they reported extreme weather events have resulted in bad agricultural harvest which forces poor households to reconsider migration as they cannot afford the cost of migration.

Heterogeneity analysis shows that the negative relationship between weather shocks and temporary migration holds primarily for male-headed, urban, and non-minority households compared to female-headed, rural, and ethnic minority households. Even though intermittent weather shocks negatively affect temporary migration, we find that persistent weather shocks are positively correlated with migration over a long period of time. This finding is consistent with the qualitative accounts of local farmers who said many farmers give up farming and move to another place if they experience weather shocks repeatedly.

Our key findings may be in contrast with most published studies and a popular belief that weather shocks induce migration. We investigate the potential channel and show that the negative relationship is mediated by the negative effects of weather shocks on household capability to migrate. We demonstrate empirically that weather shocks reduce agricultural revenue among poor farming households, reducing their capability of migrate. The negative relationship holds for the poorest households in the bottom 40% of consumption distribution and it holds primarily for education migration. Perhaps poor households delay or forfeit sending children to cities for education because their capability of support child education is decreased due to weather-induced reduction in agricultural revenue. These results demand further scrutiny in other countries and contexts.

This analysis has two important limitations. First, migration information available in the LSMS-ISA data is likely an underestimate of the actual migration flow because the survey instrument elicits migration information by asking about the number of months a member is away from the household in the last 12 months. In addition, individuals or households who moved to a different location between the survey rounds are not always tracked. Second, household-level weather shocks (self-reported) are likely an overestimate of the actual weather shocks because farmers may have incentive to overreport weather shocks in the hope of increased public support. It is expected that the effects of possible underestimation of migration and the possible overestimation of weather shocks likely negate each other, but the direction of the net effects is difficult to assess.

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TABLES

Table 1. Sample size

Survey year	All households	Agricultural households
2009/10	2,975	2,264
2010/11	2,716	2,099
2011/12	2,850	2,183
2013/14	3,119	2,443
2015/16	3,305	2,493
2017/18	3,176	2,622
2019/20	3,078	2,412

Source: LSMS-ISA database

Table 2. Summary statistics of migration variables

	Survey year			
	2009/10	2011/12	2015/16	2019/20
	1	*2*	*3*	*4*
Household has a migrant (dummy)	0.502	0.708	0.435	0.348
	(0.500)	(0.455)	(0.496)	(0.476)
Number of households	**2,975**	**2,807**	**3,305**	**3,006**
Migrant households				
Number of migrants	2.110	3.267	2.079	1.795
	(1.602)	(2.672)	(1.545)	(1.225)
Number of labor migrants	0.328	0.377	0.249	0.166
	(0.693	(0.821)	(0.541)	(0.414)
Number of education migrants	0.874	0.818	0.999	0.820
	(1.340)	(1.256)	(1.304)	(1.204)
Number of other economic migrants	0.867	1.398	0.379	0.226
	(1.227)	(1.981)	(0.890)	(0.648)
Migrant months (#)	2.469	3.593	2.362	2.035
	(1.849)	(2.252)	(1.866)	(1.440)
Labor migrant months (#)	0.310	0.335	0.274	0.149
	(0.821)	(0.772)	(0.791)	(0.440)
Education migrant months (#)	0.821	0.736	1.083	0.957
	(1.280)	(1.171)	(1.413)	(1.376)
Other economic migrant months (#)	0.093	0.450	0.328	0.163
	(0.464)	(1.100)	(0.964)	(0.459)
Number of migrant households	**1,494**	**1,987**	**1,397**	**1,038**

Notes: Point estimates are sample means. Standard deviations are in the parentheses.

Table 3. Summary statistics of model variables

	Survey year			
	2009/10	2011/12	2015/16	2019/20
Weather shocks	*1*	*2*	*3*	*4*
Weather shocks (1=yes, 0=no)	0.470	0.239	0.186	0.200
	(0.499)	(0.427)	(0.389)	(0.400)
Drought (1=yes, 0=no)	0.458	0.201	0.156	0.117
	(0.498)	(0.401)	(0.363)	(0.321)
Flood (1=yes, 0=no)	0.021	0.053	0.018	0.038
	(0.144)	(0.224)	(0.134)	(0.190)
Average daily rainfall (mm)	0.0047	0.0051	0.0050	0.0053
	(0.0026)	(0.0024)	(0.0026)	(0.0024)
Average daily temperature (kelvin)	295.18	294.68	295.33	295.08
	(1.636)	(1.570)	(1.430)	(1.380)
Agricultural characteristics				
Agricultural household (1=yes, 0=no)	0.763	0.778	0.754	0.803
	(0.425)	(0.416)	(0.431)	(0.398)
Land ownership certificate (1=yes, 0=no)	0.175	0.161	0.146	0.261
	(0.380)	(0.368)	(0.353)	(0.439)
Land area (acres)	1.957	2.242	0.970	1.076
	(4.534)	(5.618)	(2.264)	(2.335)
Asset and income				
Asset index	0.000	-0.010	0.000	0.001
	(1.999)	(2.030)	(2.108)	(2.132)
Consumption expenditure (0000 shilling/month/capita)	10.81	16.51	11.71	11.58
	(13.49)	(343.84)	(17.74)	(12.91)
Household demographics				
Head's age (years)	44.9	46.4	44.5	48.5
	(15.24)	(15.12)	(16.16)	(15.67)
Head is female (1=yes, 0=no)	0.282	0.311	0.350	0.357
	(0.450)	(0.463)	(0.477)	(0.479)
Head is married (1=yes, 0=no)	0.729	0.736	0.724	0.701
	(0.445)	(0.441)	(0.447)	(0.458)
Head completed secondary school or higher	0.147	0.151	0.181	0.149
	(0.354)	(0.358)	(0.385)	(0.356)
Rural household (1=yes, 0=no)	0.428	0.434	0.480	0.444
	(0.495)	(0.496)	(0.500)	(0.497)
Household size (#)	6.303	7.472	4.786	5.147
	(3.326)	(3.861)	(2.926)	(2.753)
Number of children (0-14 years)	2.900	3.032	2.038	2.290
	(2.144)	(2.199)	(1.882)	(1.859)
Number of youth (15-34 years)	1.884	2.017	1.655	1.618
	(1.517)	(1.668)	(1.346)	(1.331)
Number of adult (35-64 years)	0.980	1.051	0.911	1.001
	(0.834)	(0.850)	(0.823)	(0.806)

Number of elderly (<64 years)	0.182	0.254	0.182	0.238
	(0.452)	(0.580)	(0.449)	(0.508)
Number of households	**2,975**	**2,714**	**2,807**	**3,007**

Notes: Point estimates are sample means. Standard deviations are in the parentheses.

Table 4. Weather shocks and migration (two-way fixed effects)

	All households			Agricultural households		
	Household has migrants	*Number of migrants*	*Migrant months*	*Household has migrants*	*Number of migrants*	*Migrant months*
Weather shocks	*1*	*2*	*3*	*4*	*5*	*6*
Weather shocks (*drought, flood, high temp, landslide, etc.*)	-0.022**	-0.10***	-0.093***	-0.017*	-0.097***	-0.073**
	(0.0098)	(0.027)	(0.032)	(0.010)	(0.027)	(0.031)
Drought	-0.018*	-0.090***	-0.070**	-0.013	-0.083***	-0.045
	(0.011)	(0.029)	(0.033)	(0.011)	(0.029)	(0.032)
Flood	-0.0014	-0.018	-0.12*	0.0085	0.0066	-0.087
	(0.022)	(0.067)	(0.069)	(0.023)	(0.071)	(0.070)
Control covariates	Yes	Yes	Yes	Yes	Yes	Yes
Observations	**17,021**	**17,021**	**17,021**	**13,631**	**13,631**	**13,631**

Notes: Each point estimate is a coefficient estimate from a separate regression. Standard errors are in parentheses. Level of significance * $p < .10$, ** $p < .05$, *** $p < .01$

Weather shock consists of householders' experience of drought, flood, high temperature, irregular rainfall, landslides etc.

Control covariates include land area (acres), household wellbeing status (asset index and consumption expenditure), household head's characteristics (age, gender, marital status, education), household demographics (household size, number of children, number of youth, number of adults, and an indicator for rural residence).

Table 5. Effects of daily average rainfall and temperatures on migration (two-way fixed effects)

	All households			Agricultural households		
	Household has migrants	*Number of migrants*	*Migrant months*	*Household has migrants*	*Number of migrants*	*Migrant months*
	1	*2*	*3*	*4*	*5*	*6*
First cropping season						
Rainfall shock	-0.033	-0.017	-0.012	-0.031	-0.0065	-0.052
	(0.029)	(0.090)	(0.10)	(0.030)	(0.094)	(0.11)
Temperature shock	-0.061**	0.038	-0.091	-0.078***	0.044	-0.043
	(0.028)	(0.074)	(0.092)	(0.031)	(0.084)	(0.090)
Second cropping season						
Rainfall shock	-0.045	-0.050	-0.20*	-0.027	0.022	-0.12
	(0.032)	(0.078)	(0.12)	(0.041)	(0.091)	(0.12)
Temperature shock	-0.045	0.12	-0.063	-0.065*	0.098	-0.025
	(0.029)	(0.076)	(0.12)	(0.033)	(0.088)	(0.13)
Control covariates	Yes	Yes	Yes	Yes	Yes	Yes
Observations	**17,024**	**17,024**	**17,013**	**13,630**	**13,630**	**13,630**

Notes: Each point estimate is a coefficient estimate from a separate regression. Standard errors are in parentheses. Level of significance * $p < .10$, ** $p < .05$, *** $p < .01$

Rainfall shock for an enumeration area is defined as the average rainfall greater (less) than regional average plus (minus) 3 Standard Deviations. Temperature shock is defined the same way. Weather shock is a combination of the two shocks.

Rainfall is measured in millimeters (mm). Temperature is measured in Kelvin (K).

Control covariates include land area (acres), household wellbeing status (asset index and consumption expenditure), household head's characteristics (age, gender, marital status, education), household demographics (household size, number of children, number of youth, number of adults, and an indicator for rural residence).

Table 6. Weather shocks and the number of different types of migrants (two-way fixed effects)

	All households			Agricultural households		
	Labor migrants	*Education migrants*	*Other economic migrants*	*Labor migrants*	*Education migrants*	*Other economic migrants*
	1	*2*	*3*	*4*	*5*	*6*
Weather shocks (*drought, flood, high temp, landslide, etc.*)	-0.0087	-0.050***	0.0017	-0.0030	-0.049***	0.0055
	(0.0089)	(0.016)	(0.011)	(0.0090)	(0.017)	(0.011)
Control covariates	Yes	Yes	Yes	Yes	Yes	Yes
Observations	**17,021**	**17,021**	**17,021**	**13,631**	**13,631**	**13,631**

Notes: Each point estimate is a coefficient estimate from a separate regression. Standard errors are in parentheses. Level of significance * $p < .10$, ** $p < .05$, *** $p < .01$

Weather shock consists of householders' experience of drought, flood, high temperature, irregular rainfall, landslides etc.

Control covariates include land area (acres), household wellbeing status (asset index and consumption expenditure), household head's characteristics (age, gender, marital status, education), household demographics (household size, number of children, number of youth, number of adults, and an indicator for rural residence).

Table 7. Weather shocks and the duration of migration (two-way fixed effects)

	Number of months member(s) lived away from the household in the last 12 months			
	1-3 months	*4-6 months*	*7-9 months*	*10-12 months*
	1	*2*	*3*	*4*
All households				
Weather shocks	-0.015*	-0.012	-0.025***	-0.0074
	(0.0083)	(0.0085)	(0.0089)	(0.0085)
Control covariates	Yes	Yes	Yes	Yes
Observations	17021	17021	17021	17021
Agricultural households				
Weather shocks	-0.011	-0.010	-0.023**	-0.0047
	(0.0087)	(0.0089)	(0.0095)	(0.0087)
Control covariates	Yes	Yes	Yes	Yes
Observations	13631	13631	13631	13631

Notes: Each point estimate is a coefficient estimate from a separate regression. Standard errors are in parentheses. Level of significance * $p < .10$, ** $p < .05$, *** $p < .01$
Weather shock consists of householders' experience of drought, flood, high temperature, irregular rainfall, landslides etc.
Control covariates include land area (acres), household wellbeing status (asset index and consumption expenditure), household head's characteristics (age, gender, marital status, education), household demographics (household size, number of children, number of youth, number of adults, and an indicator for rural residence).

Table 8. Weather shocks and migration along the consumption distribution

	Number of migrants			Migrant months		
	Bottom 40%	*Middle 40%*	*Top 20%*	*Bottom 40%*	*Middle 40%*	*Top 20%*
	1	*2*	*3*	*4*	*5*	*6*
Weather shocks	-0.090**	-0.082*	-0.12	-0.12**	-0.019	-0.065
	(0.043)	(0.048)	(0.094)	(0.051)	(0.056)	(0.12)
Control covariates	Yes	Yes	Yes	Yes	Yes	Yes
Observations	**6848**	**6868**	**3305**	**6847**	**6864**	**3299**

Notes: Each point estimate is a coefficient estimate from a separate regression. Standard errors are in parentheses. Level of significance * $p < .10$, ** $p < .05$, *** $p < .01$

Weather shock consists of householders' experience of drought, flood, high temperature, irregular rainfall, landslides etc.

Control covariates include land area (acres), household wellbeing status (asset index and consumption expenditure), household head's characteristics (age, gender, marital status, education), household demographics (household size, number of children, number of youth, number of adults, and an indicator for rural residence).

Table 9. Weather shocks reduce agricultural production and revenue.

	Log (Value of production)			Log (Agricultural revenue)		
	Bottom 40%	*Middle 40%*	*Top 20%*	*Bottom 40%*	*Middle 40%*	*Top 20%*
	1	*2*	*3*	*4*	*5*	*6*
Weather shocks	-0.20***	0.020	-0.055	-0.27*	0.16	0.51*
	(0.062)	(0.055)	(0.12)	(0.15)	(0.15)	(0.28)
Control covariates	Yes	Yes	Yes	Yes	Yes	Yes
Observations	**6226**	**5662**	**1722**	**6226**	**5662**	**1722**

Notes: Each point estimate is a coefficient estimate from a separate regression. Standard errors are in parentheses. Level of significance * $p < .10$, ** $p < .05$, *** $p < .01$

Weather shock consists of householders' experience of drought, flood, high temperature, irregular rainfall, landslides etc.

Control covariates include land area (acres), household wellbeing status (asset index and consumption expenditure), household head's characteristics (age, gender, marital status, education), household demographics (household size, number of children, number of youth, number of adults, and an indicator for rural residence).

Table 10. Effects of weather shocks on migration – heterogeneity analysis

	Household has one or more migrants					
	Female-headed	*Male-headed*	*Rural*	*Urban*	*Ethnic minority*	*Ethnic non-minority*
	1	*2*	*3*	*4*	*5*	*6*
Weather shocks						
Weather shocks (*drought, flood, high temp, landslide, etc.*)	-0.013	-0.025**	-0.018*	-0.068**	-0.015	-0.039**
	(0.017)	(0.012)	(0.010)	(0.026)	(0.012)	(0.017)
Drought	-0.014	-0.022*	-0.019	-0.062**	-0.0036	-0.056***
	(0.018)	(0.013)	(0.012)	(0.028)	(0.013)	(0.018)
Flood	-0.032	0.018	0.018	-0.053	-0.033	0.064
	(0.044)	(0.026)	(0.023)	(0.071)	(0.026)	(0.047)
Control covariates	Yes	Yes	Yes	Yes	Yes	Yes
Observations	**5,621**	**11,392**	**12,985**	**4,028**	**11,528**	**4,532**

Notes: Each point estimate is a coefficient estimate from a separate regression. Standard errors are in parentheses. Level of significance * $p < .10$, ** $p < .05$, *** $p < .01$
Weather shock consists of householders' experience of drought, flood, high temperature, irregular rainfall, landslides etc.
Control covariates include land area (acres), household wellbeing status (asset index and consumption expenditure), household head's characteristics (age, gender, marital status, education), household demographics (household size, number of children, number of youth, number of adults, and an indicator for rural residence).

FIGURES

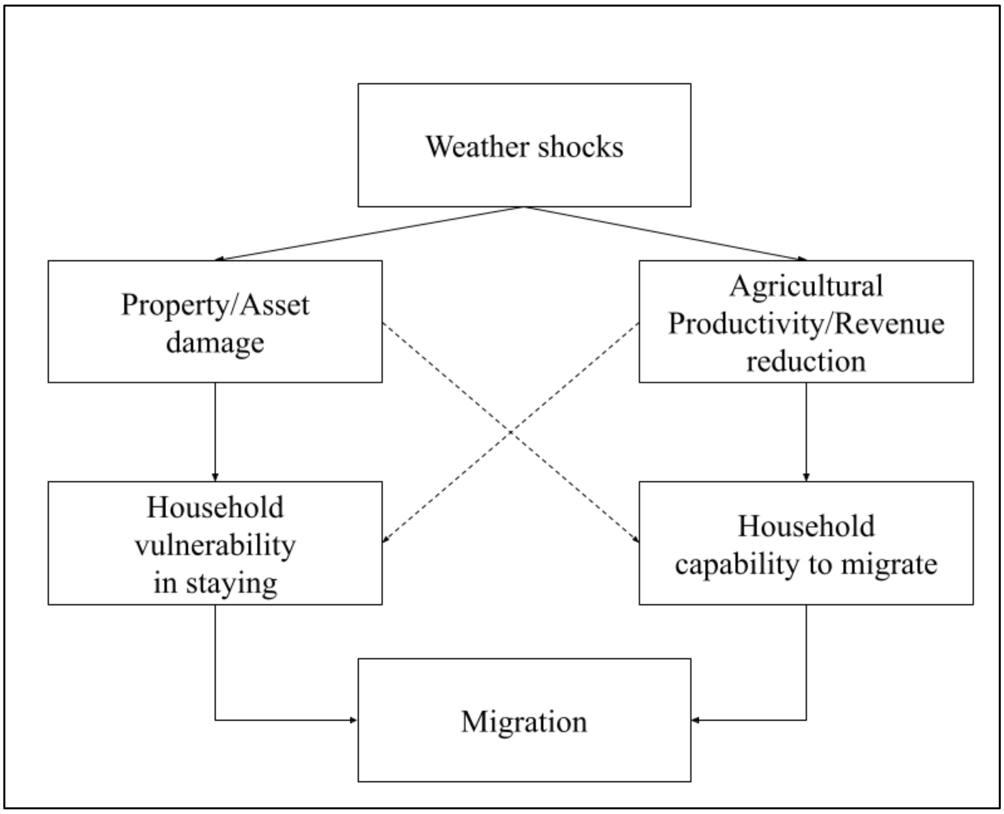
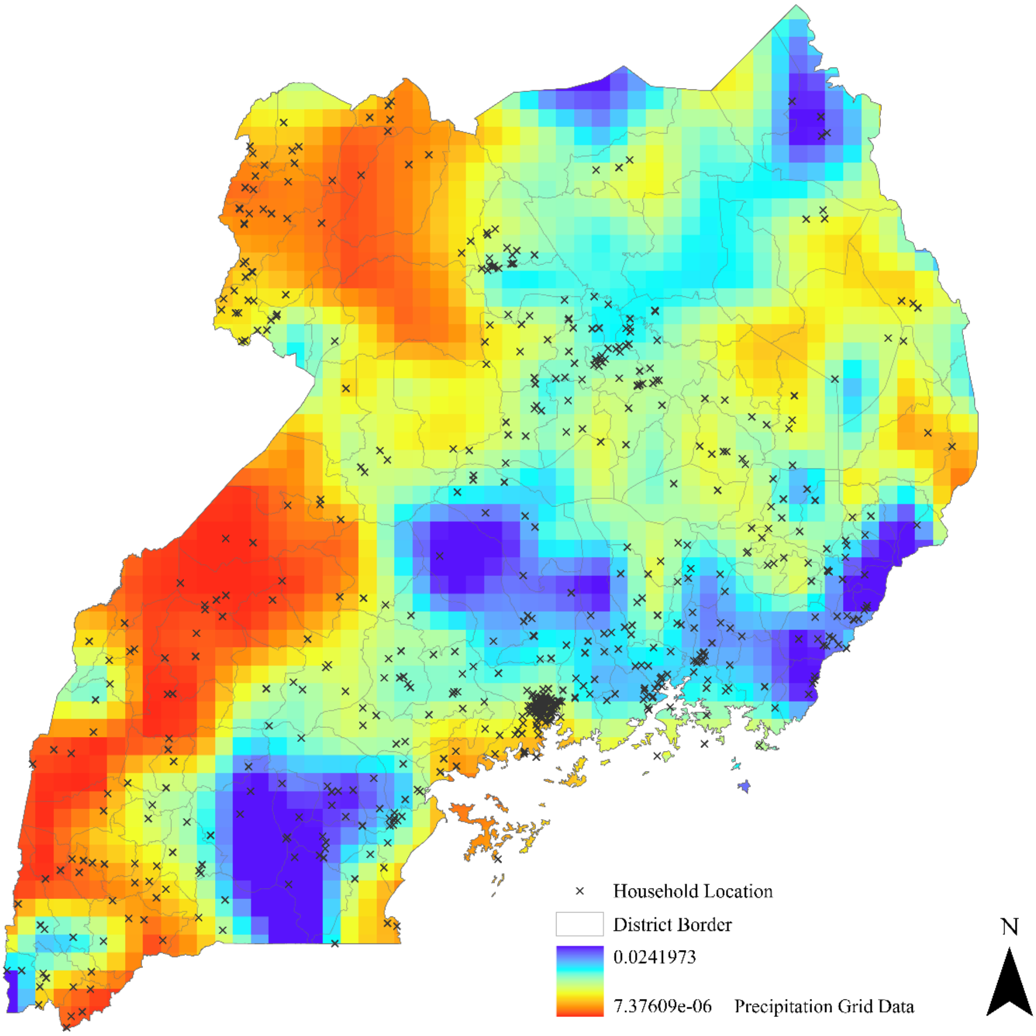


Figure 1. Conceptual framework



Note: 2019 September precipitation data from ERA-Land hourly data, Copernicus Climate Change Service (C3S) Climate Data Store (CDS).

Figure 2. Matching LSMS modified locations and the gridded precipitation data.

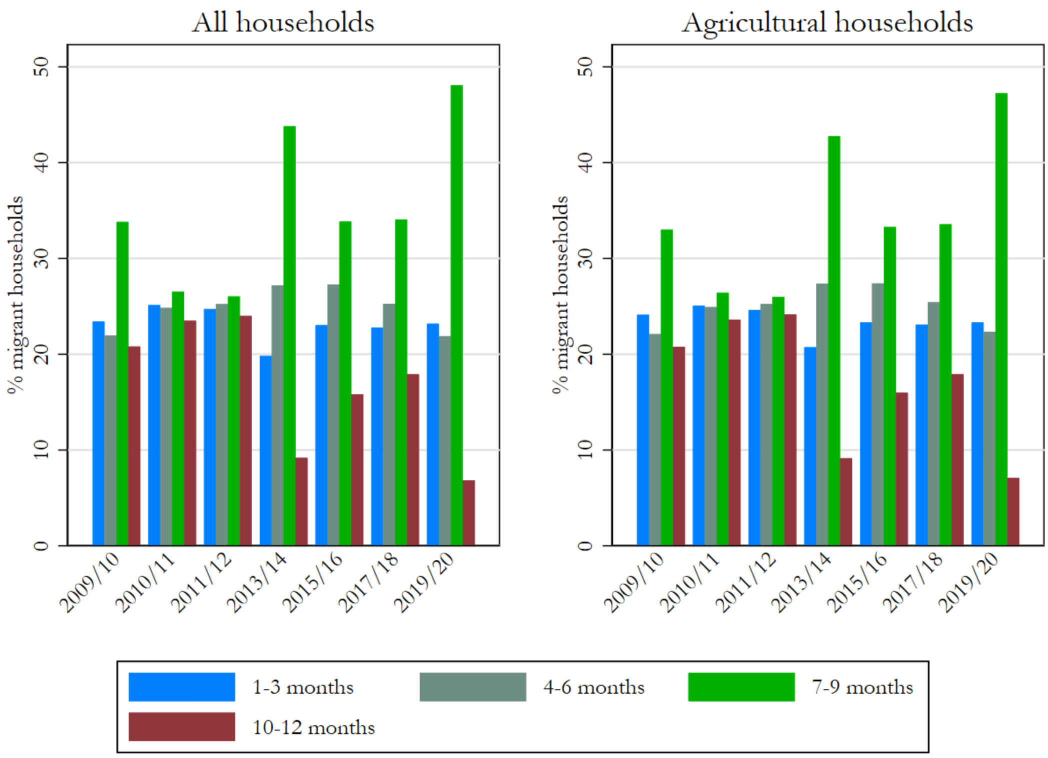


Figure 3. Distribution of migrant households by the duration of migration

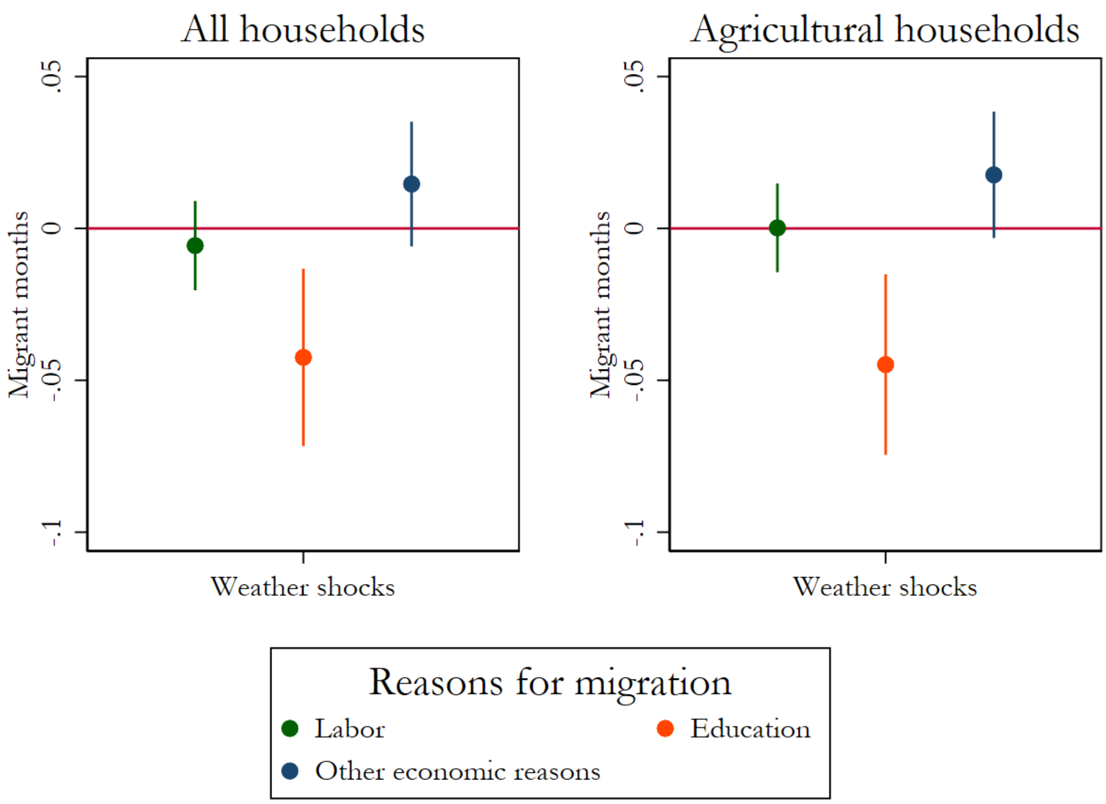


Figure 4. Effects of weather shocks on migrant months

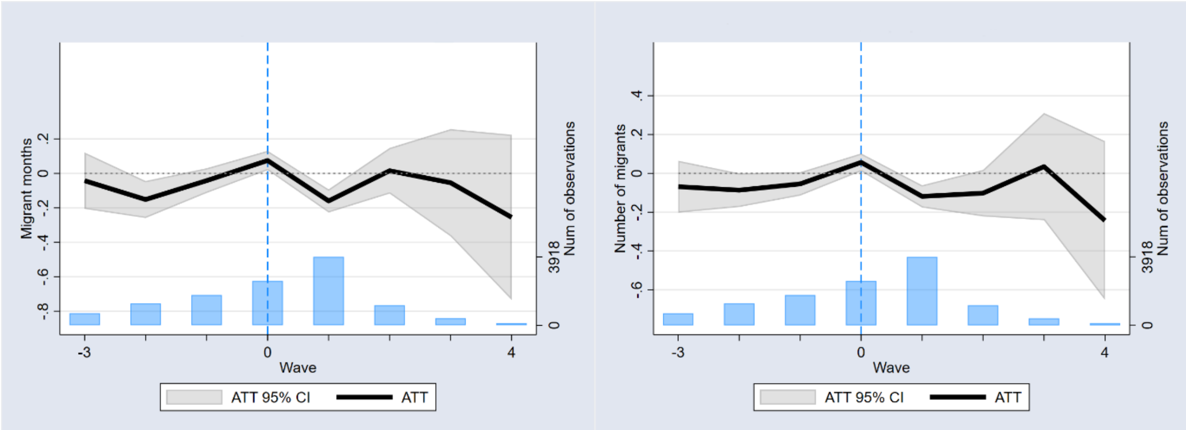


Figure 5. Effects of weather shocks on migration (Synthetic control results)

APPENDIX A

Table A1. Effects of weather shocks on migration – Diff-in-Diff results

	All households			Agricultural households		
	Household has migrants	*Number of migrants*	*Migrant months*	*Household has migrants*	*Number of migrants*	*Migrant months*
	1	*2*	*3*	*4*	*5*	*6*
Weather shocks (*drought, flood, high temp, landslide, etc.*)	-0.020 (0.021)	-0.12^{**} (0.053)	-0.14^{**} (0.067)	-0.0070 (0.022)	-0.10^{*} (0.056)	-0.12^{*} (0.069)
Control covariates	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7937	7937	7937	5969	5969	5969

Notes: Each point estimate is a coefficient estimate from a separate regression. Standard errors are in parentheses. Level of significance * $p < .10$, ** $p < .05$, *** $p < .01$

Weather shock consists of householders' experience of drought, flood, high temperature, irregular rainfall, landslides etc.

Control covariates include land area (acres), household wellbeing status (asset index and consumption expenditure), household head's characteristics (age, gender, marital status, education), household demographics (household size, number of children, number of youth, number of adults, and an indicator for rural residence).

Table A2. Effects of persistent weather shocks on migration (Pooled OLS)

	Number of years household had at least one migrant	
	All households	*Agricultural Households*
	1	*2*
Number of years households experienced		
Weather shocks (*drought, flood, high temp, landslide, etc.*)	0.19^{***}	0.20^{***}
	(0.027)	(0.027)
Drought	0.22^{***}	0.22^{***}
	(0.029)	(0.029)
Flood	0.12^{*}	0.12^{*}
	(0.068)	(0.066)
Control covariates	Yes	Yes
Observations	**17,021**	**13,670**

Notes: Each point estimate is a coefficient estimate from a separate regression. Standard errors are in parentheses. Level of significance * $p < .10$, ** $p < .05$, *** $p < .01$
Weather shock consists of householders' experience of drought, flood, high temperature, irregular rainfall, landslides etc.
Control covariates include land area (acres), household wellbeing status (asset index and consumption expenditure), household head's characteristics (age, gender, marital status, education), household demographics (household size, number of children, number of youth, number of adults, and an indicator for rural residence).

Table A3. Two-way Mundlak (TWM) results

	All households			Agricultural households		
	Household has migrants	*Number of migrants*	*Migrant months*	*Household has migrants*	*Number of migrants*	*Migrant months*
Weather shocks	*1*	*2*	*3*	*4*	*5*	*6*
Weather shocks (*drought, flood, high temp, landslide, etc.*)	-0.029***	-0.11***	-0.11***	-0.024**	-0.11***	-0.097***
	(0.0098)	(0.027)	(0.032)	(0.0099)	(0.027)	(0.031)
Drought	-0.028***	-0.10***	-0.095***	-0.023**	-0.099***	-0.080**
	(0.011)	(0.029)	(0.033)	(0.011)	(0.029)	(0.031)
Flood	-0.0082	-0.044	-0.15**	0.00042	-0.025	-0.13*
	(0.022)	(0.068)	(0.068)	(0.023)	(0.071)	(0.069)
Control covariates	Yes	Yes	Yes	Yes	Yes	Yes
Observations	**17,005**	**17,005**	**16,994**	**13,611**	**13,611**	**13,611**

Notes: Each point estimate is a coefficient estimate from a separate regression. Standard errors are in parentheses. Level of significance * $p < .10$, ** $p < .05$, *** $p < .01$

Weather shock consists of householders' experience of drought, flood, high temperature, irregular rainfall, landslides etc.

Control covariates include land area (acres), household wellbeing status (asset index and consumption expenditure), household head's characteristics (age, gender, marital status, education), household demographics (household size, number of children, number of youth, number of adults, and an indicator for rural residence).

Table A4. Placebo regression results

	All households			Agricultural households		
	Household has migrants	*Number of migrants*	*Migrant months*	*Household has migrants*	*Number of migrants*	*Migrant months*
Randomly generated weather shocks	*1*	*2*	*3*	*4*	*5*	*6*
Weather shocks	-0.0026	-0.028	-0.025	-0.0043	-0.026	-0.019
	(0.0075)	(0.022)	(0.030)	(0.0084)	(0.025)	(0.032)
Drought	-0.0038	-0.031	-0.037	-0.0027	-0.020	-0.019
	(0.0080)	(0.025)	(0.032)	(0.0087)	(0.028)	(0.032)
Flood	-0.0060	-0.0083	-0.043	-0.022	-0.0086	-0.11
	(0.021)	(0.064)	(0.078)	(0.022)	(0.070)	(0.077)
Control covariates	Yes	Yes	Yes	Yes	Yes	Yes
Observations	**17,031**	**17,031**	**17,020**	**13,627**	**13,627**	**13,627**

Notes: Each point estimate is a coefficient estimate from a separate regression. Standard errors are in parentheses. Level of significance * $p < .10$, ** $p < .05$, *** $p < .01$

Weather shock consists of householders' experience of drought, flood, high temperature, irregular rainfall, landslides etc.

Control covariates include land area (acres), household wellbeing status (asset index and consumption expenditure), household head's characteristics (age, gender, marital status, education), household demographics (household size, number of children, number of youth, number of adults, and an indicator for rural residence).

APPENDIX B

Table B1. Summary statistics of model variables for all seven survey periods

	Survey year						
	2009/10	2010/11	2011/12	2013/14	2015/16	2017/18	2019/20
	1	*2*	*3*	*4*	*5*	*6*	*7*
Weather shocks							
Drought	0.458	0.269	0.201	0.237	0.156	0.171	0.117
	0.498	0.444	0.401	0.425	0.363	0.376	0.322
Flood	0.021	0.038	0.053	0.032	0.018	0.022	0.038
	0.144	0.192	0.224	0.175	0.134	0.147	0.190
Weather shocks	0.470	0.298	0.239	0.277	0.186	0.233	0.201
	0.499	0.457	0.427	0.448	0.389	0.423	0.400
Average daily rainfall (meter)	0.0047	0.0052	0.0051	0.0047	0.0050	0.0050	0.0053
	0.0026	0.0027	0.0024	0.0020	0.0026	0.0022	0.0024
Average daily temperature (Kelvin)	295.181	294.925	294.681	294.883	295.333	294.891	295.079
	1.636	1.492	1.570	1.248	1.427	1.415	1.376
Agricultural characteristics							
Agricultural household	0.762	0.773	0.778	0.783	0.754	0.816	0.803
	0.426	0.419	0.416	0.412	0.431	0.387	0.398
Land ownership certificate (1=Yes, 0=No)	0.175	0.150	0.161	0.182	0.146	0.279	0.261
	0.380	0.357	0.368	0.386	0.353	0.449	0.439
Land area (acres?)	1.957	1.941	2.242	0.996	0.970	0.910	1.075
	4.534	4.449	5.618	1.755	2.264	2.093	2.335
Asset and income							
Asset index	0.000	0.000	-0.010	0.000	0.000	0.013	0.000
	1.999	1.852	2.030	2.121	2.108	2.111	2.132
Consumption expenditure	10.811	9.643	16.512	10.212	11.708	11.378	11.577
	13.488	14.578	343.843	15.285	17.736	23.614	12.909