The Impact of Rainfall Shock on Agricultural Production and Household Welfare: The Case of Rural Cote D'Ivoire

By

AZIA, Herve

THESIS

Submitted to

KDI School of Public Policy and Management

In Partial Fulfillment of the Requirements

For the Degree of

MASTER OF PUBLIC POLICY

2022

The Impact of Rainfall Shock on Agricultural Production and Household Welfare: The Case of Rural Cote D'Ivoire

By

AZIA, Herve

THESIS

Submitted to

KDI School of Public Policy and Management

In Partial Fulfillment of the Requirements

For the Degree of

MASTER OF PUBLIC POLICY

2022

Professor Merfeld, Joshua D.

The Impact of Rainfall Shock on Agricultural Production and Household Welfare: The Case of Rural Cote D'Ivoire

By

AZIA, Herve

THESIS

Submitted to

KDI School of Public Policy and Management

In Partial Fulfillment of the Requirements

For the Degree of

MASTER OF PUBLIC POLICY

Committee in charge:

Professor Merfeld, Joshua D., Supervisor

Professor Lee, Ju-Ho

Professor Lee, Changkeun

Approval as of August, 2022

ABSTRACT

THE IMPACT OF RAINFALL SHOCK ON AGRICULTURAL PRODUCTION AND HOUSEHOLD WELFARE: THE CASE OF RURAL COTE D'IVOIRE

BY

AZIA HERVE

In rural economies, how do weather extremes affect agricultural production and household welfare? Using Cote d'Ivoire's Harmonized Survey of Household Living Conditions 2018-2019 data conducted by the Institut National de la Statistique (2018), I investigated how households in rural zones that entirely depend on rainfall for their agricultural activities are affected. Using an OLS model, I estimate the effect of self-reported rainfall shock on household's main crops (rice, maize, yam) production and their welfare in rural Cote d'Ivoire. The result from the analysis shows that households that reported weather shock observe a decrease of 25% and 18% in yam and rice production, 8% and 3.2% in non-food consumption and consumption expenditure compared to the household that did not face rainfall shock. If nothing is done household that undergo weather shock could see their ability to send their children to school or subscribe to healthcare service reduce. These results could also lead children of those households drop from school and increase in farming works or other activities.

This study contributes to the few literatures that used self-reported weather shock to assess household's level of poverty in rural zones.

농촌 경제에서 기상이변은 농업 생산과 가계 복지에 어떤 영향을 미칩니까? 국립 통계청(2018)에서 수행한 코트디부아르의 2018-2019 가구 생활 조건 조화 조사 데이터를 사용하여 농업 활동을 강우량에 전적으로 의존하는 농촌 지역의 가구가 어떻게 영향을 받는지 조사했습니다. OLS 모델을 사용하여 가정의 주요 작물(쌀, 옥수수, 참마) 생산과 코트디부아르 시골의 복지에 대한 자가 보고된 강우 충격의 영향을 추정합니다. 분석 결과, 기상 충격을 보고한 가구는 강우 충격을 받지 않은 가구에 비해 마와 쌀 생산량이 25% 및 18%, 비식량 소비 및 소비 지출이 8% 및 3.2% 감소하는 것으로 나타났습니다. 아무 조치도 취하지 않으면 날씨 충격을 받은 가정에서 자녀를 학교에 보내거나 의료 서비스에 가입하는 능력이 감소할 수 있습니다. 이러한 결과는 또한 해당 가구의 어린이가 학교를 그만두고 농사 또는 기타 활동을 증가시킬 수 있습니다.

이 연구는 농촌 지역에서 가구의 빈곤 수준을 평가하기 위해 자체 보고된 기상 충격을 사용한 소수의 문헌에 기여합니다.

ACKNOWLEDGEMENTS

First, I would like to express my deepest gratitude to my family for their countless support during my study in South Korea. Secondly, my academic program at KDIS would not have been possible without my benefactor, the government of South Korea through NIIED, I remain forever indebted to the Korean government and the wonderful people of South Korea for the privilege to experience this great adventure and for the opportunity to have a premium education. My experience in the KDI school exceeded my expectations and imagination and this owed so much to my thesis supervisors Prof. Merfeld Joshua and Prof. Lee Hu Jo. To all the professors at KDIS, who have given up to their sleep to the pursuit and spread of knowledge acquired, my appreciation for you all is profound. To all my friends, Abdul Wahab, Piiga Souleymane, you will be forever remembered for your support through the thorough brainstorming we had on my thesis.

Lastly, I would like to thank Prof. Inbok Rhee. Through his advice I was able to enroll in classes like Econometrics, Impact Evaluation to understand what a research should be and the motivation behind.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

INTRODUCTION

Considering that agriculture supports millions of disadvantaged households in rural areas around the world (World Bank, 2017), the growth of radial weather would exacerbate the vulnerability of households in developing countries (Skoufias et al., 2011). Climate variability and droughts are important stress factors in Africa, where rural households have to deal with such factors for decades (Mortimore & Adams, 2001). The increasing impacts of climate change affect the rural population which entirely depends on rain-fed agricultural activities (Kouadio et al 2011). Considering these factors, I examine the effect of self-reported radial rainfall in 14 districts in Cote d'Ivoire.

This study is done on household's main crops (rice, maize, and yam) production and their welfare in the rural zones. With a predominant rural population that mostly relies on rainfall to grow crops, I focus on the past 3 years' reported weather shocks and agricultural production as stated in the survey conducted by Institut National de la Statistique (INS[1], 2018).

Objectives of the Study

There are two basic objectives I would like to focus on in this study.

First, I look at the weather shock on agricultural production to show how radial rainfall influences agricultural production in rural Cote d'Ivoire to find the cropping techniques farmers can use to mitigate the impact of rainfall unpredictability on their livelihoods.

Secondly, I estimate how the shock affects households' total consumption per capita and their per capita consumption expenditure.

[1] Institution specialized in modernizing national statistical data collection systems in cote d'ivoire in collaboration with World Bank

Using the Harmonized Survey of Household Living Conditions 2018-2019 conducted by the INS Cote d'Ivoire, I use the production regression to show the influence of self-reported radial rainfall on Rice, Maize, and Yam yields. I consider these three crops for various reasons, but for the purposes of this study, I will focus on two of them:

According to the study conducted by Louis Dreyfus (2018), rice, yam, and maize are staple foods in Cote d'Ivoire accounting for more than 60% of households in rural areas' total food consumption. Likewise, these crops are primarily grown by smallholder farmers, whose livelihoods are largely dependent on their own production (Koffi Eugène et al., 2012). This might mean any variation in weather, unfavorable or beneficial, could have an impact on households' daily living conditions. The high variability in rainfall the unfavorable most locations of Cote d'Ivoire become (Koffi Eugène et al., 2012), allowing the development of several cryptogamic illnesses or deficiencies, which limit yields to a varying degree depending on the year (Mangini et al., 2012). Although other publications have investigated the consequences of weather shocks, this study uniquely contributes to the field of weather shocks in several ways. To the best of my knowledge, this study is the first to use self-reported plot locations and covariate shocks to examine the effects of rainfall on agricultural production in rural Cote d'Ivoire.

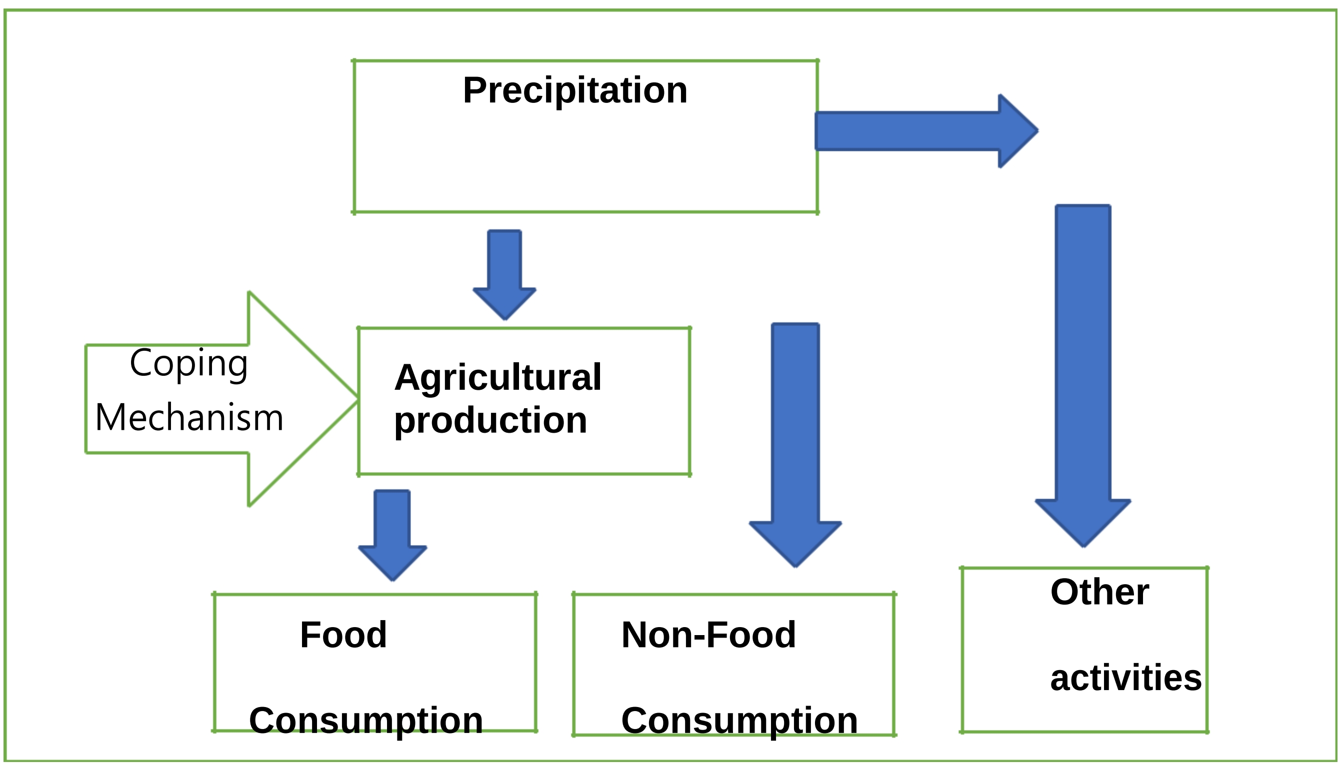
This study is organized in 6 major parts as follow. Part 1 introduce the study along with the objectives of the studies, Part 2 shows previous studies that examines the impact of weather shock on agricultural production, how this shock is reported by different category of households. It also relates the background information on Cote d'Ivoire's agricultural industry and weather change. Part 3 focuses on the description of the variables, the data sources, and the methodology. The empirical strategy is presented in Part 4, the findings are in Part 5, and the discussions and conclusion followed by the limitation and future work in Part 6.

BACKGROUND AND PREVIOUS STUDIES

1. Background of the Study

This chapter provides an overview of relevant literature elaborating the historical background for Cote d'Ivoire agricultural production and weather variability. This begins by visualizing the environment, agricultural output, coping systems, non-food consumption, and food consumption as components of a simple system (Figure 1), in which non-food consumption and food consumption are important dimensions of households' welfare (Amare et al., 2018a). The agricultural output is directly influenced by the precipitation, which indirectly impacts both food and non-food consumption at the household level.

Figure 1: Environment Impact and Agricultural Challenges



Source: FAO, the future of food and agriculture (2017)[2]

Food consumption is influenced by precipitation primarily through current agricultural production (Figure 1). This is notably true in rural zones, where agricultural production and other income-generating activities are mostly influenced by rainfall (Dercon & Krishnan, 2000). A negative income or food provided by other activities and agricultural production caused by weather shock results in a fall in total consumption and household revenue variations (Jacoby & Skoufias, 1998). In general, households are better equipped to protect their productions from '*idiosyncratic shocks*', (shocks affecting only one household and are distinct from *covariate shocks*, that affect the entire society) (Hoddinott, 2006). A previous study conducted by Dercon and Krishnan (2000) to establish the relationship between the '*covariate and idiosyncratic shocks*' [3] on household consumption expenditure, has found that covariate shocks have a greater impact than idiosyncratic shocks. Furthermore, Hoddinott (2006) concluded that when consumption is impacted by covariate shocks, both food and non-food consumption are affected differently, and food consumption is generally preferred than non-food consumption when this occurs simultaneously (Skoufias & Quisumbing, 2005).

Many studies also found out that when households' consumption is hit by a shock, depending on who the household's head is (male or female), one category of consumption may be more impacted than others, and food consumption may take precedence over the others (Duflo & Udry, 2004).

2. **Previous Studies on Weather Variability**

[2] Prepared in the context of resolving agricultural trends for the future work under SDG 2030 agenda in Rome

[3] Generally employed to emphasize on household poverty comparison within household community. It is convenient to look at the difference in magnitude affecting individuals; one may converge towards community shock to consider the consistency of the impact.

The goal of including these previous studies of radial weather is to understand the environmental impact due to climate change on different zones in Côte d'Ivoire. A study done by Kouadio (2003) in the Geophysical Research, draws a conclusion based on rainfall data collected from 22 different weather stations located over Ivorian territory between 5 and 11°N and 3 to 8.5°W. According to this study, the monthly time series rainfall collected between 1964-1997 divides the country into three climatic zones in the north, the south, and the Sahel (Kouadio et al., 2003). The rainy season occurs from June to August and September with August having a high volume of rain in the Sahelian region. The seasonal rainfall cycle in the middle zones has a slightly bimodal structure, a rainy season from June to September, a protracted dry season from December to February and a short dry season in August in the country (Kouadio, 2011). This concludes the variability of rainfall in most regions in Cote d'Ivoire.

3. **Previous Studies using Self-reported Rainfall Shocks**

According to Luc (2010), when households experience a weather shock, its impact reflects on the value of their agricultural output on which they mostly rely on in rural areas. Once the agricultural output is impacted, it leaves a negative mark on consumption (Dercon & Christiaensen, 2007).

This study relies on subjective shock measures obtained from households' responses to developed two major groups (yes or no). Even though this study used self-reported weather shocks, it can provide a good value estimation of shock reports for those who have experienced negative or positive rainfall shocks. However, it is also important to note that some households do not report a shock if the impact is minimal, and they could easily handle it.

To illustrate this argument, I explore previous studies conducted on self-reported shock techniques. Træ rup (2011) investigated self-reported weather shocks from households' responses and concluded that shocks reported by households on short-term patterns appear to reflect less variation in rainfall estimate.

The process of reporting shocks can be either over-reporting or under-reporting (Bound' et al., 2001). For instance, reported incomes, education, health-related issues, transfers, unemployment, and weather are all self-reported shocks investigated in previous studies (Carletto et al., 2013).

It has been discovered, for example, that self-employment income or environmental revenue from the extraction of common natural resources is under-reported (Parvathi & Nguyen, 2018). Despite the existence of numerous pieces of research on self-reported shocks, research on validating covariate self-reported weather shocks remains most valuable because climate data is observable as well as exogenous (Nguyen & Nguyen, 2020). Several writers in capturing covariate shocks identified no higher effects in reporting weather shocks, and the only effect that could influence the covariate shock is when covariate shock is muddled up with the effect of other shared region features (Nguyen & Nguyen, 2020). Other researchers utilize a community's average of reported shock events as this method is nevertheless vulnerable to the self-reporting bias inherent in each reported shock occurrence (Berloffa & Modena, 2014).

4. Possible Sources of Covariate self-reported shock biases

Errors can occur at any point during a survey. According to Bound' et al., (2001) and Parvathi & Nguyen (2018), three causes of measurement errors that occur during a survey could be '*cognitive processes*', '*social perception'*, and the '*surveying process'*.

The cognitive process can be defined as the strength of the memory trace: "the stronger the trace, the less effort needed to locate and retrieve the information." This is the most likely process to cause errors in reporting shocks (Bound' et al., 2001, p. 3745).

When reported-shocks are “*memories associated, biases in reporting shocks can be both downward and upward, depending on the direction of the error-variable connection”* (Beegle et al., 2012). Regarding social perception, it generally occurs in reporting natural disaster shocks by rural households in low-income countries (Nguyen & Nguyen, 2020). Households generally report natural disaster shock, based on reward attached to the survey participation (Parvathi & Nguyen, 2018). In survey process, researchers discovered a link between gender, education level, age, and residence location with the incidence of health shock reporting inaccuracies (Okura et al., 2004). According to Christiaensen (2007) health shocks reported during survey are more frequently by individuals with better salaries, less serious illnesses, to take time off. For instance, households with low incomes are tempted to report fewer health concerns Gertler et al., 2002), and the desire to receive assistance (Groot, 2000), this could bring in the issue of over-reporting shocks during surveys (Baker, 2004). In addition, measurement error during the survey process could occur when surveyors undertake surveys in different conditions (Bound’ et al., 2001).

In general, researchers on self-reported shocks discovered that the likelihood of over-reporting a shock is connected to the type of shock reported (diseases in health shock), the time of occurrence, the severity of the shock, the features of the respondent, and the justification that motivates the participants. However, biases in self-reported shocks can be attenuated, especially when they are used as explanatory variables (Baker, 2004). In this study, self-reported weather shock is not related to any respondent’s motivation, such as remuneration or reward for reporting shock or the household's coping ability, as is the case in self-reported health shocks (Quisumbing & Maluccio,2003). Furthermore, the reported weather shock in EHCVM[4] survey is a covariate shock

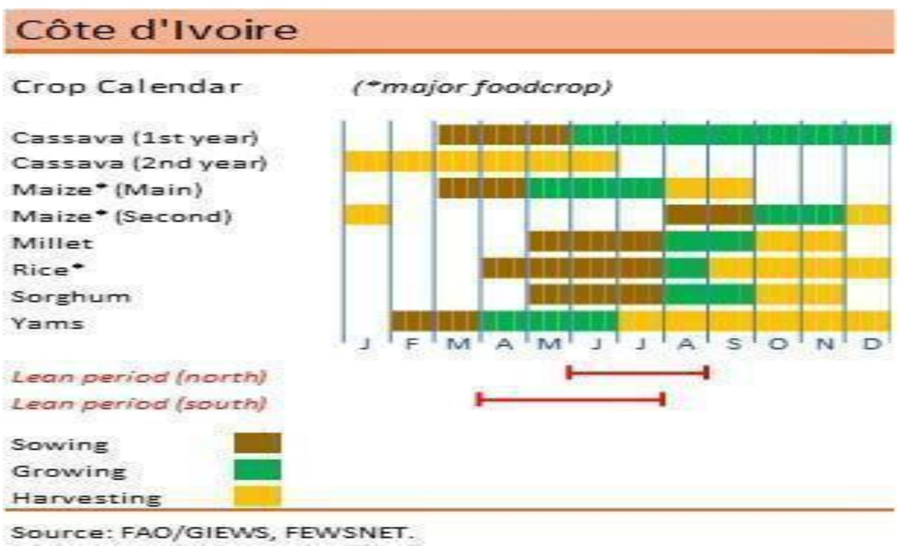
[4] Enquête Harmonisée sur les conditions des vies des menages en Cote d’Ivoire presented in 2018/2019. https://data.worldbank.org

and reported by a large number of surrounding households. This reduces the bias that could occur in cognitive processes. The proclivity to report weather shocks is determined by the unique features that influence shocks in a community; households that avoid damage because of the weather shock or households' farming activities that did not encounter any damage will not report shock (Tesliuc et al., 2000).

5. **Major Food crops Seasonal Calendar in Cote d'Ivoire**

According to FAO (2021) the agriculture industry accounts for 80% of Côte d'Ivoire's GDP with 26% for the major crops and employs 46% of the working population and feeds two-thirds of the Ivorian population

Figure 2: Seasonal calendar for crops in Cote d'Ivoire



Source: FAO (2021)

The agricultural productivity in Cote d'Ivoire is characterized by a bimodal season (FAO, 2021). There is the rice sowing season starting from April to July, growing season from August to December, and harvesting season in September to December. Yam is planted from February to March, grows from April to June, and is harvested from July to December. There are two sowing periods for maize. March to April is the first period, and August to September is the second period.

METHODOLOGY AND DATA

The data for this research comes from the Harmonized Survey of Household Living Conditions 2018-2019 in Cote d'Ivoire and collected through the multi-topic household questionnaire which was distributed to all families, for both agricultural production and household well-being analysis.

The instrument gathered data on food and non-food consumption, consumption expenditure, food security, and so on.

The descriptive statistics (Table 2 in appendices) show that the data is composed of 12,992 households, with on average of 5 members in each. Among the 12,992 households, 59 percent (7,717) live in rural areas. Females dominate the household as heads since 82 percent of household heads are female. On average, the data shows that the household heads are not old (42 years old). In addition to individuals' characteristics, the dataset shows that the largest areas of plot used by the households are Yam (8 ha), followed by maize (3ha) and Rice (2ha).

For the purpose of this study, the analysis of the rainfall shock on agricultural productivity was conducted using households actively involved in agricultural activities during the last three years.

1. **Covariate Self-Reported Rainfall shock**

Previous studies have used meteorological data, but as previously stated, this study relies on covariate self-reported rainfall shock because it captures the impact of the shock on individual households within regions, particularly when households do not have their plot located in the vicinity. It also helps us to determine the vulnerability of a particular household being affected. In the survey, a household responds “Yes” when it has experienced the rainfall shock and "No," when it has not experienced any rainfall shock. This methodology allows us to make a clear distinction between the affected and non-affected. A binary variable representing the rainfall shock condition is then established, with "1" representing a negative rainfall shock and "0" otherwise.

2. **Measuring Household Consumption Expenditure**

Household consumption expenditure refers to the expenditure incurred by households on food and non-food items to meet various needs over a set period.

3. **Per Capita Food and Non-Food Consumption**

Food consumption per capita shows the consumption of food items that individual households consumed over a set of periods, and it is obtained by dividing total household food consumption by household size. In addition, the percentage to which the shock affects each household member in the community will be reflected by the individual household member's food consumption within families. On the other hand, non-food consumption such as literacy, schooling, entertainment, electricity, health care services etc. reflect the level of the household living conditions in the rural area (Amare et al., 2018a).

4. **Food Diversity**

Food Diversity provides a wide overview of the food consumed by a family in a community and it will be measured by the Shannon Index[5].

EMPIRICAL STRATEGY

In this chapter, I will use an OLS model to show how reported radial rainfall affects rice, maize and yam production and household's welfare. First, I estimate the effect of radial rainfall on maize, rice, and yam output through the production function during the three years prior to the 2018/2019 agricultural season at the plot level in rural Cote d'Ivoire. I also account for some demographic and socioeconomic factors that could affect output in this model. Secondly, I regress the rainfall shock on food and non-food consumption to see how much the shock affects individual households' food and non-food consumption. To minimize the effect of unobservable traits across plots and households, I included a significant number of control variables in both production and the household welfare model.

1. **Agricultural Yields Model**

I use a multiple regression model with agricultural output (rice yields, yam yields, and maize yields) as dependent variables, self-reported rainfall shock as independent variable, and other control variables. The logarithm of the total quantity of rice, yam, and maize yield on all household's plots in kilogram (kg) is used for the three crops production ($lnP_{i,h,d}$) presented in equation (I)

---

[5] Index developing the capacity of richness and evenness of species within a community, taking zero as value if there is no diversity. Meaning that zero as value of the index shows only one specie in the community.

$$\ln \mathbf{P}_{i,h,d} = \beta_0 + \beta_1 RS_{i,h,d} + \beta_2 X_{h,d} + \beta_3 PL_{i,h,d} + \sigma_d + \varepsilon_{h,d} \qquad \text{(I)}$$

where i represents the plot area; h represents each household within district; d represents district; lnP denotes the logarithm of agricultural output; RS represents the measure of rainfall shock reported by the households; PL represents the vector of the plot characteristics.

X represents the control variables added to capture plots that resist the rainfall shock better and other variables that could also influence the production

σ_d represents the district fixed effects; ε represents the error term.

Rice yields for rice production, maize yields for maize production, and yam yields for yam production are the outcomes of interest. They are weighed in kilograms (kg).

2. The Household Welfare Model

Households in the rural zones get affected when facing shocks (Luc et al., 2010) specially in their main activities. The impact of these shocks often reverses the daily food and non-food consumption. This is seen in the household welfare regression model where food and non-food consumption per capita are measured against the rainfall shock. To estimate this impact, I construct the following equation.

$$\ln \mathbf{W}_{h,d} = \beta_0 + \beta_1 \mathbf{RS}_{h,d} + \beta_2 \mathbf{X}_{h,d} + \sigma_d + \varepsilon_{h,d} \qquad \text{(II)}$$

where h represents household; d represents district; lnW measures the logarithm of the household welfare; RS represents the measure of the rainfall shock reported by the households; X controls for the unobservable variables that could affect the household consumption other than rainfall shock; σ_d represents the district fixed effects and ε is the error term.

2.1 **Control variables**

2.1.1 **Household composition**

The household composition is as follows:

The age proportion of children aged [0-14] is obtained by dividing the number of children [0-14] by the household size; males proportion aged [15-39] is obtained by dividing the number of males aged [15-39] by the household size; females proportion aged [15-39] is obtained by dividing the number of females aged [15-39] by the household size; male proportion with the age category of [40-59] is obtained by dividing the number of males aged [40-59] by household size; female proportion with the age category of [40-59] is obtained by dividing the number of females aged [40-59] by household size;

2.1.2 **Household Head Characteristics**

In the household head characteristics, I use the head as a dummy variable. Female equal to “1” for female head, “0” otherwise, the household head's age and the household head's highest level of education.

2.1.3 **Heterogeneity of Impact**

Moylan (2008) and Vesco (2021), used an interaction term between rainfall shock and the type of household or plot to assess the effect of a weather shock on different households within the community. In this study there is no need to include an interaction term between self-reported rainfall shock and the type of household or plot because in equations (I) and (II) I used covariate reported rainfall shock which directly captures individual household reporting shock within the community

RESULTS

The results from the reported rainfall shocks on Rice, Yam, and Maize Yields, as well as variables representing household welfare, are presented in this chapter.

I estimate equation (I) to see if the rainfall shock reported by households has an impact on agricultural production. The logarithm of rice, yam, and maize yields shows the percentage of agricultural output each household produced during the 2018/2019 agricultural season.

1. **Rainfall shock, agricultural production**

Equation (I) estimates the log of rice yields, maize yields, and yam yields as dependent variables and measured in kilograms; the reported rainfall shock dummy is used as an independent variable with additional control variables to see how radial rainfall affects agricultural productivity. Table 3: Regression Results-Agricultural production

VARIABLES	(1) Yam Yield	(2) Maize Yield	(3) Rice Yield
Self-Reported Rainfall shock	-0.248**	-0.039	-0.181*
	(0.120)	(0.106)	(0.091)
Constant	7.369***	5.306***	4.556***
	(0.931)	(1.537)	(0.804)

District Fixed Effect	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	1,021	808	1,143
R-squared	0.135	0.387	0.267

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The results in Table 3 presents the regression of the self-reported rainfall shock on the log of the agricultural output in kilograms (Kg). The full Table 3 (in appendices) includes variables representing the plot area, agro-ecological zones to control for the similarity in climatic conditions, inputs such as pesticides, inorganic fertilizer, and labor forces, household characteristics and the district fixed effect. Table 3 shows a decline in quantity of the three crops relative to the rainfall shocks. The production of yam is significantly decreasing by 25 percent in total quantity produced, Rice suffered an 18 percent decrease, and Maize a 4 percent decrease.

2. **Rainfall shock, household welfare**

I estimate equation (II) to assess the effect of the radial rainfall on household consumption. The log of per capita food and non-food consumption, and per capita expenditure on all commodities is used to interpret the amount of food and non-food household consumed or spent on food and non-food by individual household within the community. The consumption expenditure per capita shows correlation between rainfall shock reported by households and their consumption of food items and non-food goods.

Table 4: Welfare Regression results

VARIABLES	(1) Per capita Non- Food Consumption	(2) Per capita Food Consumption	(3) Per capita Consumption Expenditure	(4) Shannon Index
Reported Rainfall Shock	-0.080***	-0.019	-0.032**	-0.020*
	(0.019)	(0.018)	(0.016)	(0.012)
Constant	12.009***	12.745***	13.195***	0.433***
	(0.094)	(0.080)	(0.076)	(0.057)
Controls	Yes	Yes	Yes	Yes
District Fixed Effect	Yes	Yes	Yes	Yes
Observations	12,992	12,992	12,992	12,640
R-squared	0.542	0.449	0.529	0.104

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The non-food consumption per capita as well as the consumption expenditure per capita presented in Table 4 show a significant negative decrease of 8 percent and 3.2 percent respectively. In comparison to the households that did not face rainfall shock during the previous three rainy seasons before the survey, households that reported rainfall shock saw an 8.0 percent decline in their non-food consumption of individual household members. The interesting finding of this study is that rainfall shock on households' consumption of food items is not significant. foreseeably, this could mean that households whose agricultural production decreases due to the rainfall shock save their production for self-consumption and decrease non-food consumption. This could be seen in Table 4 presenting a decrease of 3.2 percent in household per capita consumption expenditure.

3. **Robustness Check**

Another option to examine the effect of rainfall shock is to use the meteorological rainfall data from the same period coupled with the dataset to check if the main outcome of interest, the reported rainfall shock, behaved differently.

According to the study conducted by Amare (2018) using a negative rainfall of one standard deviation below the mean in the wet season in West African countries demonstrated the potential impacts on household consumption due to the change in their agricultural productivity. I then used two (2) standard deviations away from the mean rainfall as a negative rainfall obtained from the cumulative precipitation index calculated from a long-term mean period of 2006-2017. As a result, in Table 5, there is an 11.8, 7.4 and 1.6 percent decrease in the total quantity of yam yields, rice yields, and maize yields. Compared to the results when using self-reported rainfall shock in table 3, I observe that the magnitude of the shock coefficient slightly changes. This could be explained by the fact that the negative rainfall shock used for the robustness check is taken on the clustered population in the same district and the self-reported rainfall shock's results are from an individual household's report within the district.

DISCUSSION AND CONCLUSIONS

The aim of this study was to find the impact of radial rainfall reported by households in the EHCVM survey on agricultural production and the extent to which the shock has affected their welfare in the rural Cote d'Ivoire. This study uses Cote d'Ivoire's Harmonized Survey of Household Living Conditions 2018-2019 data conducted by the INS. The key finding is that households that fully depend on rain-fed agriculture for their livelihood spend 3.2 percent less on their total consumption expenditure per capita (food and non-food consumption) and reduce their non-food consumption by 8 percent while there is no change in their food consumption.

The interesting part of this study is that households without any other activity than farming could severely undergo poor living conditions compared to those that are not affected. This could result in the reduction of households' ability to send their children to school, and to subscribe to healthcare which are basic human needs. If nothing is done their condition could considerably decrease to the point that children of households that face rainfall shocks increase in farming works.

To mitigate this shock, actions need to be taken by households by adopting new cropping techniques and developing spatialized management tools that are aimed at optimizing the use of surface and underground water to optimize the management of irrigation techniques. Foremost, there is a need to identify and make inventories of areas of farmland that have been adversely affected by climate change and have become unsuitable for agricultural production especially during dry seasons. With government support, farmers should be equipped with water shooting devices that could dispatch water in the farms. Also, workshops and training should be organized to teach isotopic techniques that could enable farmers to access information and strategies for better water management in agriculture during droughts.

1. **Limitation of this Study**

For lack of data, an appropriate study on the methods of coping mechanisms could not be done to develop proper techniques for households that are more exposed to weather shocks. Also, because there are many factors that may be influential, some of which are not captured in this work, it is difficult to precisely establish the extent to which weather shock on agricultural production impacts households' welfare in rural areas of Cote d'Ivoire.

2. **Recommendation for Future Work**

There is an increasing controversy on Cote d'Ivoire cocoa production due to the high participation of children in cocoa farms (Grootaert, 1998). The International Labor Organization (ILO) is more concerned about the role of children involved in farming activities in rural Cote d'Ivoire (Nkamleu & Kielland, 2018). My results have shown that more households depend on rain-fed agriculture which leads to a decrease in non-food consumption. According to Grootaert (1998), any drop in labor force participation of adults is compensated by an increase in the participation of younger household members in order to avoid a fall in household incomes. This could probably lead for further studies to show how radial rainfall affects children in rural communities.

BIBLIOGRAPHY

Amare, M., Jensen, N. D., Shiferaw, B., & Cissé, J. D. (2018a). Rainfall shocks and agricultural productivity: Implication for rural household consumption. *Agricultural Systems*, *166*, 79–89. https://doi.org/10.1016/j.agsy.2018.07.014

Amare, M., Jensen, N. D., Shiferaw, B., & Cissé, J. D. (2018b). Rainfall shocks and agricultural productivity: Implication for rural household consumption. *Agricultural Systems*, *166*, 79–89. https://doi.org/10.1016/j.agsy.2018.07.014

Baker, J. (2004). An investigation of relationships among instructor immediacy and affective and cognitive learning in the online classroom. *The Internet and Higher Education*, *7*, 1–13. https://doi.org/10.1016/j.iheduc.2003.11.006

Beegle, K., de Weerdt, J., Friedman, J., & Gibson, J. (2012). Methods of household consumption measurement through surveys: Experimental results from Tanzania. *Journal of Development Economics*, *98*(1), 3–18. https://doi.org/10.1016/j.jdeveco.2011.11.001

Berloffa, G., & Modena, F. (2014). Measuring (In)Security in the Event of Unemployment: Are We Forgetting Someone? *Review of Income and Wealth*, *60*(S1). https://doi.org/10.1111/roiw.12062

Bound', J., Brown, C., & Mathiowetz, N. (2001). *MEASUREMENT ERROR IN SURVEY DATA*. Carletto,

C., Gourlay, S., Winters, P., & Bank, T. W. (2013). *From Guesstimates to GPStimates Land Area Measurement and Implications for Agricultural Analysis*. http://econ.worldbank.org.

Clarida Jordi Gali Mark Gertler, R., Clarida, R., Gali, J., & Gertler, M. (2002). *NBER WORKING PAPER SERIES A SIMPLE FRAMEWORK FOR INTERNATIONAL MONETARY POLICY*

ANALYSIS A Simple Framework for International Monetary Policy Analysis. http://www.nber.org/papers/w8870

Dercon, S., & Christiaensen, L. (2007). *Consumption risk, technology adoption and poverty traps: evidence from Ethiopia*. http://econ.worldbank.org.

Dercon, S., & Krishnan, P. (2000). Vulnerability, seasonality and poverty in Ethiopia. *The Journal of Development Studies*, *36*(6), 25–53. https://doi.org/10.1080/00220380008422653

Duflo, E., & Udry, C. (2004). *NBER WORKING PAPER SERIES INTRAHOUSEHOLD RESOURCE ALLOCATION IN CÔ TE D'IVOIRE: SOCIAL NORMS, SEPARATE ACCOUNTS AND CONSUMPTION CHOICES Intrahousehold Resource Allocation in Côte d'Ivoire: Social Norms, Separate Accounts and Consumption Choices*. http://www.nber.org/papers/w10498

FAO. (2017). *The future of food and agriculture and challenges*.

FAO. (2021). The impact of disasters and crises on agriculture and food security: 2021. In *The impact of disasters and crises on agriculture and food security: 2021*. FAO. https://doi.org/10.4060/cb3673en

Groot, W., & Maassen Van Den Brink, H. (2000). Overeducation in the labor market: a meta-analysis. In *Economics of Education Review* (Vol. 19). www.elsevier.com/locate/econedurev

Grootaert, C. (1998). *Environmentally and Socially Sustainable Development Network The World Bank Child Labor in Côte d'Ivoire: Incidence and Determinants*.

Hoddinott, J. (2006). Shocks and their consequences across and within households in rural Zimbabwe. *Journal of Development Studies*, *42*(2), 301–321. https://doi.org/10.1080/00220380500405501

Institut National de la Statistique (INS). (2018). *Enquête Harmonisée sur les Conditions de Vies des Ménages 2018-2019*. 2019.

Jacoby, H. G., & Skoufias, E. (1998). Testing Theories of Consumption Behavior Using Information on Aggregate Shocks: Income Seasonality and Rainfall in Rural India. *American Journal of Agricultural Economics*, *80*(1), 1–14. https://doi.org/10.2307/3180264

Koffi Eugène, K., Bi Tié Albert, G., & Amani Michel, K. (2012). Analyze of climate variability and change impacts on hydro-climate parameters: case study of Côte d'Ivoire. In *International Journal of Scientific & Engineering Research* (Vol. 3, Issue 2). http://www.ijser.org

Kouadio, K. Y., Aman, A., Ochou, A. D., Ali, K. E., & Assamoi, P. A. (2011). Rainfall Variability Patterns in West Africa: Case of Cote d'Ivoire and Ghana. In *Article in Indian Journal of Environmental Health* (Vol. 5). https://www.researchgate.net/publication/229086604

Kouadio, Y. K., Ochou, D. A., & Servain, J. (2003). Tropical Atlantic and rainfall variability in Côte d'Ivoire. *Geophysical Research Letters*, *30*(5). https://doi.org/10.1029/2002GL015290

Louis Dreyfus. (2018). *Fondation d'entreprise*. www.louisdreyfusfoundation.org

Luc, T. T., Quy, C., Do, T., Dang, L., The, T., & Bank, W. (2010). *Natural Disasters and Household Welfare Evidence from Vietnam*. http://econ.worldbank.org.

Mangini, P. R., Medici, E. P., & Fernandes-Santos, R. C. (2012). Tapir health and conservation medicine. In *Integrative Zoology* (Vol. 7, Issue 4, pp. 331–345). https://doi.org/10.1111/j.1749-4877.2012.00323.x

Mortimore and Adams. (2001). *Farmer adaptation, Change and "Crisis" the Sahel global environmental change;11,49-57,.*

Moylan, H. G. (2008). *THE IMPACT OF RAINFALL VARIABILITY ON AGRICULTURAL PRODUCTION AND HOUSEHOLD WELFARE IN RURAL MALAWI*.

Nguyen, G., & Nguyen, T. T. (2020). Exposure to weather shocks: A comparison between self-reported record and extreme weather data. *Economic Analysis and Policy*, *65*, 117–138. https://doi.org/10.1016/j.eap.2019.11.009

Nkamleu, G. B., & Kielland, A. (2018). *Modeling farmers' decisions on child labor and schooling in the cocoa sector: a multinomial logit analysis in Côte d'Ivoire*.

Okura, Y., Urban, L. H., Mahoney, D. W., Jacobsen, S. J., & Rodeheffer, R. J. (2004). Agreement between self-report questionnaires and medical record data was substantial for diabetes, hypertension, myocardial infarction and stroke but not for heart failure. *Journal of Clinical Epidemiology*, *57*(10), 1096–1103. https://doi.org/10.1016/j.jclinepi.2004.04.005

Parvathi, P., & Nguyen, T. T. (2018). Is Environmental Income Reporting Evasive in Household Surveys? Evidence From Rural Poor in Laos. *Ecological Economics*, *143*, 218–226. https://doi.org/10.1016/j.ecolecon.2017.07.022

Quisumbing, A., & Maluccio, J. (2003). Resources at Marriage and Intrahousehold Allocation: Evidence from Bangladesh, Ethiopia, Indonesia, and South Africa. *Oxford Bulletin of Economics and Statistics*, *65*, 283–327. https://doi.org/10.1111/1468-0084.t01-1-00052

Skoufias, E., & Quisumbing, A. R. (2005). Consumption Insurance and Vulnerability to Poverty: A Synthesis of the Evidence from Bangladesh, Ethiopia, Mali, Mexico and Russia. *The European Journal of Development Research*, *17*(1), 24–58. https://doi.org/10.1080/09578810500066498

Skoufias, E., Rabassa, M., & Olivieri, S. (2011). *The Poverty Impacts of Climate Change A Review of the Evidence The World Bank Poverty Reduction and Economic Management Network Poverty Reduction and Equity Unit*.

Tesliuc, E., Bank, W., & Lindert, K. (2000). *Risk and vulnerability in Guatemala: a quantitative and qualitative assessment Scaling up Delivery Systems for Social Safety Nets (Book Chapter) View project*. http://www.worldbank.org/sp.

Træ rup, S., & Mertz, O. (2011). Rainfall variability and household coping strategies in northern Tanzania: A motivation for district-level strategies. *Regional Environmental Change*, *11*, 471–481. https://doi.org/10.1007/s10113-010-0156-y

Vesco, P., Kovacic, M., Mistry, M., & Croicu, M. (2021). Climate variability, crop and conflict: Exploring the impacts of spatial concentration in agricultural production. *Journal of Peace Research*, *58*(1), 98–113. https://doi.org/10.1177/0022343320971020

World Bank. (2017). *THE WELFARE EFFECTS OF EXTREME WEATHER EVENTS-INSIGHTS FROM THREE APEC CASE STUDIES*.

Appendices

Table1: Mean test of Dependent, Independent, Control Variables

Variables	No Rainfall Shock	Mean1	Rainfall Shock	Mean2	MeanDiff
Household Size	11617	4.611	1375	5.491	-0.880***
Children (6-14)	11617	1.128	1375	1.418	-0.291***
Adult (15-64)	11617	2.410	1375	2.642	-0.232***
Female Head	11617	0.808	1375	0.911	-0.103***
Age	11617	41.88	1375	43.23	-1.353***
Level of education	11617	2.601	1375	1.925	0.676***
Highest certificate	11617	0.778	1375	0.287	0.491***
Marital status	11617	2.267	1375	2.368	-0.101***
Household Health	11617	0.0630	1375	0.0840	-0.021***
Household residence zones	11617	1.569	1375	1.807	-0.238***
Region	11617	15.37	1375	16.46	-1.093***
Input					
Plot Area (Yam farm)	1423	6.610	361	12.36	-5.752
Plot Area (Maize farm)	915	2.388	289	2.346	0.0420
Plot Area (Rice Yam)	1237	1.393	346	1.570	-0.177

Labor force Family (Yam farm)	1424	0.870	361	0.934	-0.063**
Labor force Family (Maize farm)	915	0.898	289	0.986	-0.088***
Labor force Family (Rice farm)	1237	0.871	346	0.925	-0.053**
Labor force Non-family (Yam farm)	1424	0.588	361	0.604	-0.0160
Labor force Non-family (Maize farm)	915	0.471	289	0.540	-0.069*
Labor force Non-family (Rice farm)	1237	0.559	346	0.523	0.0360
Pesticide (Rice farm)	1237	0.740	346	0.740	0
Pesticide (Maize farm)	915	0.730	289	0.792	-0.062**
Pesticide (Yam farm)	1424	0.195	361	0.213	-0.0180
Inorganic Fertilizer (Rice farm)	1237	0.271	346	0.292	-0.0210
Inorganic Fertilizer (Maize farm)	915	0.459	289	0.453	0.00600
Inorganic Fertilizer (Yam farm)	1424	0.00900	361	0.0140	-0.00500
Inorganic Fertilizer (Rice farm)	6360	0.00400	1268	0.00300	0.00100
Rice Yields	885	978.8	256	929.7	49.14
Yam Yields	628	1736	178	1723	13.07
Maize Yields	820	3059	198	1532	1526
Food consumption	11617	12.18	1375	11.87	0.308***
Non-Food Consumption	11617	12.35	1375	12.15	0.202***
Shannon Index	11275	0.678	1365	0.616	0.061***

Table 2: Summary Statistics for all Variables

Variable	Obs	Mean	Std. dev.	Min	Max
Rainfall Shock	12,992	.1058344	.3076373	0.	1
Household Size	12,992	4.704126.	2.997814.	1.	32
Children (0-5)	12,992	.9659021	1.100937	0	9
Children (6-14)	12,992	1.158405	1.400925	0	13
Adult (15-64)	12,992	2.434344	1.479493	0	22
Female head	12,992	.8188116	.385189	0	1
Household age	12,992	42.02009	13.94396	12	102
Household Educ. Level	12,992	2.529326	2.162956	1	9
Household Highest Certificate	12,992	.7257543	1.708579	0	10
Household handicap	12,992	.0649631	.2464701	0	1
Household					

Lieu of Residence	12,992	1.594058	.4910923	1	2
Region	12,992	15.48268	10.14259	1	33
Plot Area Yam Farm	1,784	7.783331	157.5443	1.00e-06	500
Plot Area Maize Farm	1,204	2.386071	2.797684	.000025	40
Plot Area Rice Farm	1,583	1.427865	3.8244	.000025	100
Labor Force Family Rice Farm	1,785	.8823529	.4801521	0	4
Labor Force Family Maize Farm	1,204	.9210963	.386282	0	3
Labor Force Family Yam Farm	1,583	.8831333	.4232345	0	4
Non-family Labor Force Yam Farm	1,785	.5983193	.5823425	0	4
Non-Family Labor Force Maize Farm	1,204	.486711	.5353562	0	3
Non-Family Labor Force Rice Farm	1,583	.5552748	.5374199	0	3
Pesticide Rice Farm	1,583	.739103	.4392626	0	1
Pesticide Maize Farm	1,204	.7458472	.4355648	0	1
Pesticide Yam Farm	1,785	.2005602	.4005318	0	1

Inorganic Fertilizer Rice Farm	1,583	.2754264	.4468701	0	1
Inorganic Fertilizer Maize Farm	1,204	.4584718	.4984795	0	1
Inorganic Fertilizer Yam Farm	1,785	.010084	.0999397	0	1
Fertilizer Spreader	7,628	.0039329	.0625933	0	1

Table 3: Regression Results Agricultural production

VARIABLES	(1) Yam Yield	(2) Maize Yield	(3) Rice Yield
Self-Reported Rainfall shock	-0.248**	-0.039	-0.181*
	(0.120)	(0.106)	(0.091)
Plot Characteristics Plot Area	-0.000	0.187***	0.008
	(0.000)	(0.040)	(0.012)
Non-family Labor force	0.520***	0.138*	0.200***
	(0.090)	(0.084)	(0.067)
Family Labor force	0.053	0.120	0.096
	(0.108)	(0.107)	(0.088)
Number of Workers (15 -64)	0.037	0.031	0.024
	(0.054)	(0.050)	(0.039)
Input Inorganic fertilizer	-0.509	0.467***	0.370***
	(0.585)	(0.123)	(0.091)
Pesticide	0.342***	0.351***	0.357***
	(0.131)	(0.120)	(0.087)
Agroecological Zone	-0.287*	-0.065	0.156
	(0.155)	(0.292)	(0.144)
Household Size	0.043*	0.030	0.049***
	(0.025)	(0.023)	(0.017)
Manager Characteristics (1 = Female) Female Manager	0.325**	0.481***	0.292**
	(0.138)	(0.175)	(0.136)
Age	-0.003	-0.005	-0.001
	(0.004)	(0.004)	(0.003)
Education Level	0.046	-0.076**	-0.013

	(0.040)	(0.038)	(0.026)
Milieu			
Rural Area	0.233*	0.130	-0.102
	(0.132)	(0.135)	(0.097)
District Fixed Effects			
Bas-Sassandra	-1.313**	-0.472	-0.097
	(0.535)	(0.562)	(0.408)
Comoé	-2.308***	-0.469	0.168
	(0.573)	(0.756)	(0.400)
Denguelé	-1.911**	-0.582	
	(0.867)	(1.326)	
Goh-Djiboua	-0.966*	-0.346	0.264
	(0.550)	(0.477)	(0.278)
Lacs	-1.806**	-0.564	1.202*
	(0.765)	(1.313)	(0.652)
Lagunes	-1.268	-1.214*	0.423
	(0.877)	(0.697)	(0.418)
Montagnes	-2.635***	-0.319	-0.265
	(0.701)	(1.016)	(0.496)
Sassandra-Marahoué	-1.847***	-0.677	0.157
	(0.647)	(1.000)	(0.511)
Savanes	-1.121*	-0.164	0.215
	(0.605)	(0.764)	(0.403)
Vallée de Bandama	-1.452**	-0.516	-0.214
	(0.707)	(0.791)	(0.491)
Woroba	-0.901	-0.010	0.370
	(0.563)	(0.759)	(0.395)
Zanzan	-1.389**	-0.939	-0.424
	(0.555)	(0.759)	(0.712)
Constant	7.369***	5.306***	4.556***
	(0.931)	(1.537)	(0.804)
Observations	1,021	808	1,143
R-squared	0.135	0.387	0.267

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Welfare Regression results

VARIABLES	(1) Per capita Non- Food Consumption	(2) Per capita Food Consumption	(3) Per capita Consumption Expenditure	(4) Shannon Index
Reported Rainfall Shock	-0.080***	-0.019	-0.032**	-0.020*
	(0.019)	(0.018)	(0.016)	(0.012)
Household Size	-0.070***	-0.065***	-0.067***	-0.001
	(0.003)	(0.003)	(0.003)	(0.002)
% Children (0-5)	-0.906***	-0.727***	-0.809***	0.078*
	(0.067)	(0.061)	(0.055)	(0.044)
% Children (6-14)	-0.645***	-0.498***	-0.594***	0.075*
	(0.063)	(0.057)	(0.051)	(0.042)
% Male (15-39)	0.222***	0.210***	0.213***	0.000
	(0.062)	(0.053)	(0.050)	(0.040)
% Female (15-39)	0.198***	0.039	0.097*	0.185***
	(0.066)	(0.058)	(0.053)	(0.041)
% Male (40-59)	0.244***	0.248***	0.238***	-0.022
	(0.067)	(0.055)	(0.052)	(0.042)
% Female (40-59)	0.032	-0.166***	-0.076	0.110**
	(0.070)	(0.060)	(0.057)	(0.044)
Female Head	-0.069***	-0.128***	-0.100***	-0.037***
	(0.021)	(0.018)	(0.017)	(0.011)
Household Marital status	-0.030***	-0.030***	-0.028***	-0.015***
	(0.006)	(0.006)	(0.005)	(0.004)
Household handicap	0.000	0.030	0.017	0.003
	(0.024)	(0.023)	(0.021)	(0.015)
Age	0.021***	0.005*	0.013***	0.007***

	(0.003)	(0.003)	(0.003)	(0.002)
Level of Education	0.098***	0.035***	0.067***	0.008***
	(0.004)	(0.003)	(0.003)	(0.002)
District Fixed Effect				
Abidjan	0.170***	0.197***	0.063**	0.083***
	(0.030)	(0.026)	(0.025)	(0.019)
Bas-Sassandra	0.066*	0.169***	0.111***	0.029
	(0.035)	(0.033)	(0.030)	(0.022)
Comoé	0.593***	0.432***	0.341***	0.228***
	(0.027)	(0.022)	(0.021)	(0.018)
Denguelé	0.195***	0.231***	0.145***	0.175***
	(0.039)	(0.034)	(0.032)	(0.026)
Goh-Djiboua	0.057**	0.043*	0.045**	0.154***
	(0.027)	(0.025)	(0.023)	(0.018)
Lacs	-0.054**	0.004	-0.040**	0.051***
	(0.024)	(0.021)	(0.019)	(0.018)
Lagunes	-0.101***	0.052**	-0.130***	0.188***
	(0.029)	(0.023)	(0.022)	(0.017)
Montagnes	-0.159***	-0.139***	-0.128***	0.019
	(0.025)	(0.023)	(0.021)	(0.018)
Sassandra-Marahoué	0.052*	0.015	0.049**	0.049***
	(0.027)	(0.024)	(0.022)	(0.019)
Savanes	0.180***	-0.014	0.067***	-0.034*
	(0.026)	(0.025)	(0.022)	(0.020)
Vallée du Bandama	0.162***	0.048*	0.079***	0.051***
	(0.027)	(0.025)	(0.022)	(0.019)
Woroba	-0.040	-0.002	-0.026	0.011
	(0.027)	(0.025)	(0.023)	(0.019)
Yamoussoukro	0.093***	0.283***	0.190***	0.149***
	(0.029)	(0.025)	(0.023)	(0.019)
Constant	12.009***	12.745***	13.195***	0.433***
	(0.094)	(0.080)	(0.076)	(0.057)
Observations	12,992	12,992	12,992	12,640
R-squared	0.542	0.449	0.529	0.104

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 5: Robustness Check

VARIABLES	(1) Rice Yield	(2) Yam Yield	(3) Maize Yield
Negative Rainfall shock	-0.016	-0.112***	-0.074
	(0.088)	(0.046)	(0.057)
Observations	1,141	1,021	806
R-squared	0.260	0.129	0.382

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1