Essays on Smallholder Behavior in Response to Resource Challenges in Sub-Saharan Africa

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(ABSTRACT)

This dissertation consists of three chapters that address two major resource challenges faced by smallholder farmers in Sub-Saharan Africa: (i) weather shocks and (ii) limited land access for agricultural production. The first chapter looks at how weather shocks affect millet production and millet market price seasonality in Niger. In this paper, we use district-level longitudinal production and price data, along with high-resolution rainfall data to investigate the distinct impacts of positive and negative rainfall shocks on millet production and millet price seasonality in Niger. We find that a one standard deviation decrease in seasonal rainfall from historical averages is associated with declines in millet market price initially after harvest, but strong upward pressure on market prices 6 months after harvest. As a result, drought exacerbates existing price seasonality, which in turn can amplify negative impacts on households. Social protection programs need to account for potential increases in seasonal price variability in the design of programs to enhance household resilience to weather shocks.

To better understand the household behavior that gives rise to the price responses observed in the first chapter, we explore weather shock impacts on household millet market participation in Niger in the second chapter. We merge a nationally representative household panel data with high-resolution spatially disaggregated rainfall data. We find that households are more likely to participate in the market as net sellers with negative rainfall shocks, but marketed quantity for net sellers decreases with negative rainfall shocks. Diversification into non-agricultural activities can mediate the impacts of negative rainfall

shocks on market participation and lead to increases in volume of sales. Policies that support household involvement in the rural nonfarm economy through training and access to credit to help expand businesses may also stimulate millet market participation.

In the third chapter, we use a rich dataset of 1,123 households to examine the determinants of individual household member access to groundnut fields, the predominant cash-crop in the Groundnut Basin of Senegal. The analysis also explores the implications of limited land access on groundnut productivity of young adult and female field managers. We find that young adults and females have fewer opportunities to access land compared to older and male household members. Further, we show that higher productivity may not be driving differential access to fields among older adults. Results suggest that with equal access, young adults may be as or more productive groundnut cultivators than older adults. Programs to increase young adult and female economic opportunities should focus on closing gaps in access to resources for production rather than decreasing observed production disparities.

Essays on Smallholder Behavior in Response to Resource Challenges in Sub-Saharan Africa

Ange Thomas Kakpo

(GENERAL AUDIENCE ABSTRACT)

This dissertation addresses two major challenges that small farmers face in Sub-Saharan Africa: (i) erratic changes in weather patterns and (ii) land access for agricultural production. We divide the dissertation in three chapters. The first two chapters focus on weather shocks, while the third chapter focuses on land access.

In the first chapter, we discuss how low and high rainfall affect the seasonal variation of market prices for the most important staple grain (millet) in Niger (West Africa). We find that lower rainfall than usual makes households sell their millet in the post-harvest period when market prices are generally low, and makes them buy back millet in the lean season when market prices are often high. As a result, policies that aim support household resilience to climate shocks should design programs that account for potential increases in seasonal price variability.

In the second chapter, we study how low rainfall levels affect Niger millet farmers' decision to sell or not sell their harvest, as well as the association between low rainfall and the quantity of millet sold and bought. We distinguish three groups of farmers: (i) net buyers who have higher millet purchases than sales, (ii) autarkic who have zero millet purchases and millet sales, and (iii) net sellers who have higher sales than purchases. Our findings show that lower rainfall increases net sellers' probability to sell their millet, whereas it decreases the quantity they sell. Our results also reveal that households who diversify their sources of income into non-agricultural activities increase millet net sales even with low

rainfall levels. Policies that support household involvement in these non-agricultural activities may also stimulate millet market participation.

In the third chapter, we study the factors that affect household members' access to a groundnut field in Senegal with a particular focus on young adults and females. We show that females and young adults are less likely to access a field compared to older and male household members. Our results also suggest that with equal access, young adults may be as or more productive groundnut cultivators than older adults. Programs to increase young adult and female economic opportunities should focus on closing gaps in access to resources for production.

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CHAPTER 1: Weather Shocks and Food Price Seasonality in Sub Saharan Africa: Evidence from Niger

Ange T. Kakpo, Bradford F. Mills and Stéphanie Brunelin

Abstract

Semi-Arid regions of Sub-Saharan Africa are vulnerable to weather shocks, especially rural areas where households depend on rainfed agriculture and access to stable food markets are limited by high transaction costs. Understanding how weather shocks affect rural Sub-Saharan African households through both production and market price changes is crucial in designing sustainable and effective programs to increase resilience. Weather shock impacts on agricultural production and market prices are well documented in Africa. But little is known about the impacts of weather shocks on market price seasonality, which is an important determinant of food security. We investigate the distinct impacts of positive and negative rainfall shocks on millet production and millet price seasonality in Niger using district-level longitudinal production and price data, along with high-resolution rainfall data. We find that a one standard deviation decrease in seasonal rainfall from historical averages is associated with declines in millet market price initially after harvest, but strong upward pressure on market prices 6 months after harvest. As a result, drought exacerbates existing price seasonality, which in turn can amplify negative impacts on households. Social protection programs need to account for potential increases in seasonal price variability in the design of programs to enhance household resilience to weather shocks.

Keywords: Weather Shocks, Price seasonality, Millet, Niger.

1.1. Introduction

Sub-Saharan Africa (SSA) has experienced one of the highest rates of population growth in the world over the past three decades, increasing from 425,840,821 in 1985 to 958,577,179 people in 2015 (United Nations, 2019[1]). Direct consequences of rapid population growth are increased food demand and the need to increase both staple food supply and stable access to food commodity markets. At the same time, extreme weather events like droughts are recurrent and make millions of smallholder farmers vulnerable to food insecurity. Moreover, exposure to extreme weather events is expected to increase in many areas of SSA in coming years (Mirza, 2003). Rural semi-arid regions of West Africa are particularly vulnerable to rainfall shocks, as households are largely dependent on rainfed agriculture and access to staple food markets are limited by high transaction costs (Padgham et al., 2015). Understanding how weather shocks affect rural West African households through both production and market price changes is crucial for the design of sustainable and effective programs to increase household resilience.

There is ample empirical evidence of links between weather shocks and economic, social, and political outcomes. Adverse weather conditions have been shown to reduce crop yields (Amare et al., 2018; Arslan et al., 2017; Bezabih et al., 2014; Kubik and Maurel, 2016; Schlenker and Lobell, 2010), households farm income (Noack et al., 2019) and household food consumption (Gao and Mills, 2018; Letta et al., 2018). Similarly, adverse weather conditions lead to a reduction of livestock weight gains and milk production (Thornton, 2012) and increased infant mortality and reduced life expectancy (Andalón et al., 2016; Meierrieks, 2021). Other studies find that negative weather shocks increase both internal (Gray et al., 2020) and international migration (Bazzi, 2017), as well as violent conflicts in SSA countries (Maystadt and Ecker, 2014; O'Loughlin et al., 2014).

[1] https://population.un.org/wpp/Download/Standard/Population/

Market prices are an important channel of weather shock impacts. Adverse weather conditions are associated with higher food market prices (Chen and Villoria, 2019; Hill and Fuje, 2020; Mirzabaev and Tsegai, 2012), price dispersion, along with increased market integration, and price transmission (Aker, 2012; Hatzenbuehler et al., 2020; Mirzabaev and Tsegai, 2012). Research to date has not explored the effects of weather shocks on market price seasonality in SSA, even though price seasonality is pronounced in many SSA staple food markets. Prices often peak in the hungry season when household stocks are exhausted and the current crop is not ready for harvest.

We add to the literature on weather shock impacts by investigating how rainfall-induced production shocks affect market price seasonality. Specifically, we match a time series of high-resolution district-level rainfall data with millet production data and millet market price data from Niger to answer two research questions: (i) How do rainfall shocks affect millet production? (ii) How do rainfall shocks affect market price seasonality? We model the effects of rainfall shocks on production and price seasonality in two steps. We first use a district-level Fixed-Effects (FE) regression to quantify rainfall shock effects on millet production. We then use rainfall shock variables as covariates in a second district-level FE regression with monthly millet prices as the dependent variable. The effects of rainfall shocks on millet price seasonality are determined by interacting rainfall shocks with month indicators to quantity impacts in each of the 12 months following a shock.

Rainfall shock impacts on millet market price seasonality in Niger is particularly relevant for several reasons. Niger is one of the poorest countries in the World (UNDP[2], 2018), ranked 189th (last) in the Human Development Index. Agriculture is the main sector of Niger's economy, contributing about 40% of the country's GDP. About 75% of Niger's rural population is engaged in agriculture (World Bank[3], 2018), making agriculture the

[2] http://hdr.undp.org/en/countries/profiles/NER
[3] Website consulted on 11/21/2019. https://data.worldbank.org/indicator/SL.AGR.EMPL.ZS?end=2019&locations=NE&start=1991&view=chart

dominant household livelihood strategy. Niger is also frequently affected by weather shocks, given its reliance on rainfed agriculture and frequent droughts (Aker, 2012). Millet is the primary staple crop in Niger, both in terms of production and consumption, particularly for the rural poor. From 2010 to 2014, millet production accounted for between 68 to 80% of total cereal production in Niger (INS[4], 2018), with an estimated per capita consumption of 0.6 kg/day. Millet is generally planted at the beginning of the growing season (around June) and is harvested around October. Household millet stocks are usually high during the harvest and immediate post-harvest seasons (October to January), and low during the lean season (May to September). Given rural households' reliance on millet, weather-induced millet production shocks often translate into consumption shortfalls (Gao and Mills, 2018). This study focuses on the two important pathways, production and price, by which rainfall shocks influence household well-being. As most weather shocks in Niger are drought related, we employ the most common drought-related measure in semi-arid areas, rainfall anomaly (measured as the standardized deviation of seasonal rainfall from historical averages, and also called a rainfall z-score). We compute rainfall z-scores by district and year and construct measures of positive and negative rainfall shocks indicators to investigate the effects of rainfall shocks on millet production and millet price seasonality.

We show that positive rainfall shocks increase millet production, while negative rainfall shocks decrease production. Specifically, a one standard deviation increase in seasonal rainfall with respect to historical rainfall averages increases production by approximately 20%, while a one standard deviation decrease in seasonal rainfall with respect to historical rainfall averages decreases production by 18%. Further, we show that a negative rainfall shock decreases price initially after harvest (relative to baseline seasonal changes), but price becomes higher relative to baseline seasonal changes later in the lean season. By contrast, positive rainfall shocks have a consistent negative impact on millet prices post-

[4] National Statistics Institute in Niger. Website consulted on 11/21/2019. http://niger.opendataforafrica.org/

harvest into the lean season. The result of these asymmetric responses to rainfall shocks is that positive rainfall shocks smooth price seasonality while unfavorable rainfall shocks exacerbate price seasonality.

The rest of the paper is organized as follows. The next section presents the conceptual framework for millet market price formation and price seasonality in response to rainfall shocks. Section 3 describes the data used for this study and presents summary statistics. Sections 4 presents the empirical model and identification strategy. The results are presented in section 5. Section 6 discusses our results and lays out policy recommendations. Section 7 concludes the paper.

1.2. Conceptual framework

Negative rainfall shocks are generally expected to decrease household millet market supply and place upward pressure on market prices. However, shock impacts are more complex when households are both millet producers and millet consumers and also face strong seasonal credit or liquidity constraints (Sadoulet and De Janvry, 1995). Under these conditions households may increase market sales at harvest following a negative rainfall shock, as the strong need to address seasonal credit constraints raises the shadow price of millet sales (Stephens and Barrett, 2011). The result is a commonly observed SSA smallholder phenomena of households selling at low prices at harvest and then later purchasing the same commodity in the lean season at higher prices (Alderman and Shively, 1996; Barrett, 2007). If negative rainfall shocks trigger a substantial share of households to pursue such sell low, buy high marketing strategies, then negative shocks will place initial downward pressure on market prices at harvest and later in the lean season will place upward pressure on market prices when household stocks are exhausted. These forces can, in aggregate, generate increases in market price seasonality.

Previous studies have linked sell low, buy high strategies directly to credit and liquidity constraints. (Stephens and Barrett, 2011) find that access to liquidity in the form of credit or off-farm income increases farmers' ability to take advantage of arbitrage opportunities and reduces the likelihood of selling low and buying high. On the other hand, post-harvest liquidity constraints (e.g. paying for children's school fees) are shown to generate sell low, buy high behavior (Dillon, 2020). Burke et al. (2019) employ a randomized controlled trial to show that providing timely access to credit at harvest to maize farmers in Kenya increases grain storage, and reduces household use of sell low, buy high strategies. Directly relevant for this paper, they find that increased provision of credit to households decreases price seasonality in local maize markets.

Several factors are associated with the lack of credit among smallholder farmers in Niger. Transaction costs linked to geographical distance usually translate into higher interest rates, leading to a low credit access by the rural poor (Pedrosa and Do, 2011). Moreover, investments in climate-resilient technologies are perceived as high-risk by local microfinance institutions, thereby reducing the financial support needed to improve access to credit (IFAD, 2019*)*. Land access is another barrier to smallholder farmers credit access in Niger. Land is often used as collateral for agricultural credit and most rural borrowers are unable to provide property titles (World Bank, 2011). Stoeffler et al. (2020) find that medium-term (18 months) continuous cash transfers reduce liquidity constraints and foster productive asset accumulation.

Two inter-related factors make rural households in Niger likely to face binding credit and/or liquidity constraints at harvest with a negative rainfall shock. First, negative rainfall shocks affect all crops, not just millet. This leads to a sharp drop in income relative to expectations. Lack of credit or other income smoothing mechanisms leave households with limited short-term ability to adjust to new income levels, and raise the shadow price of millet sales as a short-term income smoothing mechanism. Second, households may have purchased or borrowed inputs with the expectation of repayment at harvest. Lower millet production levels and associated incomes raise the shadow price of millet sales to repay debts. Rainfall shocks may affect millet price seasonality in Niger by changing households subjective intra-annual discount rates in the face of impending scarcity. Short-term money scarcity makes individuals more present biased when making intertemporal money-related decisions, and more focused on meeting pressing needs at the expense of longer-term economic well-being (Carvalho et al., 2016). In the Niger context, an increase in present bias associated with a poor harvest will also increase the household shadow price of millet sales immediately after harvest to meet immediate needs, even if households will need to purchase millet later in the hungry season at a higher market price.

The influences of negative rainfall shocks on household use of sell low, buy high strategies and on associated amplifications of market price seasonality are largely empirical questions, the latter of which is directly addressed in the rest of this paper.

1.3. Data and Summary Statistics

1.3.1. Data

This study uses three types of longitudinal data: millet price, millet production and rainfall. Millet price data comes from 89 markets and production data comes from 36 districts in Niger. The analysis focuses on 46 markets and 32 districts where less than 50% of observations are missing[5]. The selected markets and districts are located in the major millet producing areas of Niger. The price data contains monthly price information from 1990 to 2016, and the production data contains yearly production information from 1985 to 2016. The price data is obtained from Niger's Market Information System (SIMA). The SIMA was set up by Niger's Office of Food Products (OPVN) in 1989 to provide various stakeholders (public authorities, private operators, and farmers) with price information to help them make more informed decisions. Currently, the SIMA follows 74

[5] Results are robust to alternative exclusion criteria of 20% and 10% of missing market prices and available from the authors upon request.

markets[6] (including eight cross-border marketplaces in Nigeria and Benin) and 44 food products. The millet production data is obtained from Niger's Ministry of Agriculture.

We merge the millet production and millet price data with gridded daily rainfall from 1985 to 2016 at 0.05 degree spatial resolution. The rainfall data come from the National Oceanic and Atmospheric Administration (NOAA) website[7]. After download, we extract rainfall values for each day in the 32 districts retained for the analysis over the period 1985 - 2016 by averaging rainfall values for all of the grid points in a given district. To analyze the effects of rainfall shocks on production and price, we construct rainfall z-scores for each district ($zscore_{it}^{Rain}$), calculated as follows:

$$zscore_{it}^{Rain} = \frac{R_{it} - \overline{R}_i}{R_i^{SD}} \quad (1)$$

Where R_{it} is cumulative rainfall in district i and growing season t; $\overline{R}_i$ is the 30-year (1981-2010) average of seasonal rainfall in district i, and R_i^{SD} is the standard deviation of cumulative seasonal rainfall in district i. Since annual rainfall shows no clear trend over time, we focus on deviation from long-term district averages. The rainfall z-scores are then used to construct positive and negative rainfall shock dummies initially defined as $zscore_{it}^{Rain} > 1$ and $zscore_{it}^{Rain} < -1$ respectively. We justify the choice of the ±1 SD threshold by estimating the quadratic relationship between rainfall z-scores and the percentage change in detrended production (figure 1.1). For rainfall z-scores lower than -1, millet production decreases more sharply than it increases for rainfall z-scores higher than 1. Production decreases with respect to average are even higher for rainfall z-scores lower than -1.5, whereas for rainfall z-scores higher than 1.5, we observe very little change in production with respect to average. Production and price responses with ±0.7 SD (mild rainfall shocks) and ±1.5 SD (strong rainfall shocks) thresholds are also examined in the analysis as robustness checks.

[6] SIMA Website : http://simaniger.cilss.int/index.php/marches/

[7] https://www.ncei.noaa.gov/data/

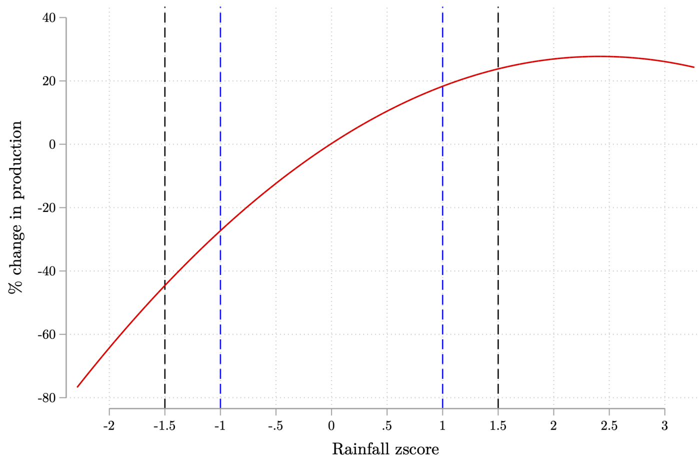

Figure 1.1: Changes in millet production as a function of rainfall z-scores

Notes: The red line reflects the equation $Pr_{it} = \beta_1 \ zscore_{it}^{Rain} + \beta_2 (zscore_{it}^{Rain})^2$ where Pr_{it} is the percentage change of millet production in district i and year t, with respect to the linearly detrended average production in district i.

Figure 1.2 shows the percentage of districts experiencing positive and negative ± 1 SD rainfall shocks over time. There are years with neither a positive nor a negative rainfall shock. In other years more than 50% of districts have a negative rainfall shock, and in some years, more than 80% have a positive rainfall shock. The inter-annual variability of average rainfall across all districts is presented in figure A1. Average rainfall shows large fluctuations between years. Rainfall is also generally higher in the southern districts (figure A2).

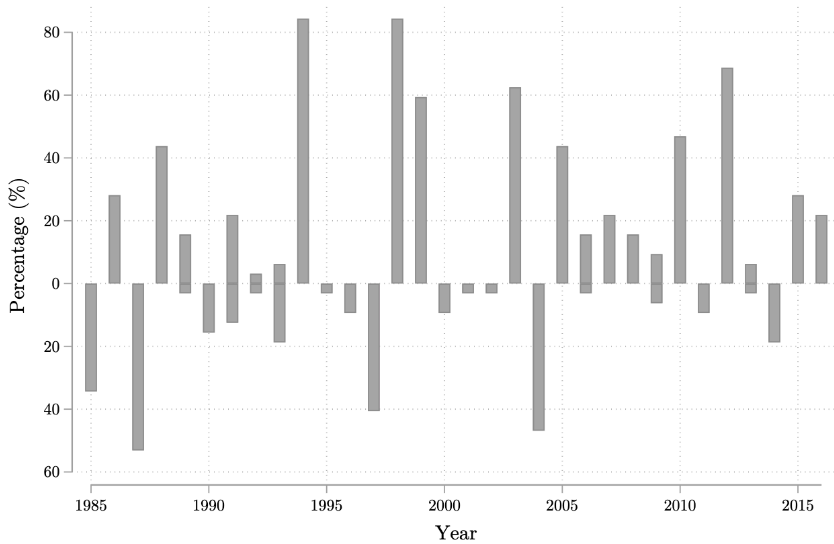

Figure 1.2: Share of districts experiencing positive and negative rainfall shocks by year

Notes: The bars facing up represent the yearly percentages of districts with positive rainfall shocks and the bars facing down represent the yearly percentages of districts that have experienced negative rainfall shocks.

1.3.2. Spatial and temporal variability of millet production and millet price

Figure 1.3 shows annual variation millet production in Niger from 1985 to 2016 around a clear linear upward trend. Millet production has trended upward over the years, with substantial fluctuations around a linear trend. To examine production fluctuations over the years, we compute production z-scores:

$$zscore_{it}^{Prod} = \frac{Y_{it} - \bar{Y}_{it}}{\sigma_i^Y} \quad (2)$$

Where Y_{it} is millet production in district i, and growing season t; $\bar{Y}_{it}$ is the long-term average of millet production in district i adjusted for the linear time trend. σ_i^Y is the long-term standard deviation of millet production around a linear time trend. We then define positive production shock as equal to 1 when $zscore_{it}^{Prod}$> 1 and 0 otherwise, and negative production shock as equal to 1 when $zscore_{it}^{Prod}$it < -1 and 0 otherwise. Figure 1.4 presents yearly averages of district production z-scores after detrending.

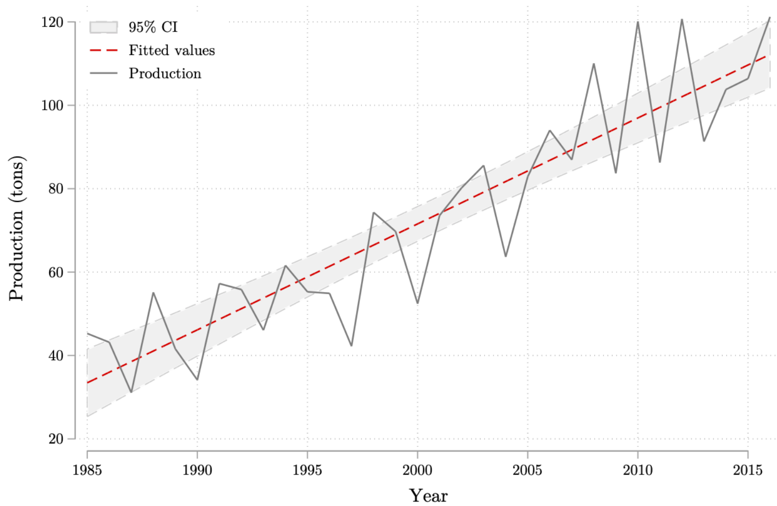

Figure 1.3: Millet production overtime

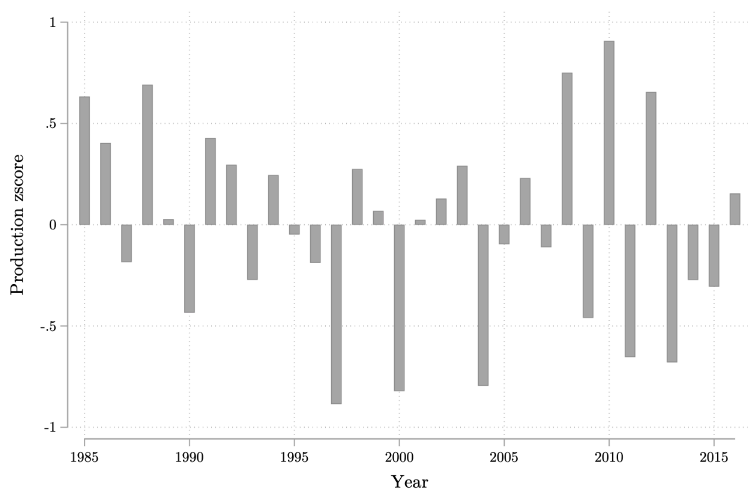

Figure 1.4: Average yearly production z-scores

Over the 1985 to 2016 period, millet production in Niger is larger in southern districts (figure A3), due to more favorable climatic conditions in the south while average coefficient of variation (CV) of millet production by district over the same period (figure A4) increases as one moves northward into less climatically favorable districts. Figure A5 shows the inter-annual distribution of monthly millet price over the period 1990 to 2016.

Similar to the production patterns, average monthly millet price has fluctuated over the years with a general upward trend. We also observe large seasonal variations in prices (figure A6). Prices are low on average, right after harvest in October, trend up during the lean season (January to August), and decrease with the approach of harvest in the next October.

1.3.3. Summary Statistics

Descriptive statistics in table 1.1 show that average annual millet production is approximately 73 tons per district, and average millet price of 158 CFA[8] francs/kg, with significant variability within and across districts in both cases. Rainfall conditions over the period 1985-2016 have not been favorable with average cumulative seasonal rainfall per district of just over 400 mm. In good rainfall years with rainfall greater than one standard deviation above the historical rainfall average, seasonal rainfall is on average 1.6 standard deviation higher than historical rainfall averages and in bad rainfall years, the average seasonal rainfall is approximately 1.3 standard deviation lower than historical rainfall averages. The average production z-scores for districts that experienced positive and negative production shocks are 1.5 standard deviations higher and 1.4 standard deviations lower than long-term productions averages, respectively.

1.3.4. Cross sectional dependence and non-stationarity

Millet production levels from different districts are not independent from each other due to covariate exposure to rainfall. Likewise, millet prices across districts are likely to be correlated due to market price transmission (Aker, 2012; Hatzenbuehler et al., 2020). Failing to account for cross-sectional dependence in panel data settings can result in inconsistent estimates and invalid standard errors (Meierrieks, 2021; Sarafidis and Wansbeek, 2012). We test our production, price, and rainfall data for the presence of cross-sectional dependence

[8] The CFA franc is the currency used in Niger. 1US$ = 550 CFA francs: https://www.xe.com/currencyconverter/convert/?Amount=373andFrom=XOFandTo=USD, consulted on March 5, 2021.

using the CD-test of Pesaran (2015). As shown in table 1.2, all three variables are affected by cross-sectional dependence. We account for cross-sectional dependence by estimating Driscoll-Kraay standard errors that are robust to general forms of spatial and temporal dependence in panel data for all of our regressions.

Moreover, since both production and price are trending overtime (figure 1.3 and figure A5), they could be non-stationary. Non-stationarity can also lead to inconsistent estimates. We test for the presence of non-stationarity using a Fisher-based panel unit root test proposed by (Choi, 2001). Fischer tests suggest stationarity for the production, price and rainfall data (table 2).

1.4. Empirical approach

The empirical objective of this study is to identify the impacts that positive and negative rainfall shocks have on millet production and on millet price seasonality in Niger. First, we regress production on positive and negative rainfall shocks. Second, we regress monthly price on rainfall shocks.

A crucial concern in our identification strategy is the timing of rainfall shock transmission to prices. In other words, in the event that millet crops experience a rainfall shock during the crop season, will prices respond immediately or will prices only respond later after lower production levels are reflected in the market stocks? To answer this important timing question, we quantify the impacts of rainfall shocks on the seasonal pattern of prices.

Our empirical model for millet production is specified as follows:

$$ln(Y_{it}) = \alpha + \beta_1 \text{Pos\_rain}_{it} + \beta_2 \text{Neg\_rain}_{it} + \mu_i + \delta_t + \varepsilon_{it} \tag{3}$$

Where Y_{it} is millet production in season t and district i; Pos_rain_{it} and Neg_rain_{it} stand for our positive and negative rainfall shock indicators respectively; δ_t is a linear time trend that captures area expansion and technology advancement (e.g. adoption of improved varieties and other factors that boost millet production overtime); μ_i is district fixed-effects that capture all time-invariant district-specific determinants of millet production and ε_{it} is the error term.

To determine rainfall shock impacts on price seasonality, we interact rainfall shock indicators from equation 3 with month indicators and run the following regression:

$$\ln(\mathrm{P_{itm}}) = \gamma + \rho_1 Pos\_rain_{\mathrm{i,t-1}} + \rho_2 Neg\_rain_{\mathrm{i,t-1}} + \sum_{\mathrm{m=2}}^{12}[\chi_{1m} Neg\_rain_{\mathrm{i,t-1}} * \mathrm{D_m}] + \sum_{\mathrm{m=2}}^{12}[\chi_{2m} Pos\_rain_{\mathrm{i,t-1}} * \mathrm{D_m}] + \mathrm{D_m} + \phi_\mathrm{t} + \nu_\mathrm{i} + \omega_{\mathrm{1itm}} \quad (4)$$

Where P_{itm} is millet price in month m, agricultural[9] year t, and district i. $Pos\_rain_{\mathrm{i,t-1}}$ and $Neg\_rain_{\mathrm{i,t-1}}$ represent positive and negative rainfall shock variables in the past cropping season respectively; ν_i is the district fixed-effect. ϕ_t captures agricultural year fixed-effects, which capture any aggregate time-varying determinants of price, such as nation-wide policies. D_m is an indicator variable for month m (first month is October and twelfth month is September). Equations 3 and 4 are all estimated using Fixed-Effects (FE) regressions, which capture time-invariant district heterogeneity and Niger-wide agricultural year trends. As mentioned in section 3.4, we estimate Driscoll-Kraay standard errors to control for cross-sectional dependence and heteroskedasticity.

1.5. Results

1.5.1. Effects of rainfall shocks on millet production

Table 1.3, column 1 displays the main regression results for positive and negative rainfall shock impacts on millet production. As expected, we find that positive rainfall shocks are associated with increases in production and negative rainfall shocks are associated with decreases in production. Estimates are all statistically significant at the 1% level, and economically important. A positive rainfall shock increases production by approximately

[9] The agricultural year for millet in Niger goes from October (the harvest month) to September. As such, a rainfall shock in growing season t-1, will affect millet price in agricultural year t.

20%[10] while a negative rainfall shock decreases production by approximately 18%. The results suggest that early warning systems with triggers to monitor negative rainfall shocks in the growing season can predict a significant share of millet production shortfalls in the semi-arid conditions found in Niger.

1.5.2. Effects of rainfall shocks on millet price seasonality

We now turn to rainfall shock effects on price seasonality. Millet price is regressed on the interaction between rainfall shocks and month indicators, with October[11] being the base, along with year and month fixed-effects. The results for positive and negative rainfall shocks are presented in columns (1) and (4) of table 1.4 respectively. Figure 1.5 plots the month specific effects of a positive rainfall shock (Panel A) and a negative rainfall shock (Panel B) on ln(price) relative to the seasonal baseline with no shock. Positive rainfall shocks lead to initial insignificant price decreases ranging from approximately 1% to 3% immediately after harvest[12]. As the season progresses, the impact of positive rainfall shocks on price becomes statistically significant. The largest price decreases occur during the June-August growing season (4-6% price decrease) before becoming insignificant again at the approach of the next harvest season in September.

By contrast, negative rainfall shocks significantly decrease price by 7 - 9% in the immediate post-harvest October-January period. Prices then rise relative to the seasonal baseline and are 2-6 % higher in May through August (jointly significant at the 1% level) in what is commonly referred to as the lean season, before returning to baseline no-shock levels at the approach of the new harvest in September.

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[10] Note that the coefficients presented in table 3 are the marginal effects of rainfall shocks on ln(production). To compute the marginal effects on production, we use the following formula: $\%\Delta\text{production} = 100(e^{\beta} - 1)$ where β is the estimated coefficient of the regressor.

[11] We choose October as the base because the marketing season technically starts in October. The growing season for millet starts in June ends in September, and harvest begins in October. The graph of within-year price variability in figure A4 also supports the choice of October as the base month.

[12] Monthly marginal effects of October, November and December are jointly significant at the 1% level.

Panel A Panel B

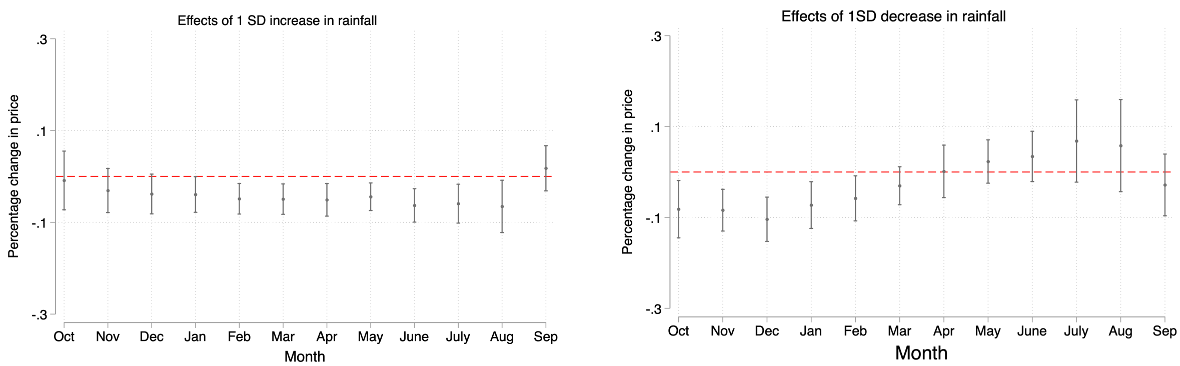

Figure 1.5: Effects of rainfall shocks on price seasonality

Notes: Panel A shows the marginal effects of positive rainfall shocks on price. Panel B shows the marginal effects of negative rainfall shocks on price. The circles represent the point estimates, and the bars indicate 95% confidence intervals. The regression includes year, months, and district Fixed-Effects.

Figure 1.6 shows these seasonal price trends for a positive rainfall shock compared to the seasonal no-shock baseline trend (Panel A) and for a negative rainfall shock compared to baseline (Panel B). These asymmetrical price responses are consistent with expectations under either liquidity constraints or under behavioral responses to scarcity in our conceptual framework. Initial downward pressure on millet market prices in the face of negative rainfall shocks suggest sell-low buy high strategies may be adopted when negative rainfall shocks exacerbate household seasonal credit constraints and or increase household subjective discount rates in the face of scarcity. The household shadow price for millet sales rises relative to the market price inducing millet sales immediately after harvest and exerting downward pressure on market prices. Later on, as the next agricultural season approaches, household millet stocks are exhausted and new credit and pressing needs increase millet demand and price rises in a delayed response to negative rainfall shocks.

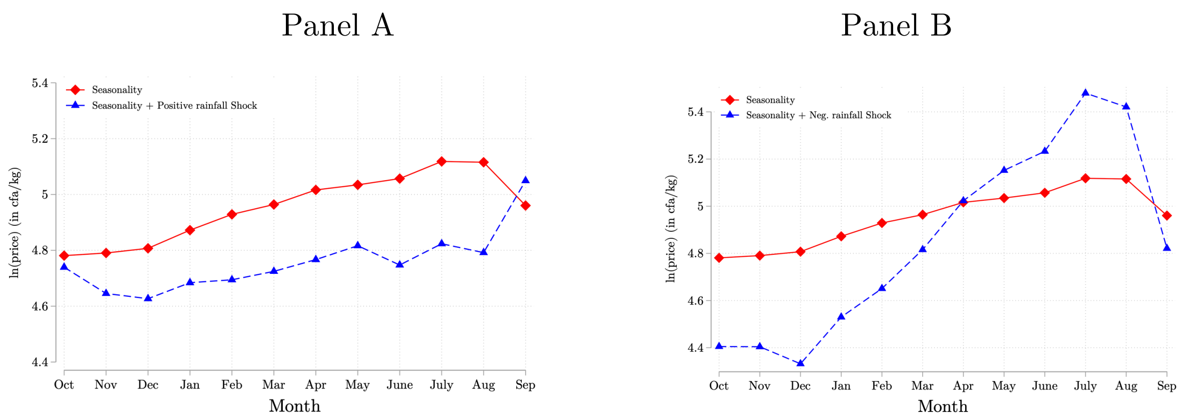

Figure 1.6: Shifts in the baseline price seasonality curve

1.5.3. Sensitivity analysis

We test the sensitivity of our results to alternative assumptions on clustering of standard errors and alternative model specifications. Specifically, we vary the intensity of our shock measures by defining strong and mild positive and negative rainfall shocks dummies as ± 1.5 SD and ± 0.7 SD, respectively, compared to the long-term (1981 - 2010) rainfall average. Overall, our results are robust to these alternative definitions of positive and negative rainfall shocks. Looking at rainfall shocks effects on production (columns 2 and 3 of table 1.3), we find strong positive rainfall shocks to increase production by 19%, while mild positive rainfall shocks increase production by 14%. By contrast, strong negative shocks appear to have very high impacts on millet production, with a 44% decrease in production, more than twice as large as mild negative shocks (a 19% decrease in production). The marginal effects of mild and strong rainfall shocks on price seasonality are shown in columns (2)-(3) and (5)-(6) of table 1.4, respectively and also plotted in figures A7 and A8. These results are consistent with our initial findings; positive rainfall shocks smooth out price seasonality while negative rainfall shocks exacerbate price seasonality. Strong negative rainfall shocks generate greater initial price decreases and also greater price increases later in the lean season, thus strongly amplifying already pronounced price seasonality in millet markets. The asymmetric response also remains consistent, with downward initial pressure on prices immediately post-harvest following a negative shock, and upward pressure in the lean season exacerbating market price seasonality while positive rainfall shocks dampen price seasonality.

1.5.4. Robustness checks

We test the robustness of our results to alternative assumptions on clustering of standard errors and to alternative model specifications for ±1.5 SD and ±1 SD thresholds for rainfall shocks. Clustering standards at the district level for the production results (column 1 of Table A1) and the price results (figure A9.) and using the spatial correction proposed by Conley (1999) with thresholds 500 kilometers[13] for the production results (column 2 of Table A.1.) and the price results (figure A10.) yield similar results to our initial results in terms of significance of parameter estimates.

Second, we check whether our results are driven by larger millet districts, by estimating rainfall shock impacts on production and price seasonality in the top 25% and bottom 25% of millet producing districts. We report the production results in column 2 of Appendix Table A2 and we report the price results in Appendix figures A11 and A12. Positive and negative rainfall shock impacts on millet production in the top 25% and bottom 25% districts are similar in magnitude and are statistically significant. Likewise, we observe the same price response to positive and negative rainfall shocks in the top 25% (Appendix figure A11) and bottom 25% districts (Appendix figure A12.), with negative rainfall shock causing an exacerbation of existing price seasonality and positive rainfall shocks leading to a smoothing of price seasonality.

Third, we check the robustness of our results to an alternative rainfall specification. We calculate zscore using rainfall for the vegetative period (July to August) most critical for millet production. We define positive and negative rainfall shock indicators using this new

[13] This means that we are accounting for error correlation between districts that are located within a 500 km radius of each other.

zscore, and regress them on production and price. We report the production results in column 3 of Appendix Table A2, and we illustrate the price results in Appendix figure A13. Rainfall shock impacts on production for the July – August period are statistically significant, but are lower in magnitude when compared to our initial growing season-based rainfall shock impacts. Further, we find no statistically significant impacts of July-August rainfall shocks on price seasonality, indicating that the full growing season rainfall shock measures are more relevant in price formation than the shorter vegetative period ones in the Niger context.

1.6. Discussion and Policy implications

1.6.1. Discussion

A number of studies have examined positive weather shock (Buhaug et al., 2015) and negative weather shock (Amare et al., 2018; Arslan et al., 2017; Bezabih et al., 2014;) impacts on agricultural production. This study investigates the distinct impacts of positive and negative rainfall shocks on millet production and market prices in Niger. Production responses to mild and moderate rainfall shocks are fairly symmetric, but large negative rainfall shocks generate production decreases that are greater in magnitude than increases from large positive rainfall shocks. On the other hand, we show that mild, moderate and strong negative and positive rainfall shocks all generate asymmetric price responses. Negative rainfall shocks decrease price immediately after harvest (relative to baseline seasonal changes), but place upward pressure on prices later in the lean season relative to baseline. Positive rainfall shocks decrease prices later in the lean season, but have weak initial impacts on market prices. Notably, strong negative rainfall shocks produce large amplifications in existing price seasonality and further increase the burden that negative weather shocks impose on farm households.

We posit several possible pathways through which rainfall shocks influence millet price seasonality and generate observed asymmetric price responses. Negative rainfall shocks reduce production of important cash crops like groundnut and cotton along with millet. Associated declines in expected income may trigger seasonal credit and liquidity constraints that raise the shadow price for millet sales and make the household more willing to sell at a lower market price immediately post-harvest. Households must then buy millet at a higher price later in the lean season when needs are pressing. Resulting sell-low buy high strategies do not maximize household intertemporal economic well-being, but are consistent with empirical findings on household behavior under credit constraints (Burke et al., 2019) and under scarcity (Mullainathan and Shafir, 2013).

1.6.2. Policy implications

Our study reveals that household production decreases and exacerbated millet market price seasonality jointly tax household resilience to negative rainfall shocks. Household social protection programs and market infrastructure investments need to address both impact pathways to increase future resilience to negative rainfall anomalies. Escalating production responses to negative rainfall shocks highlight the need for early warning systems and associated social protection responses that are calibrated based on shocks. Rainfall shock exacerbation of existing price seasonality emphasizes the need for rapid social protection responses to reduce household use of sell-low, buy-high marketing strategies and other negative short-term coping strategies. Market price drops immediately post-harvest in response to negative shocks suggest that interventions need to occur right after harvest. Further, the relatively frequent incidence of strong negative weather shocks in Niger suggests that continuous maintenance of social protection program infrastructure is warranted for rapid dispersal of program payments in simple forms like unconditional cash transfers calibrated to rainfall anomalies.

Existing studies suggest market integration in Niger tends to be localized, but increases in drought years (Aker, 2012; Araujo Bonjean et al., 2010; Shin, 2010). Our study does not explicitly examine market integration through millet trade flows. However, high levels of price seasonality and price responsiveness to negative rainfall shocks suggest possibilities exist to improve both spatial and temporal market integration. Price seasonality can be reduced through investments in improved storage options that put downward pressure on lean season prices by increasing the profitability of holding millet. Transportation and market infrastructure investments can lower millet market trade costs and smooth price impacts of negative rainfall shocks across regions. As figure 1.2 indicates, while district negative shocks are common, it is relatively rare that more than 20% of districts experience a negative rainfall shock in a given year. This lack of broad covariate negative rainfall shocks suggests enhanced inter-regional millet trade, along with international trade with Nigeria and Benin, can play an important role in smoothing district-specific millet shortfalls and, later, lean season price spikes from negative rainfall shocks.

1.7. Conclusion

This study adds to the growing literature about weather shock impacts in agriculture by shedding light on impacts of a crucial component of household food security in developing countries: market price seasonality. Novel empirical results show that negative rainfall shocks increase price seasonality, thereby intensifying household exposure to negative weather shock impacts. The results are consistent with pressures on market prices arising from sell-low, high-buy coping behavior documented by Burke et al., (2019); Stephens and Barrett, (2011), and (Dillon, 2020). Future research is needed to document underlying household behavior driving weather shock impacts on millet price seasonality. Household panel datasets with sufficient weather variability can determine exactly how household marketing behavior responds to weather and production shocks in order to generate observed changes in millet market price seasonality. Specific mechanisms to assist households in generating more productive long-term responses can also be identified in future research.

Table 1.1: Summary statistics

	Mean	SD	Min	Max
Production (kg)	72899	47489	31	312535
Price (Cfa/kg)	158	65	27	373
Cumulative seasonal rainfall (mm)	404	128	56	934
Negative Rainfall shock (z-score)	-1.31	0.28	-2.29	-1.006
Positive Rainfall shock (z-score)	1.55	0.52	1.00	3.26
Negative Production shock (z-score)	-1.44	0.37	-2.76	-1.00
Positive Production shock (z-score)	1.5	0.42	1.00	3.05

Notes: The production row shows the summary statistics for annual production per district over the period 1985-2016. The price row represents the summary statistics for district-level monthly millet price for the period 1990 - 2016. Negative and positive rainfall (production) shocks show the average z-scores for districts in that fall in those categories.

Table 1.2: Testing for cross-sectional dependence and non-stationarity

Variable	CD test statistic	Mean Absolute Correlation	Fischer inverse chi-squared statistic
Production	81.01***	0.64	258.95***
	(0.000)		(0.000)
Price	290.41***	0.91	867.48***
	(0.000)		(0.000)
Rainfall	74.31***	0.59	278.19***
	(0.000)		(0.000)

Notes: *** and ** indicate statistical significance at 1% and 5% respectively. The null hypothesis for the CD test is cross-sectional independence and the alternative hypothesis is cross-sectional dependence. The null hypothesis for the non-stationarity test is that all panels contain unit roots and the alternative hypothesis is that at least one panel is stationary.

Table 1.3: Effects of positive and negative rainfall shocks on ln(production)

Dependent variable: ln(production)			
	± 1 SD	± 0.7 SD	± 1.5 SD
Positive rainfall shock t	0.181***	0.135***	0.170***
	(0.0262)	(0.0327)	(0.0365)
Negative rainfall shock t	-0.200***	-0.210***	-0.577**
	(0.0626)	(0.0542)	(0.233)
Constant	10.20***	10.25***	10.21***
	(0.0510)	(0.0502)	(0.0490)
District Fixed-Effects	Yes	Yes	Yes
Time trends	Yes	Yes	Yes
Observations	1,023	1,023	1,023
Within R2	0.43	0.44	0.42
Number of districts	32	32	32

Notes: Driscoll-Kraay standard errors in parentheses. Weather measures are indicator variables for exposure to positive or negative rainfall shock in year t and in district i. In the first column, we define rainfall shocks as ±1 standard deviation (SD) from the historic (1981 - 2010) seasonal rainfall average in a given district. In the second and third columns, we define rainfall shocks as ±1.5 SD and ±0.7 SD from the historic (1981 - 2010) seasonal rainfall average respectively. *** indicates statistical significance at 1% level.

Table 1.4: Effects of positive and negative rainfall shocks on price

	Dependent variable: ln(price)					
	Positive rainfall shock			Negative rainfall shock		
Month	1 SD	0.7 SD	1.5 SD	1 SD	0.7 SD	1.5 SD
October	-0.009	0.004	0.046	-0.082*	-0.066*	-0.173***
	(0.033)	(0.031)	(0.044)	(0.032)	(0.026)	(0.047)
November	-0.031	-0.019	0.019	-0.084***	-0.060**	-0.099
	(0.025)	(0.024)	(0.033)	(0.023)	(0.020)	(0.051)
December	-0.038	-0.018	-0.019	-0.104***	-0.057**	-0.133**
	(0.022)	(0.023)	(0.022)	(0.025)	(0.020)	(0.044)
January	-0.039*	-0.015	-0.024	-0.073**	-0.062**	-0.036
	(0.020)	(0.022)	(0.021)	(0.026)	(0.019)	(0.043)
February	-0.049**	-0.023	-0.037*	-0.058*	-0.046*	-0.019
	(0.017)	(0.018)	(0.018)	(0.025)	(0.020)	(0.043)
March	-0.049**	-0.026	-0.038*	-0.03	-0.040*	-0.015
	(0.017)	(0.014)	(0.019)	(0.021)	(0.018)	(0.056)
April	-0.051**	-0.028	-0.044*	0.001	-0.009	0.093
	(0.018)	(0.014)	(0.020)	(0.029)	(0.023)	(0.064)
May	-0.044**	-0.019	-0.037*	0.023	0.003	0.095
	(0.015)	(0.014)	(0.016)	(0.024)	(0.019)	(0.061)
June	-0.063***	-0.034*	-0.060**	0.034	0.021	0.115*
	(0.019)	(0.015)	(0.019)	(0.028)	(0.023)	(0.049)
July	-0.059**	-0.037*	-0.046*	0.068	0.043	0.248***
	(0.022)	(0.018)	(0.020)	(0.046)	(0.035)	(0.047)
August	-0.065*	-0.033	-0.04	0.058	0.042	0.196***
	(0.029)	(0.023)	(0.026)	(0.052)	(0.043)	(0.059)
September	0.018	0.032	0.053*	-0.028	-0.031	-0.097*
	(0.025)	(0.022)	(0.024)	(0.035)	(0.025)	(0.046)
District Fixed-Effects	YES	YES	YES	YES	YES	YES
Year Fixed-Effects	YES	YES	YES	YES	YES	YES
Month Fixed-Effects	YES	YES	YES	YES	YES	YES
Within R2	0.8996	0.8989	0.8987	0.90	0.8989	0.8987
Number of districts	30	30	30	30	30	30

Notes: Driscoll-Kraay standard errors in parentheses. Our weather measures are dummy variables indicating exposure to a positive or a negative rainfall shock in year t and in district i. In column (1) and column (4), we define rainfall shocks as ±1 standard deviation (SD) from the historic (1981 - 2010) seasonal rainfall average in a given district. In column (2) and column (5), we define rainfall shocks as ±1.5 SD from the historic (1981 - 2010) seasonal rainfall average, and in columns (3) and (6) we define rainfall shocks as ±0.7 SD from the historic (1981 - 2010) seasonal rainfall average. The table shows the estimated marginal effects of positive and negative rainfall shocks on ln(price). ***, ** and * indicate statistical significance at 1%, 5%, and 10% respectively.

Table 1.5: Effects of positive and negative production shocks on price

	Dependent variable: ln(price)					
	Positive production shock			Negative production shock		
Month	1 SD	0.7 SD	1.5 SD	1 SD	0.7 SD	1.5 SD
October	0.003	-0.002	0.001	-0.018	-0.02	-0.017
	(0.020)	(0.0180)	(0.024)	(0.031)	(0.032)	(0.027)
November	0.004	-0.003	0.001	-0.039	-0.037	-0.028
	(0.016)	(0.0150)	(0.016)	(0.030)	(0.028)	(0.027)
December	0.016	0.007	0.026	-0.033	-0.031	-0.04
	(0.018)	(0.0150)	(0.016)	(0.027)	(0.025)	(0.023)
January	0.006	0.000	0.008	-0.031	-0.019	-0.034
	(0.018)	(0.0150)	(0.016)	(0.024)	(0.024)	(0.023)
February	-0.017	-0.025*	-0.001	-0.007	-0.006	0.022
	(0.016)	(0.0120)	(0.015)	(0.032)	(0.029)	(0.045)
March	-0.029	-0.036**	-0.001	0.011	0.007	0.028
	(0.015)	(0.0130)	(0.014)	(0.019)	(0.021)	(0.026)
April	-0.037*	-0.047***	-0.02	0.053**	0.052**	0.068*
	(0.016)	(0.0130)	(0.019)	(0.017)	(0.018)	(0.027)
May	-0.037*	-0.038**	-0.022	0.054**	0.064***	0.06
	(0.015)	(0.0130)	(0.017)	(0.020)	(0.018)	(0.039)
June	-0.045**	-0.048***	-0.03	0.075***	0.082***	0.084**
	(0.014)	(0.0130)	(0.019)	(0.018)	(0.018)	(0.032)
July	-0.054*	-0.050**	-0.033	0.081***	0.098***	0.089**
	(0.022)	(0.0190)	(0.022)	(0.024)	(0.023)	(0.028)
August	-0.041	-0.036	-0.025	0.069*	0.099**	0.038
	(0.026)	(0.0230)	(0.025)	(0.030)	(0.031)	(0.033)
September	0.016	0.014	0.069**	0.009	0.033	0.01
	(0.024)	(0.0200)	(0.026)	(0.025)	(0.030)	(0.042)
District Fixed-Effects	YES	YES	YES	YES	YES	YES
Year Fixed-Effects	YES	YES	YES	YES	YES	YES
Month Fixed-Effects	YES	YES	YES	YES	YES	YES
Within R2	0.899	0.901	0.898	0.899	0.901	0.898
Number of districts	30	30	30	30	30	30

Notes: Driscoll-Kraay standard errors in parentheses. Our weather measures are dummy variables indicating exposure to a positive or a negative rainfall shock in year t and in district i. In column (1) and column (4), we define rainfall shocks as ± 1 standard deviation (SD) from the historic (1981 - 2010) seasonal rainfall average in a given district. In column (2) and column (5), we define rainfall shocks as ± 1.5 SD from the historic (1981 - 2010) seasonal rainfall average, and in columns (3) and (6) we define rainfall shocks as ± 0.7 SD from the historic (1981 - 2010) seasonal rainfall average. The table shows the estimated marginal effects of positive and negative production shocks on ln(price). *** and ** indicate statistical significance at 1% and 5% respectively.

CHAPTER 2: Weather shocks and smallholder market participation in Sub-Saharan Africa: Evidence from millet farmers in Niger

Ange T. Kakpo, Bradford F. Mills and Stéphanie Brunelin

Abstract

Agriculture in Sub-Saharan Africa (SSA) is dominated by smallholder farmers who mostly practice semi-subsistence farming and are characterized by low participation in staple crop markets. Previous studies have linked this low market participation to factors such as age, gender, market price, ownership of private assets, and transaction costs, but no study has focused on weather shock impacts on market participation. This study examines weather shock impacts on millet market participation in Niger, a country where the majority of farmers practice subsistence farming, and where weather shocks are constant threats to rural households' livelihoods. We merge a two-year household panel data with spatially disaggregate rainfall data and market price data, and employ a two-stage Heckman type estimation procedure to explore and isolate negative rainfall shock impacts on household millet market participation. We find that households are more likely to participate in the market as net sellers with negative rainfall shocks, but marketed quantity for net sellers decreases with negative rainfall shocks. Diversification into non-agricultural activities can mediate the impacts of negative rainfall shocks on market participation and lead to increases in volume of sales. Policies that aim to stimulate millet market participation in Niger should support household involvement in the rural nonfarm economy through training and access to credit to help expand their business.

Keywords: Weather Shocks, Smallholder, Market Participation, Niger.

2.1. Introduction

Commercialization of staple crops is an important avenue to reduce food insecurity and alleviate poverty among smallholder farmers in Sub-Saharan Africa (SSA) (Birhanu et al., 2021). Production of staple crops has the dual objective of providing poor households with food to survive and of generating income. However, SSA agriculture is, dominated by smallholder farmers who mostly practice semi-subsistence farming, and are characterized by low participation in staple crop markets (Levinsohn and McMillan, 2013; Barrett, 2008; Jayne et al., 2006; Renkow et al., 2004). Documenting factors that affect this low market participation in SSA will facilitate the transition from semi-subsistence agriculture to a market-oriented one. This can generate gains from trade for smallholder farmers, and increase their resilience against negative weather shocks (Manda et al., 2021), thereby reduce food insecurity (Manda et al., 2020).

A large body of the literature has explored factors that affect smallholder participation in staple food markets in SSA. Smallholder farmers' decision to sell and the quantities they sell depend on their on-farm incomes (Osmani and Hossain, 2015), output prices (Omiti et al., 2009; Ouma et al., 2010; Goetz, 1992), farm size (Masuku et al., 2001), private assets (Boughton et al., 2007), years of farming experience and gender (Ouma et al., 2010), and market transaction costs (Key, Sadoulet, deJanvry, 2000), among other factors. The role of weather has received less attention in the literature, but weather shocks influence household staple cereal marketing decisions through four distinct pathways: production, income, price, and demand. First, weather influences production and thus, household sale and purchase decisions. Second, weather influences household income across all crops and, in-turn, household sale and purchase decisions. Third, weather influences aggregate market price and, thus, household sale and purchase decisions. Fourth, weather influences households' millet consumption decisions through income, and hence it affects their millet sale and purchase decisions.

This study examines weather shock impacts on millet market participation in Niger, a country where the majority of farmers practice subsistence farming, and where weather shocks are constant threats to rural households' livelihoods. Specifically, we merge two waves of a nationally representative household survey with spatially disaggregate high-resolution rainfall data and market price data, to explore and isolate negative rainfall shock impacts on household's market participation decisions and intensity of market participation. We categorize households into three well known regimes of market participation (net buyer, autarkic, and net sellers), and employ a two-stage Heckman type estimation procedure to analyze the associations between rainfall shocks and market participation.

We find that households are more likely to participate in the market as net sellers with negative rainfall shocks but, marketed quantity for net sellers decreases with negative rainfall shocks. Further, our results show that households view price as an important driver of net sale and net purchase quantities but also consider factors other than price for market entry. Distance to the nearest market is one such factor. The farther households are from their nearest market, the less likely they are to participate in the market as net sellers. Diversification into non-agricultural activities can increase volume of sales even with negative rainfall.

The rest of this paper is organized as follows. The next section lays out the conceptual framework, where we show how weather shocks can affect households' market participation in the presence of transaction costs. Section 3 describes the data and presents summary statistics of the variables used in our analysis. In section 4, we discuss our empirical framework and identification strategy. Section 5 presents the results and section 6 concludes the paper.

2.2. Conceptual framework

Non-separable agricultural household models have been employed by development economists to explore the impacts of policy changes and shocks on households' labor supply, migration, income distribution, market participation, nutrition and savings in developing countries. The use of non-separable agricultural household models relies on the assumption that there is a missing market for one or many goods (for e.g., a market failure for labor). In this case, the household cannot make production and consumption decisions sequentially. High market transaction costs can cause market failure as they increase the likelihood of households abstaining from participation in the market (Taylor E., 2002). This section presents a non-separable agricultural household model that highlights how market transaction costs influence weather shock impacts on millet market participation in Niger.

Millet market participation is measured by non-zero household marketed surplus, which depends on the quantity of millet produced and the quantity of millet consumed by the household. Household millet production depends on farm inputs (land, labor, fertilizer, etc.), household demographic characteristics such as age, gender, education, etc. as well as exogenous shifters such as weather shocks. Household millet demand depends on income, and household preferences. Both millet supply and millet demand are affected by the effective market price faced by the household, which in turn, as we will show, can be influenced by market transaction costs.

The role of transaction costs in market participation has been well documented. Transaction costs are observed and unobserved costs associated with the trade of good and services. They can be classified in two categories: variable and fixed transaction costs. Variable transaction costs depend on the quantity of good traded and may include unit market sales tax. Fixed transaction costs are invariant to the volume of trade and include costs of searching for potential traders, time spent bargaining for price, and screening buyers to avoid contract defaults (Key et al., 2000). When variable transaction costs for market participation are really high, they effectively decrease the price received by sellers, and increase the price paid by buyers. This results in a subjective price band with an upper limit equal to the effective purchase price (shadow plus transaction costs), and a lower limit equal to the effective sale price (shadow price minus transaction costs) (figure 2.1). With high transaction costs (t_v), households may be forced to opt for autarky, if market price (p_m) falls within this price band ($p_i - t_v < p_m < p_i + t_v$). On the other hand, households participate in the market as net buyers when millet market price is very low and falls below the subjective sales price (i.e., when $p_m < p_i$ - t_v) and participate as net sellers when market price is high enough to surpass the effective purchase price (i.e., when $p_m > p_i + t_v$).

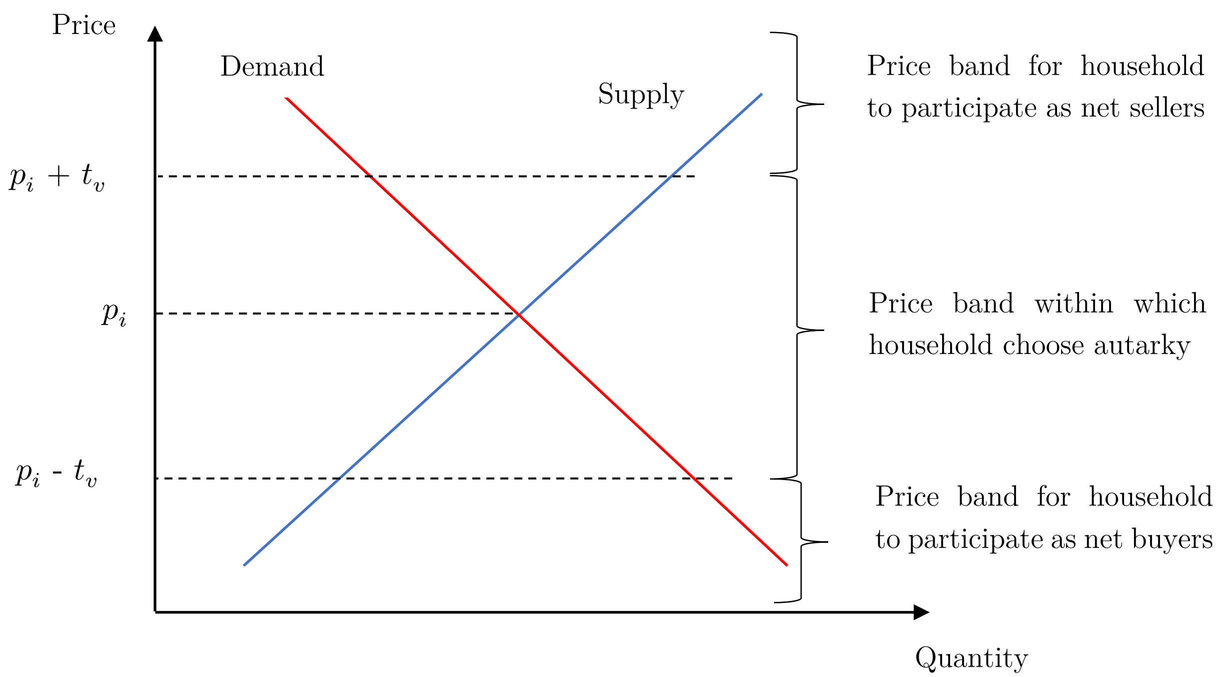

Figure 2.1: Household market participation behavior under transaction costs

Building on the Key et al., (2000) market participation model, we show how weather shocks can affect market participation, in the presence of fixed and variable transaction costs. We start with a traditional non-separable agricultural household model (Sadoulet and De Janvry, 1995), with simultaneous millet production and consumption decisions. We assume that households produce a set of agricultural goods including a staple crop (millet) and other cash crops using a production technology $g(q_i;\, x,\, \theta, z^q)$, where q_i is the output of agricultural good i, x is the amount of good i used as input. θ is a vector of exogenous supply shocks, such as weather shocks. z^q is a vector of household socio-demographic characteristics, which affect production. Households with preference z^h maximize utility $U(c;\, z^h)$, over consumption of the agricultural goods subject to the following constraints:

(1) $\sum_i^N p_i^m(q_i - c_i + E) + S = 0$: Cash constraint

(2) $g(q_i;\, x,\, \theta, z^q) = 0$: Production technology

(3) $q_i + A_i = c_i + x_i$: Resource balance

(4) $c_i, q_i,\, x_i \geq 0$: Non-negativity constraint.

Where p_i^m is the market price of good i. S represents net transfers received by the household. E is the household's initial total time endowment. A_i is total endowment in good i.

The Lagrangian[14] of the utility maximizing problem is:

(5) $\mathcal{L} = U\,(c;\, z^h) + \sum_{i=1}^n \alpha_i\,(q_i + A_i - c_i - x_i)$

$$+ \lambda\, g(q_i;\, x, \theta, z^q) + \mu\,\{\textstyle\sum_i^N p_i^m(q_i - c_i + E) + S\}$$

Where α, λ and μ are the Lagrange multipliers. The first order conditions (FOCs) are:

(6) $\frac{\partial U}{\partial C_i} - \alpha_i - \mu p_i^m = 0,$

(7) $\alpha_i + \lambda \frac{\partial g}{\partial q_i} + \mu p_i^m = 0,$

(8) $-\alpha_i + \lambda \frac{\partial g}{\partial x_i} = 0$

From this model, we can derive the reduced form of the agricultural supply and demand functions (Sadoulet and deJanvry, 1995):

(9) Supply function: $q^* = q^*(p_i, x_i, z^q, \theta)$

(10) Demand function: $c^* = c^*(p_i,\, y^*, E, z^h)$

[14] We assume that households in this specification do not need to plan for weather related shocks ex-ante by incorporating them their objective function. Rather, they react ex-post in consumption and inputs.

y^* is the household full income equal to:

(11) $\pi^* + \sum_i^N p_i E_i + \mathrm{S}$, where $\pi^* = \sum_i^N p_i q_i$ is household's profit; z^h is a vector of household characteristics that affect utility. p_i is the household decision price (shadow price) for market participation, which takes the following form:

$$(12) \qquad p_i = \begin{cases} p_i^m - t_v & \text{if seller} \\ p_i^m + t_v & \text{if buyer} \\ \frac{\alpha_i}{\mu} & \text{if self} - \text{sufficient} \end{cases}$$

The decision price, p_i, includes the variable transaction costs t_v when good i is marketed, but is equal to the household's unobservable internal shadow price ($\tilde{p} = \frac{\alpha_i}{\mu}$) when the good is not marketed. The variable transaction costs t_v are unobserved and are assumed to be affected by observed exogenous factors δ^t.

This model allows us to analyze the impacts of weather shocks on household millet market participation through their supply and demand responses. Since weather shocks affect production through θ, the impacts of weather shocks on production are $\frac{\partial q^*}{\partial \theta}$. A negative weather ($\theta_n$) shock decreases production ($\frac{\partial q^*}{\partial \theta_n}$ <0), household profits ($\frac{\partial \pi^*}{\partial \theta_n}$ <0) and full income ($\frac{\partial y^*}{\partial \theta_n}$ <0). The impacts of negative weather shocks on consumption are transmitted through profits:

$$(12) \qquad \frac{\partial c^*}{\partial \theta_n} = \frac{\partial c^*}{\partial y^*}\frac{\partial y^*}{\partial \pi^*}\frac{\partial \pi^*}{\partial \theta_n},$$

where $\frac{\partial c^*}{\partial y^*}$ is the income response to millet consumption. Millet is a normal good, so the income elasticity of food consumption is positive ($\frac{\partial c^*}{\partial y^*}$). Using equation (11), we can conclude that if π^* increases, so does full income y^* and hence $\frac{\partial y^*}{\partial \pi^*} > 0$. Therefore, negative weather shocks put downward pressure on millet consumption ($\frac{\partial c^*}{\partial \theta_n} < 0$).

As a result, negative weather shocks shift the millet supply curve upward and shift the millet demand curve downward. Since weather shocks affect not only millet, but also all other cash crops that farmers grow, we posit that negative rainfall shocks exert strong negative income effects, which may result in a large downward shift in the demand curve. We graphically show how supply and demand shifts result in new household millet shadow prices, which together with market price levels, determine household's choice of a market participation regime and result in changes in equilibrium quantities. To determine how negative weather can affect each of the three categories of market participation, we distinguish three main cases: (i) the case when the household is autarkic (ii) the case when the household is a net buyer and (iii) the case when the household is a net seller.

Case 1: Negative weather shock impacts on autarkic households

For autarkic households, market price (p_m) falls within the subjective price band price band for self-sufficiency. In the event of a negative weather shock, the upward supply shift and the resulting downward demand shift push shadow prices down from p_a to p'_a. The subjective price band also shifts downward, and since market price still belongs this new price band, no changes in market participation are observed (figure 2.2). The shifts in supply and demand result in reduced equilibrium quantity.

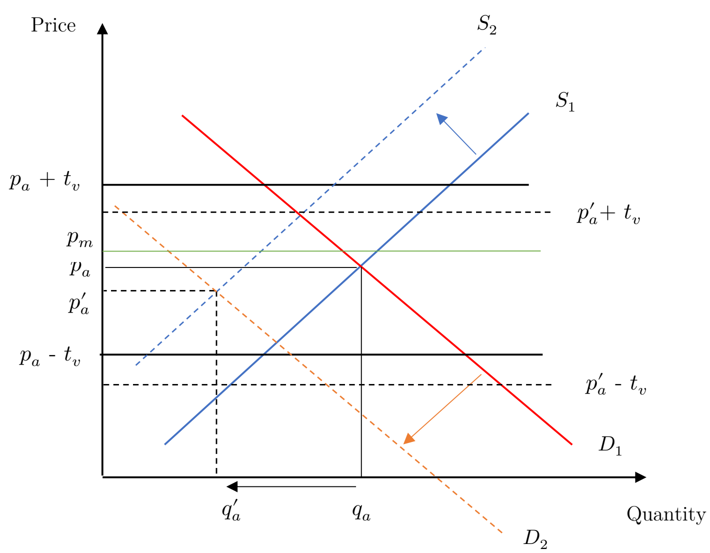

Figure 2.2: Impacts of negative weather shocks on autarkic households

Case 2: Negative weather shocks impacts on net buyer households

For net buyers, market price is below the subjective price band. With negative weather shocks, the shifts in supply and demand result in a decrease of shadow prices, which in turn pushes the subjective price band down. In the case of a strong demand shift, market price may fall within the new subjective price band, and households will switch from being in autarky to being a net buyer. Overall, net buyer households are less likely to participate in the market as net buyers with negative weather shocks and their net purchase (the difference between quantity demanded and quantity supplied at the effective purchase price) may increase or decrease depending on the shape of the supply and demand curves.

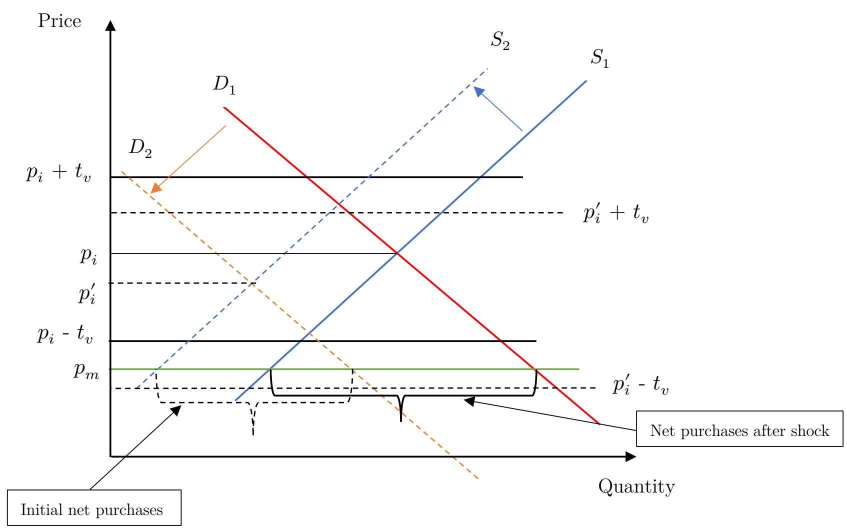

Figure 2.3: Impacts of negative weather shocks on net buyer households

Case 3: Negative weather shocks impacts on net seller households

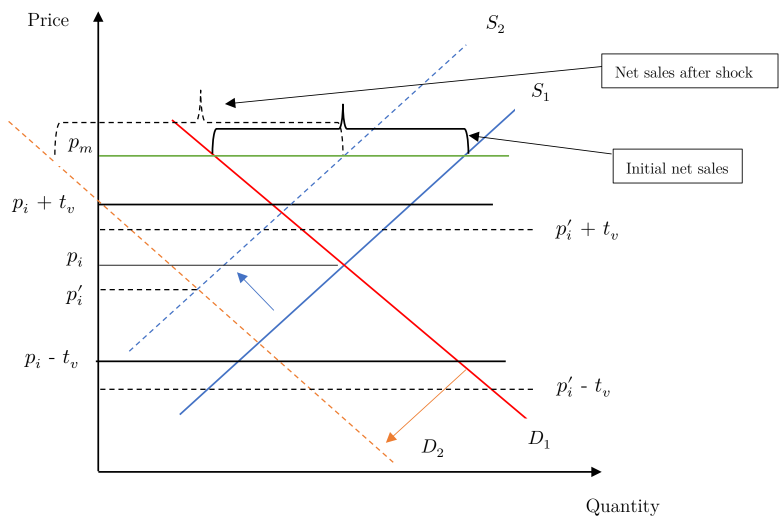

Figure 2.4: Impacts of negative weather shocks on net seller households

Similar to autarkic and net buyer households, negative weather shocks result in a decrease of millet shadow and a downward shift of the subjective price band in the case of net sellers. Since market price is above the initial price band for autarky, net seller households are more likely to remain net sellers with negative weather shocks, and their net sales (the difference between quantity supplied and quantity demanded at the selling price) may increase or decrease depending on the shape of the supply and demand curves.

In sum, weather shock impacts on household market participation choice are mostly unambiguous. With negative rainfall shocks, households who were initially autarkic are more likely to remain in autarky. Households who were initially net buyers are less likely to continue being net buyers with a negative rainfall shock, while households who were initially net sellers will remain net sellers. On the other hand, negative rainfall shock impacts on net sales and net purchases are ambiguous. Whether negative rainfall shocks decrease or increase net sales and net purchases depends on the shape of the supply and demand curves, and remains an empirical question.

From the three cases discussed above, we assume a household choice of a market participation regime depends on factors that shift supply, demand, and transaction costs.

Generally, the household first makes a market participation choice ($\boldsymbol{M_i}$) based on their shadow price, which can be expressed as follows:

$$\boldsymbol{M}_i = f(p^m, \delta^t, \theta, x, z^q, z^h) \qquad (13)$$

Second, conditional on the market participation regime, the household chooses the following supply and demand functions:

$$\begin{aligned} q_s &= f(p^m, \delta^t, \theta, x, z^q, z^h) && \text{for a net seller} \\ q_b &= f(p^m, \delta^t, \theta, x, z^q, z^h) && \text{for a net buyer} \qquad (14) \\ q_a &= f(\tilde{p}, \theta, x, z^q, z^h) && \text{for an autarkic household} \end{aligned}$$

2.3. Data and summary statistics

2.3.1. Data

We explore weather shock impacts on millet market participation by using a two-wave household panel data from the Living Standard Measurement Survey (LSMS) for Niger. The survey took place in 2011 and 2014, and collected household level crop production information, household-level output price, as well as household-level marketing information (including quantity sold, quantity purchased, quantity retained in stock, and plans for use of retained stock). The LSMS is nationally representative survey of all of Niger's 8 regions, covering 270 enumeration areas (EA).

In each wave, households are visited twice. The first visit was scheduled to take place in the planting season (June to September), which coincides with the lean season and the second visit was scheduled to take place in the harvest season (from October to December). During both visits, investigators administered two questionnaires: a household questionnaire and an agriculture questionnaire. The same household questionnaire is used during both visits to collect information on household's socio-demographic characteristics, education, health, wage employment, income sources, and food consumption expenditures, among other topics. On the other hand, the agriculture questionnaire administered in the first visit is different from the one used in the second visit. During the first visit, the agriculture questionnaire collects information on households' access to land and planting practices, including the type and quantity of farm inputs used during the rainy season, the types of crops grown and cost of inputs used. The agriculture questionnaire used during the second visit collects information on quantity of crop harvested, different uses of harvest (quantity consumed, quantity sold, quantity stored, quantity gifted, quantity used for seeds and quantity used to feed animals), value of crop sales, revenues from livestock production, farm equipment used in agricultural production, self-reported climate shocks, and strategies used to cope with these shocks.

In 2011, the two visits were executed as planned, but in 2014 they were delayed. During the first visit of the 2011 survey, all households were investigated in the lean season (between June and September), and in the second visit all households were surveyed in the harvest season (between August and November). In 2014, however, the first visit was delayed and took place between August and November 2014, and the second visit occurred between January and March 2015. As a result, only 29% of households were surveyed in the lean season for the first visit in 2014, while the remaining households were surveyed in the harvest season. In the second visit, all households were surveyed in the post-harvest season. Since household millet sale information was only collected during the second visit, the sample for this study is restricted to households visited in the second round. Our final sample consists of 2956 household-year observations.

We merge the household data with gridded rainfall data at the 0.05-degree spatial resolution obtained from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) for the years 1981 - 2016. We use this data to compute rainfall zscore for every EA and for the growing seasons corresponding to each survey year, as follows:

$$\text{Zscore} = \frac{R_{jt} - \overline{R}_j}{\overline{\sigma}_j}$$

Where R_{jt} is total rainfall in EA j and growing season t. $\overline{R}_j$ is the 30-year (1981-2010) rainfall average in EA j and $\overline{\sigma}_j$ is the 30-year rainfall standard deviation in EA j. We use the zscore to construct a continuous negative rainfall shock variable as shown below:

$$\text{Negative rainfall shock} = \begin{cases} \text{Zscore} & \text{if} \quad \text{Zscore} < 0 \\ 0 & \text{Otherwise} \end{cases}$$

We merge the household and rainfall data with millet market price information from Niger's Market Information Systems (SIMA) for the relevant household marketing periods in each wave. To do so, we identify the closest millet market to the EA where each household lives and compute the average millet market price for that EA in the lean, harvest and post-harvest seasons for 2011 and 2014. Price information for the post-harvest season in 2011 was dropped since households were only surveyed in the lean and harvest seasons in that year.

2.3.2. Summary statistics

Table 2.1 presents a description of all variables used in our analysis and table 2.2 presents the summary statistics for these variables by wave and for the full sample. Panel A presents information on household marketing strategies. Consistent with the conceptual framework, we define three market participation regimes based on millet net sale: (i) net sellers who have a positive net sale, (ii) autarkic who have zero net sale and (iii) net buyers who have a negative net sale. Our sample is dominated by autarkic (57% in 2011 and 53% in 2014) and net buyers (36% in 2011 and 38% in 2014). Net sellers make up less than 10% of the sample (7% in 2011 and 9% in 2014). This is consistent with the low participation in staple crop markets documented among smallholder farmers in SSA countries (Levinsohn & McMillan, 2013; Jayne et al., 2006; Renkow et al., 2004). We compute net sale (sales less purchases) and net purchase (purchases less sales) quantities, such that net sales are positive for net sellers, zero for autarkic households and unobserved for net buyers. On the other hand, net purchases are positive for net buyers, zero for autarkic and unobserved for net sellers[15]. Although millet net sales in both years are very low, the average net sale in 2014 (28 kg) is higher than the average net sale in 2011 (10 kg). The average millet net purchase is very low, and is similar across years (1.23 kg in 2011 and 1.28 kg in 2014).

Panel B presents household characteristics. The average household head (HH) is relatively young (about 46 years old), has a 9% chance of being female and a 13% chance of having formal education. The majority of households (90%) live in rural areas and cultivate an average 4.5 hectares of millet.

Panel C displays the strategies that households adopt in response to perceived negative rainfall shocks and Panel D shows observed rainfall shock measures. Adoption of agricultural technologies is the most used coping strategy in both years (28% in 2011 and 30% in 2014), followed by diversification to non-agricultural activities (26% in 2011 and 24% in 2014) and temporary migration of a household member (15% in 2011 and 21% in 2014). Off-season agricultural production is the least adopted coping strategy. On average, 2011 recorded a stronger negative rainfall shock than 2014. While the total rainfall in the 2011 growing season (330 mm) is 0.5 standard deviation below the 30-year rainfall average, the total rainfall in the 2014 growing season (366 mm) is 0.2 standard deviation below the 30-year rainfall average.

2.4. Empirical framework and estimation strategy

As noted in the conceptual framework, households participate in the market in a two-step process. First, households decide whether to participate in the market either as net sellers,

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[15] This approach is similar to the one used in Burke et al., (2015) and Bellemare and Barrett (2006) who argue that transactions costs affect net sellers and net buyers in fundamentally different ways and used two separate regressions to study household market participation behavior.

net buyers, or they choose autarky. Second, conditional on being a net seller or a net buyer, households choose millet sale and purchase quantities, respectively. This two-step decision process is similar to the one described in Goetz (1992) and thus a selectivity correction should be applied during estimation of the relationship between outcome and explanatory variables in the two stages. As such, we estimate rainfall shock impacts on millet market participation using a double-hurdle (DH) model, where the parameters in the two hurdles can be estimated simultaneously using maximum likelihood estimation (MLE)[16]. First, we examine the association between rainfall shocks and household market participation decision. Second, we estimate rainfall shock impacts on net quantity sold and net quantity purchased. Following Bellemare and Barrett (2006), we construct an ordinal outcome variable in the first stage by classifying millet net sales values into our three market participation categories, with net sales being negative for net buyers, zero autarkic households, and positive for net sellers millet net sales values. The first stage regression then has a categorical dependent variable, which takes the value 0, if the household is net buyer of millet, 1 if the household opts for autarky, and 2 if the household is a net seller of millet. In the second stage, we compute nonnegative values for millet net sales and net purchases and estimate two separate regressions for net sellers and net buyers, respectively.

As outlined in our conceptual framework, household millet market participation is determined by millet supply, the resulting income effects that affect millet demand and market transaction costs. We specify the discrete market participation decision as a function of supply shifters, demand shifters, and determinants of transaction costs (equation 15). As supply shifters, we control for negative rainfall shock (our key variable of interest), human capital (age of the household head), gender (a dummy for female-headed household), education (a dummy for whether the household head has formal education), land holdings

[16] Because of the separability of the MLE function, the two equations of the DH model can be estimated separately.

(area planted of millet), millet market price, use of farm inputs (a dummy for whether the household has used a farm input during the growing season), and other household characteristics such as the number of members aged 9 year or younger and 65 years or older in the household, and a dummy for whether the household head is polygamous. Moreover, supply shifters include a variable that controls for the timing of the survey. This is because the 2014 agriculture survey was delayed and there is a high chance this is causing large differences between the quantity of millet consumed and quantity of millet sold among households surveyed in 2011 and 2014. For instance, households visited 30 days after the start of the survey may have consumed more from their stocks and would then have lower supply and potentially higher demand. To account for these differences, we control for the number of days since the start of the agriculture questionnaire in 2011.

Demand shifters include variables that affect household income and market price. We use household non-millet income[17] and household livestock ownership (measured with tropical livestock unit) as proxies for household income. Increases in non-millet income can alleviate household liquidity constraints and lead to lower millet sales and higher millet demand. By the same token, a significant decrease in non-millet income may decrease household millet demand, and result in higher millet sales as a way to help reduce household cash constraints. Livestock sale is also often used as a strategy to cope against negative weather shocks (Acosta et al., 2021), and we expect households with higher livestock units to be associated with higher millet demand, and lower millet sales. As demand shifters, we also include the variable that controls for the survey timing.

[17] We exclude income from millet sales as this can cause endogeneity. Households with higher income from millet sales are likely to have higher millet sales, and household with high millet sales are most likely those who had a high income, resulting in simultaneity bias.

For variables that affect transaction costs, we control for distance to the closest market and the share of other households living in the same EA who have sold millet. Higher distance to the market has been associated with higher transaction costs and lower market participation among smallholder farmers (Okoye et al., 2016). Conversely, households who live in a village where more households sell millet may face lower transaction costs and as a result be more likely to participate in the market.

The market participation decision specification is shown in equation 15:

$$\boldsymbol{M}_{ijt} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1} S_{jt} + \boldsymbol{X}'_{ijt}\boldsymbol{\delta_1} + \boldsymbol{Z}'_{1ij}\boldsymbol{\lambda_1} + \overline{\boldsymbol{X}}_{ij}\boldsymbol{\gamma_1} + D_t + \mu_i + \varepsilon_{ijt} \tag{15}$$

Where M_{ijt} is household i's choice of a market participation regime (with $\boldsymbol{M}_{ijt}$ taking on the value 0 if the household is a net buyer, 1 if the household is autarkic and 2 if the household is a net seller) in EA j and year $\boldsymbol{t}$. $\boldsymbol{S}$ is negative rainfall shock in EA j and year t. $\boldsymbol{X}$ is a vector of time-variant determinants of supply, demand, and transaction costs, and $\overline{\boldsymbol{X}}$ are the corresponding time averages**.** $\boldsymbol{Z_1}$ represents our time-constant variables. μ_i is unobserved time-invariant heterogeneity, which affect the household market participation decision. D_t represents year fixed-effects and ε_{ijt} is the idiosyncratic error term.

The net sales and net purchases regression specifications (equations 16 and 18) control for the variables included in equation 15, except the ones that affect transaction costs. We omit transaction costs variables from the second stage regression as a way of imposing exclusion restrictions[18]. The decisions on net sale and net purchase quantities conditional on market participation are expressed as follows:

$$\boldsymbol{q}^{\boldsymbol{s}^*}_{ijt} = \boldsymbol{\alpha_0} + \boldsymbol{\beta_2} \boldsymbol{S}'_{jt} + \boldsymbol{W}'_{ijt}\boldsymbol{\delta_2} + \boldsymbol{Z}'_{1ij}\boldsymbol{\lambda_2} + \overline{\boldsymbol{W}}_{ij}\boldsymbol{\gamma_2} + D_t + \mu_i + \vartheta_{ijt} \tag{16}$$

[18] Proper identification of DH models requires at least one exclusion restriction. This is imposed by adding a variable in the first stage (preferably a variable has that a statistically significant association with the first stage), but not the second stage.

$$
\boldsymbol{q}^{\boldsymbol{s}}_{ijt} = \begin{cases} \boldsymbol{q}^{\boldsymbol{s}^*}_{ijt} & \text{if } \boldsymbol{M}_{ijt} = 2 \\ 0 & \text{if } \boldsymbol{M}_{ijt} = 1 \\ \text{unobserved} & \text{if } \boldsymbol{M}_{ijt} = 0 \end{cases} \tag{17}
$$

$$
\boldsymbol{q}^{\boldsymbol{b}^*}_{ijt} = \boldsymbol{\delta_0} + \boldsymbol{\beta_3} \boldsymbol{S}'_{jt} + \boldsymbol{W}'_{ijt} \boldsymbol{\delta_3} + \boldsymbol{Z}'_{ij} \boldsymbol{\lambda_3} + \overline{\boldsymbol{W}}_{ij} \boldsymbol{\gamma_3} + D_t + \mu_i + \omega_{ijt} \tag{18}
$$

$$
\boldsymbol{q}^{\boldsymbol{b}}_{ijt} = \begin{cases} \boldsymbol{q}^{\boldsymbol{b}^*}_{ijt} & \text{if } \boldsymbol{M}_{ijt} = 0 \\ 0 & \text{if } \boldsymbol{M}_{ijt} = 1 \\ \text{unobserved} & \text{if } \boldsymbol{M}_{ijt} = 2 \end{cases} \tag{19}
$$

Where $\boldsymbol{q}^{\boldsymbol{s}^*}_{ijt}$ and $\boldsymbol{q}^{\boldsymbol{b}^*}_{ijt}$ are the inverse hyperbolic sine (arcsinh) of the underlying latent variables of net sale (q^s_{ijt}) and net purchase (q^b_{ijt}) quantities respectively. We use the arcsinh because the transformation preserves zero net sales and net purchases values, while behaving like a natural log transformation. Further, the coefficients in a specification where both the dependent and the independent variables are transformed using the arcsinh function (arcsinh - arcsinh specification) can be interpreted as elasticities (Bellemare and Wichman, 2020)[19]. $\boldsymbol{W}$ is a vector of time-varying determinants of supply and demand shifters and $\overline{\boldsymbol{W}}$ are the corresponding time averages.

Although equation 15 can be estimated using a fixed-effects (FE) model, we use the Correlated Random Effect (CRE) estimator, because the FE is understood to produce biased and inconsistent estimates for panel data with small length for nonlinear models (Greene, 2004). The Random Effects (RE) model, makes the strong assumption of no correlation between unobserved time-invariant heterogeneity and explanatory variables. The CRE approach, which was developed by Mundlak (1978), relaxes this assumption. Mundlak assumes the unobserved time-invariant heterogeneity can be decomposed in averages over

[19] We also use the arcsin transformation for the explanatory variables that contain many zeros or those have large values.

time of time-varying covariates ($\overline{\boldsymbol{X}}_{ij}$) and a time-invariant error term (μ_i), which has zero mean conditional on the entire history of the covariates. μ_i is therefore uncorrelated with the time-varying covariates ($\boldsymbol{X}'_{ijt}$) and with the time-averaged covariates ($\overline{\boldsymbol{X}}_{ij}$). The CRE is an attractive approach because unlike the FE model, it produces coefficient estimates for time-invariant covariates. Moreover, the CRE provides coefficient estimates that can be interpreted as the within FE estimates. In equations 15, 16 and 18, the coefficients of interest $\boldsymbol{\beta_1}$, $\boldsymbol{\beta_2}$, and $\boldsymbol{\beta_3}$ can be interpreted as FE estimates. We estimate equations 16 and 18 using a tobit CRE model. The choice of the tobit model is motivated by the fact that the net sale and net purchase variables contain large number of zeros, due to the presence of autarkic households.

Causal identification of all parameter estimates requires that the error term from equation 15 (ε_{ijt}) is uncorrelated with the error term from equation 16 (ϑ_{ijt}) and with the error term from equation 18 ($\boldsymbol{\omega}_{ijt}$). Testing for the presence of correlation error terms between hurdles follows an approach similar to Heckman's test for sample selection bias. We start by using results from the ordered probit model to generate an Inverse Mills Ratio for net sellers (IMR seller) and for net buyers (IMR buyer). The net sale and net purchase regressions are then estimated with IMR seller and IMR buyer added as explanatory variables, respectively. The null hypothesis that the error terms between the first and second hurdles are correlated is tested using the coefficient estimates of the IMR's. If the coefficient of an IMR is statistically insignificant, then we reject the null hypothesis, drop the IMR and re-estimate the model. However, if the IMR coefficient is statistically significant, we fail to reject the null, and the IMR is used to control for the correlation between hurdles.

Under this CRE probit, CRE Tobit framework, and due to the strict exogeneity of the rainfall shock variable used in our regressions, the estimated coefficients for $\boldsymbol{\beta_1}$, $\boldsymbol{\beta_2}$, and $\boldsymbol{\beta_3}$

are unbiased and consistent, and represent the causal impacts of rainfall shocks on market participation decision and on the intensity of market participation.

2.5. Results and discussions

2.5.1. Impacts of negative rainfall shocks on market participation decision

Results for the first stage ordered probit CRE regression are presented in table 3. The table presents marginal effects estimates of the determinants of market participation decision. The estimated coefficients from this regression are shown in appendix table B1. The results indicate that a negative rainfall shock is positively associated with a higher likelihood of participating in the market as a net seller or an autarkic household, but is negatively associated with a higher likelihood of participating in the market as a net buyer. In particular, a 1 standard deviation decrease in seasonal rainfall with respect to long-term rainfall averages increases the household probability of participating in the market as a net seller and as autarkic by 2.7% and 3.4% respectively, and decreases the household probability of participating in the market as a net buyer by 6%. These results are consistent with predictions from our conceptual framework. Negative rainfall shocks appear to exert strong negative income effects on households and force them to sell their millet to generate cash and meet pressing household needs. These results are also consistent with findings from previous studies on smallholder farmers' marketing behaviors when facing liquidity constraints (Kakpo et. al., forthcoming; Dillon, 2020). Similarly, households are less likely to participate in the market as buyers and more likely to be in autarky.

Interestingly, increases in non-millet income are positively associated with higher probability of being a net seller and negatively associated with higher probability of being a net buyer. This finding suggests that households who sell cash crops may also engage in millet marketing. The results also imply that household with higher farm income likely possess more productive assets and have better access to improved agricultural technologies, enabling them to generate higher marketable surplus. This is consistent with findings, which suggest that wealthier households are more likely to sell than are poorer ones (Barrett, 2008).

Having formal education decreases the probability of being autarkic or net seller, but increases the probability of being a net buyer. This is likely due to the fact that households with formal education are less engaged in millet farming and are more likely to consume from own production or participate in the market as buyers. We also find that households living in rural areas are more likely to be autarkic or net sellers, and less likely to be net buyers.

Age and gender have no statistically significant impact on the market participation decision. Likewise, market price, farm input use, dependency ratio, land holdings, being a household with polygamous head and livestock ownership do not affect market participation choice. Distance to market is negatively associated with the probability of participating in the market as a net seller and as an autarkic household. Longer distance to market is often linked to higher market transaction costs and lower market participation (Okoye et al., 2016). These results thus confirm the widely documented knowledge that transaction costs may constitute a barrier to market entry for smallholder farmers in SSA. However, households that are more distant are more likely to net buyers. Households living in areas where other households are selling millet are more likely to participate in the market as net sellers, which reinforces the idea that social networks have a positive influence on household market participation (Abdul-Rahaman and Abdulai, 2020).

Being surveyed towards the end of the survey period makes households more likely to participate in the market as net buyers and less likely to participate in the market as autarkic or as net sellers. This may be due to the fact that stocks are more likely to be exhausted later in the survey period, and households are more likely to have made a purchase.

2.5.2. Impacts of negative rainfall shocks on the intensity millet market participation

Table 2.4 presents the marginal effects from the second stage Tobit CRE regression. The IMR for net sellers and the IMR for net buyers are both statistically significant at the 1% level. Thus, we retain the IMR seller in the net sales regression and IMR buyer in the net purchases regression to correct for correlation of error terms between the first and second stage. Results show that negative rainfall shocks have negative and statistically significant impacts on both net sales and net purchases. Consistent with our conceptual, negative rainfall shocks generate negative supply and demand responses, and as predicted, we also observe a greater supply response. These results suggest that, conditional on being net sellers, households sell less millet when they experience negative rainfall shocks. This means that although households are more likely to participate in millet marketing as net sellers with negative rainfall shocks, the marketed surplus for net sellers is lower in years with negative rainfall shocks compared to years with no shock. Similar results are found for maize market participants in Mozambique (Boughton et al., 2007). As shown in the conceptual framework, negative income effects from rainfall shocks also lead to less demand for net buyers. We find that, households who participate in the market as net buyers buy less millet with negative rainfall shocks. Being a household with a polygamous head has no statistically significant impact on net sales, but has a strong positive and statistically significant impact on net purchases. One possible explanation is that households who have more members are expected to have higher millet demand. Higher market prices are positively associated with higher millet supply, with a 1% increase in price causing an 8% increase in millet supply for net sellers. Net purchases also increase with price, with a lower price elasticity of demand for net buyers than for net sellers.

Volume of sales increase with non-millet income for a given net seller. This is consistent with our earlier market participation results, and shows that wealthier net sellers are more likely to register higher millet marketed supply. Contrary to findings from previous studies (Alene et al., 2008; Boughton et al., 2007), which find evidence that livestock ownership has a positive effect on volume of sales, we find that livestock ownership is associated with lower marketed supply for net sellers, possibly highlighting the fact that households who own livestock perceive a reduced risk from food insecurity, and prefer to sell less of their millet stocks. This may also reflect these households concentrate on livestock production and have less millet to sell. Since we are analyzing a sample of households surveyed in the post-harvest period when millet prices are generally low, these results underscore the importance of private assets ownership in limiting the use of negative short-term coping strategies such as the sell low, buy high marketing strategy. Consistent with the first stage results, we find that net sellers and net buyers who are surveyed later registered more sales and more purchases, respectively.

2.5.3. Heterogeneity analysis

In this section, we analyze whether household use of coping strategies mediate negative rainfall shock impacts on market participation. Households listed multiple strategies they use to cope with perceived rainfall shocks over the 12 months prior to survey. We interact the four most adopted coping strategies (adoption of agricultural technologies, use of off-season agricultural production, migration of a household member, and diversification to non-agricultural activities) with our rainfall shock variable to examine their influence on household market participation decision and intensity of participation. We present the first stage results in table 2.5 and the second stage results in table 2.6. The estimated coefficients for the first stage results are presented in appendix table B2. With negative rainfall shocks, households who adopt agricultural technologies are more likely to be net buyers, and less likely to be autarkic or net sellers. Conversely, households who practice off-season agricultural production show a higher probability of being net sellers or autarkic, and a lower probability of being net buyers, with a negative rainfall shock. These results suggest that households that adopt agricultural technologies may be more likely to use markets to smooth shortfalls due to weather shocks. Perhaps by directing technologies and most of their resources towards more profitable cash crops, and relying on markets to meet staple food needs in the face of rainfall shocks. By contrast, households with off-season agricultural production appear to be less likely to buy in the face of negative rainfall shocks. Perhaps due the presence of alternative off-season food sources. Results from table 2.6 also show that net sellers and net buyers who have diversified into non-agricultural activities increased their net sales and net purchases, respectively when they experience negative rainfall shocks. These results also emphasize the positive influence off-farm income has on overall market participation.

2.6. Conclusion

Smallholder participation in SSA staple crop markets has received a lot of attention over the past four decades as it is an important avenue to reduce food insecurity and alleviate poverty in the face of variable climatic conditions. Increased smallholder market participation has been shown to yield positive welfare gains among poor households in developing countries (Melesse, 2015). However, efforts to help poor SSA households transition from semi-subsistence agriculture to market-oriented production have not been effective. Smallholder participation in SSA staple crop markets has remained very low over the years (Minten and Barrett, 2008). A large body of the literature has explored the determinants of household participation in SSA staple crop markets. These studies show that better smallholder market participation depends on four main factors: household private assets (land, livestock, wealth assets, etc.), access to improved agricultural technologies, transaction costs, and market price. Weather shocks continue to be a threat to households' livelihoods in SSA, and can also affect market participation, but the role of weather on market participation has received little attention.

The current study bridges this gap. We match a two-year household panel dataset with spatially disaggregated high-resolution rainfall data to examine weather shock impacts on millet market participation in Niger. Overall, our results show that households are more likely to participate in the market as net sellers with negative rainfall shocks, but marketed quantity for net sellers decreases in years with negative rainfall shocks. Increased probability of market participation as a net seller in response to negative rainfall shocks may be due to the negative income effects generated by rainfall shocks, which force households to sell their harvest in order to meet pressing household needs.

Further, our results imply that households consider factors other than price for market entry as net sellers or net buyers, but view price as an important driver of net sale and net purchase quantities. Distance to the nearest market is one such factor. The farther households are from their nearest market, the less likely they are to participate in the market as net sellers. Diversification into non-agricultural activities can increase volume of sales even with negative rainfall, confirming our findings that household with other income opportunities are likely to participate more in markets, including millet marketing.

Two important policy implications emerge from our findings. Our findings show that diversification into non-agricultural activities increases net seller marketed quantity. As such, policies that aim to stimulate millet market participation in Niger need to focus on investment in the rural non-farm economy. Specifically, such policies should support households who own nonfarm enterprises with training and access to credit to help expand their business and address entry constraints for those are non-enterprise owners. Second, increased millet market participation can be achieved at a large scale in Niger if policymakers invest in road infrastructures. As we show in this study, distance to market is negatively associated with a higher probability of participating in the market. The average distance to market in our sample is quite far at 65 km, and with remoteness, households often have to sell their products to intermediaries at prices lower than market prices. With improved road infrastructures, transaction costs associated with distance will become less of a determinant to market entry.

Table 2.1: Description of the variables included in the analysis

Variables	**Description**
Net seller (1=yes)	Dummy for being a net seller of millet
Net buyer (1=yes)	Dummy for being a net buyer of millet
Autarkic (1=yes)	Dummy for being autarkic
Net sales (kg)	Net sales of millet: equal to quantity sold minus quantity bought
Net purchases (kg)	Net purchase of millet: equal to quantity bought minus quantity sold
Millet market price (CFA franc)	Average millet market price in the EA where the household lives
Non-millet farm income (CFA franc)	Income from sale of crops other than millet
Age of the household head (years)	Age of the household head
Female household head (1=yes)	Dummy for female-headed household
Formal education (1=yes)	Dummy for whether the household head has formal education
Household living in a rural area (1=yes)	Dummy for whether the household head lives in a rural area
Household has used at least one farm input (1=yes)	Dummy for whether the household head has used at least one farm input in the growing season prior to survey
Dependency ratio (members aged 0-9 or >60)	Number of members younger than 9 years old and older than 60 years old in the household
Area planted of millet (ha)	Area planted of millet in the growing season prior to survey year
Dummy for polygamous household head (1=yes)	Dummy for whether the household head is polygamous
Tropical livestock unit	The total number of tropical livestock that the household possesses. Livestock considered includes cattle, sheep, goat, laying hens, poultry, and other poultry.
Distance to nearest market (KMs)	Distance from the EA where the household lives to the nearest market
Share of HHs who sold millet by cluster (%)	The share of other households living in the same EA as household head who have sold millet.
Days since start of the agriculture survey in 2011 (days)	Number of days since the start of the agriculture survey in 2011, which is November 4, 2011
Dummy for adopting agricultural technologies (1=yes)	Dummy for whether the household has adopted agricultural technologies as a coping strategy against perceived negative rainfall shock
Dummy for off-season agricultural production (1=yes)	Dummy for whether the household has used off-season agricultural production as a coping strategy against perceived negative rainfall shock
Dummy for migration (1=yes)	Dummy for whether one household member has migrated as a way to cope against perceived negative rainfall shock
Dummy for diversification (1=yes)	Dummy for whether the household has diversified its activities to non-agricultural activities as a coping strategy against perceived negative rainfall shock
Total rainfall in the growing season (mm)	Total cumulative rainfall in the growing season of prior to survey year
Negative rainfall shock	Average standardized deviation from long-term rainfall average for the growing season prior to survey year

Table 2.2: Summary statistics of the variables included in the analysis

	2011		2014		Full sample	
	Mean	SD	Mean	SD	Mean	SD
Panel A: Millet marketing						
Net seller (1=yes)	0.07	0.26	0.09	0.28	0.08	0.27
Net buyer (1=yes)	0.36	0.48	0.38	0.49	0.37	0.48
Autarkic (1=yes)	0.57	0.5	0.53	0.5	0.55	0.5
Net sales (kg)	9.95	47.57	27.99	106.65	17.94	79.86
Net purchases (kg)	1.23	2.27	1.28	2.07	1.26	2.18
Millet market price (CFA franc)	198.87	24.54	235.29	25.8	215.13	30.96
Non-millet farm income (CFA franc)	13171.65	97589.51	47705.98	246191.3	28838.27	181610.26
Panel B: Household characteristics						
Age of the household head (years)	45.66	14.62	47.79	14.06	46.63	14.41
Female household head (1=yes)	0.07	0.26	0.12	0.32	0.09	0.29
Formal education (1=yes)	0.13	0.34	0.12	0.32	0.13	0.33
Household living in a rural area (1=yes)	0.90	0.3	0.9	0.3	0.9	0.3
Household has used at least one farm input (1=yes)	0.58	0.49	0.7	0.46	0.63	0.48
Dependency ratio (members aged 0-9 or >60)	0.42	0.19	0.4	0.18	0.41	0.19
Area planted of millet (ha)	4.58	4.14	4.39	4.15	4.5	4.15
Dummy for polygamous household head (1=yes)	0.24	0.43	0.27	0.44	0.25	0.43
Tropical livestock unit	1.1	1.29	1.06	1.17	1.08	1.24
Distance to nearest market (KMs)	66.59	45.34	62.95	39.49	64.94	42.81
Share of HHs who sold millet by cluster (%)	2.43	6.12	2.74	6.38	2.57	6.24
Days since start of the agriculture survey in 2011 (days)	24.66	11.84	101.66	10.08	59.59	39.91
Panel C: Coping strategies						
Dummy for adopting agricultural technologies (1=yes)	0.28	0.45	0.30	0.46	0.29	0.45
Dummy for off-season agricultural production (1=yes)	0.12	0.33	0.14	0.34	0.13	0.34
Dummy for migration (1=yes)	0.15	0.35	0.21	0.41	0.18	0.38
Dummy for diversification (1=yes)	0.26	0.44	0.24	0.43	0.25	0.43
Panel D: Weather variables						
Total rainfall in the growing season of year t (mm)	330.24	86.19	366.66	101.22	346.76	95.04
Negative rainfall shock in the growing season of year t	0.5	0.61	0.18	0.28	0.35	0.51
Number of observations	1,615		1,341		2956	

Notes: Sample is restricted to second round only.

Table 2.3: Ordered Probit CRE results for rainfall shock impacts on participation in millet marketing

	Marginal effects		
	Net buyer	Autarkic	Net seller
Negative rainfall shock	-0.062**	0.034**	0.027**
	(0.031)	(0.017)	(0.014)
Age of the household head (years)	0.001	-0.000	-0.000
	(0.003)	(0.001)	(0.001)
Female household head (1=yes)	0.018	-0.010	-0.008
	(0.029)	(0.016)	(0.013)
Formal education (1=yes)	0.080**	-0.045**	-0.035**
	(0.031)	(0.017)	(0.014)
Household living in a rural area (1=yes)	-0.183***	0.102***	0.081***
	(0.037)	(0.021)	(0.018)
Household has used at least one farm input (1=yes)	0.051	-0.028	-0.022
	(0.041)	(0.023)	(0.018)
Dependency ratio (members aged 0-9 or >60)	-0.059	0.033	0.026
	(0.111)	(0.062)	(0.049)
Area planted of millet (ha)	-0.003	0.002	0.001
	(0.004)	(0.002)	(0.002)
Dummy for polygamous household head (1=yes)	0.037	-0.021	-0.017
	(0.023)	(0.013)	(0.010)
Tropical livestock unit	-0.007	0.004	0.003
	(0.015)	(0.008)	(0.007)
Arcsin (Non-millet farm income (CFA franc))	-0.018***	0.010***	0.008***
	(0.003)	(0.002)	(0.001)
Arcsin (Millet market price (CFA franc))	0.220	-0.122	-0.097
	(0.149)	(0.084)	(0.066)
Arcsin (Distance to nearest market (KMs))	0.041***	-0.023***	-0.018***
	(0.014)	(0.008)	(0.007)
Arcsin (Share of HHs who sold millet by cluster)	-0.066***	0.037***	0.029***
	(0.009)	(0.006)	(0.004)
Days since start of the agriculture survey in 2011 (days)	0.002**	-0.001**	-0.001**
	(0.001)	(0.001)	(0.000)
Observations	2956	2956	2956
Household fixed-effects	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes

Notes: The dependent variable is an ordered categorical variable, which takes 0 if the household is a net buyer, 1 if the household autarkic and 2 if the household is a net seller. The table shows the marginal effects of each variable on the different categories of the dependent variable. The regression includes household and year fixed-effects. Arcsin is the inverse hyperbolic since function. Robust standard errors clustered at the household level in parentheses. ***, ** and * indicated statistical significance at the 1%, 5%, and 10% respectively.

Table 2.4: Tobit CRE results for rainfall shock impacts on millet net sales and net purchases

	Marginal effects	
	Net sales	Net purchases
Negative rainfall shock	-3.134***	-0.326**
	(1.006)	(0.148)
Age of the household head (years)	-0.101	0.002
	(0.086)	(0.012)
Female household head (1=yes)	1.357	0.136
	(1.022)	(0.143)
Formal education (1=yes)	0.327	0.121
	(0.985)	(0.132)
Household living in a rural area (1=yes)	-2.213	-0.223
	(1.961)	(0.166)
Household has used at least one farm input (1=yes)	0.381	0.014
	(0.893)	(0.162)
Dependency ratio (members aged 0-9 or >60)	-3.825	0.246
	(2.795)	(0.503)
Area planted of millet (ha)	-0.086	-0.021
	(0.101)	(0.023)
Dummy for polygamous household head (1=yes)	1.007	0.285***
	(0.621)	(0.104)
Tropical livestock unit	-1.058**	-0.070
	(0.426)	(0.071)
Arcsin (Non-millet farm income (CFA franc))	0.255**	0.046**
	(0.124)	(0.018)
Arcsin (Millet market price (CFA franc))	7.936**	1.469**
	(3.398)	(0.653)
Days since start of the agriculture survey in 2011 (days)	0.081**	0.009*
	(0.032)	(0.005)
IMR seller	-11.921***	
	(1.262)	
IMR buyer		-1.000***
		(0.248)
Observations	1831	2661
Household fixed-effects	Yes	Yes
Year fixed-effects	Yes	Yes

Notes: The dependent variable for column 1 is inverse hyperbolic sine of millet net sales and the one for column 2 is inverse hyperbolic sine of millet net purchases. Each regression includes household and year fixed-effects. Arcsin is the inverse hyperbolic since function. Robust standard errors clustered at the household level in parentheses. ***, ** and * indicated statistical significance at the 1%, 5%, and 10% respectively.

Table 2.5: Ordered Probit CRE results for rainfall shock impacts on market participation by coping strategy

	Marginal effects		
	Net buyer	Autarkic	Net seller
Negative rainfall shock	-0.087**	0.048**	0.039**
	(0.033)	(0.019)	(0.015)
Dummy for adopting agricultural technologies (1=yes)	-0.014	0.008	0.006
	(0.039)	(0.022)	(0.017)
Dummy for off season agricultural production (1=yes)	0.124**	-0.069**	-0.055**
	(0.061)	(0.034)	(0.027)
Dummy for migration (1=yes)	-0.031	0.017	0.014
	(0.053)	(0.030)	(0.024)
Dummy for diversification (1=yes)	-0.024	0.013	0.011
	(0.039)	(0.022)	(0.017)
Negative rainfall shock # Dummy for adopting agricultural technologies	0.188***	-0.105***	-0.083***
	(0.064)	(0.036)	(0.029)
Negative rainfall shock # Dummy for off season agricultural production	-0.199*	0.111*	0.088*
	(0.091)	(0.051)	(0.040)
Negative rainfall shock # Dummy for migration	0.041	-0.023	-0.018
	(0.088)	(0.049)	(0.039)
Negative rainfall shock # Dummy for diversification	0.054	-0.030	-0.024
	(0.074)	(0.041)	(0.033)
Observations	2956	2956	2956
Household controls	Yes	Yes	Yes
Household fixed-effects	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes

Notes: The dependent variable for column 1 is inverse hyperbolic sine of millet net sales and the one for column 2 is inverse hyperbolic sine of millet net purchases. Each regression includes other controls, household fixed-effects and year fixed-effects. Arcsin is the inverse hyperbolic since function. Robust standard errors clustered at the household level in parentheses. ***, ** and * indicated statistical significance at the 1%, 5%, and 10% respectively.

Table 2.6: Impacts of short-term coping strategies on net sales and net purchases

	Marginal effects	
	Net sales	Net purchases
Negative rainfall shock	-3.627**	-0.461**
	(1.121)	(0.176)
Dummy for adopting agricultural technologies (1=yes)	1.034	0.046
	(0.902)	(0.183)
Dummy for off season agricultural production (1=yes)	4.186**	-0.142
	(1.969)	(0.292)
Dummy for migration (1=yes)	-0.069	0.294
	(1.112)	(0.216)
Dummy for diversification (1=yes)	-1.559	-0.315
	(1.061)	(0.188)
Negative rainfall shock # Dummy for adopting agricultural technologies	3.140	0.523
	(2.720)	(0.355)
Negative rainfall shock # Dummy for off season agricultural production	-5.641	-0.497
	(4.104)	(0.448)
Negative rainfall shock # Dummy for migration	-5.030	-0.478
	(3.210)	(0.455)
Negative rainfall shock # Dummy for diversification	9.206***	0.844**
	(3.498)	(0.348)
IMR Seller	-12.045***	
	(1.269)	
IMR Buyer		-1.012***
		(0.251)
Observations	1831	2661
Household controls	Yes	Yes
Household fixed-effects	Yes	Yes
Year fixed-effects	Yes	Yes

Notes: The dependent variable for column 1 is inverse hyperbolic sine of millet net sales and the one for column 2 is inverse hyperbolic sine of millet net purchases. Each regression includes other controls, household fixed-effects and year fixed-effects. Arcsin is the inverse hyperbolic since function. Robust standard errors clustered at the household level in parentheses. ***, ** and * indicated statistical significance at the 1%, 5%, and 10% respectively.

CHAPTER 3: Field Access and Productivity in the Senegal Groundnut Basin

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Abstract

Access to arable land for agricultural production in sub-Saharan Africa (SSA) is increasingly rationed due to rising land scarcity and rapid population growth in rural areas. This growing land scarcity in SSA may exacerbate generational and gender disparities in land access and agricultural productivity. We use a rich dataset of 1,123 households from rural Senegal to examine the determinants of individual household member access to groundnut fields, the predominant cash-crop in the Groundnut Basin of Senegal, and the implications of limited land access for groundnut productivity of young adult and female field managers. We employ a triple-hurdle model to control for selectivity in land access and field measurement in farmer productivity estimates. We find that young adults and females have fewer opportunities to access land compared to older and male household members, respectively. Emerging rental markets for land appear to increase, rather than decrease these disparities. Further, we show that higher productivity may not be driving differential access among older adults. Results suggest that with equal access, young adults may be as or more productive groundnut cultivators than older adults. The findings also support that programs to increase young adult and female economic opportunities should focus on closing gaps in access to resources for production rather than decreasing observed production disparities.

Keywords: Land Access, Field Productivity, Triple-Hurdle Model, Senegal.

3.1. Introduction

In sub-Saharan Africa (SSA) access to arable land for agricultural production is increasingly rationed with rising land scarcity and rapid population growth in rural areas (Jayne et al. 2014). Land scarcity has also been associated with the rise in agricultural land sales and rental markets in some areas, and has fueled a debate over whether land markets increase or decrease equity in land access (Chamberlin and Ricker-Gilbert 2016). A related concern is that generational and gender disparities in land access and agricultural productivity may be amplified by growing land scarcity (Kilic et al. 2015; Filmer and Fox 2014).

Gender disparities in agricultural production in Sub-Saharan Africa are well documented. Although women comprise a roughly half of agricultural workers, a study of six SSA countries finds that women farmers produce between 13 and 25 percent less than men (World Bank 2014). Rigorous empirical decompositions identify unequal access to land and lower quality land as important factors in gender productivity gaps (e.g. Burke and Jayne 2021; Smale et al. 2019; Udry 1996). Young adults also show lower productivity than older adult household members, but there is little research on the roles of land and other factors, relative to accumulated human capital in agricultural production, in age-related agricultural productivity gaps in SSA (Sumberg et al. 2012).

In this paper we examine the determinants of individual household member access to groundnut fields, the predominant cash-crop in the Groundnut Basin of Senegal, and the implications of rationed land access for groundnut productivity. The approach differs from the previous literature which focuses on gender, and to a lesser extent young adult productivity differences without accounting for rationed field access. The results address two broad sets of questions that will guide support for smallholder agricultural in situations of emerging land scarcity like those found in the Groundnut Basin of Senegal and other regions of SSA. First, what are the key factors that determine household allocation of land to individual members under land scarcity? Importantly, do emerging rental markets increase or decrease household member land access? Second, are unobserved factors associated with selective land access also associated with individual household member differences in agricultural productivity? Or can we safely examine the determinants of individual household member agricultural productivity separately from their ability to access land?

3.2. Groundnut production and field access in the Senegal Groundnut Basin

Groundnut production in rural areas of the Senegal Groundnut Basin provides an excellent vignette to examine land allocation decisions and their association with field productivity. The Groundnut Basin faces a number of constraints that are common across SSA, including increasing land scarcity (Faye et al. 2021), degraded soils (World Bank 2018), variable rainfall (World Food Program 2014, Mechiche-Alami et al. 2020), high rates of out-migration of male young adults (FAO 2020), and limited opportunities for young adults who remain in rural areas (Estruch et al. 2019).

Groundnuts are a cornerstone of the rural economy in the Groundnut Basin. Around 70% of the Groundnut Basin population participate in groundnut farming and groundnuts account for over 35% of household revenue (Diagne 2014). Groundnuts are grown on rainfed fields in the single annual agricultural cropping season. Further, groundnuts are exclusively grown in a groundnut – cereal crop rotation and the two crops cover over 85% of agricultural land (DAPSA, 2020). Groundnuts are grown for household collective consumption and income, but also represent one of the few available income generating opportunities for individual household members, particularly rural young adults and females.

Opportunities to manage a field for individual income have become increasingly limited with rural population increases and fixed agricultural land area. Most adult household members assist in household groundnut production. However, relatively few household members manage their own fields for individual income. Estruch et al. (2019) find that while 81% of young adults 15 – 34 years of age work in agriculture in rural Senegal, 70% of young adults do so as unpaid agricultural labors within the household. Similarly, Mills et al (2021) find that 93 percent of household heads manage a groundnut field and 86 percent of young adults contribute labor to groundnut production, but only 18 percent of young adults manage a field where they retain most of the income. Rural households in Senegal operate within a gerontocratic and patriarchal social structure, where the elder male household heads manage agricultural economic opportunities including allocation of land to household members for agricultural production (Niang et al. 2017). What are unclear is the relative roles that social hierarchy and customs, expected productivity, and opportunity costs of time play in household head field allocation decisions, how emerging land scarcity is changing this balance of factors in land allocation decisions, and how land allocation decisions influence observed productivity differences of household members.

3.3. Conceptual Framework

The household head is responsible for intra-household allocation of the agricultural lands to which the household has a traditional inheritance claim (Niang et al 2017). However, there is broad consensus that a unitary model of household decision making does not adequately represent the production or consumption decisions of households in SSA (Hill 1975; Haddad et al. 1997; Bobonis 2009). Other household members have varying degrees of influence on field allocation decisions, as well as other agricultural production decisions that may lead decisions lead to productivity disparities between household members (Udry 1996; Owens 2001). Some collective household models suggest individuals may bargain over household allocations, but Pareto efficiency is achieved through trade (Browning and Chiappori 1998; Rangel and Thomas 2012). However, allocative efficiency is often rejected in studies of West African households (Duflo and Udry 2004). Adding further complexity to groundnut field allocation decisions in Senegal is the fact that some fields are collectively farmed for household consumption and household income needs, while other groundnut fields, are allocated to individual household members who retain most of the fields revenues (Rangel and Thomas 2003).

Agricultural land markets offer one avenue to overcome intrahousehold inefficiencies in land allocation. However, as mentioned, there is currently limited access to fields for groundnut cultivation through land markets. Officially most rural land cannot be bought or sold in Senegal under customary tenure practices and is legally held by the state as ‘national domain (Niang et al 2017). Individual household members do occasionally borrow or rent fields for groundnut production, but these transactions occur largely outside of the legal framework for land tenure. Figure 3.1 presents an overview of the household field allocation decision with a household head and other household members. Without loss of generality, we focus on the field allocation decision for one communal field and multiple individual household member fields. We assume the household allocates land to maximize the weighted utility from household field production (U_H) and field production of the individual members (U_i), where ϖ_i are the bargaining weights of individual household members and s_i is the share of field revenues retained by the individual. Individual household members can also rent land for production (r_i) if rental land is available in the market.

$$U_H\left(I_H(x_H)+\ \sum_{i=1}^{n}[(1-s_i)I_i(x_i+r_i)]\right)+\ \sum_{i}^{n}[\varpi_i U_i\big(s_i I_i(x_i+r_i)\big)]$$

$$s.t.\ \ x_T = x_H + \sum_{i=1}^{n} x_i$$

The first order conditions for optimal allocation between communal and individual fields is:

$$\frac{\partial U_H}{\partial I_H}\frac{\partial I_H}{\partial x_H} = \left[(1-s_i)\frac{\partial U_H}{\partial I_i} + s_i\varpi_i\frac{\partial U_i}{\partial I_i}\right]\frac{\partial I_i}{\partial x_i}$$

If the household head values groundnut income kept by the individual producer ($s_i\varpi_i\frac{\partial U_i}{\partial I_i}$) less than they value income to the household ($\frac{\partial U_H}{\partial I_H}$ or $\frac{\partial U_H}{\partial I_i}$), then $\frac{\partial I_i}{\partial x_i} > \frac{\partial I_H}{\partial x_H}$. Assuming decreasing economies of scale in production ($\frac{\partial^2 I_i}{\partial {x_i}^2} < 0$), then less land will be allocated to individual producers and individual plots will be farmed more intensively. As noted, groundnuts must be grown in a crop rotation with a cereal, usually millet, and there are limits on field divisibility. The first order conditions imply that the relevant constraint for access to any field is that expected individual productivity on an allocated field must exceed household field productivity by:

$$\frac{\frac{\partial I_i}{\partial x_i}}{\frac{\partial I_H}{\partial x_H}} > \left[1 - s_i + s_i \varpi_i \left(\frac{\partial U_i}{\partial I_i} \Big/ \frac{\partial U_H}{\partial I_H}\right)\right]^{-1} = \text{RPT}$$

We refer to this RHS equation as the relative productivity threshold (RPT). The RPT decreases with individual bargaining power $\partial RPT \big/ \partial \varpi_i < 0$, implying individuals with greater bargaining power will be more likely to have access to groundnut fields. Similarly, the RPT increases with the share of groundnuts retained by the individual, implying individuals who do not share revenues with the household will have less access to groundnut fields. The RPT will decrease with increasing marginal utility of individual income $\partial RPT \, / \, \partial(\frac{(\partial U_i)}{\partial x_i}) < 0$. Individuals with relatively high marginal utility of income from groundnut production or, equivalently, few alternative income generating opportunities will be more likely to be allocated groundnut fields. Finally, more productive individuals in terms of income generation per unit of land will be more likely to exceed the RPT, thus establishing a direct link between field productivity and field access.

Land quality

If the household head accounts for land quality in land allocations, $I_i(x_i, a_i)$, then similar to land allocations $\frac{\partial I_i}{\partial a_i} > \frac{\partial I_H}{\partial a_H}$. Assuming diminishing returns to land quality, $\frac{\partial^2 I_i}{\partial {a_i}^2} < 0$, the household head will tend to allocate lower quality land for individual fields based on the same factors outlined above for the land allocation decision.

Rental land

As noted, land cannot legally be bought or rented in Senegal. In many areas of the Groundnut Basin there is a missing rental market for land and land rental is not an option. However, in several areas de-facto rental markets have emerged. In this case, rental markets provide another avenue for individuals to access land. By the same token, active rental markets can create an opportunity for household heads to rent out fields rather than allocate them to individual household members. If active rental land markets increase or decrease individual access to groundnut fields is thus left as an empirical question. If individuals do procure land through rental markets, the net returns on production must be sufficient to cover the additional market determined rental costs. This suggests the most productive farmers will bid up rental prices and that observed productivity will be higher on rented fields than household allocated fields.

Endogenous Censoring

The conceptual framework highlights the potential role of expected individual productivity in field allocation decisions. In this case, an observed sample of field producers is likely to be endogenously censored and unobserved heterogeneity may bias productivity estimates. A second form of endogenous censoring arises in the current application from the fact that some households, particularly those with household members that rent fields in grey markets, were less willing than others to allow surveyors to measure the size of their fields. This censoring of observed measured fields raises additional concerns about selection bias in productivity estimation.

3.4. Empirical Framework

As indicated in the conceptual framework, individual groundnut productivity is likely to influence field allocation decisions, as well as procurement of rented fields and, thereby, measurement of groundnut fields in productivity analysis. Our rural Groundnut Basin sample consists of 7,527 individuals 16 years of age or older living in 1,123 households. Of these, 2,558 individuals in the sample are responsible for the management of a groundnut field. However, we have complete data for only 1,983 individuals growing groundnuts. In the vast majority of cases (559 out of 575) missing data is due to the fact that interviewers were not able to measure the area of individual groundnut fields. Hence, we observe farmer groundnut productivity only if they meet two selection criteria. First, the individual has access to at least one groundnut field. Second, conditional on access, the size of their fields is measured (figure 3.2). Further, the variables that influence these two sample selection mechanisms are different. Given the censored data at hand, the appropriate estimation technique is the triple-hurdle model similar to the one developed by Burke et al. (2015). The triple hurdle model consists of three jointly estimated equations; one for field access, one for field measurement, and one for field productivity estimation.

Let $\boldsymbol{X_1}$ denote the vector of regressors that are assumed to affect the field access decision, $\boldsymbol{X_2}$ the vector of regressors that influence field measurement and $\boldsymbol{X_3}$ the vector of regressors that affect producer productivity. For a given person $\boldsymbol{i}$, we can write the system of equations as follows:

$$\begin{cases} y_{1i}^* = \boldsymbol{X_{1i}\beta_1} + \varepsilon_{1i} & (1) \\ y_{2i}^* = \boldsymbol{X_{2i}\beta_2} + \varepsilon_{2i} & (2) \\ y_{3i}^* = \boldsymbol{X_{3i}\beta_3} + \varepsilon_{3i} & (3) \end{cases}$$

$$\text{with } \begin{pmatrix} \varepsilon_{1i} \\ \varepsilon_{2i} \\ \varepsilon_{3i} \end{pmatrix} \sim n\left(\begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, \sum \right) \text{ and } \sum = \begin{bmatrix} 1 & \rho & \sigma_{13} \\ \rho & 1 & \sigma_{23} \\ \sigma_{31} & \sigma_{32} & \sigma_{33} \end{bmatrix}$$

Where $y_{m,i}^*$, $\boldsymbol{m} = 1, 2, 3$ are the underlying latent variables, $\boldsymbol{\varepsilon_i}$, $\boldsymbol{i} = 1, 2, 3$ are standard normal error terms. $\boldsymbol{\sum}$ is the variance-covariance matrix of the error terms from the three equations with $\boldsymbol{\rho}=\mathrm{Cov}(\varepsilon_{1i}, \varepsilon_{2i})$ and $\mathrm{V}(\varepsilon_{1i}) = V(\varepsilon_{2i}) = 1$. $\sigma_{31} = \sigma_{13}=\mathrm{Cov}(\varepsilon_{1i}, \varepsilon_{3i})$ and $\sigma_{23} = \sigma_{32} = \mathrm{Cov}(\varepsilon_{2i}, \varepsilon_{3i})$.

The observed outcomes in each stage can be represented as follows:

$$\begin{cases} y_{1i} = 1 & \text{if} \quad y_{1i}^* > 0 \\ y_{1i} = 0 & \text{Otherwise} \end{cases} \tag{4}$$

$$\begin{cases} y_{2i} = 1 & \text{if} \quad y_{1i}^* > 0 \ \textit{and} \ y_{2i}^* > 0 \\ y_{2i} = 0 & \text{if} \quad y_{1i}^* > 0 \ \textit{and} \ y_{2i}^* < 0 \\ y_{2i} = \text{unobserved} & \text{if} \quad y_{1i}^* < 0 \end{cases} \tag{5}$$

$$\begin{cases} y_{3i} = y_{3i}^* \quad \text{if} \quad y_{1i} = 1 \text{ and } y_{2i} = 1 \\ y_{3i} = \text{unobserved otherwise} \end{cases} \tag{6}$$

Where $\boldsymbol{y_{1i}}$ is an indicator variable for individual household member field access, $\boldsymbol{y_{2i}}$ is an indicator variable for measurement of the individual fields and $\boldsymbol{y_{3i}}$ is person-level groundnut productivity.

3.4.1. Estimation of the triple hurdle model

We estimate all parameters in equations (1) – (3) simultaneously using Maximum Likelihood Estimation (MLE). The simultaneous estimation of all equations ensures consistent standard errors and controls for selection bias in the observed outcomes. Identification of production equation parameter estimates is based on credible exclusion restrictions in the first two stages with inclusion of variables that only influence the outcome in that stage. In the first and second stages, probit models are applied to estimate the field access and field measurement decisions, respectively, and in the third stage a log-normal specification is applied to estimate individual groundnut productivity.

The resulting sample likelihood function of our triple-hurdle model is:

$$f(\boldsymbol{y_i}, \mathbf{X_i}, \boldsymbol{\beta_1}, \boldsymbol{\beta_2}, \boldsymbol{\beta_3}, \textstyle\sum) = \sum_{i=1}^{N} [\Phi(a_i)]^{y_{1i}=0} + [\left(1 - \Phi(a_i)\right)\Phi(b_i)]^{\boldsymbol{y_{1i}=1, y_{2i}=0}}$$
$$+ \left[c_i + \sigma_{13} \frac{\phi(\mathrm{a}_i)\Phi[(b_i - \rho a_i)(1-\rho^2)^{-1/2}]}{F(\mathrm{a}_i,\ \mathrm{b}_i;\ \rho)} + \sigma_{23} \frac{\phi(\mathrm{b}_i)\Phi[(a_i - \rho \mathrm{b}_i)(1-\rho^2)^{-1/2}]}{F(\mathrm{a}_i,\ \mathrm{b}_i;\ \rho)}\right]^{\boldsymbol{y_{1i}=1, y_{2i}=1}}$$

Where $a_i = \mathrm{X_{1i}}\beta_1$, $b_i = \mathrm{X_{2i}}\beta_2$ and $c_i = \mathrm{X_{3i}}\beta_3$. ϕ is the standard normal univariate density function and $\boldsymbol{\Phi}$ is the standard cumulative distribution function. $\boldsymbol{F}$ is the bivariate normal cumulative distribution evaluated at $\mathrm{X_{1i}}\beta_1$, $\mathrm{X_{2i}}\beta_2$ and ρ.

3.4.2. Variables included in the triple-hurdle model

3.4.2.1. Field access

Following the conceptual framework, we expect high individual bargaining power within the household, low access to non-groundnut income earning opportunities, and high expected groundnut field productivity to be associated with a greater likelihood that an individual household member manages a groundnut field. We include proxies for these factors in the specification of individual groundnut field access. The individual relationship to the household head is arguably the most important determinant of bargaining power in the field allocation decision. We include indicator variables for spouse, son-daughter, son or daughter in-law, parent, brother or sister, brother or sister in-law, with the baseline group being other unrelated household members. Age is expected to play an important role in field access. Rural areas of the groundnut basin have a gerontocratic social structure and elder household members have greater bargaining power in land allocation decisions. In the field access equation, we include indicator variables for the age groupings 16-20, 21-25, 25-29, 30-35, and 36-40 years of age to estimate age-related differences in field access relative to the baseline group of 41years of age and older. Similarly, females generally have less bargaining power under the patriarchal social structure and are less likely to have access to groundnut fields.

Emphasis on groundnut farming also differs among the region's main ethnic groups (Mandinka, Sere, Woolf, Fulani). The Fulani who emphasize livestock production over agricultural activities and maybe less likely to have access to fields. We include indicator variables for Sere, Woolf, Fulani ethnic groups to account for these differences with Mandinkas and other less prevalent ethnic groups combined as the baseline.

Education opportunities are relatively limited in the rural Groundnut Basin and split between French, Arabic, and, to a lesser extent, Koranic school instruction. Survey data indicate that 18% of young adults have not attended school, 25% attended primary school, 51% of young adults attended secondary school, and only 5% went on to university (Toure et al. 2021). Attendance of secondary school or beyond may increase other earnings opportunities and reduce the likelihood of groundnut field access. We include indicator variables for type of school attended relative to no school, as well as interaction terms between type of school attended and completion of secondary school or beyond to allow for differential impacts of school type on groundnut field access. One quarter of young adults migrate to other areas within Senegal, but 78% of these migrants still contribute to household groundnut production (Toure et al. 2021). Some domestic migrants even continue to manage groundnut fields, but higher opportunity costs of time are expected to make migrants much less likely to manage groundnut fields than other household members. Greater land availability is expected to decrease household land constraints and increase field access. We include two proxies for household land availability. The first is the share of groundnut fields of other households in the same village (from the cluster of 15 households in the sample) fallowed at least once in the previous three cropping seasons. We also interact this village fallow proxy for land availability with young adult (16-29 years of age) and female indicator variables to allow land availably to have age and gender specific impacts. The second proxy for land availability is access to land through land rental markets, which we measure as the share of groundnut fields of other households in the same village that are rented.

3.4.2.2. Measured fields

As noted, missing field data is primarily driven by household head refusal to allow measurement of groundnut fields. In 97% of the cases of missing data the survey team was not able to measure fields of an individual. Variables in the probit model specification for individuals with complete field data differ from those in the probit model for field access. The specification includes household head education, age, and ethnicity, as these characteristics may influence the household head understanding of the goals of the survey and trust in the surveyor. We also include fixed effects for each of the main survey interviewers, as some interviewers may have been better than others in explaining the survey purpose and reason for measuring groundnut fields and obtaining household cooperation in field measurement.[20] Heads in households with rented fields may be likely to permit field measurement because of concerns that field rental is not legally sanctioned and concerns the field measurement may lead to a conflict with the field provider. We include an indicator variable for whether the household has any member with rented groundnut fields.

2.4.2.3. Productivity

The logarithm of yield per hectare aggregated across all the individual's groundnut fields is specified as a function of field characteristics, field inputs, and field manager characteristics. Field characteristics includes total size of all fields managed by the individual, with the expectation that marginal productivity decreases with field size under the individual's management. The total number of fields managed by the individual is also included in the model. We expect that productivity may also decrease with more fields, although most individuals (82%) manage only one field. An indicator of if the manager has a field where the groundnuts are used for household consumption or household income is included in the specification. As demonstrated in the conceptual framework, we expect household fields to be less intensively cultivated and to have lower yields. Similarly, more distant fields may be less intensively cultivated due to travel time costs. On the other hand, as discussed, rented fields may be more intensively cultivated in order to cover the additional costs of land rental. Finally, we include a measure of inherent field quality based on historic crop-specific NDVI levels in second half of October. We expect the field quality measure to be positively correlated with yield.

[20]In 22% of the missing data cases the field was rented. By contrast, only 7% of fields with complete data are rented.

The following inputs are accounted for in the yield equation, kilograms of groundnut seed planted, if all or part of the groundnut seed for the fields was purchased seed in market rather than saved from last year's harvest, kilograms of inorganic fertilizer used on the fields, and amount in CFA spent on pesticides and insecticides. Other measures of field soil fertility inputs include the share of the manger's fields that receive organic manure from livestock and the share of fields that were fallowed at least once over the previous three cropping seasons.

Individual characteristics of the field cultivator are expected to influence yields as proxies for accumulated human capital from farming. The age of the groundnut field manager is also expected to influence individual human capital. We include indicator variables for the age groupings 16-20, 21-25, 25-29, 30-35, and 36-40 years to estimate age-related differences in yield relative to the baseline 40+ years of age group. Gender may also influence human capital accumulation, particularly if groundnut field management opportunities are historically limited for females. The specification includes an indicator variable for female field managers, and also interacts the female indicator variable with age groups to see if the gender yield gap may increase over time due to more limited accumulation of groundnut field management experience. We also allow for yield differences across major ethnic groups. Similar to the field access model specification, we allow type of education (French, Arabic, Koranic, none) and secondary education by education type to influence groundnut field productivity. A key question is whether secondary education increases an individual's groundnut productivity or decreases groundnut-specific human capital accumulation and groundnut productivity. Finally, we include an indicator variable that identifies temporary migrant field managers. Migrant constraints on supervision of fields may result in lower yields.

3.4.3. Alternative specifications

We also estimate the specifications above with the sub-sample of all non-household heads and for the sub-sample of young adult 16-29 years of age non-household heads. Household heads are older and are responsible for all fields grown for household consumption and income. These two sub-samples allow us to focus on individually managed fields. In a final alternative specification, we estimate the individual groundnut equation alone using OLS for the full sample and two alternative sub-samples to highlight how accounting for selective field access and censored field measurement influences productivity estimates.

3.5. Data

The data comes from a representative sample of 1,123 rural[21] households in the heart of the Groundnut Basin (the provinces of Kaolack and Kaffrine and the department of Koumpentoum within the province of Tambacounda) surveyed in February and March of 2020. The survey sample is drawn in two stages. First, 75 rural villages are chosen as a population weighted random sample of all villages in the study region with populations less than 900 persons in the Senegal Census of 2014 (figure 3.2). Second, 15 households are randomly drawn from village lists of all households that contain young adults and that cultivate groundnuts.[22] The final sample consists of 7,527 individual household members 16 years or older. The household survey was conducted with the household head, or other member responsible for overall management of the household, and contains information on the demographic composition of the household (focusing on members 16 years of age and older), fields cultivated, field-specific details on inputs and outputs associated with groundnut production, and roles of young adult members of the household in groundnut production. If the household head agreed, all groundnut fields were also are visited and field

[21] Rural is defined as villages with populations less than 900 people.

[22] The initial sample was 1,125 households based on 75 villages and 15 households per village. However, two households were lost due to incorrect unique identifying numbers.

perimeters were walked using a GPS-enabled field measurement application. Household residences were also geo-referenced, enabling the estimation of distance from the household residence to fields.

Historic normalized difference vegetative index (NDVI) measures, a standard measure of vegetative health between -1 and +1, were extracted from Google Earth Engine for the 2016 to 2020 cropping seasons for all digitally referenced fields based on 10-meter resolution Sentinel 2 multispectral satellite imagery (MSI). Field quality measures were then generated based on field cropping histories for the previous three cropping seasons and the average crop-specific inter-quartile ranking of NDVI for the second half of October in each year when biomass is usually at its peak. The field quality measure identifies fields with consistently higher or lower biomass production.

Descriptive statistics for the dependent and independent variables employed in the field access, field measurement and productivity equations are presented in table 3.1. In terms of field access, 34% of our sample had access to a groundnut field. Looking at sample household composition, 15% are household heads, 21% are spouses and 29% are sons or daughters of the household head. Household members in the sample are mostly young (aged 16 to 29) adults (53%) and male (52%). Twenty-six percent have a French education, 41% have a koranic education and 61% can read and write. Turning to the sample of individuals allocated a groundnut field, 78% had their fields measured and had complete data. The average age of household members in the growers sample is 51 years old. This is much older than the average age of 32 years old for the sample of all individuals 16 years of age and older. Only 10% individuals live in households with at least one rented groundnut field. For the variables used in the productivity estimation, the groundnut yield is 0.89 tons and the cultivator manages 1.84 hectares on average. Most growers only manage one field and the average home to field distance is 1.2 kilometers. About half of the cultivators purchase groundnut seeds in the market, and growers use on average 190 kg of groundnut seeds. The application rate for chemical fertilizer is relatively low at 115 kg of chemical fertilizer and 19% of their fields see application of organic manure.

3.6. Results

We estimate the triple hurdle model for all persons 16 years of age and older and the two sub-samples of all non-household heads and of all young adults 16 to 29 years of age. Correlation coefficients between the field access, field measurement and productivity equations are presented in table 3.2. For the full sample, the error term in the field access equation shows a strong negative correlation with the productivity equation. This suggests that unobserved factors that make individuals more likely to gain field access may also be associated with lower groundnut productivity. By contrast, in the young adult non-household head sub-sample, the field access and productivity error correlation coefficient is positive. So, among young adults, unobserved factors that are associated with greater field access may also be associated with greater productivity. It is also worth noting that the error correlation coefficient between field measurement and productivity is negative and significant in the full sample, suggesting unobserved factors associated with non-measurement of fields may also be associated with higher productivity.

Taken together, these results highlight the importance of accounting for both selective access and selective agreement to provide field measurement information when estimating individual groundnut productivity.

3.6.1. Field access

Table 3.3 presents marginal effect estimates for the determinants of field access for the three samples. Table C1 presents the associated initial model parameter estimates used to calculate the marginal effects. As expected, in the full sample being a household head generates the largest increase in field access (47%) relative to the baseline group of unrelated individuals living in the household. Spouses, brothers and sisters, sons and daughters, and brothers and sisters in-law of the household head show much levels of differential field access (between 6% and 11%) relative to unrelated household members. These estimated relationships between household membership status and field access are largely consistent for the sub-samples of non-household heads and young adult non-household heads.

Household members also have greater access to groundnut fields as they get older. In the full sample, young adults 16 to 20 years of age are 21% less likely to manage a groundnut field, relative to adults 40 years of age and older. The influence of age on groundnut field access decreases for older young adults; 21 to 25 year olds and 26-29 year olds are 11% and 8% less likely respectively to have groundnut field access compared to adults 40 years of age and older. Reduced access to groundnut fields in younger age groups is also found in the non-household head and young adult non-household head samples. Similarly, females are estimated to have less access to fields than males (between 10% in the full sample and 17% in the non-household head sample). But we find no differential influence of age on field access for females.

Education type has a limited influence on field access. Koranic education is associated with 6% to 9% greater field access in the non-household head and youth non-household head samples, respectively, relative to no education. However, French secondary or above education is negatively associated with field access in all three samples; likely due to enhanced labor market opportunities. In the young adult non-household sample, we also see a strong positive association between Koranic secondary and above education and field access. Functional literacy (ability to read and write) shows no association with field access and, as expected, temporary migration is associated with reduced field access.

The association between village land scarcity (as measured by the share of village land of other households that is fallowed) and groundnut field access appears to be strongly mediated by age and gender. In the full sample, village fallow share shows no association with individual groundnut field access. However, young adults show greater access and females show less access with increases in the share of village land that is fallowed. In the young adult sample, the association between field land and labor access is positive, and females continue to show lower access with higher village shares of fallowed land. The results may be due to young adult males' ability to gain access to groundnut fields by clearing fallow land. These opportunities do not extend to females. Finally, a higher share of rented land among other households in the village is strongly associated with lower household member access to groundnut fields, suggesting that the emergence of land rental markets leads to lower, not higher, land access within households.

3.6.2. Field measurement

Table 3.4 presents marginal effects associated with the relatively parsimonious specification of the determinants of fields being measured and having complete data for the sample of all groundnut fields. Model coefficients underlying the marginal effects are presented in table C2. Enumerator fixed-effects are significant as a group, indicating that some enumerators were more effective than others in getting household head permission to measure the household groundnut fields. Ethnicity and household head education, on the other hand, have no impact on field measurement, and the age of the household head is only significant in the young adult sample. As expected, the presence of rented groundnut fields in the household shows a strong negative association with successful field measurement in all three samples, reducing the probability of field measurement between 14% in the full sample and 41% in the young adult sample.

3.6.3. Field productivity

Marginal effects of variable impacts on the logarithm of individual yields across all their fields are presented in table 3.5 for our three samples, with associated model parameter estimates in table C3. Yield is negatively associated with groundnut area cultivated, with a 10% increase in area associated with a 2.0% to 2.5% decrease yields. However, yields increase when the field manager has multiple fields. In the full sample, yields are also higher when the cultivator has rented fields. This relationship is not found in the non-household head and young adult samples, so the relationship between productivity and field rental may apply mainly to household heads. On the other hand, non-household heads show a decrease in yields with distance of the field from the household. Time cost of travel may lead to less intensive cultivation on distant fields. As noted, household heads manage the groundnut fields cultivated for household consumption and, as predicted in the conceptual framework, yields are lower when the household head has a field for household consumption.

Turning to input use, yields are significantly lower when the field manager purchases some seed for planting from the market rather than only using seed stored by the household. This finding highlights the difficulties that farmers in the Groundnut Basin face in obtaining new high-quality groundnut seed. Yields increase with the quantity of seed and fertilizer applied to fields, as well as with the value of pesticides applied to fields in the full sample and non-household head sample. Yields also increase with share of fields that receive organic manure from livestock in the full sample. Fallowing fields in the previous three cropping seasons is not associated with changes in yield. But as measured through field quality, the historical performance of fields, is associated with higher yields, suggesting that there is an inherent persistent component to field quality. Interestingly, while position within the household appears to be very important in field access, status within the household does not appear to strongly influence yields after controlling for other factors like input use and field quality.

The one exception being that the small sample of parents of the household head show significantly higher yields in the full sample.

Age has no impact on yields in the full sample. But in the non-household head and young adult samples, young adults aged 16 to 20 actually show higher yields compared to those 40 years of age after controlling for selectivity in field access. In fact, in the non-household head sample, field managers 21 to 35 years of age also show higher yields. This suggests that higher productivity may not be driving great field access among older adults. Further, with equal access, young adult may be more productive groundnut cultivators than older adults non-household heads.

Females do not show a differential influence of age on yields. However, they do show around 9% lower yields overall than males in the full sample. But this yield gap is smaller than conventional gender productivity estimates (World Bank, 2014). Education type has, at best, a small impact on yield. French education and functional literacy show weak negative and positive associations with yields (*p=0.10*), respectively, in the full sample, while having a secondary or above French education is positively associated with yields in the young adult sample. Temporary migrants also show slightly higher yields on their field than non-migrants in the non-household head sample.

3.6.4. OLS estimation of field productivity

Table C4 provides OLS logarithm of yield estimates that do not control for selective field access and field measurement for comparison. Several differences from the triple-hurdle model estimates in table 3.5 are notable. For the full sample household heads show a much greater boost in estimated productivity (23%) in the OLS model compared to nonrelatives and females show a much greater yield penalty (37%) relative to males. In neither model does age influence productivity in the full sample. However, in the OLS model higher yields are no longer observed in the non-household head and young adult samples. These comparative results, combined suggest that selective field access and selective field measurement may explain a significant portion of household relationship and gender productivity differences. Further, young adults may show higher, not lower, levels of productivity when unobserved heterogeneity in field access and field measurement are accounted for in the estimation of field productivity.

3.7. Discussions and Conclusions

Groundnut cultivation is often considered to be one of the default income earning opportunities for young adults and females in rural areas of the Senegal Groundnut Basin. This paper shows that opportunities for groundnut cultivation are actually quite scarce for young adults and females and depend on their ability to gain access to limited land. Further, findings suggest that emerging rental markets may further limit rather than enhance household member land access. Widespread domestic temporary out-migration is a common response to limited income earning opportunities, particularly among young adult males. This strategy limits field access but not field productivity (Toure, 2021).

There are no simple solutions to increase young adult access to land in the Groundnut Basin. Intrahousehold land allocation decisions are made by older male household heads and they appear to favor themselves and other older males with the household. This intra-household distribution of bargaining power for field access will only change over generations. When arable land does appear to be available for cultivation, young adult male access appears to improve. But arable land not under continuous cultivation is becoming extremely rare in the Groundnut Basin and most other areas of SSA. Improving household land tenure may spur long-term investments in land under traditional-use-rights cultivation, but is unlikely to increase access for the next generation of farmers or female in the short-term.

Our results also imply intra-household land allocation decisions may not be driven by differences in household members productivity. In fact, unobserved factors associated with access may be leading to large observed male-female and young adult-older adult productivity gaps. When these unobserved factors like differential access to productive assets are controlled for, young adults actually show evidence of greater productivity than older non-household heads. Similarly, gender productivity gaps are significantly reduced when differential field access is accounted for in the analysis.

Perhaps the most important policy implication of our findings is that young adults and females can cultivate groundnuts with similar levels of productivity as older males who control land access when given similar opportunities and resources. Dissemination of this knowledge may help increase young adult and female bargaining power within households for access to land. The finding also has implications that design of programs to increase young adult and female economic opportunities should focus on closing gaps in access to resources for production rather than addressing skills gaps in management practices.

Table 3. 1: Descriptive statistics of the variables included in regression

	Field Access (n=7527)		Field Measurement (n=2258)		Field Productivity (n=1984)	
	Mean	SD	Mean	SD	Mean	SD
Field access (yes=1)	0.34	0.47				
Field measurement (yes=1)			0.78	0.42		
ln(yield) (tons/ha)					-0.58	0.92
ln (field size) (ha)					0.17	0.94
Number of fields					1.31	0.80
Share of rented field (individual level)					0.02	0.10
ln (average distance to field) (km)					6.79	0.98
Has field for household consumption (1=yes)					0.24	0.43
Groundnut seeds purchased in the market (1=yes)					0.50	0.50
ln(Quantity of seeds) (Kg)					4.78	1.02
ln(Quantity of chemical fertilizer) (Kg)					2.44	2.59
Share of fields with manure					0.19	0.38
Share of fallowed fields					0.15	0.35
ln(Amount spent on pesticides) (CFA Franc)					7.07	2.53
Field quality					2.45	0.74
Household head (yes=1)	0.15	0.36			0.45	0.50
Spouse (yes=1)	0.21	0.41			0.17	0.37
Son or daughter (yes=1)	0.29	0.46			0.16	0.36
Son or daughter in law (yes=1)	0.05	0.22			0.02	0.14
Parent (yes=1)	0.05	0.21			0.04	0.20
Brother or Sister	0.12	0.32			0.10	0.30
Brother or Sister in law (yes=1)	0.05	0.23			0.03	0.16
Age of Household head (years)			51.42	13.87		
Age 16 to 20	0.31	0.46			0.10	0.31
Age 21 to 25	0.14	0.35			0.09	0.28
Age 26 to 29	0.08	0.26			0.07	0.25
Age 30 to 35	0.15	0.36			0.16	0.36
Age 36 to 40	0.08	0.28			0.12	0.32
Female	0.48	0.50			0.28	0.45
Household head has secondary education (yes=1)			0.06	0.23		
French education	0.26	0.44			0.15	0.36
Arabic Education	0.09	0.29			0.08	0.28
Koranic	0.41	0.49			0.53	0.50
Wolof	0.57	0.49	0.63	0.48	0.64	0.48
Fulani	0.24	0.43	0.18	0.38	0.18	0.39
Serere	0.14	0.35	0.14	0.35	0.13	0.34
Can read and write (yes=1)	0.61	0.49			0.64	0.48
Temporary migration	0.05	0.08			0.08	0.28
Village Fallow Share	0.06	0.08				

Share of rented fields (village level)	0.16	0.37		
Household has rented a groundnut field (1=yes)			0.10	0.30

Table 3. 2: Estimated correlation coefficients between error terms

	Full sample			Non-Household heads			Youth non-Household heads		
	Coef	SE	Sig	Coef	SE	Sig	Coef	SE	Sig
ρ_12	0.212	0.122		-0.861	0.091	***	-0.861	0.032	***
ρ_13	-0.722	0.081	***	-0.138	0.247		0.566	0.108	***
ρ_23	-0.470	0.049	***	0.005	0.221		-0.131	0.144	

Coef stands for estimated coefficients and SE stands for robust standard errors clustered at the household level. Sig stands for significance level. *** indicates statistical significance at the 1% level. ρ_12 is the correlation coefficient between the error terms of the field access equation and the field measurement equation. ρ_13 is the correlation coefficient between the error terms of the field access equation and the productivity equation. ρ_23 is the correlation coefficient between the error terms of the field measurement equation and the productivity equation.

Table 3. 3: Marginal effects of the determinants of field access

	Full Sample			Non-Household Heads			Youth Adult non-Household Heads		
	ME	SE	Sig	ME	SE	Sig	ME	SE	Sig
Household head (yes=1)	0.463	0.025	***						
Spouse (yes=1)	0.107	0.025	***	0.153	0.035	***	0.199	0.045	***
Son or daughter (yes=1)	0.043	0.023	*	0.068	0.032	**	0.043	0.033	
Son or daughter in law (yes=1)	0.055	0.035		0.074	0.050		0.128	0.051	**
Parent (yes=1)	0.041	0.029		0.036	0.042				
Brother or sister	0.078	0.024	***	0.115	0.034	***	0.112	0.036	***
Brother or sister in law (yes=1)	0.054	0.032	*	0.082	0.046	*	0.071	0.048	
Age 16 to 20	-0.213	0.024	***	-0.308	0.039	***	-0.155	0.032	***
Age 21 to 25	-0.119	0.023	***	-0.168	0.041	***	-0.028	0.033	
Age 26 to 29	-0.087	0.027	***	-0.140	0.044	***			
Age 30 to 35	-0.032	0.022		-0.087	0.040	**			
Age 36 to 40	-0.004	0.028		-0.007	0.048				
Female	-0.111	0.024	***	-0.166	0.038	***	-0.144	0.051	***
Female*Age 16 to 20	0.028	0.029		0.063	0.045		0.043	0.048	
Female*Age 21 to 25	0.029	0.029		0.064	0.047		0.024	0.048	
Female*Age 26 to 29	0.004	0.035		0.038	0.054				
Female*Age 30 to 35	-0.003	0.028		0.035	0.046				
Female*Age 36 to 40	-0.002	0.034		-0.011	0.055				
French education	-0.010	0.020		0.001	0.031		0.036	0.037	
Arabic education	0.032	0.025		0.058	0.037		0.069	0.044	
Koranic education	0.024	0.017		0.056	0.026	**	0.086	0.033	***
French*Secondary education	-0.070	0.020	***	-0.107	0.031	***	-0.131	0.033	***
Arabic*Secondary education	-0.032	0.036		-0.018	0.052		-0.004	0.051	
Koranic*Secondary education	-0.053	0.031	*	-0.053	0.046		-0.285	0.076	***
Can read and write (yes=1)	0.015	0.014		0.005	0.021		-0.028	0.025	
Wolof	-0.008	0.038		-0.012	0.053		0.024	0.060	
Fulani	-0.164	0.039	***	-0.255	0.057	***	-0.188	0.066	***
Serere	-0.021	0.041		-0.025	0.058		0.043	0.066	
Temporary migration	-0.083	0.015	***	-0.099	0.021	***	-0.051	0.021	**
Village Fallow share	0.033	0.137		0.548	0.158	***	0.636	0.199	***
Village Fallow share*Youth	0.456	0.110	***	0.043	0.125				
Village Fallow share*Female	-0.433	0.153	***	-0.747	0.191	***	-0.866	0.273	***
Share of rented fields (village level)	-0.246	0.080	***	-0.245	0.109	**	-0.268	0.127	**
Observations	7527			6410			3798		

ME stands for Marginal Effects and SE stands for robust standard errors clustered at the household level. Sig stands for significance level. ***, ** and * indicated statistical significance at the 1%, 5%, and 10% respectively.

Table 3. 4: Marginal effects of the determinants of field measurement

	Full sample		Sig	Non-Household Heads		Sig	Young Adult Non-Household Heads		Sig
	ME	SE	Sig	ME	SE	Sig	ME	SE	Sig
Wolof	-0.01	0.06		0.036	0.088		0.059	0.131	
Fulani	-0.022	0.06		0.008	0.095		0.051	0.139	
Serere	-0.033	0.06		-0.012	0.096		0.077	0.143	
Household head has secondary education (yes=1)	-0.025	0.03		0.073	0.063		0.044	0.095	
Age of Household head	0.001	0.001		0.002	0.001		0.003	0.002	**
Household has rented a groundnut field (1=yes)	-0.137	0.02	***	-0.248	0.051	***	-0.405	0.097	***
Enumerator fixed-effects	Yes			Yes			Yes		
Observations	7527			6410			3798		

ME stands for Marginal Effects and SE stands for robust standard errors clustered at the household level. Sig stands for significance level. ***, ** and * indicated statistical significance at the 1%, 5%, and 10% respectively.

Table 3. 5: Marginal effects of the determinants of productivity

	Full Sample			Non-Household Heads			Young Adult Non-Household Heads		
	ME	SE	Sig	ME	SE	Sig	ME	SE	Sig
ln(Field size) (ha)	-0.223	0.016	***	-0.201	0.014	***	-0.226	0.024	***
Number of fields	0.044	0.009	***	0.056	0.021	***	0.053	0.028	**
Share of rented field (individual level)	0.234	0.049	***	0.017	0.055		0.094	0.13	
ln(Distance to field) (km)	-0.007	0.006		-0.018	0.009	**	-0.027	0.023	*
Field used for household consumption (1=yes)	-0.067	0.017	***						
Groundnut seeds purchased in the market (1=yes)	-0.089	0.015	***	-0.050	0.017	***	-0.052	0.031	*
ln(Amount spent on seeds) (CFA Franc)	0.120	0.017	***	0.088	0.016	***	0.120	0.037	***
ln(Amount spent on chemical fertilizer) (CFA Franc)	0.025	0.003	***	0.022	0.004	***	0.034	0.008	***
Share of fields with manure	0.041	0.018	**	0.030	0.021		0.008	0.056	
Share of fallowed fields	0.035	0.020	*	-0.008	0.022		-0.038	0.037	
ln(Amount spent on pesticides) (CFA Franc)	0.008	0.003	***	0.008	0.004	**	0.005	0.006	
Field quality	0.022	0.010	**	0.021	0.011	*	0.017	0.022	
Household head (yes=1)	0.097	0.054	*						
Spouse (yes=1)	0.095	0.040	**	-0.028	0.045		-0.059	0.073	
Son or daughter (yes=1)	0.026	0.042		-0.015	0.044		0.005	0.061	
Son or daughter in law (yes=1)	0.050	0.049		-0.012	0.057		-0.062	0.074	
Parent (yes=1)	0.164	0.048	***	0.078	0.053				
Brother or sister	0.048	0.041		-0.046	0.045		-0.022	0.065	
Brother or sister in law (yes=1)	0.004	0.052		-0.061	0.051		-0.101	0.082	
Age 16 to 20	0.007	0.035		0.174	0.047	***	0.112	0.059	**
Age 21 to 25	-0.001	0.029		0.096	0.045	**	0.025	0.053	
Age 26 to 29	0.003	0.032		0.092	0.050	*			
Age 30 to 35	0.036	0.023		0.084	0.043	*			
Age 36 to 40	0.012	0.023		0.073	0.047				
Female	-0.139	0.040	***	0.041	0.044		0.028	0.086	
Female*Age 16 to 20	0.028	0.044		0.000	0.051		0.045	0.075	
Female*Age 21 to 25	-0.001	0.047		-0.047	0.055		0.005	0.081	
Female*Age 26 to 29	-0.049	0.054		-0.081	0.063				
Female*Age 30 to 35	-0.002	0.039		-0.048	0.052				
Female*Age 36 to 40	0.011	0.043		-0.072	0.058				
French education	-0.045	0.028		-0.041	0.035		-0.067	0.077	
Arabic education	0.041	0.036		-0.025	0.048		-0.016	0.093	
Koranic education	-0.001	0.021		-0.029	0.029		-0.034	0.068	
French*Secondary education	-0.031	0.033		0.039	0.038		0.091	0.058	
Arabic*Secondary education	-0.099	0.048	**	-0.065	0.058		-0.071	0.089	**
Koranic*Secondary education	-0.046	0.040		-0.019	0.060		0.104	0.107	
Can read and write (yes=1)	0.030	0.018	*	0.037	0.025		0.024	0.058	
Wolof	-0.040	0.053		-0.011	0.065		-0.050	0.062	
Fulani	-0.029	0.056		0.130	0.072	*	0.077	0.08	
Serere	0.037	0.056		0.037	0.070		-0.014	0.075	
Temporary migration	-0.035	0.023		0.068	0.025	***	0.024	0.036	
Observations	7527			6410			3798		

ME stands for Marginal Effects and SE stands for robust standard errors clustered at the household level. Sig stands for significance level. ***, ** and * indicated statistical significance at the 1%, 5%, and 10% respectively.

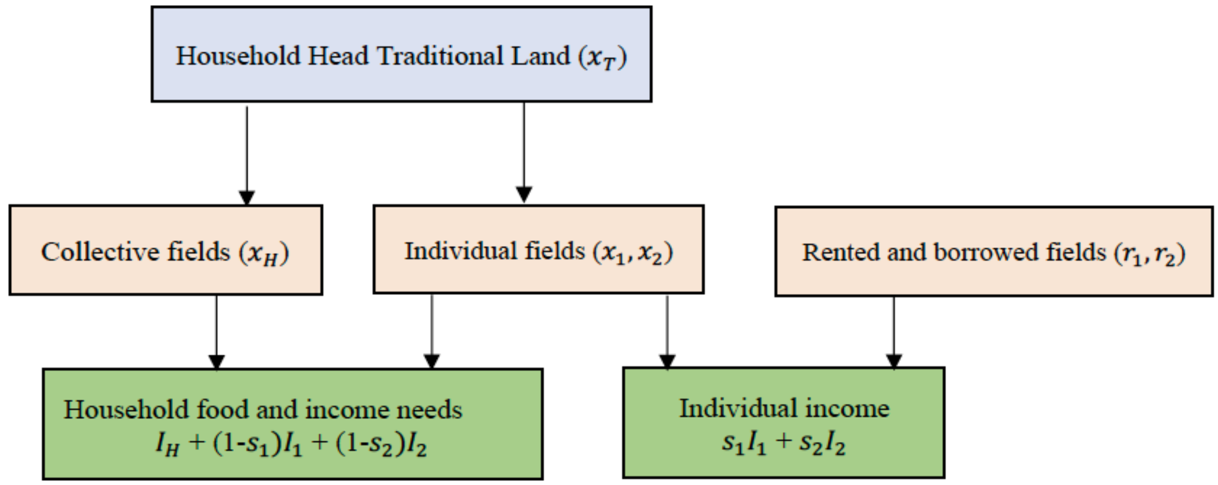

Figure 3.1: Household field allocation

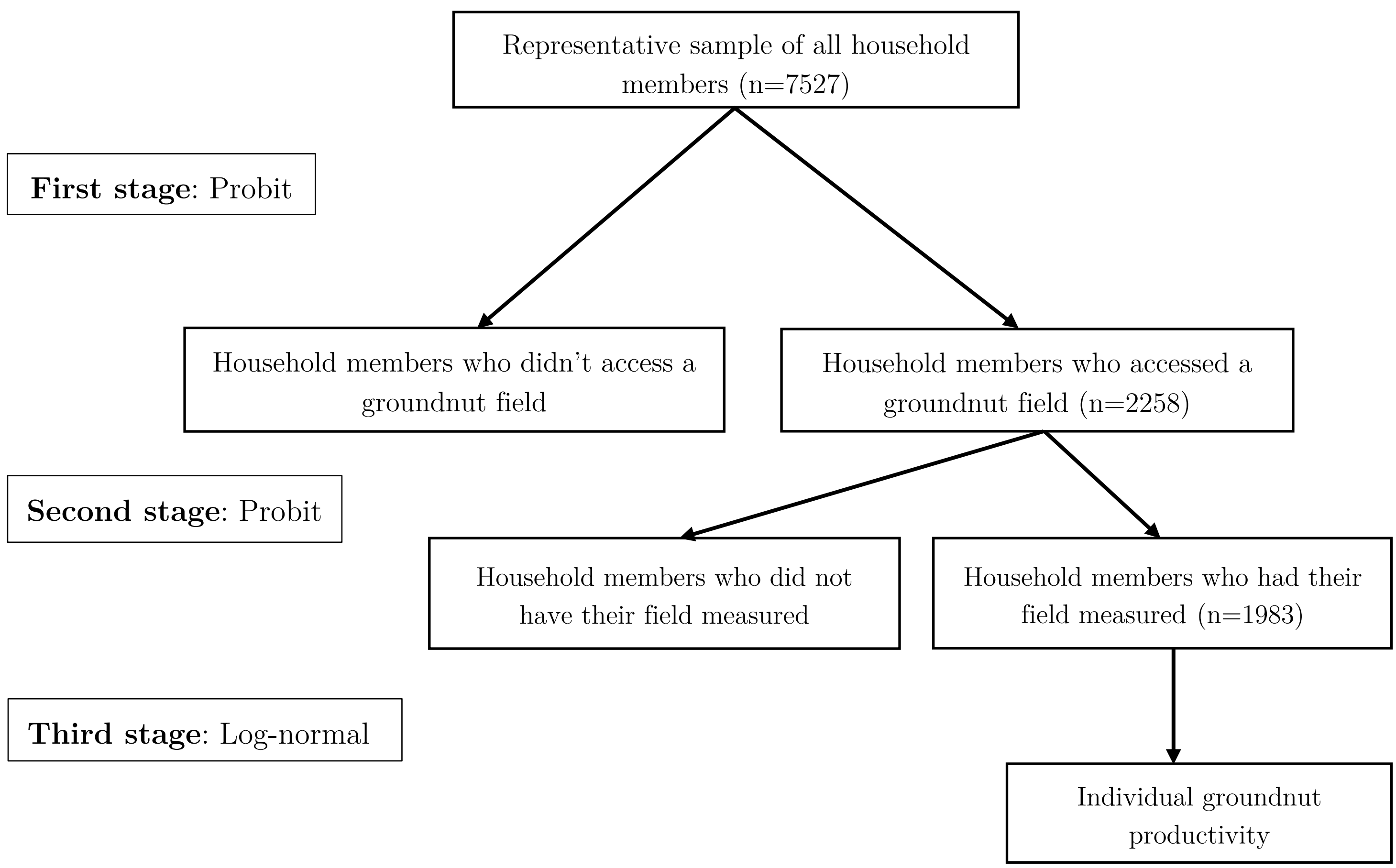

Figure 3.2: Illustration of the data generating process of our sample

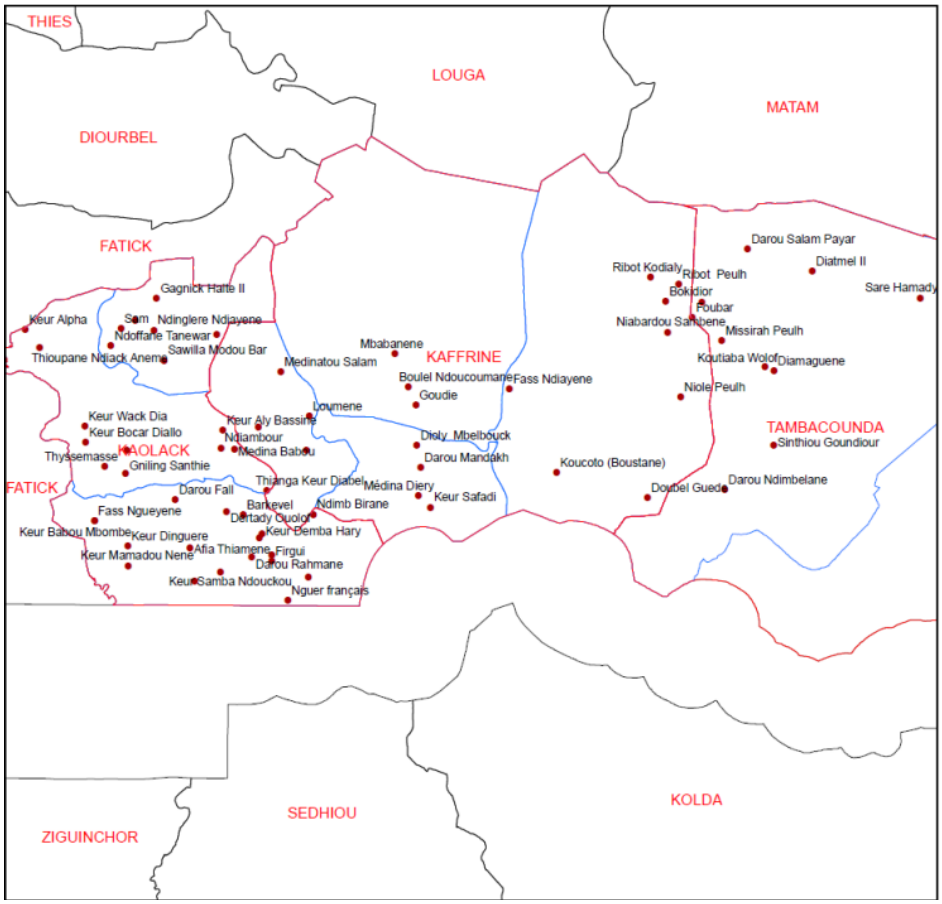

Figure 3.3: Survey village sample

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Appendices

Appendix A (Appendix to Chapter 1)

A.1 Spatial and temporal variability of rainfall, production and price

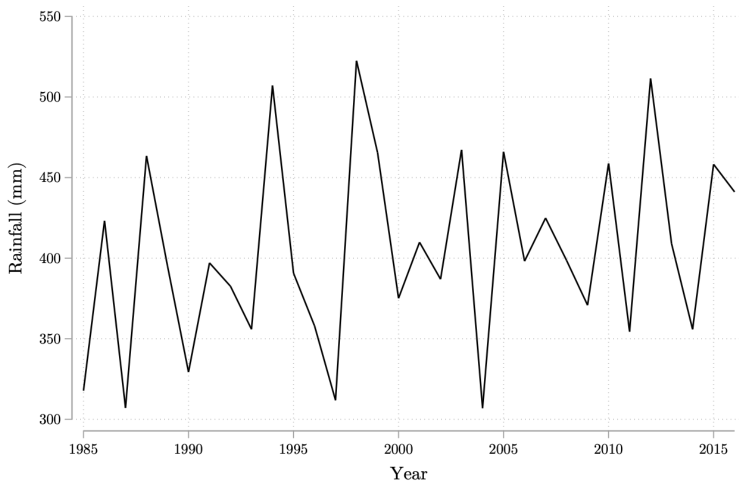


Figure A1: Yearly variability of rainfall

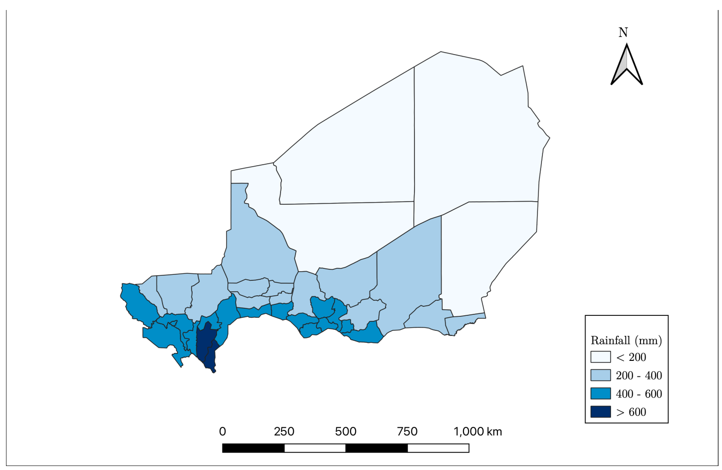


Figure A2: Spatial variability of rainfall

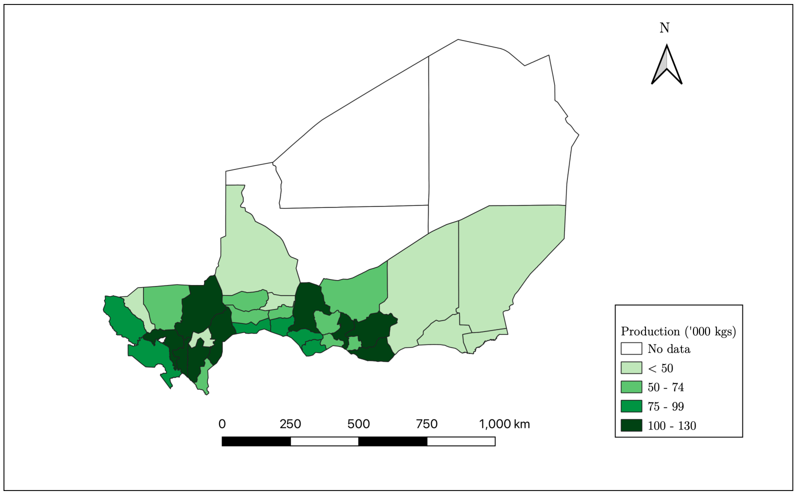


Figure A3: Spatial variability of rainfall

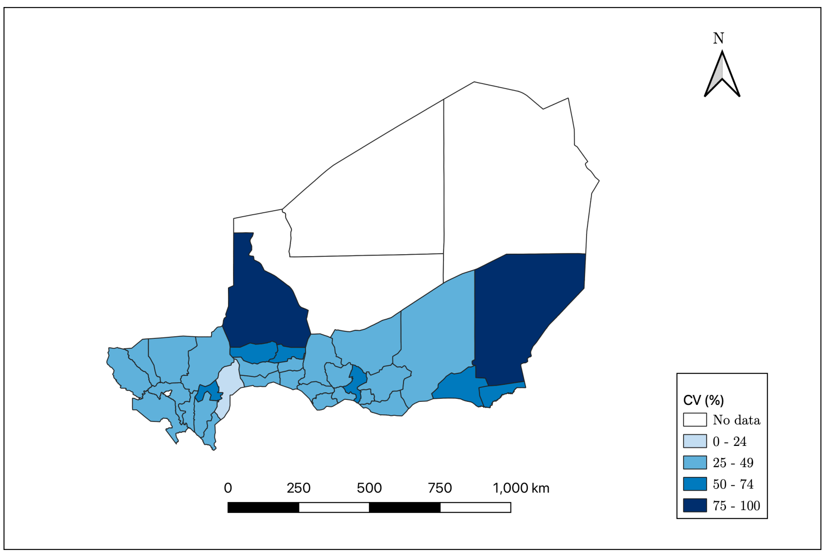


Figure A4: CV of millet production by district

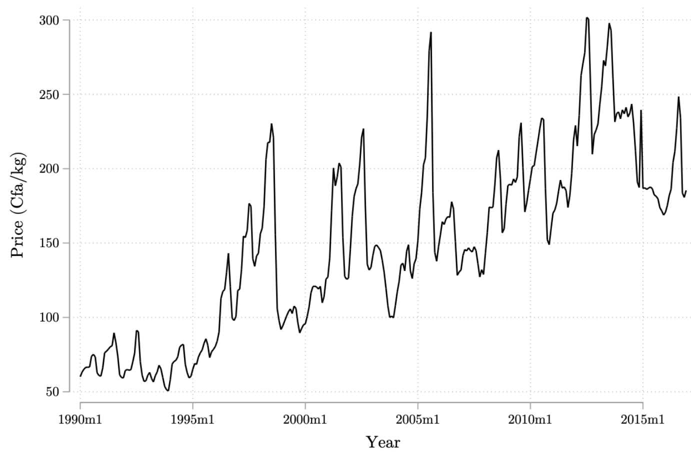


Figure A5: Average monthly millet price overtime

Notes: This graph shows the inter-annual distribution of monthly millet price over the period 1990 to 2016. 1990m1, 1995m1, 2000m1, 2005m1, 2010m1 and 2015m1 represent the average millet price across districts in January of the years 1990, 1995, 2000, 2005, 2010 and 2015 respectively.

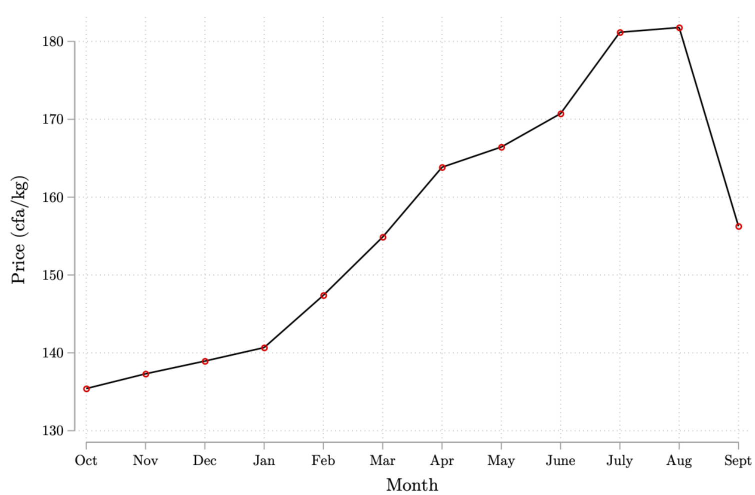


Figure A6: Millet price seasonality

Notes: This graph shows the intra-annual variation of millet price. Each circle represents the average millet price across years and districts in that particular month for the period 1990-2016.

A.2 Effects of strong rainfall shocks on price seasonality

Panel A Panel B

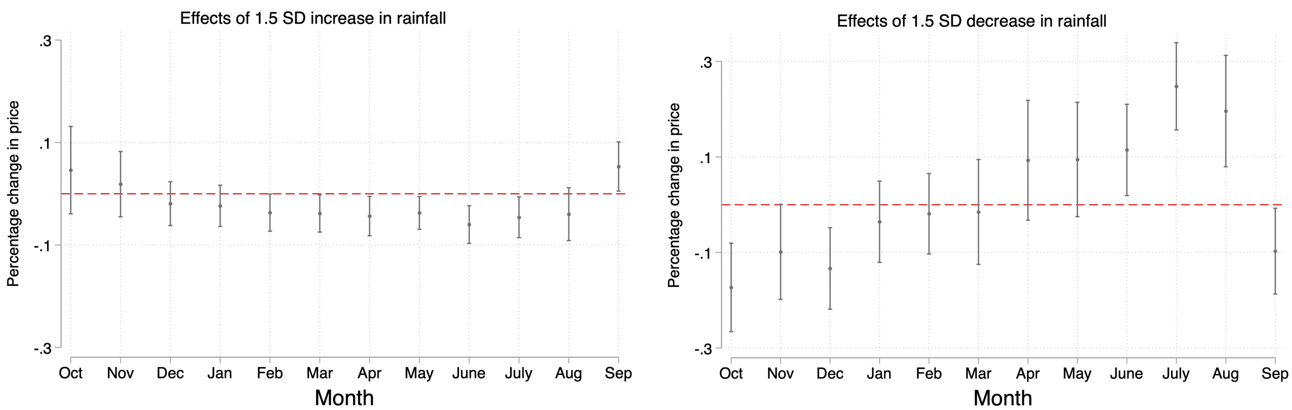


Figure A7: Effects of strong positive and negative rainfall shocks on price seasonality

Notes: Panel A shows the marginal effects of strong positive rainfall shocks on ln(price). Panel B shows the marginal effects of strong negative rainfall shocks on ln(price). The circles represent point estimates, and the bars indicate 95% confidence intervals. The regression includes year, months, and district Fixed-Effects.

Panel A Panel B

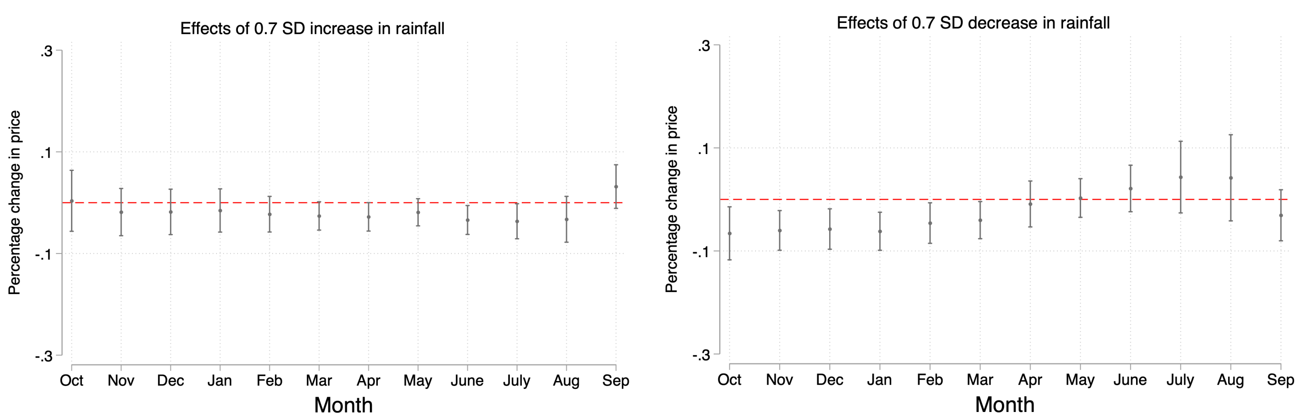
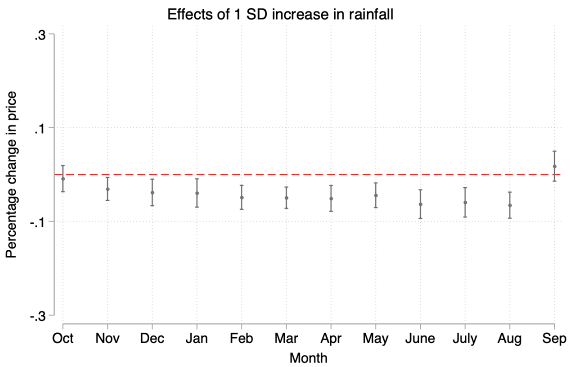


Figure A8: Effects of mild positive and negative rainfall shocks on price seasonality

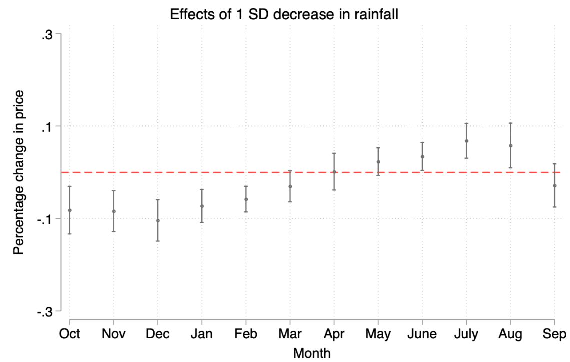
Notes: Panel A shows the marginal effects of mild positive shocks on ln(price). Panel B shows the marginal effects of mild negative rainfall shocks on ln(price). The circles represent point estimates, and the bars indicate 95% confidence intervals. The regression includes year, months, and district Fixed-Effects.

A.3 Robustness check using district-level clustering of standard errors

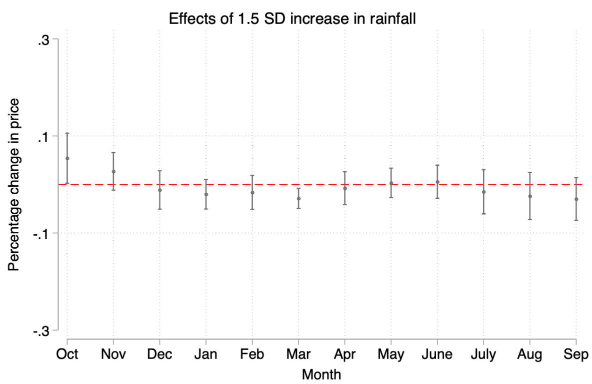
Panel A



Panel B



Panel C



Panel D

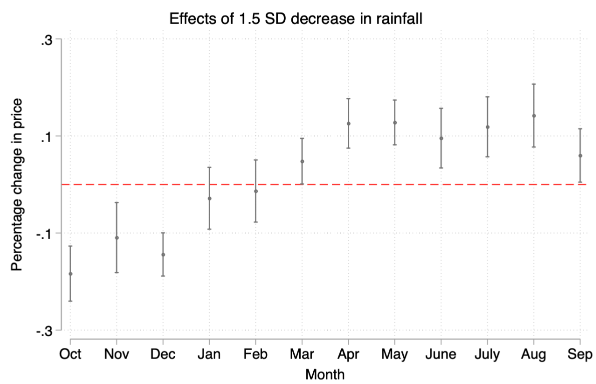
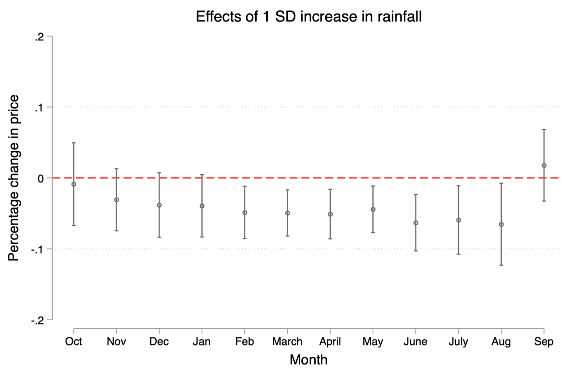


Figure A9: Robustness checks using district-level clustering

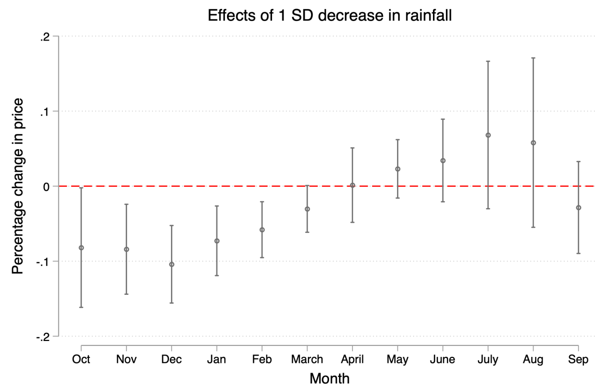
Notes: Panel A shows the marginal effects of positive rainfall shocks on price. Panel B shows the marginal effects of negative rainfall shocks on price. Panel C and Panel D show the marginal effects of strong positive and strong negative rainfall shocks on price respectively. Circles represent point estimates and the bars indicate 95% confidence intervals. Each regression estimates standard errors clustered at the district-level, and includes year, months, and district Fixed-Effects.

A.4 Robustness check using Conley (1999) standard errors

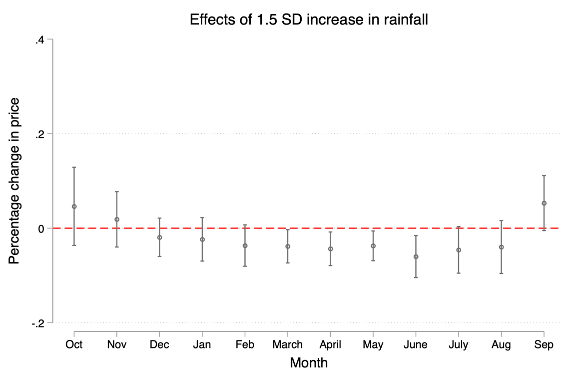
Panel A



Panel B



Panel C



Panel D

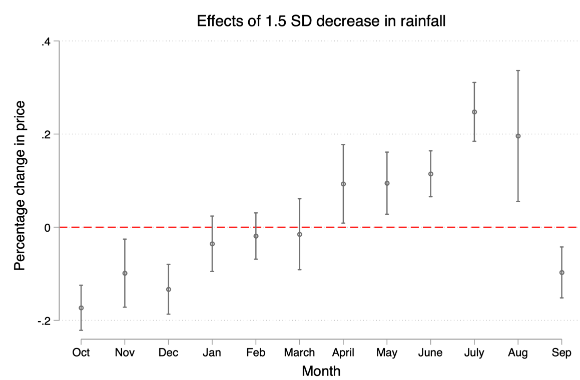
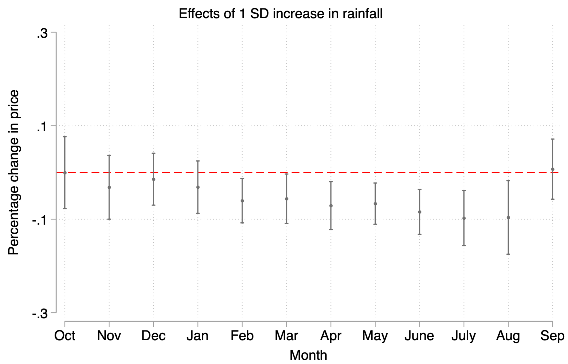


Figure A10: Robustness checks to using Conley (1999) standard errors

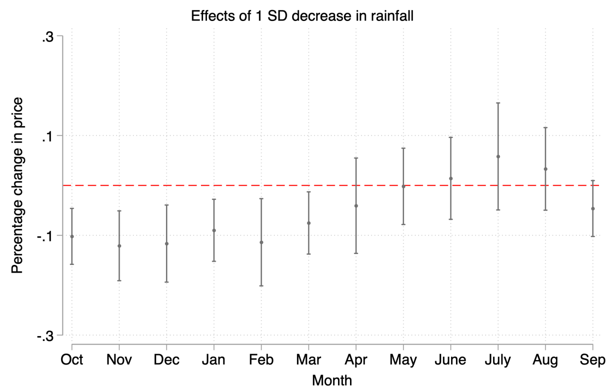
Notes: Panel A shows the marginal effects of positive rainfall shocks on price. Panel B shows the marginal effects of negative rainfall shocks on price. Panel C and Panel D show the marginal effects of strong positive and strong negative rainfall shocks on price respectively. Circles represent point estimates, and the bars indicate 95% confidence intervals. Each regression estimates Conley (1999) standard errors, and includes year, months, and district Fixed-Effects.

A.5 Heterogenous impacts of rainfall shocks on price seasonality

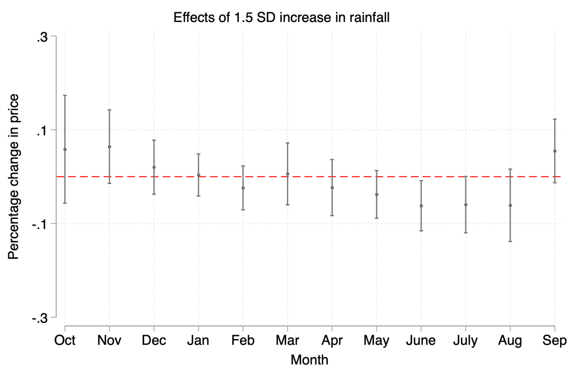
Panel A



Panel B



Panel C



Panel D

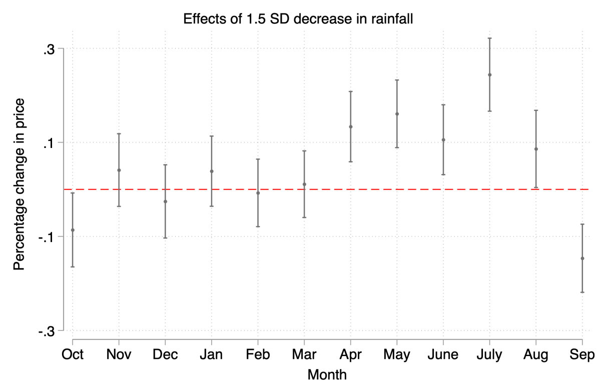


Figure A11: Rainfall shock impacts on price seasonality in the top 25% districts

Notes: Panel A shows the marginal effects of positive rainfall shocks on price for the top 25% millet producing districts. Panel B shows the marginal effects of negative rainfall shocks on price for the top 25% millet producing districts. Panel C and Panel D show the marginal effects of strong positive and strong negative rainfall shocks on price respectively, for the top 25% millet producing districts. The circles represent point estimates, and the bars indicate 95% confidence intervals. Each regression estimates Driscoll-Kray standard errors, and includes year, months, and district Fixed-Effects.

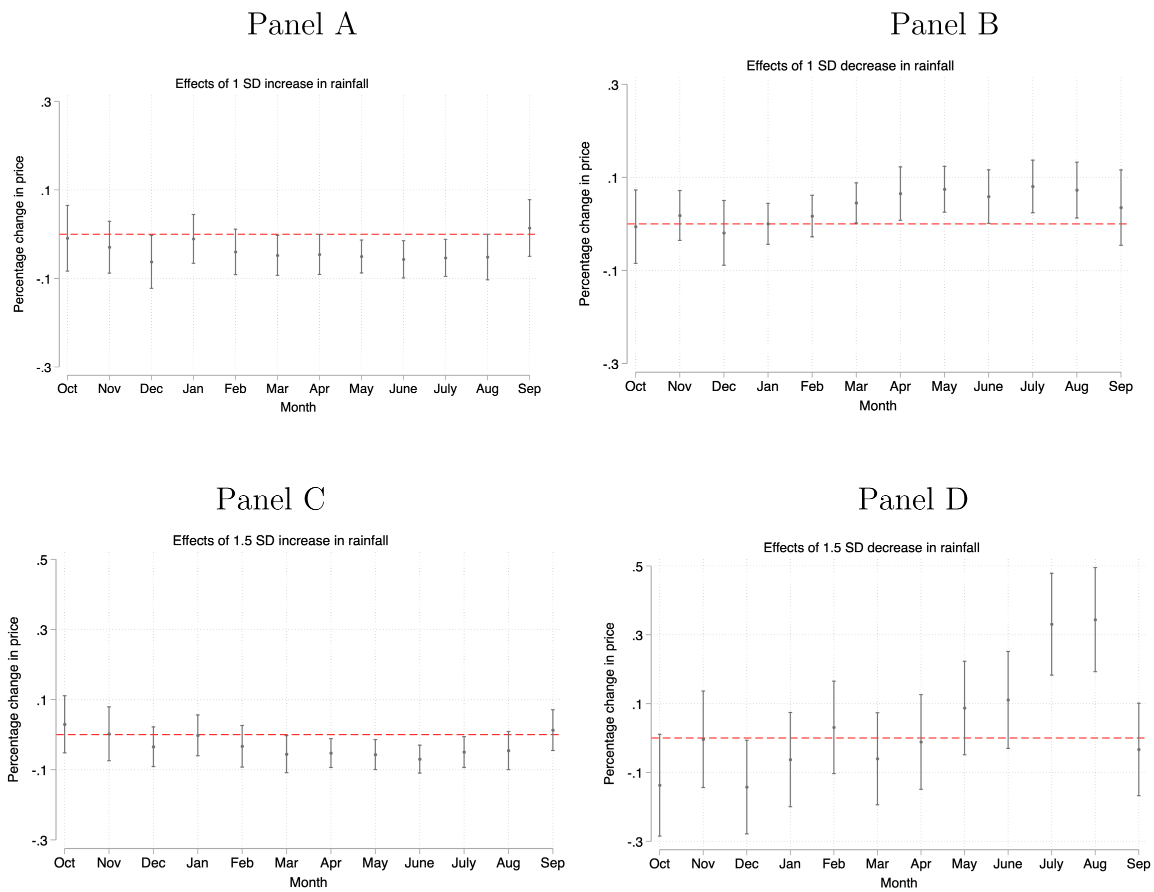


Figure A12: Rainfall shock impacts on price seasonality in the bottom 25% districts

Notes: Panel A shows the marginal effects of positive rainfall shocks on price for the bottom 25% millet producing districts. Panel B shows the marginal effects of negative rainfall shocks on price for the bottom 25% millet producing districts. Panel C and Panel D show the marginal effects of strong positive and strong negative rainfall shocks on price respectively, for the bottom 25% millet producing districts. The circles represent point estimates, and the bars indicate 95% confidence intervals. Each regression estimates Driscoll-Kray standard errors, and includes year, months, and district Fixed-Effects.

A.6 Robustness check of rainfall shock impacts on price seasonality using the July-August zscore

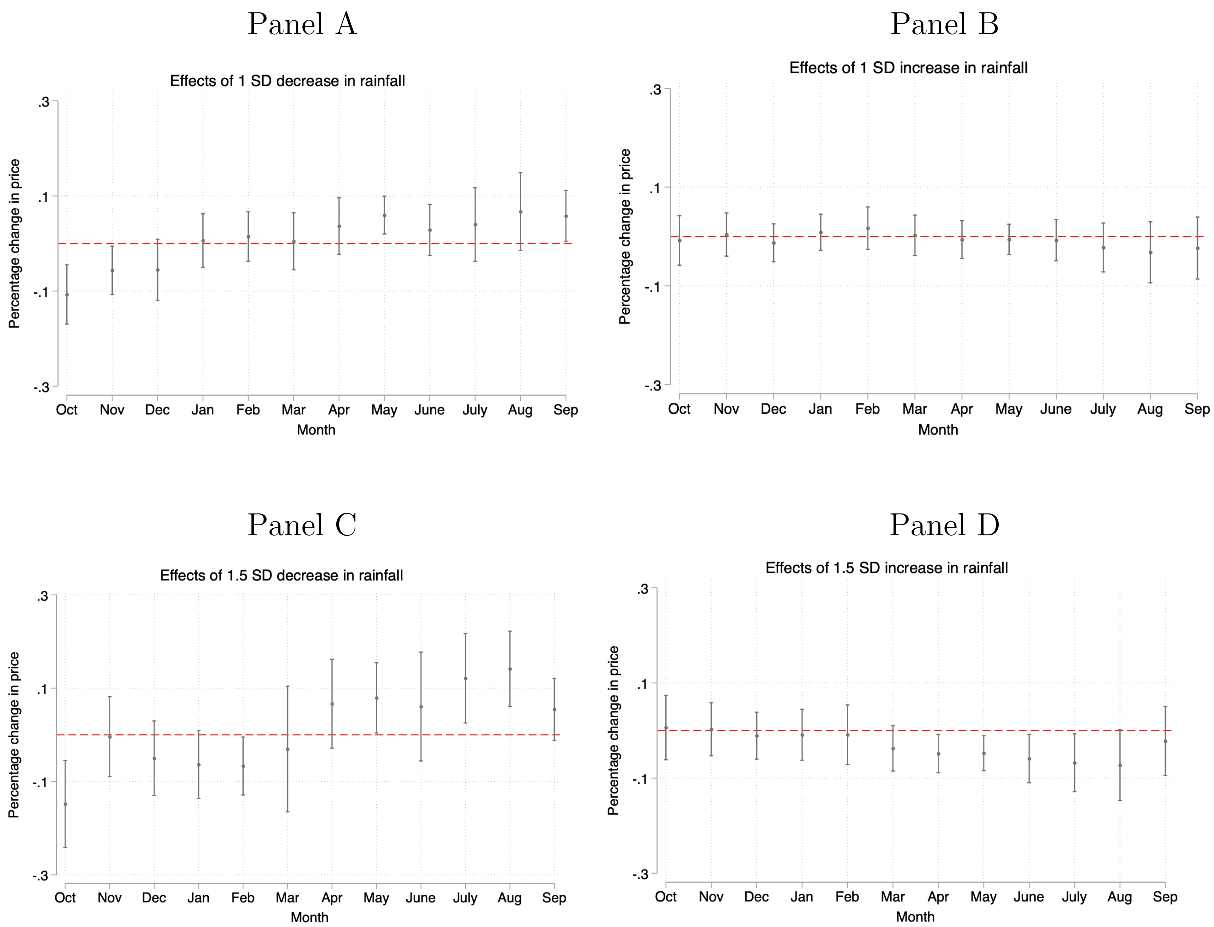


Figure A13: Robustness checks for rainfall shock in the July-August period

Notes: Panel A shows the marginal effects of positive rainfall shocks on price. Panel B shows the marginal effects of negative rainfall shocks on price. Panel C and Panel D show the marginal effects of strong positive and strong negative rainfall shocks on price respectively. We define shocks using rainfall for the July-August period. The circles represent point estimates, and the bars indicate 95% confidence intervals. Each regression estimates Driscoll-Kray standard errors, and includes year, months, and district Fixed-Effects.

A.7 Robustness check of rainfall shock impacts on production

Table A1: Robustness checks of weather shock impacts on production

	District clustering		Conley SE		July-August window	
	1SD	1.5SD	1SD	1.5SD	1SD	1.5SD
Positive rainfall shock	0.181***	0.170***	0.181***	0.170***	0.105***	0.177***
	(0.0427)	(0.0587)	(0.0415)	(0.0596)	(0.0335)	(0.0465)
Negative rainfall shock	-0.200***	-0.577***	-0.200***	-0.577***	-0.238**	-0.297***
	(0.0314)	(0.176)	(0.0713)	(0.192)	(0.102)	(0.0942)
District Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Time Trends	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,023	1,023	1,023	1,023	1,023	1,023
Within R-squared	0.432	0.424	0.432	0.424	0.422	0.418
Clustering						
Driscoll-Kray					Yes	Yes
District	Yes	Yes				
Conley			Yes	Yes		

Notes: The dependent variable is log production. Weather measures are indicator variables for exposure to positive or negative rainfall shocks in year t and in district i. The first column presents estimates from equation 3 using district-level clustering of standard errors. The second column presents estimates using the Conley (1999) standard errors with thresholds 500 km, and the third column presents estimates using a July-August rainfall zscore and Driscoll-Kray standard errors. *** indicates statistical significance at 1% Standard errors are presented in parentheses.

A.8 Heterogeneous impacts of rainfall shocks on production

Table A2: Heterogenous impacts of rainfall shocks on production

	Top 25%		Bottom 25%	
	1SD	1.5SD	1SD	1.5SD
Positive rainfall shock	0.181***	0.167***	0.183***	0.157***
	(0.027)	(0.037)	(0.025)	(0.035)
Negative rainfall shock	-0.200**	-0.538**	-0.200***	-0.509***
	(0.062)	(0.180)	(0.061)	(0.082)
District Fixed-Effects	Yes	Yes	Yes	Yes
Time Trends	Yes	Yes	Yes	Yes
Observations	1,023	1,023	1,023	1,023
Within R-squared	0.433	0.426	0.438	0.438

Notes: The dependent variable is log production. Weather measures are indicator variables for exposure to positive or negative rainfall shocks in year t and in district i. The first column presents estimates for the top 25% millet producing districts and the second column shows estimates for the bottom 25% millet producing districts. *** and ** indicate statistical significance at 1% and 5% respectively. Driscoll-Kray standard errors are presented in parentheses.

Appendix B (Appendix to Chapter 2)

B.1 Estimated coefficients of rainfall shock impacts on market participation choice

Table B1: Ordered Probit estimated coefficients for rainfall shock impacts on millet market participation

VARIABLES	Estimates
Negative rainfall shock	0.220**
	(0.111)
Age of the household head (years)	-0.003
	(0.009)
Female household head (1=yes)	-0.065
	(0.104)
Formal education (1=yes)	-0.284**
	(0.112)
Household living in a rural area (1=yes)	0.651***
	(0.140)
Household has used at least one farm input (1=yes)	-0.180
	(0.146)
Dependency ratio (members aged 0-9 or >60)	0.210
	(0.397)
Area planted of millet (ha)	0.011
	(0.016)
Dummy for polygamous household head (1=yes)	-0.133
	(0.083)
Tropical livestock unit	0.026
	(0.053)
Non-millet farm income (CFA franc)	0.065***
	(0.011)
Millet market price (CFA franc)	-0.781
	(0.532)
Distance to nearest market (KMs)	-0.147***
	(0.052)
Share of HHs who sold millet by cluster	0.234***
	(0.034)
Days since start of the agriculture survey in 2011 (days)	-0.008**
	(0.004)
Observations	2,956
Household FE	Yes
Year FE	Yes

Notes: Robust standard errors clustered at the household level in parentheses. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% respectively.

B.2 Estimated coefficients of rainfall shock impacts on market participation choice by coping strategy

Table B2: Estimated coefficients of rainfall sock impacts on millet market participation by coping strategy

VARIABLES	Estimates
Negative rainfall shock	0.312**
	(0.121)
Age of the household head (years)	-0.002
	(0.009)
Female household head (1=yes)	-0.067
	(0.105)
Formal education (1=yes)	-0.287**
	(0.112)
Household living in a rural area (1=yes)	0.648***
	(0.141)
Household has used at least one farm input (1=yes)	-0.208
	(0.147)
Dependency ratio (members aged 0-9 or >60)	0.221
	(0.404)
Area planted of millet (ha)	0.013
	(0.016)
Dummy for polygamous household head (1=yes)	-0.133
	(0.084)
Tropical livestock unit	0.028
	(0.054)
Non-millet farm income (CFA franc)	0.066***
	(0.011)
Millet market price (CFA franc)	-0.598
	(0.532)
Distance to nearest market (KMs)	-0.143***
	(0.051)
Share of HHs who sold millet by cluster	0.234***
	(0.034)
Days since start of the agriculture survey in 2011 (days)	-0.008**
	(0.004)
Dummy for adopting agricultural technologies (1=yes)	0.049
	(0.140)
Dummy for off-season agricultural production (1=yes)	-0.444**
	(0.220)
Dummy for migration (1=yes)	0.110
	(0.192)
Dummy for diversification (1=yes)	0.087

	(0.139)
Negative rainfall shock # Dummy for adopting agricultural technologies	-0.675***
	(0.231)
Negative rainfall shock # Dummy for off-season agricultural production	0.716**
	(0.328)
Negative rainfall shock # Dummy for migration	-0.147
	(0.318)
Negative rainfall shock # Dummy for diversification	-0.193
	(0.267)
Observations	2,956
Household FE	Yes
Year FE	Yes

Notes: Robust standard errors clustered at the household level in parentheses. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% respectively.

B.3 Distribution of rainfall shock measures by year and for the full sample

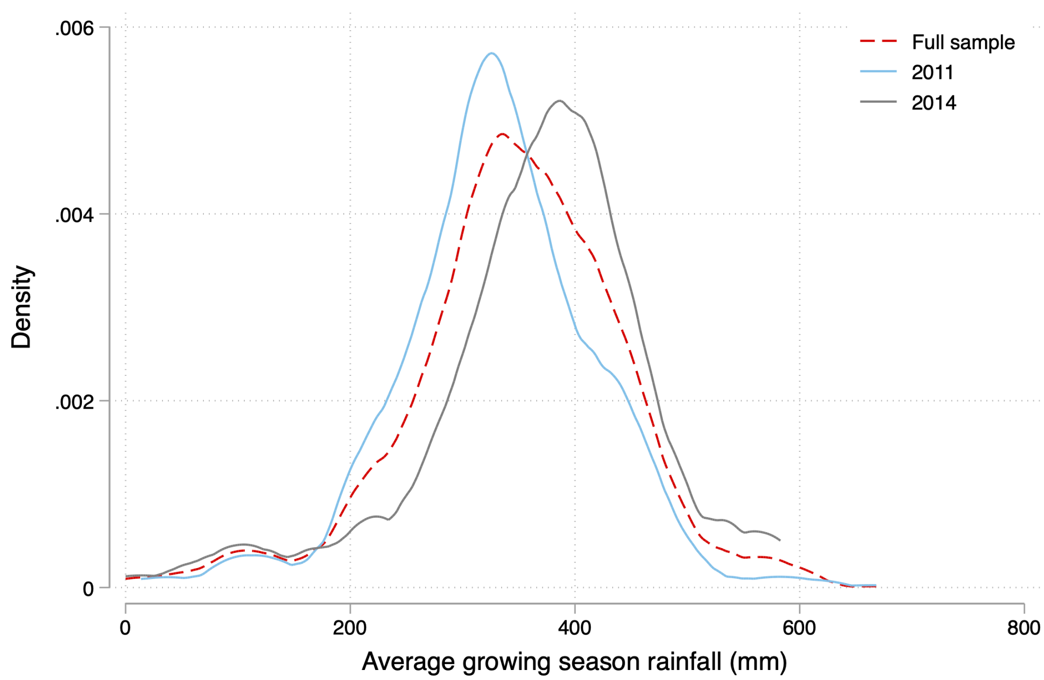


Figure B1: Distribution of growing season rainfall by survey year and for the full sample

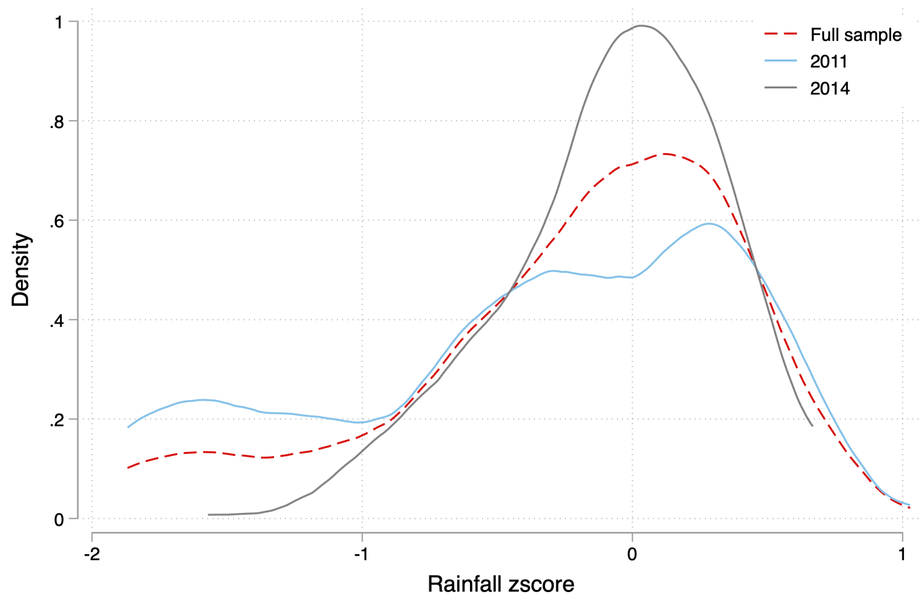


Figure B2: Distribution of rainfall zscore by survey year and for the full sample

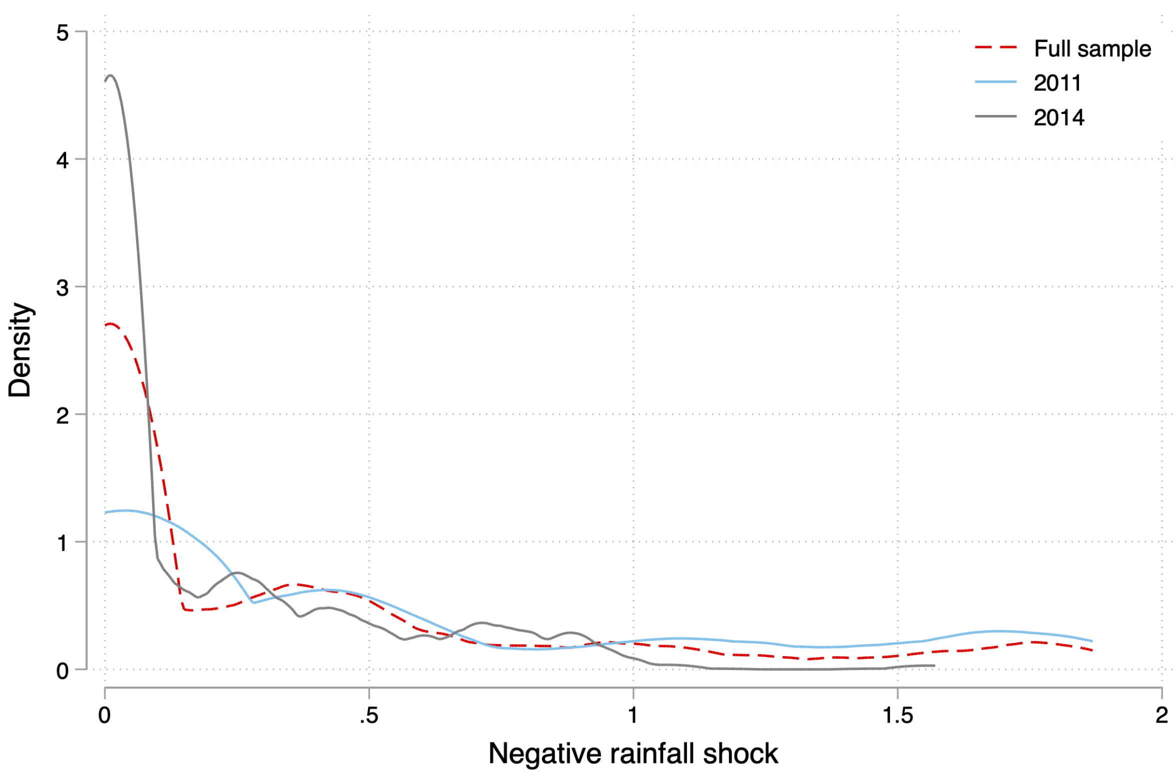


Figure B3: Distribution of negative rainfall shock by survey year and for the full sample

Appendix C (Appendix to Chapter 3)

C.1 Estimated coefficients of the determinants of field access

Table C1: Estimated coefficients of the determinants of field access

	Full Sample			Non-Household Heads			Youth Adult Non-Household Heads		
	Coef	SE	Sig	Coef	SE	Sig	Coef	SE	Sig
Household head (yes=1)	1.931	0.123	***						
Spouse (yes=1)	0.448	0.104	***	0.454	0.104	***	0.667	0.151	***
Son or daughter (yes=1)	0.179	0.094	*	0.202	0.095	**	0.145	0.110	
Son or daughter in law (yes=1)	0.229	0.148		0.219	0.149		0.428	0.169	**
Parent (yes=1)	0.170	0.122		0.108	0.125				
Brother or sister	0.324	0.101	***	0.341	0.103	***	0.374	0.123	***
Brother or sister in law (yes=1)	0.226	0.135	*	0.244	0.136	*	0.236	0.161	
Age 16 to 20	-0.888	0.099	***	-0.916	0.119	***	-0.518	0.107	***
Age 21 to 25	-0.494	0.097	***	-0.498	0.123	***	-0.093	0.111	
Age 26 to 29	-0.365	0.111	***	-0.416	0.132	***			
Age 30 to 35	-0.134	0.092		-0.260	0.120	**			
Age 36 to 40	-0.019	0.118		-0.020	0.143				
Female	-0.462	0.101	***	-0.494	0.114	***	-0.482	0.170	***
Female*Age 16 to 20	0.117	0.119		0.187	0.136		0.144	0.161	
Female*Age 21 to 25	0.122	0.122		0.191	0.141		0.079	0.161	
Female*Age 26 to 29	0.015	0.145		0.114	0.159				
Female*Age 30 to 35	-0.013	0.116		0.103	0.137				
Female*Age 36 to 40	-0.009	0.141		-0.033	0.163				
French education	-0.040	0.084		0.004	0.091		0.119	0.122	
Arabic education	0.132	0.102		0.172	0.111		0.229	0.147	
Koranic education	0.102	0.071		0.166	0.076	**	0.288	0.109	***
Wolof	-0.035	0.158		-0.036	0.157		0.079	0.201	
Fulani	-0.684	0.164	***	-0.757	0.167	***	-0.628	0.218	***
Serere	-0.089	0.173		-0.075	0.173		0.142	0.219	
French*Secondary education	-0.291	0.085	***	-0.319	0.092	***	-0.439	0.111	***
Arabic*Secondary education	-0.132	0.149		-0.055	0.155		-0.013	0.170	
Koranic*Secondary education	-0.221	0.130	*	-0.158	0.137		-0.953	0.252	***
Can read and write (yes=1)	0.060	0.057		0.016	0.063		-0.094	0.083	
Wolof	-0.035	0.158		-0.036	0.157		0.079	0.201	
Fulani	-0.684	0.164	***	-0.757	0.167	***	-0.628	0.218	***
Serere	-0.089	0.173		-0.075	0.173		0.142	0.219	
Temporary migration	-0.347	0.061	***	-0.294	0.062	***	-0.170	0.072	**
Village Fallow share	0.138	0.572		1.627	0.467	***	2.127	0.656	***
Village Fallow share*Youth	1.900	0.455	***	0.129	0.372				
Village Fallow share*Female	-1.806	0.638	***	-2.218	0.568	***	-2.895	0.905	***

	Coef	SE	Sig	Coef	SE	Sig	Coef	SE	Sig
Share of rented fields (village level)	-1.025	0.332	***	-0.729	0.321	**	-0.896	0.421	**
Observations	7527			6410			3798		

Coef. stands for estimated coefficients and SE stands for robust standard errors clustered at the household level. Sig stands for significance level. ***, ** and * indicated statistical significance at the 1%, 5%, and 10% respectively.

C.2 Estimated coefficients of the determinants of field measurement

Table C2: Estimated coefficients of the determinants of field measurement

	Full sample			Non-Household heads			Youth Adult Non-Household Heads		
	Coef	SE	Sig	Coef	SE	Sig	Coef	SE	Sig
Wolof	-0.049	0.276		0.127	0.309		0.198	0.441	
Fulani	-0.105	0.286		0.030	0.335		0.171	0.472	
Serere	-0.159	0.297		-0.043	0.341		0.261	0.478	
Household head has secondary education (yes=1)	-0.122	0.162		0.258	0.219		0.147	0.321	
Age of household head	0.004	0.003		0.007	0.004	*	0.012	0.005	**
Household has rented a groundnut field (1=yes)	-0.670	0.121	***	-0.878	0.154	***	-1.367	0.208	***
Enumerator fixed-effects	Yes			Yes			Yes		
Observations	7527			6410			3,798		

Coef. stands for estimated coefficients and SE stands for robust standard errors clustered at the household level. Sig stands for significance level. ***, ** and * indicated statistical significance at the 1%, 5%, and 10% respectively.

C.3 Estimated coefficients of the determinants of productivity

Table C3: Estimated coefficients of the determinants of productivity

	Full Sample			Non-Household Heads			Young Adult Non-Household Heads		
	Coef	SE	Sig	Coef	SE	Sig		SE	Sig
ln(Field size) (ha)	-0.633	0.038	***	-0.683	0.051	***	-0.709	0.060	***
Number of fields	0.124	0.026	***	0.191	0.070	***	0.167	0.075	**
Share of rented field (individual level)	0.667	0.136	***	0.057	0.188		0.295	0.325	
ln(Distance to field) (km)	-0.021	0.018		-0.063	0.029	**	-0.084	0.049	*
Field used for household consumption (1=yes)	-0.190	0.047	***						
Groundnut seeds purchased in the market (1=yes)	-0.252	0.043	***	-0.168	0.057	***	-0.163	0.079	**
ln(Quantity of seeds) (Kg)	0.340	0.047	***	0.300	0.055	***	0.377	0.080	***
ln(Quantity of chemical fertilizer) (Kg)	0.071	0.009	***	0.075	0.013	***	0.107	0.016	***
Share of fields with manure	0.117	0.051	**	0.102	0.072		0.027	0.118	
Share of fallowed fields	0.100	0.058	*	-0.029	0.076		-0.119	0.086	
ln(Amount spent on pesticides) (CFA Franc)	0.023	0.008	***	0.028	0.012	**	0.017	0.013	
Field quality	0.063	0.027	**	0.070	0.036	*	0.053	0.049	
Household head (yes=1)	0.276	0.164	*						
Spouse (yes=1)	0.271	0.119	**	-0.096	0.153		-0.184	0.226	
Son or daughter (yes=1)	0.075	0.120		-0.052	0.150		0.015	0.162	
Son or daughter in law (yes=1)	0.143	0.141		-0.042	0.195		-0.195	0.220	
Parent (yes=1)	0.466	0.138	***	0.265	0.178				
Brother or sister	0.135	0.120		-0.155	0.153		-0.069	0.190	
Brother or sister in law (yes=1)	0.011	0.148		-0.206	0.175		-0.318	0.220	
Age 16 to 20	0.021	0.100		0.591	0.167	***	0.349	0.153	**
Age 21 to 25	-0.004	0.083		0.327	0.156	**	0.078	0.139	
Age 26 to 29	0.008	0.091		0.311	0.171	*			
Age 30 to 35	0.103	0.064		0.283	0.148	*			
Age 36 to 40	0.033	0.065		0.248	0.161				
Female	-0.395	0.116	***	0.140	0.150		0.087	0.237	
Female*Age 16 to 20	0.079	0.126		0.001	0.174		0.141	0.207	
Female*Age 21 to 25	-0.003	0.135		-0.161	0.188		0.017	0.210	
Female*Age 26 to 29	-0.140	0.154		-0.274	0.215				
Female*Age 30 to 35	-0.006	0.110		-0.162	0.177				
Female*Age 36 to 40	0.031	0.123		-0.245	0.196				
French education	-0.128	0.080		-0.139	0.120		-0.211	0.167	
Arabic education	0.116	0.103		-0.084	0.164		-0.051	0.222	
Koranic education	-0.003	0.059		-0.099	0.097		-0.105	0.157	
French*Secondary education	-0.087	0.096		0.133	0.129		0.283	0.148	*
Arabic*Secondary education	-0.282	0.138	**	-0.219	0.195		-0.223	0.212	
Koranic*Secondary education	-0.131	0.115		-0.066	0.203		0.327	0.304	
Can read and write (yes=1)	0.087	0.053		0.124	0.084		0.076	0.131	
Wolof	-0.115	0.151		-0.036	0.221		-0.156	0.166	
Fulani	-0.083	0.159		0.442	0.245	*	0.242	0.204	
Serere	0.105	0.159		0.126	0.237		-0.043	0.203	

Temporary migration	-0.101	0.067		0.230	0.087	***	0.074	0.092	
Observations	7527			6410			3,798		

Coef. stands for estimated coefficients and SE stands for robust standard errors clustered at the household level. Sig stands for significance level. ***, ** and * indicated statistical significance at the 1%, 5%, and 10% respectively.

C.4 OLS estimates of the determinants of productivity

Table C4: OLS estimates of the determinants of productivity

	Full Sample			Non-Household Heads			Young Adult Non-Household Heads		
	Coef	SE	Sig	Coef	SE	Sig	Coef	SE	Sig
ln(Field size) (ha)	-0.627	0.039	***	-0.665	0.054	***	-0.699	0.068	***
Number of fields	0.124	0.026	***	0.166	0.083	**	0.195	0.066	***
Share of rented field (individual level)	0.466	0.132	***	0.332	0.203		0.134	0.256	
ln(Distance to field) (km)	-0.023	0.020		-0.031	0.029		-0.038	0.057	
Field used for household consumption (1=yes)	-0.205	0.048	***						
Groundnut seeds purchased in the market (1=yes)	-0.263	0.043	***	-0.224	0.062	***	-0.223	0.078	***
ln(Quantity of seeds) (Kg)	0.354	0.049	***	0.296	0.061	***	0.373	0.097	***
ln(Quantity of chemical fertilizer) (Kg)	0.067	0.009	***	0.072	0.013	***	0.094	0.018	***
Share of fields with manure	0.121	0.054	**	0.120	0.081		-0.034	0.147	
Share of fallowed fields	0.103	0.059	*	0.045	0.077		-0.070	0.095	
ln(Amount spent on pesticides) (CFA Franc)	0.019	0.009	**	0.034	0.012	***	0.018	0.014	
Field quality	0.060	0.028	**	0.083	0.036	**	0.074	0.054	
Household head (yes=1)	0.227	0.111	**						
Spouse (yes=1)	0.275	0.107	**	0.268	0.106	**	0.247	0.153	
Son or daughter (yes=1)	0.108	0.114		0.145	0.122		0.124	0.150	
Son or daughter in law (yes=1)	0.179	0.138		0.172	0.143		0.129	0.166	
Parent (yes=1)	0.461	0.131	***	0.457	0.133	***			
Brother or Sister	0.141	0.110		0.184	0.118		0.223	0.162	
Brother or Sister in law (yes=1)	-0.016	0.151		-0.008	0.150		-0.152	0.192	
Age 16 to 20	0.047	0.090		0.077	0.121		0.080	0.138	
Age 21 to 25	0.032	0.082		0.088	0.123		0.060	0.135	
Age 26 to 29	0.006	0.090		0.100	0.137				
Age 30 to 35	0.100	0.065		0.147	0.120				
Age 36 to 40	0.039	0.065		0.324	0.129	**			
Female*Age 16 to 20	0.085	0.128		0.005	0.153		0.166	0.175	
Female*Age 21 to 25	-0.009	0.140		-0.118	0.164		0.033	0.197	
Female*Age 26 to 29	-0.125	0.154		-0.252	0.184				
Female*Age 30 to 35	0.019	0.112		-0.060	0.149				
Female*Age 36 to 40	-0.001	0.124		-0.301	0.172	*			
Female	-0.374	0.111	***	-0.228	0.129	*	-0.338	0.207	
French education	-0.153	0.081	*	-0.120	0.098		-0.253	0.160	
Arabic Education	0.062	0.107		0.055	0.142		-0.040	0.205	
Koranic	-0.035	0.060		0.019	0.084		-0.007	0.144	
Wolof	-0.102	0.126		-0.079	0.178		-0.112	0.151	
Fulani	-0.052	0.131		-0.039	0.194		-0.052	0.180	
Serere	0.081	0.135		0.166	0.185		0.057	0.170	
Can read and write (yes=1)	0.114	0.053	**	0.138	0.074	*	0.074	0.124	
French*Secondary education	-0.097	0.094		-0.143	0.106		0.057	0.147	
Arabic*Secondary education	-0.264	0.144	*	-0.308	0.193		-0.194	0.231	
Koranic*Secondary education	-0.123	0.120		-0.273	0.191		-0.157	0.193	
Temporary migration	-0.101	0.066		-0.033	0.076		-0.082	0.086	
Observations	7527			6410			3,798		

Coef. stands for estimated coefficients and SE stands for robust standard errors clustered at the household level. Sig stands for significance level. ***, ** and * indicated statistical significance at the 1%, 5%, and 10% respectively.