Essays on agricultural productivity and the impact of food price change on welfare in Africa

by

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B.Sc., University of Lomé, Togo, 2008
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AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Agricultural Economics
College of Agriculture

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Abstract

Africa is the most food-insecure continent in the world, according to the World Bank and the United Nations Food and Agricultural Organization. While low purchasing power is the main cause of food insecurity, inefficient domestic food production is also a major constraint. Our study specifically focused on four food production issues in Africa, namely, agricultural productivity, cropland use, food demand and welfare analysis, and demand-led crop breeding.

First, we assessed the impact of public spending on agricultural productivity in Africa. We estimated the effect of two government-spending measures: Agriculture Budget Share (BS) and Research Share of Agricultural GDP (RS) on agriculture total factor productivity growth (TFPG). We used a panel fixed-effect estimator to control for the country-specific characteristics of twenty-eight African economies from 1991–2012. Although North African economies appeared to have the highest TFPG, this did not translate into the highest agricultural and research budget share. Meanwhile, Central African economies exhibited the lowest BS and RS, along with the lowest TFPG of the continent. The panel fixed-effect estimator revealed a marginal impact of 6.77% for RS on TFPG after seven years. However, the cumulative marginal impact of BS on TFPG is estimated at 7.21% over the eight years that follow the budget increment. Our findings suggest that a BS of 14% and a RS of 15% are required for a country to double its TFPG in the eight following years. Therefore, additional, and continuous investment in research and development is required for a significant productivity enhancement, especially in Sub-Saharan Africa.

Second, we assessed the factors that shape cereal cropland allocation decisions in Nigeria and Niger. We theoretically derived the key cropland allocation arguments using the household model. Next, we used the World Bank LSMS-ISA data to map acreage mean centers and fit a fractional regression model using the panel fixed-effect estimator. We assessed the traditional

Mendelsohn land use model and uncovered its limitation in efficiently approximating cereal cropland allocation. We improved the appropriateness of fit of the traditional Mendelsohn model by controlling for additional factors, such as food prices, socio-demographics, and food trade factors. Overall, we found cereal acreage shares in Nigeria and Niger to be spatially heterogeneous and determined by climatic, price, and trade factors. Additionally, farmers tend to base their cropland allocation decisions upon the price of the most important staples: maize in Nigeria; millet and sorghum in Niger. Furthermore, due to their tolerance to heat and drought, sorghum and millet compete for northeast farmland in both countries, especially for rainfed croplands. Thus, our study illustrates that millet and sorghum are key choices in ensuring food security in the context of global warming and rainfall instability. Our findings fill a literature void and provide policy makers with evidence to foster geo-referenced farmer cooperatives aimed at enhancing food production. Furthermore, our findings could be incorporated into a land use framework for planning, environmental monitoring, scenario analysis, and impact assessment.

The third essay analyzed the staple foods consumption patterns of households in Niger by estimating a complete demand system. Demand elasticities are estimated using the Niger 2011 and 2014 LSMS-ISA household survey data to fit the modified Linear AIDS model. The results indicated that food consumption patterns in the country are affected by income and prices, as well as by socio-economic and geographic factors. All food items have positive expenditure elasticities and negative own-price elasticities, with rice exhibiting the most elastic demand. We found millet to be a necessity while rice and sorghum are luxuries. Additionally, our analysis revealed that urban households had a more diversified staple demand pattern. Furthermore, the welfare analysis revealed that an increase of millet price reduces rural welfare more than an increase in sorghum price. On the other hand, a sorghum price increase adversely affects the welfare of urban households the most. For example, a 20% increase of the millet or sorghum price reduces the average household welfare by 5.88% and 4.38%, respectively. This study highlights the importance of estimating staple food demand elasticities for both research and policymaking during a food price shocks. Our findings revealed that millet price is the canal that might foster support programs targeting the poorest households in Niger.

Our fourth and last essay is a theoretical argument for demand-led breeding in a small-scaled farming system. Our investigation stems from the fact that agricultural productivity lags in small-scaled farming in Sub-Saharan Africa. While inadequate production capital, water control and poor infrastructure remain important challenges, the low adoption of improved and high-yielding varieties is a key limiting factor for productivity enhancement. Often, studies elucidating improved technology implementation are focused upon the adoption (demand) rather than the creation (supply). In this analytical essay, we reviewed theoretical causes and solutions to low varietal uptake for sorghum. Consistent with much of the structural research framework, we presented asymmetric information, bounded rationality, and weak intellectual property as key causes of seed market coordination failure. Leaning on the technology adoption under uncertainty model, we showed how market-induced uncertainty, compounded with other factors, reduces farmers' willingness to trade traditional seeds for improved ones. Furthermore, we used the matching theory, supported with a general equilibrium model, to show how consumer preference drives farm-level adoption. We argued that breeding programs can benefit from effective preference matching across the food value chain while leveraging on the growing demand-led breeding literature. Finally, we presented hypotheses that can be empirically used to assess stakeholders' weigh and ranking of varietal attributes across the food value chain.

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Dedication

To my Dad Hodjo Natoyofey, my Mom Mambanike Yawa, my lovely wife Alouya Rita and my three-sources of motivation Essolaba Birewa, Edna Samtou, and Elzam Deoularo. I Love You!

Chapter 1 - Does Public Spending Trigger Agricultural Productivity Growth in Africa?

1.1 Introduction

Over the long term, productivity growth is the key to improving quality of life, eradicating poverty, and maintaining international competitiveness (Ivanic & Martin, 2018; Krugman, 1997). As such, improving productivity has become an important national agenda for many developing countries, including those of Sub-Saharan Africa (SSA). Although understanding how expenditure improves agricultural productivity is central to grasping food production prospects, the extent to which public spending induces productivity growth in Africa has not been empirically scrutinized. Although many scholars (Alston et al., 2010; Fuglie et al., 2019; Fuglie et al., 2012; Headey et al., 2010; Irz et al., 2001; and Key, 2019) have addressed agricultural productivity growth and its drivers with global, US, Canadian, and Asian perspectives, little research has been done on the African continent and none has clearly assessed the impact of public spending on productivity growth in the agriculture sector (Ghura & Just, 1992; Haley, 1991; Govereh, et al. 2006; Rezek et al., 2011; Walker & Alwang, 2015).

Justifications for government involvement in financing agriculture are varied. Many believe that spending on agriculture is the key to sustained economic growth. And, while the economic theory provides a foundation for the belief that investment in embodied and disembodied technology improves agricultural efficiency, the magnitude and mechanism of such an impact has been loosely documented. Therefore, the proposed study explores and quantifies the impact of agricultural spending on the productivity growth of this sector under heterogeneous political, physical, and socio-cultural conditions. We conduct this analysis in the framework of the endogenous growth model. That is, we consider the productivity growth within the agricultural sector to be induced by each country's social, and economic structure and policies.

More precisely, this paper addresses how and to what extent public agricultural expenditure affects productivity growth within the agricultural sector in Africa. We show that investing in research significantly and positively improves productivity growth in the agricultural sector in Africa in the long run. To achieve our research goal, we empirically estimated the impact of two agricultural expenditure proxies on the agricultural total factor productivity growth (TFPG). We proxied the agricultural expenditure of each country with its annual agricultural budget share, (hereafter budget share or BS) on one hand and the research share of the agricultural gross domestic product (hereafter research share or RS) on the other hand.

Aside from focusing on African economies, our work contributes to the literature in four important ways. First, we develop a fully-specified theoretical model that properly identifies the total factor productivity growth estimation. Second, we use a panel fixed-effects regression model to identify all relevant confounding factors to efficient estimation of public expenditure effects. Third, we provide an effective impact assessment for the Maputo Commitment and provide policymakers with an important milestone on where the continent stands with respect to the Comprehensive Africa Agriculture Development Program (CAADP). Finally, we utilize a proxy public expenditure with two variables that highlight the importance of research in fostering agricultural productivity.

In order to measure agricultural productivity, we used total factor productivity (TFP), which has become the preferred measure of productivity in the current literature (Cox, 2017). In our investigation, we theoretically predict a positive impact of government agricultural spending on the overall sector's productivity through improved soil, labor, and plant productivity. Secondly, we assumed that most agricultural development and research projects will delay the impact of public spending and therein the sector's productivity by seven to fifteen years (Headey et al., 2010; Schneider & Gugerty, 2011). Empirically, we build on the extensive literature and data published by Fuglie et al. (2012), along with the publicly-available dataset of the World Food Program and Penn World Table (PWT) to estimate a reduced form panel model for twenty-eight African countries. Our findings show a significant positive and lagged impact of increased public expenditure on TFPG of the agriculture sector.

For each of the two main independent variables (BS and RS), we conducted the estimation in three steps. First, we ran a model without controls. Second, we controlled for all agronomic and ecological confounding factors, but we did not include any lag of the independent variable. Lastly, we ran the saturated model where agronomic and ecological controls and lags were all included to identify the budget share or research share effects over the long run. For the third model, the estimation involved eighteen countries that have complete observations for all the independent and control variables. Because the effect of investment in agriculture spans overtime, we used the Akaike's (AIC) and Bayesian (BIC) information criteria to choose the optimal number of lags.

The fixed-effect panel data estimation revealed that when there is a 1% increase in the agricultural budget share, the TFPG increases by 1.96% for the following year, 1.83% on the third year, and 3.42% on year seven. Assuming a linear relationship between the BS and the TFPG, a 1% increase in BS results in a cumulative TFPG of 7.21% after eight years. We found that increasing the RS by 1% resulted in a 6.77% TFPG growth after seven years. In other words, increasing the research share by 1% induces a 1% TFPG in each of the seven subsequent years, making up a 7% increase of the TFPG by the 7th year. Alternative estimation, using the feasible generalized least squares and the panel corrected standard errors confirmed the reported estimates.

After reviewing the relevant literature, we present a conceptual model and the empirical strategy which includes the econometric model. Next, a description of the data to be used, data sources, and a description of the variables is given, along with an estimation of the reduced-form models. A conclusion reiterating the findings will close this chapter.

1.2 Literature Review

Growth in agricultural productivity is a major step towards rural poverty reduction, especially in developing countries. Poverty reduction is particularly relevant to African economies where agriculture is a major sector of the economy. In these countries, yields in agricultural productivity can generate high net social returns, abundance of food and fiber at relatively low cost to domestic consumers, and an expanded volume of exports.

With few exceptions, empirical research on productivity has focused on total factor productivity measurement and how it is affected by its intrinsic components, such as capital, labor, and land. Additionally, historical assessments of total factor productivity growth rates have been conducted with the aim to identify the portions of output growth that cannot be explained by changes in tangible inputs (Antle & John, 1998). Specifically, Fuglie et al. (2012) have conducted extensive research focused on total factor productivity measurement, drivers, and growth, providing an international perspective to the agricultural productivity and shedding light on the importance of identifying key sources of soil, labor, and plant or animal productivity.

In recent decades, a consensus has emerged regarding the critical effect of agricultural productivity growth on rural poverty reduction (Benin et al., 2009; Fan & Zhang, 2008). It is acknowledged that failure to enhance agricultural productivity can seriously impede poverty reduction and industrial growth in a context where rapid demand for food is forecasted (Fuglie et al., 2019; Ivanic & Martin, 2018). Past economic development around the world illustrates the importance of productivity. For instance, economic growth in the United States throughout the twentieth century was the direct result of the increased agricultural productivity (Capalbo & Antle, 2016). Prior to its economic takeoff, China consistently reported total factor productivity growth greater than 3% between 1970–2000. Nevertheless the productivity growth has remained between 0.5 and 2% per year in most African economies, which is considerably lower than performances realized in the United States of America and Southeast Asia during the pre-takeoff period of their development (Fuglie et al., 2012). Over time, and at the global level, Africa’s agricultural productivity has fallen further behind that of other developing regions (IFPRI, 2016). Within economies and across sectors, agricultural growth lags the overall economic growth in Africa (AGRA, 2016). Several endogenous and exogenous micro and/or macroeconomic factors (low uptake of improved technologies, poor access to irrigation, structure of food markets…) could explain this phenomenon.

In most Sub-Saharan African countries, the agricultural sector accounts for roughly 30% of the continent’s gross domestic product. However, the sector’s budget share often misrepresents its economic importance. On average, countries invest about 7% of their annual budget in the sector (Badie et al., 2016). This disparity between the economic importance of the agricultural sector and the budget share allocated to it in the continent called for ambitious action. In 2003 African countries adopted what is widely known as the Maputo Commitment on agricultural development. Through this commitment, all countries explicitly agreed to allocate at least 10% of their annual budget to achieve a 6% growth in annual agricultural output. Unfortunately, as of

2013, fewer than nine countries have fulfilled their commitment. Meanwhile, thirty countries have signed the compact (of the Maputo Commitment) pledging to promote the agricultural sector and nineteen have launched fully-funded and technically-reviewed plans to accelerate agricultural development (AU, 2013). Amid these continental efforts, there is an increasing interest in the link between public spending and agricultural productivity on the continent.

In 1970, Hayami and Ruttan conducted a comparative study of agricultural productivity across thirty-eight developed and less-developed nations, estimating a Cobb-Douglas cross-country production function. They found that resource endowments, embodied working capital, and human capital account for approximately 95% of the difference in labor productivity in agriculture across countries (Hayami & Ruttan, 1970).

Almost thirty years later, Capalbo and Antle (1998) provided a comprehensive review of agricultural productivity measurement and determinants. They argued that new and improved technologies have been substituted extensively for both land and human resources. The enhanced productivity improved total output of the sector ,which resulted in freeing resources for production of goods and services in other sectors of the economy, as reinforced by Gardner & Lesser (2003). In addition, these authors argued that only a gain in productivity could enhance the societal standards of living. Increased productivity drives full resource utilization to meet dynamic human needs. For the agricultural sector especially, the authors emphasized that productivity enhancement was the key for efficient resource use and global competitiveness. Consumers do benefit from enhanced agricultural productivity because increased productivity maintains and secures food supplies at a reasonable cost. Furthermore, Capalbo and Antle (1998), Hellin & Schrader, (2003) and Molden et al. (2013) argued that increased agricultural productivity was a key factor to inducing agriculturally-related businesses.

Public spending and its effect on the productivity of economic sectors has been the focus of several studies. Akroyd and Smith (2007) conducted a review of public spending and argued that government expenditure on research significantly contributed to agricultural productivity growth in countries like Uganda. They posited that the size of government allocations to agriculture was an indicator of its commitment to the sector. Analyzing the agricultural government expenditures of nine Latin American countries between 1950–1978, they found that an average 5% of the total government budget was allotted to agricultural production (Akroyd & Smith, 2007). Additionally, the research indicated that agricultural expenditures represented only 1% of the GDP.

Several authors specifically focused on agricultural productivity and how it contributes to economic growth. Cao and Birchenall (2013) used microeconomic farm-level data to examine the role of agricultural productivity as a determinant of China's post-reform economic growth and sectoral reallocation. Using a calibrated two-sector general equilibrium model, they presented three main findings. First, they found that agricultural TFPG is the main driver of output and employment reallocation in non-agriculture sectors. Second, they found that agricultural TFP contributes to the sectoral economic growth in most economies. Lastly, they revealed that the reallocation of workers to the non-agricultural sector was the means though which TFP influenced overall economic growth (Cao & Birchenall, 2013).

In an effort to determine the main drivers of poverty in Bangledesh, Emran and Shilpi (2016) assessed agricultural productivity, hired labor, and wages. They hypothesized that observed changes in wages and hired labor were partly due to agricultural productivity growth. Using a sub-district level panel data set to utilize the variation in rainfall across sub-districts, they confirmed the standard neoclassical theory which states that higher agricultural productivity affects wages and hired labor through labor demand; a rightward (leftward) shift increases (reduces) both wages and the amount of hired labor (Emran & Shilpi, 2016).

Quite a few studies have focused on the impact of public spending on either rural poverty or agricultural output. Nevertheless, these studies are country-specific and do not therefore account for geographic, social, political and economic differences. Also, none of these studies has focused on the effect of public funding on agricultural productivity.

Fan et al. (2000) estimated a direct and indirect effect of different types of government expenditure on rural poverty and productivity growth in India using state-level data from 1970–93. They used a simultaneous equation model and showed that, in order to reduce rural poverty, additional investments on roads and research were required. For the authors, research and infrastructure spending generated the highest productivity growth and the greatest effect in poverty reduction. They found that education had the third largest effect on productivity, while irrigation, soil, and water conservation, and health and rural community development had only modest impacts (Fan et al., 2000).

However, only a few studies focused on determinants of productivity change in Africa specifically. This literature void makes the discussion around policy-driven productivity enhancement more normative than positive. For example, Castles & Dowrick (2005) evaluated the impact of government spending on agricultural growth in Zambia, Malawi, South Africa, and Tanzania using the vector error correction model (VECM) to estimate the impact of public expenditure, private investment, and net trade on agricultural growth approximated with agricultural GDP growth. They conducted a separate estimation for each of the four countries and found a heterogeneous public expenditure impact on agricultural GDP growth.

Additionally, Iganiga & Unemhilin (2011) assessed the impact of federal government agricultural expenditure on agricultural output in Nigeria using Cointegration and Error Correction methods to estimate both the long- and short-term dynamic impacts of public expenditure on agricultural output. The results indicated that Federal government capital expenditure positively affected agricultural output, with a one-year lag. Consequently, the authors argued that investment in the agricultural sector and credit facilities enhanced agricultural production.

Overall, and to the best of our knowledge, while the literature contains evidence of the positive impacts of public expenditure on TFPG, no study directly estimated its role in Africa. Understanding the magnitude and mechanisms of public spending impact on TFPG can improve budget allocation to agriculture. Hence, this is the far-reaching objective of the current study.

1.3 Conceptual Model

In this section, we present the theoretical framework that explains the mechanism through which public spending affects agricultural productivity. Following Blankenau et al. (2007), Glomm and Ravikumar (1997), and Helms (1985), we consider the effect of BS and RS on TFP to occur in the framework of the endogenous growth model. We define (1) the three-period-lived agent problem, (2) the representative firm producing a single agricultural goods problem, (3) the government problem, and (4) the production technology. Afterwards, we consider a simple overlapping generations model of TFP.

Considering a competitive economy where we have households, a firm, and the government, we define and solve for the agent, the firm, and the government problems (See Appendix A). Based on the partial solution to this three-sector model and using a balanced government budget, we derive the steady state production capital equation as follows:

$$k = \{\tilde{\beta}[A]^{1-\mu}(1-\alpha)\varepsilon\tilde{e}^{-\mu}(1-\tau_i)\}^{1/(1-\alpha-\alpha\mu)} \quad (1)$$

Equation (1) expresses the steady state relationship between capital (k), total factor productivity (A(.)), agricultural expenditure share ($\tilde{e}$) and tax (τ_i). Equation (1) also accounts for the relative importance of the agricultural expenditure and human capital of the preceding generation in generating human capital (μ), and the constant (ε) capturing human productivity induced by their education and their farming capital. One can use the implicit function theorem to derive the impact of the agricultural expenditure share ($\tilde{e}$) on the total factor productivity [A(.)] as follows:

$$\frac{d[A]}{d\tilde{e}} = -\frac{\frac{\partial k}{\partial \tilde{e}}}{\frac{\partial k}{\partial [A(.)]}} \quad (2a)$$

Where:

$$\frac{\partial k}{\partial \tilde{e}} = \delta * \frac{-\mu}{1-\alpha-\alpha\mu} * [A(.)]^{1-\mu/1-\alpha-\alpha\mu} * \tilde{e}^{\mu-1+\alpha+\alpha\mu/1-\alpha-\alpha\mu} \quad (3)$$

and

$$\frac{\partial k}{\partial [A]} = \delta * \frac{1-\mu}{1-\alpha-\alpha\mu} * [A(.)]^{\alpha-\mu+\alpha\mu/1-\alpha-\alpha\mu} * \tilde{e}^{\mu/1-\alpha-\alpha\mu} \quad (4)$$

With $\delta = \{\tilde{\beta}(1-\alpha)\varepsilon {y_t}^{\mu}(1-\tau_i)\}^{1/(1-\alpha-\alpha\mu)}$

We can substitute (3) and (4) in (2a) and simplify equation (2a) to get equation (2b) as follows:

$$\frac{d[A]}{de} = \frac{\delta * \frac{\mu}{1-\alpha-\alpha\mu} * [A]^{1-\mu/1-\alpha-\alpha\mu} * \tilde{e}^{\mu-1+\alpha+\alpha\mu/1-\alpha-\alpha\mu}}{\delta * \frac{1-\mu}{1-\alpha-\alpha\mu} * [A]^{\alpha-\mu+\alpha\mu/1-\alpha-\alpha\mu} * \tilde{e}^{\mu/1-\alpha-\alpha\mu}} \quad (2b)$$

Equation (2b) simplifies to:

$$\frac{d[A]}{d\tilde{e}} = \frac{\mu}{1-\mu} * \frac{A}{\tilde{e}}$$

This implies:

$$\frac{d[A]}{A} = \frac{\Delta A}{A} = \frac{\mu}{1-\mu} * \frac{d\tilde{e}}{\tilde{e}}$$

That is:

$$TFPG = \left[\frac{\mu}{1-\mu}\right] * \log\,[\tilde{e}] \qquad (5)$$

Equation (5) reveals a positive effect of public spending on TFPG. The parameter $\mu, \mu \epsilon\ [0, 1]$, determines the relative importance of the agricultural expenditure and human capital of the preceding generation in generating human capital.

Let us now assume an expansionary fiscal policy in the agricultural sector where the government increases spending in agriculture through subsidies on machines, fertilizers, pesticides, seeds and other inputs, builds rural roads to improve market accessibility, and allocates more research funding for improved variety breeding and agricultural extension funds. In such a case, we expect the agricultural economy sector to respond with an overall production increase. Without getting into the induced effect of such a change on the money market, we expect the output increase to be sustainable for the long term and therefore positively impact the total factor productivity growth on the agricultural sector. There are direct and indirect effects of government expenditures on agricultural productivity. These effects are theoretically derived in the theoretical model (See Appendix A for detailed model) and shown in Figure 1.1. The direct effect goes through an economic environment created and entertained by the importance attached to the agricultural sector by the government. All forms of subsidies and food purchased by the government directly affect the productivity. The indirect effect goes two ways. On the one hand, building infrastructure, funding research and irrigation enhances production and market access, which in turn gives a positive signal to productivity. On the other hand, education, professional training, export and import policies, and minimum wage establishment induces technical improvement in food productivity, as shown in the figure below.

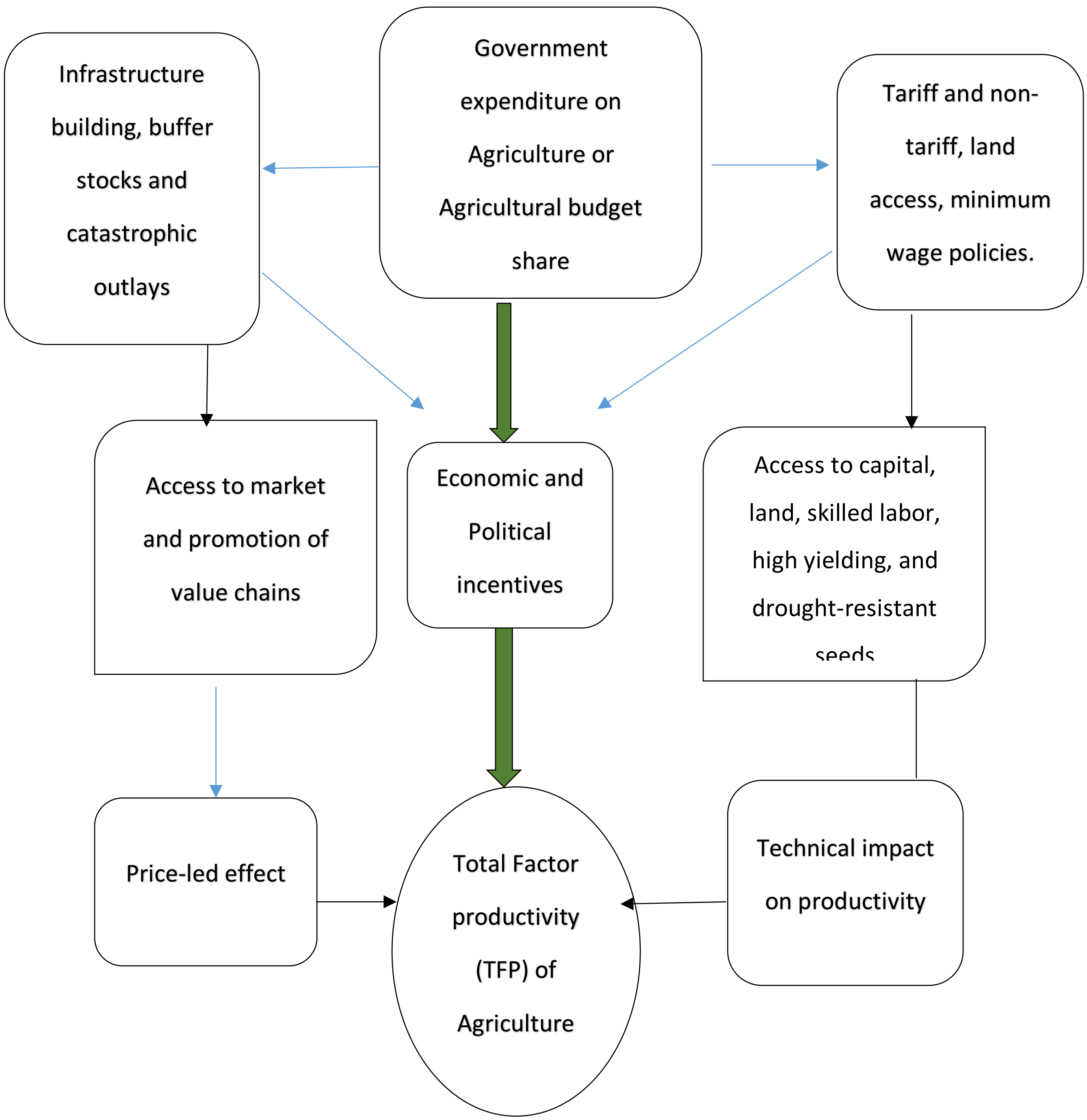
Government expenditure on Agriculture or Agricultural budget share
Infrastructure building, buffer stocks and catastrophic outlays
Tariff and non-tariff, land access, minimum wage policies.
Access to market and promotion of value chains
Economic and Political incentives
Access to capital, land, skilled labor, high yielding, and drought-resistant seeds
Price-led effect
Total Factor productivity (TFP) of Agriculture
Technical impact on productivity

Figure 1-1 Theoretical framework of the direct and indirect effect of public expenditure on agricultural productivity

Source: Author

1.4 Empirical Strategy

We conduct the empirical analysis in two steps. First, we compute descriptive statistics for the three main variables: total factor productivity growth (TFPG), agricultural budget share (BS), and research share (RS) of the agricultural gross domestic product. The descriptive statistics include long-term averages, decade averages for dynamic comparisons, and basic correlation coefficients. Next, we estimate the panel fixed-effect model with BS or RS as the main independent variable.

We estimate the following panel fixed-effect models:

$$TFPG_{it} = \gamma_i + T_t + \sum_{l=0}^{k} \beta_k (BS_{it})_{t-l} + \sum_{j=1}^{m} \gamma_j Z_{it} + D_{it} + \mu_{it} \qquad (6)$$

$$TFPG_{it} = \vartheta_i + T_t + \sum_{l=0}^{k} \delta_k (RS_{it})_{t-l} + \sum_{j=1}^{m} \rho_j Z_{it} + D_{it} + \varepsilon_{it} \qquad (7)$$

where the variables $TFPG_{it}$, BS_{it}, and RS_{it} are TFPG, BS, and RS for country i in year t. The parameters β_k and δ_k are the coefficients of level and lagged BS and RS, respectively. These are our main interest since they capture the effect of BS or RS on the TFPG. The index $t - l$ for l = *1,…,* k represents the number of lags of BS or RS in each model, determined by using the Akaike and Bayesian information criteria. Also, in equations (6) and (7), we have intercepts γ_i and ϑ_i defined as country-specific fixed effects. In addition, we controlled for potential confounding factors. These are represented by Z_{it} and include precipitation, minimum and maximum temperature, cross-effects between temperature and precipitation, food price index, and gross domestic products. Also, we controlled for the secular productivity growth and the overtime learning by doing using a year time trend T_t (Chang et al., 2016; Chuang, 1998; Marconi

& De Grip, 2015). Furthermore, we controlled for Maputo Commitment with D_{it} a dummy equal to 1 from 2004 inclusive. The dummy D_{it} captures any potential change in TFPG as a result of the Maputo Commitment. Because we controlled for all these other sources of variation in TFPG, assuming that there are no other observables confounders, we can interpret parameters β_k and δ_k as causal effects of BS and RS on TFPG, respectively. In equations (1) and (2), μ_{it} and ε_{it} represent residuals.

In accordance with Alston (2010), Alston et al. (1998), Fan (2000), and Fuglie and Heisey (2007), we include the lagged budget share ($(BS_{it})_{t-l}$) and research share ($(RS_{it})_{t-l}$) to account for the overlapping generation modelling used in the theoretical model. Also and importantly, the lags capture the long lead time between the investment or research stage of a new technology and the point at which that the infrastructure is built or the technology is adopted and begins to affect productivity. According to Fuglie and Heisey (2007), it takes about eight years (from year 7 until year 15) for a newly-introduced technology to be fully adopted. After some time of utilization, the technology eventually goes out of use, either because something better replaces it or because it loses its effectiveness.

One important question that emerges at this point is how the impact on TFPG transitions to agricultural production. We address this question by proposing a mathematical link between the TFPG and production. Given that $TFP = \frac{Production}{Labor*Captal}$, the effect β_k or δ_k on TFPG in year $t+1$ implies that: $TFP_{t+1} = TFPG_{t+1} * TFP_t = (1+\beta_k) * TFPG_t * TFP_t$

Therefore, the agricultural production in year $t+1$ is given by:

$$Production_{t+1} = (1+\beta_k)TFPG_t * TFP_t * Labor_{t+1} * Capital_{t+1} \quad (8)$$

Equation (8) reveals how the production growth, induced by the effect of BS or RS on the TFP, goes though TFPG.

1.5 Data and Descriptive Statistics

This research uses macro-level panel data from several sources. Due to limitations in data availability, only forty-three out of the fifty-four African countries are included in the study. Overall, the data includes four northern African countries and thirty-nine Sub-Saharan African nations. For most countries, the dataset covers the period running from 1991–2012, limiting our empirical analysis to this period. In this section, we conduct an exploratory analysis of the two key variables involved in this study: the total factor productivity growth and the agricultural budget share.

1.5.1 Total Factor Productivity Growth

The outcome variable of the estimation is the agricultural total factor productivity growth (TFPG). The TFPG is derived from the total factor productivity (TFP) and is defined as the ratio of total output to total inputs in a production process (Fuglie, 2012). TFP is computed by the economic research service (ERS) of the United States Department of Agricultural (USDA). According to the ERS (1996), the approach used to estimate agricultural TFP is conventional and includes outputs and inputs under the farmer's control and for which (inputs and outputs) markets exist. Outputs used in this measure are crops and livestock, while inputs include labor, capital, and materials. The TFP, as it stands in this study, excludes agricultural research inputs. Also, the TFP does not account for agricultural production externalities, such as the effects of agricultural production on natural resource depletion and environmental degradation. However, because the TFP levels computed by Fuglie (2012) are not internationally comparable, due to lack of representative data on input prices, and therefore cost shares, agricultural TFP growth rates are used in this study.

The data series is publicly available and includes total factor productivity from 1960 up to 2014. The TFP is calculated as an index using 1991 as the base period. Specifically, the TFP index is defined as the aggregate output index minus the aggregated input index (Fuglie et al., 2012). Fuglie et al. calculated the aggregated output growth in global agriculture[1], valuing about 195 crops and livestock commodities at a fixed set of average global prices. The aggregated input index was computed using input cost shares from agricultural censuses, assuming these cost shares to be representative of agricultural production for different groups of countries (Fuglie, 2008).

The minimum TFPG is -46% and was observed in Namibia in 1997. The maximum TFPG is 42% and was observed in Senegal in 1978. To the best our knowledge, the literature did not provide any rationale for these extreme statistics. We found that TFP, in most of the African countries, had an increasing trend from 1990–2012, with some disparities from one country/sub-region to another. Over the period running from 1961–2015, the TFP grew, on average, at a pace of 0.3% per year in the continent. The five countries where the TFP grew the most rapidly were Morocco (1.9%), Egypt (1.8%), Tunisia (1.6%), Swaziland (1.5%), and South Africa (1.4%). The five countries witnessing a decline in their TFP were Gambia (-1.7%), Congo DR (-1.5%), Equatorial Guinea (-0.8%), Liberia (-0.7%), and Togo (-0.6%). From 1991–2012, the time span of the empirical estimation, the average TFPG in Africa was 0.9%.

Regionally, North Africa topped the continent in terms of TFP growth with 1.7%. Southern Africa, driven by Swaziland and South Africa, followed with 0.5%. East Africa and West Africa had TFP rates of .3% and .1% per year, respectively. On average, TFP decreased in Central Africa

[1] Specifically, the FAO output index, which is a Laspeyres index

at a rate of -0.025% (see Fig. 1.a. in the Appendix). These regional disparities were due to a combination of factors including access to irrigation, mechanization, and the adoption of high-yielding and drought-tolerant crop varieties. Irrigation increases soil productivity; mechanization increases capital productivity; and high-yielding varieties increases genetic potential.

While an average of 4% of agricultural land is irrigated in Sub-Saharan Africa, Northern African countries irrigate approximatively 18% of their cultivated lands (see Figure 1.3). In fact, 44% of the water used for agricultural purposes on the continent is utilized by Algeria, Tunisia, Libya, Morocco, and Egypt (Perrin et al., 2018). Access to irrigation reduces moisture uncertainties associated with new technology adoption, which results in higher productivity. In addition, we found, based on FAO data, that Northern Africa imports 37% of the agricultural tractors on the continent, which translates to higher mechanization and better capital productivity (see Figure 1.4).

Though higher mechanization tends to lead to better capital productivity, technology diffusion in Sub-Saharan Africa is slow (Walker & Alwang, 2015). And, because the speed of diffusion of new technology is likely to be correlated with its profitability, the productivity impact of improved crop varieties may be limited (Walker & Alwang, 2015).

Overall, the productivity lag in SSA is striking low. Assessing the sources of growth in developing economies, Fuglie et al. (2019) found that labor productivity in West Asia (2.39) and Northern Africa (2.39) to be thrice that of the Sub-Saharan Africa (0.79) level over the period from 2001–2015. While the TFP growth in South Asia was over 2% per year during 2001–2015, on average, SSA registered only 0.39% per year. Fuglie et al. (2019) explained that the lag in output per worker resulting from lower capital deepening and technology adoption in SSA illustrated the difference.

Despite these facts, over the last decades, total factor productivity growth (TFPG) has increased at both the continental and regional levels in Africa. The TFPG went from -0.04% growth in the 1960s and 1970s to more than 1.0% growth in the 2000s. The same trend is observed in Central, Western, and Eastern Africa. However, Northern and Southern Africa witnessed consistent growth in the TFP over the period of study. Overall, the TFPG in Africa remains lower than that realized in Southeast Asia and North America before their economic takeoff. Fuglie et al. (2012) reported at least 3% TFPG in North America (in the 1940s) and Southeast Asia (in the 1980s).

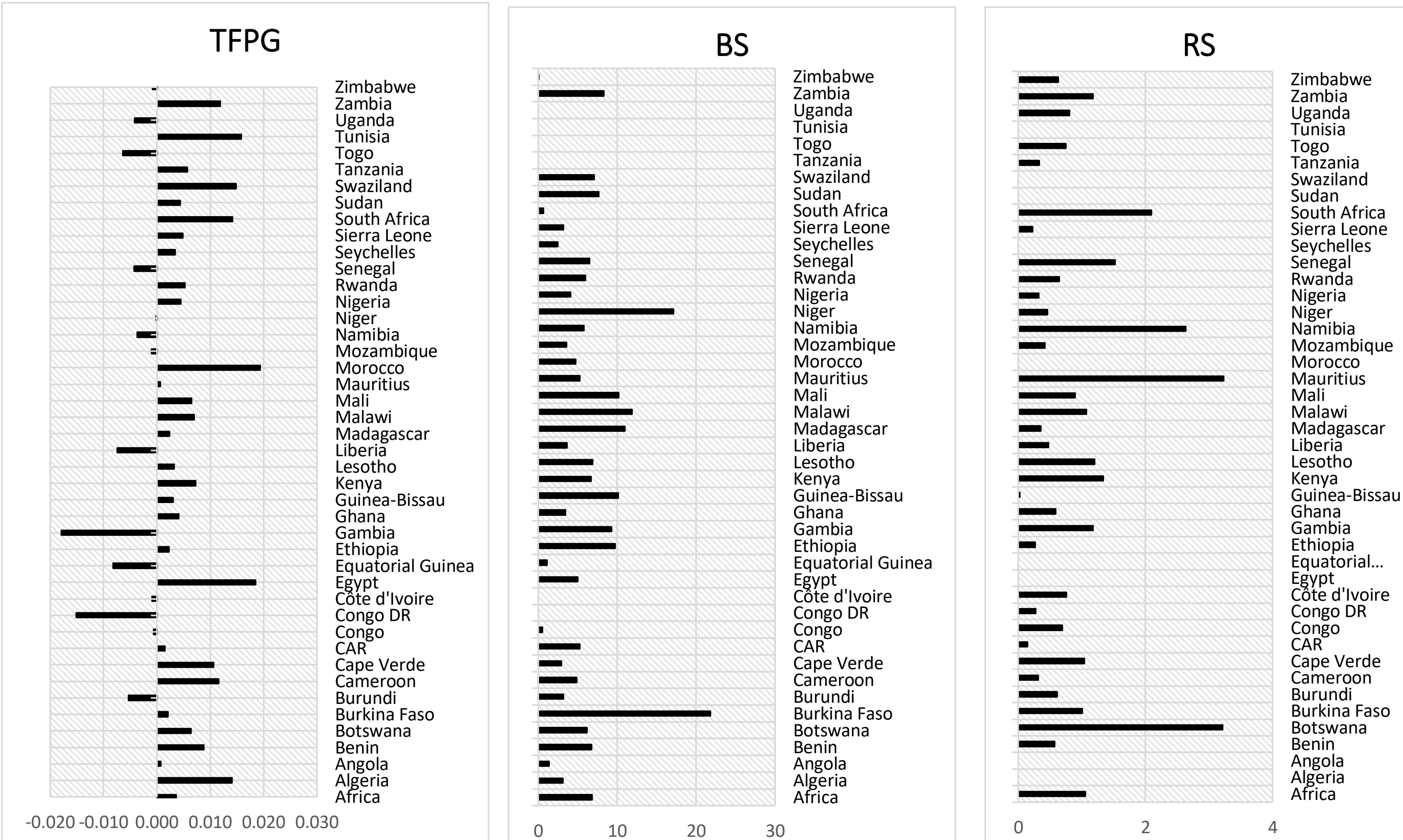

Figure 1-2 Average TFPG, BS and RS in African countries (1991-2012)

Source: Author computation based on SPEED, ASMTI and World Bank data

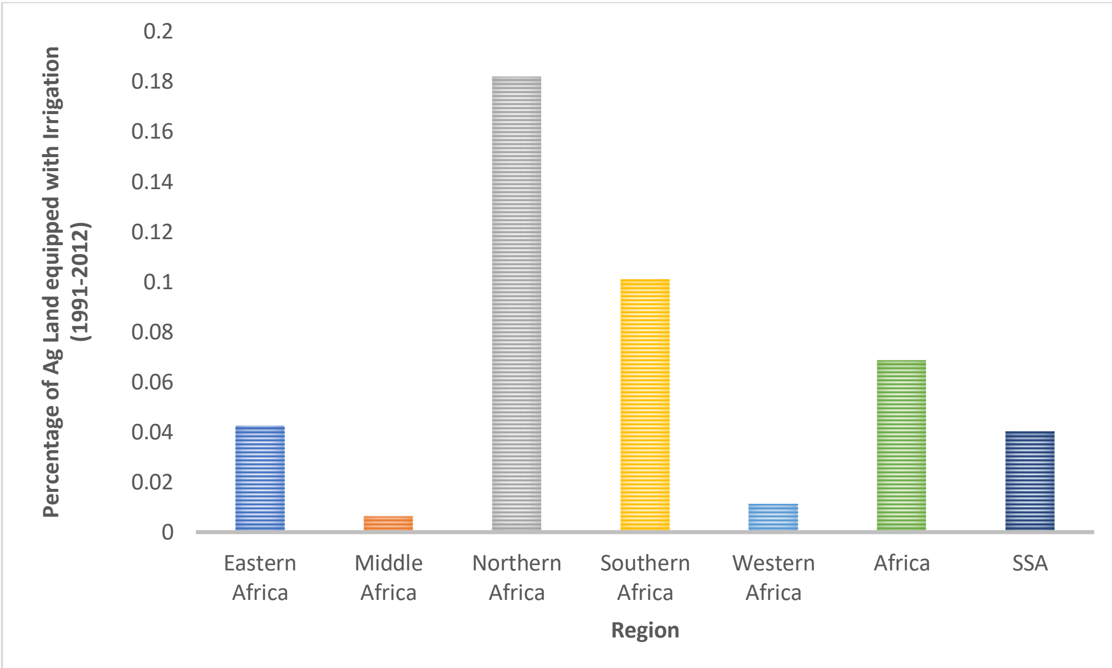

Figure 1-3 Percentage of agricultural land equipped with irrigation per region (1991-2012)

Source: FAO, 2020

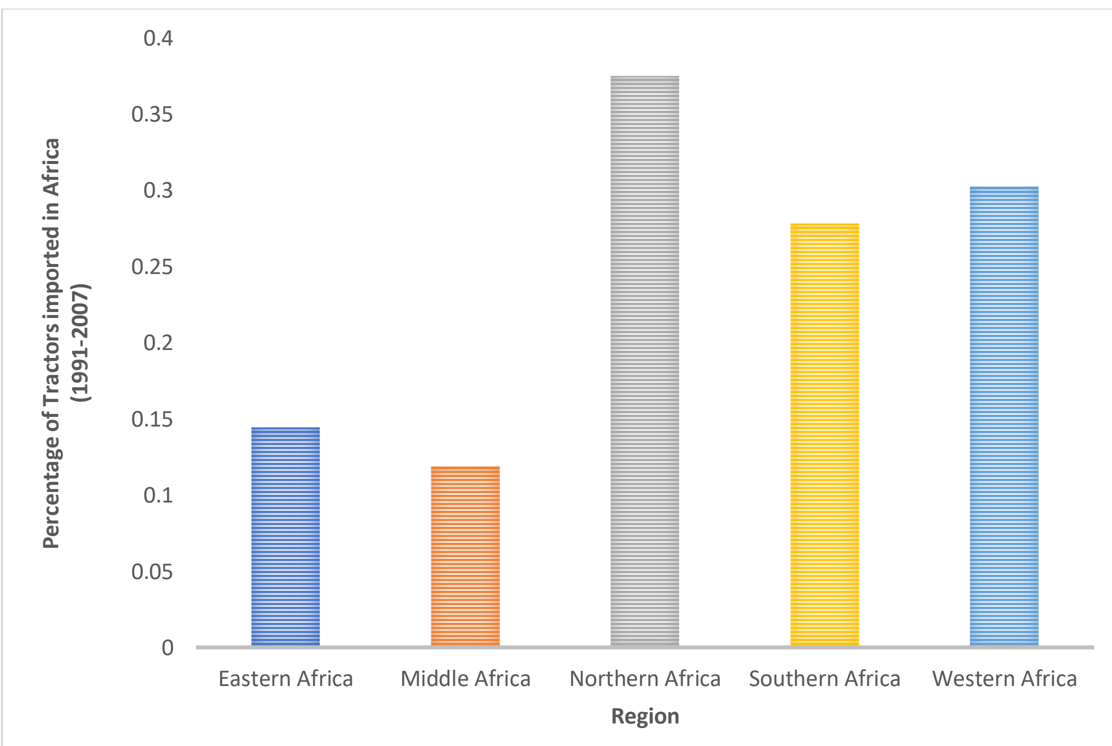

Figure 1-4 Percentage of tractors imported per region (1991-2007)

Source: FAO, 2020

1.5.2 Agricultural Budget Share (BS)

One of the two key control variables in this study is the public spending on the agricultural sector. The data on this variable are gathered from the Statistics on Public Expenditures for Economic Development (SPEED) database. Additionally, these data are collected and processed by the International Food Policy Research Institute (IFPRI) which tracks public expenditures for development. Public spending on agriculture is expressed annually as a ratio of all government spending. That is, the percentage of agricultural expenditure in the total expenditure of the government for the year in constant 2005 purchasing power parity (PPP). Items included in the agricultural expenditure ratio include farming, livestock, agricultural research services, and rural infrastructure construction.

On average, over the period running from 1980–2014, the countries included in this study spent 6.80% of their annual budget on agriculture. Based on the three-decade average, Burkina Faso (21.81), Niger (17.13), Malawi (11.86), Madagascar (11.00), and Mali (10.19) allocate the highest budget share on the continent to agriculture. Conversely, Zimbabwe (0.006), Republic of Congo (.54), South Africa (0.62), Equatorial Guinea (1.11) and Angola (1.34) allocate the lowest budget share to agriculture. Over the period running from 1980–2014, the highest BS (63.3) was observed in 1987 in Guinea-Bissau. The lowest BS (.000023) and was observed in Zimbabwe in 2007.

The regional distribution of BS (Fig. 1.b Annex) revealed that West Africa had the highest average agricultural expenditure over the period from 1980–2014. West Africa spent 9%, on average, on agriculture, while Central Africa invested only 4%. Meanwhile Eastern, Southern, and Northern Africa spent 7.58%, 5.14% and 4.43%, respectively, on agriculture. However, the fund allocation towards agriculture decreased during the 1990s and 2000s. In between the two decades, the agriculture budget share decreased from 7.79% to 5.35 % on the continent. In the same trend, West Africa, the top investor in agriculture in the 1980s and 1990s, reduced its agricultural budget share from 10.32% to 7.08%. During this period, Eastern Africa took the lead in agricultural investment in the 2000s with an annual average of 7.15%, a slight decrease from its 7.94% agriculture budget share in the 1990s.

1.5.3 Research Share of Agricultural Gross Domestic Product

The research share (RS) of the agricultural gross domestic product (GDP) is the second key independent variable in this investigation. This variable captures the relative importance of research in the agricultural annual gross domestic product. The RS is the share of annual agricultural GDP that goes to spending on salary-related expenses, operating and program costs, and capital investments by government, nonprofit, and higher education agencies. Due to the lack of availability, this variable does not include data on spending by private entities (ASTI, 2019).

Over the period running from 1980–2016, the average African RS was about 1.06%. During this period, the highest average RS was observed in Mauritius, Botswana, Namibia, South Africa, and Senegal. In these five countries, the average RS was beyond 1.5% of the agricultural GDP. The lowest average RS occurred in DR Congo, Ethiopia, Sierra Leone, Central Africa Republic, and Guinea-Bissau. In these countries, the RS did not exceed 0.3% (see Figure 1-6).

In terms of the regional aggregated average of the RS over the period from 1980–2016, the Southern African region, led by Botswana, Namibia, and South Africa, topped all other regions. The average RS in that region reached 1.5%. The Central African region, with less than 0.6% of the average RS, was the last region in this ranking (Fig. 1.c Appendix A).

Over the last four decades, the changes to the RS in African economies was heterogeneous. At the continental level, the RS is steadily decreasing. In most West African francophone countries, the RS has decreased over time. This is the case for Burkina Faso, Cote d'Ivoire, Mali, Niger, Senegal, and Togo. This decreasing trend is observed at the regional level as well in countries like Burundi, Gambia, Madagascar, Malawi, Nigeria, Tanzania, and Zambia. However, the RS in Republic of Congo, Ghana, Mauritius, and South Africa have increased over time.

1.5.4 Basic Correlation Among TFPG, BS, and RS

Prior to the empirical estimation, we compared the TFPG, the BS, and the RS to find the descriptive relationship between them. First, we found the correlation coefficient between the BS and the TFPG to be .04% for the continent over the period running from 1992–2014 (see Figure 1.5). The highest coefficient was observed in Northern Africa (8%), and lowest was observed in Central Africa (3%). The correlation coefficient between the TFPG and the BS is statistically significant at 5%.

The regional analysis of the correlation between the TFPG and the BS revealed four groups of countries. The first group is made up of South Africa, Ghana, Cameroon, Cape Verde, and Zambia, where the average TFPG is above .015%, but the BS is below 5%. The second group includes Zimbabwe, Liberia, Burundi, and Mauritius, where both the TFPG and the BS are below 0% and 6%, respectively. The third group includes countries along the fitted line of Figure 1-5. Those are countries where the BS is about 5%, and the TFPG is around .01%. This group includes countries such as Central African Republic (CAR), Rwanda, Benin, Madagascar. The fourth and last group includes countries with a high BS but with an average TFPG. This group includes Burkina Faso, Niger, and Mali, where the BS exceeds 10%, but the TFPG barely exceeds the continental average of 0.01%.

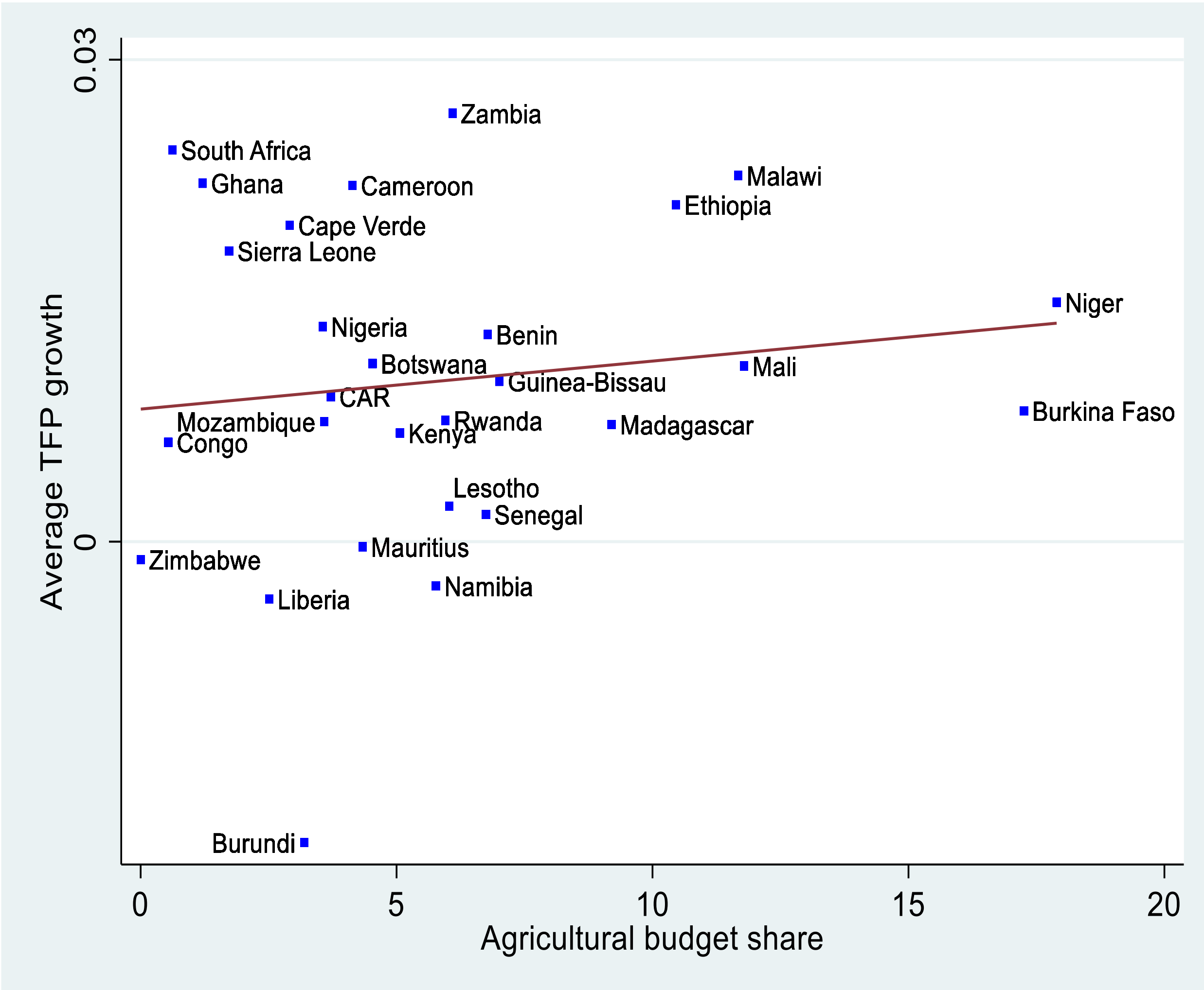

Figure 1-5 Average BS and TFPG in African countries (1991-2012)

Source: Author computation based on SPEED, ASMTI and World Bank data

When comparing the RS and the TFPG, we found a negative correlation for the continent from 1992–2014 (see Figure 1.6). The correlation coefficient between these two variables is -50% for the continent over the period of this analysis. However, the correlation is positive in Northern Africa (38%) and negative in others. The negative correlation is stronger in Central Africa (-14%).

Botswana and South Africa have a high RS along with a high TFPG, while others like Zimbabwe and Liberia have a low RS and a low TFPG.

Third and last, we found the correlation between BS and RS to be negative (19%), but not statistically different from zero for the continent. However, when disaggregated per region, the correlation is significant for some regions. The correlation is positive and significantly different from zero at 1% for Central Africa (49%) and Northern Africa (26%). On the other hand, West Africa (-16%), East Africa (-42%) and Southern Africa (-15%) have a negative correlation and drive the continent correlation down. While in Burkina Faso and Niger, the BS is high with a low RS, countries like Mauritius, Botswana, and Namibia have a high RS and a very low BS.

We highlight that the correlation coefficients only capture the descriptive strength of the relationship between the relative co-movements of two variables. In this exercise, we do not control for potential confounding factors such as agronomic and ecologic conditions, which can affect both the regressors (BS and RS) and the dependent variable (TFPG). Therefore, these correlation coefficients merely report a descriptive relationship. The panel fixed-effect regressions conducted in the upcoming section provide sound causality insights.

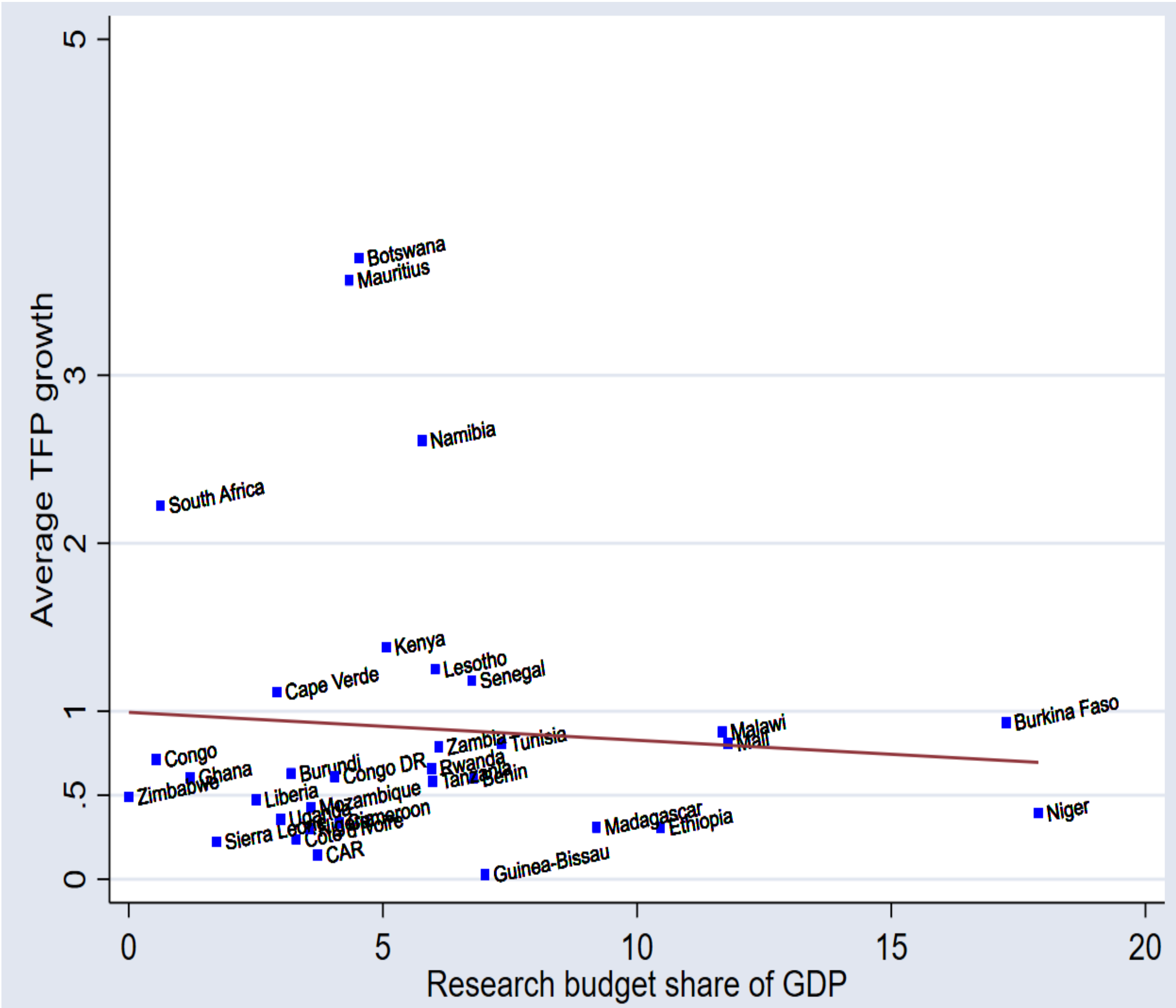

Figure 1-6 Average RS and TFPG in African countries (1991-2012)

Source: Author computation based on SPEED, ASMTI and World Bank data

1.5.5 Pre- and Post-Maputo Commitment

In this section, we provide a descriptive analysis of the TFPG, the BS, and the RS before and after the Maputo Commitment of 2003. We seek to shed light on how the 2003 Maputo Commitment of the agricultural budget share increment affected agricultural funding and productivity.

The Comprehensive Africa Agriculture Development Program (CAADP) that stemmed from the Maputo Commitment aimed to achieve 6% annual growth in the agricultural GDP by enforcing an allocation of at least 10% of public expenditures to the agricultural sector. The Commitment's goals were to create jobs for youth and women, improve food security and nutrition, and strengthen farmers' resilience (Sidler, 2017). Building upon the Maputo momentum, the African Union made an additional pledge in 2006 to allocate 1% of the agricultural GDP to agricultural research and development. This second level of the Commitment was grounded on academic evidence, showing that returns on research and extension on poverty reduction are high in the continent (Howard G. Buffett Foundation, 2013).

However, the descriptive statistics in this study show weak compliance with the Maputo Commitment (see Figure 1-7). The averaged agricultural share of the budget (BS) was 6.34% from 1991–2002. This average remained as low as 5.89% (see Figure 1-8) after the Maputo Commitment (2003–2012). In this post-Maputo era, Malawi, Burkina Faso, Ethiopia, and Niger invested more than 10% of their annual budget in the agricultural sector (see Figure 1-8). Before the Maputo Commitment, the research share of agricultural GDP was 1.08%. After the Maputo Commitment, the RS dropped to 0.98%. However, the TFPG between 2003-2012 remained volatile and reached 1.2%. This represents a 46% increase from the average 0.8% TFPG over the 1991-2002 period. The TFPG in the post-Maputo era is still driven by economies such as Botswana, Malawi, Senegal, Cape Verde, Zambia, and Cameroon.

To assess the Maputo Commitment, we added a binary dummy variable to the regression analysis. We used the dummy variable to divide the data set into two subsets, using 2004 as the year from which African governments were supposed to comply with their commitment, by increasing the agricultural share of the national budget to 10%.

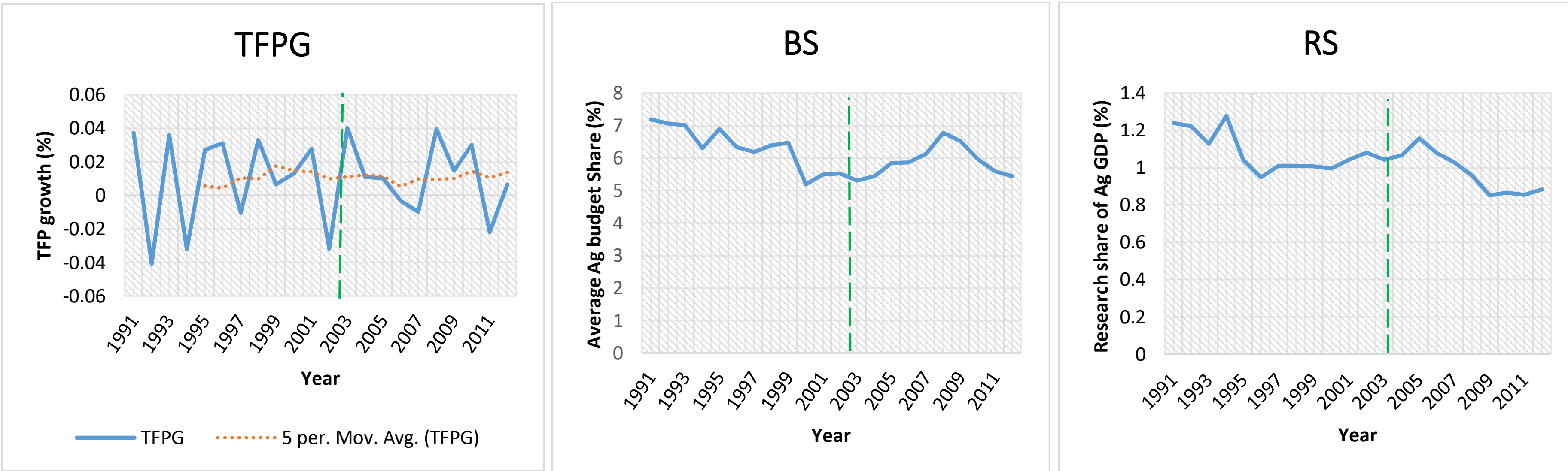

Figure 1-7 Average TFPG, BS and RS in Africa (1991-2012)

Source: Author computation based on SPEED, ASMTI and World Bank data

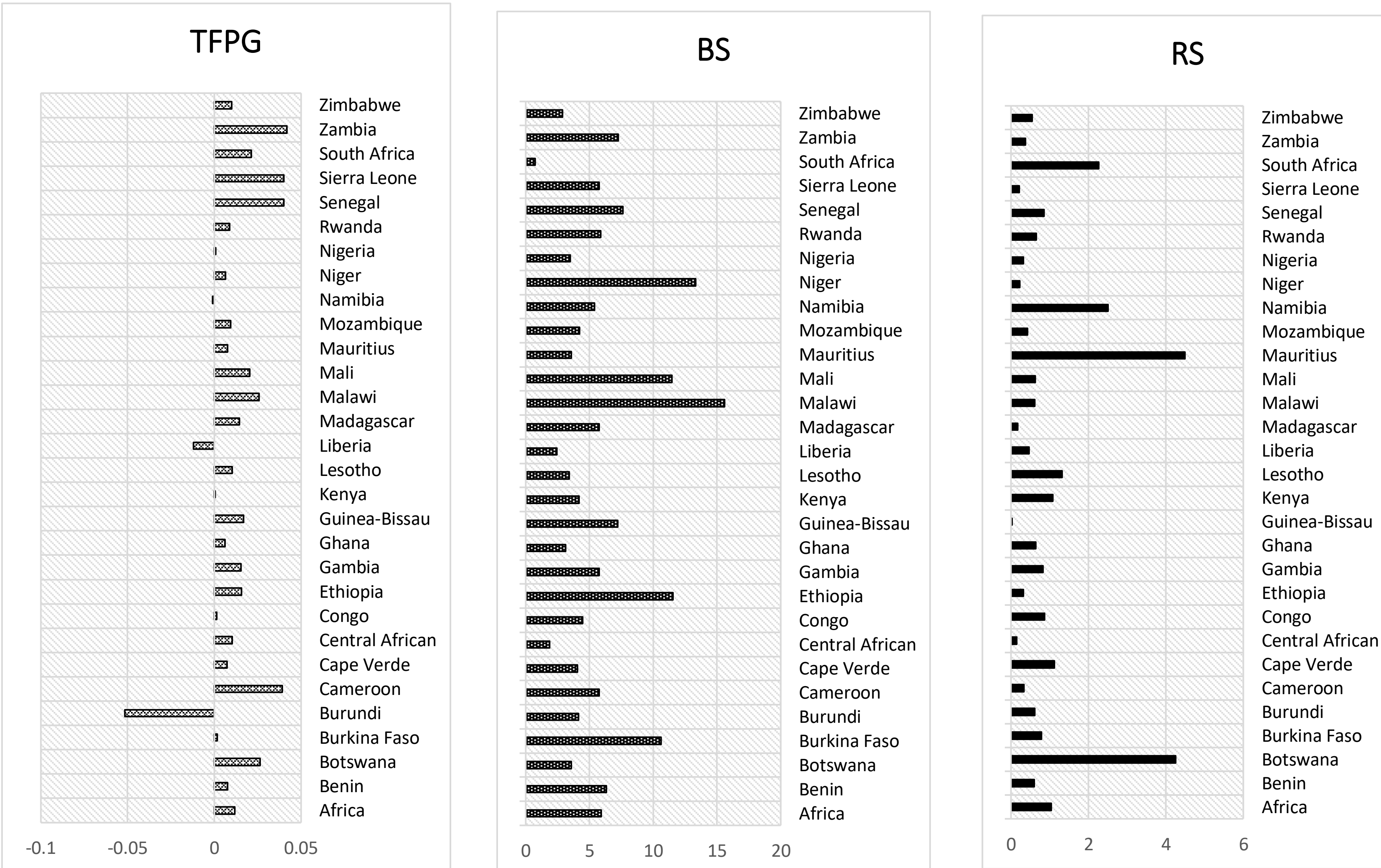

Figure 1-8 Post-Maputo Commitment Average TFPG, BS and RS in African economies (2003-2012)

Source: Author computation based on SPEED, ASMTI and World Bank data

1.6. The Impact of Public Spending on Total Factor Productivity Growth

We estimated the impact of the agricultural budget share (BS) and the research share (RS) of the agricultural gross domestic product on the total factor productivity growth (TFPG) using a panel data estimator. For each of the two main independent variables, we conducted the estimation in three steps. First, we ran a model without controls, but time trend. Second, we controlled for all agronomic, time trend and ecological confounding factors, but we did not include any lag of the independent variable (BS or RS). Third, we ran the saturated model with all agronomic and ecological controls and lags included to identify the BS or RS effect coefficients. It is important to note that for the third model, the estimation involved twenty-eight (BS) and eighteen (RS) countries that had complete observations for all the independent and control variables.

Three major problems that lead to inefficient and biased estimates in panel regression analysis include nonstationarity, autocorrelation, and heteroskedasticity. We tested the stationarity of the TFPG using both the Levin-Lin-Chu (Breitung, 1999; Breuer et al., 2002; Levin et al., 2002), and the Harris-Tzavalis (1999) unit-root tests. Both tests reported a p-value lower than 1%, which implies the rejection of the null hypothesis of the panels containing unit roots. This was not surprising since the TFPG was the result of a first-order differentiation between TFP_t and TFP_{t-1}.

Next, we tested the model for autocorrelated error terms using the Wooldridge test for autocorrelation in panel data (Montes-Rojas & Sosa-Escudero, 2018; Wooldridge, 2000). We statistically rejected the null hypothesis of no first-order autocorrelation which implied the presence of a first-order correlation in the error term. We also tested for heteroskedasticity using the Wald test. This test calculates a modified Wald statistic for groupwise heteroskedasticity in the residuals of a fixed-effect regression model (Wooldridge, 2000). The resulting test statistic distributed Chi-squared under the null hypothesis of homoscedasticity, indicating the presence of heteroskedasticity. We dealt with autocorrelated and heteroskedastic error terms using a fixed effect, robust, and clustered (at country-level) error term in the panel estimator.

Because the effect of investment in agriculture spans overtime, we used the Akaike's (AIC) and Bayesian (BIC) information criteria to choose the optimal number of lags. For RS, both the AIC and BIC decreased with the number of lags, but we observed a break at lag 14. In fact, the AIC and BIC decreased in absolute value from lag 15, showing that lag 14 was the optimal lag length for this model. For the BS, the information criteria decreased until we reached the maximum number of lags allowed by the independent and controlled variables' observations included in the dataset (Fig. 4 annex). We therefore estimated the models with 14 lags for RS and 19 lags for BS. In both models, we controlled for food price, secular growth and learning by doing (using time trend), precipitation (using annual average precipitation for each country), the annual average minimum and maximum temperature, the cross-effect of precipitation and temperature, and GDP.

The estimates reported in Table 1 imply that for every 1% increase in BS, the TFPG increases by 1.96% for the following year, 1.83% on the third year, and 3.42% on year seven. Assuming this linear effect of the agricultural budget share on the TFPG, a 1% increase in the BS, ceteris paribus, would result in a cumulative TFPG of 7.21% after eight years. The average African BS over the period from 1980–2014 was 6.8%; an increase to 7.8% would result in TFPG from its average of 0.97% to 1.04 % after eight years. This is relatively weak productivity growth, which implies that a consistent and bold increase in BS is required for a significant increase in TFP. To double its TFPG, such an average African country needs to increase the BS from 6.8% to 14%, which requires an additional 7.2% increase in the BS.

To replicate the relationship with production as expressed in equation (10), we estimated:

$$Production_{t=15} = (1 + 0.0104)TFPG_{t=1} * TFP_{t=1} * Labor_{t=15} * Capital_t \qquad (11)$$

Considering the 10% BS recommended by the Maputo protocol, an increase in BS from the 6.8% average to 10% would imply a 3.2% increase in the BS. Such an increase would result in a move in the TFPG of 23.07%. This implies that an implementation of the Maputo protocol in 2012 would induce an additional TFPG of 46.14% in 2027. In terms of food production this implies:

$$Production_{2027} = 1.46 * TFPG_{t=2012} * TFP_{t=2012} * Labor_{t=2027} * Capital_{t=2027} \quad (12)$$

On the other hand, a 1% increase in the RS would result in a 6.77% TFPG growth after seven years (Table 2). Put differently, increasing the research share of the agricultural GDP by 1% induces about 1% TFPG in each of the seven subsequent years, making up a 7% increase of the TFPG by the seventh year. In terms of country level food production, this implies:

$$Production_{t=7} = 1.07 * TFPG_t * TFP_t * Labor_{t=7} * Capital_{t=7} \quad (13)$$

These results show that it takes seven years for an additional 1% in the RS to induce a 6.77% increase in the TFPG. Meanwhile, after eight years, a 1% increase the BS triggers a 7.21% TFPG. While we could not precisely compare these two impacts, it is important to note that national research funds are involved in the BS. Therefore, taking away research outlays would reduce the impact of the BS. While the estimate of the impact of the BS on TFPG does not enable us to disaggregate the effect of research, extension, human resources, salaries, and infrastructure, the estimate of the impact of the RS on TFPG reveals the importance of research in the BS effect. If, together with nationally funded research, other outlays included in the BS induce a 7.21% TFPG after eight years, while the RS induces a 6.77% TFPG within seven years, one could argue in favor of the greater effectiveness of research funds in increasing TFPG.

Furthermore, in both models, the estimation showed that the Maputo Commitment was not successful in positively impacting TFPG in Africa. The dummy for the Maputo Commitment is negative and non-significant in the BS model. On the other hand, in the RS model, we found the TFPG to be lower in the post-2003 era than before 2003. This finding is not surprising because in Figures 1-6 and 1-7, we found no significant differences in the BS and RS before or after the Maputo Commitment. Without increased agricultural expenditure on irrigation, mechanization, and innovation, one could hardly expect the TFP to grow significantly.

To determine the budget and research shares' effect on the TFPG at a regional level, we ran the estimation model with ten lags for Western, Eastern, Central and Southern Africa. Due to the reduced number of observations, we could neither run the estimation for Northern Africa (with only 44 observations) nor include more than ten lags in each model. Because we did not use the number of lagged variables required by the AIC and BIC tests, the regional level estimates are inefficient and therefore interpreted as correlations instead.

We found a positive and significant effect of BS on TFPG for West and Central Africa. In West Africa, a marginal increase in the BS resulted in a cumulative TFPG of 1.8% after ten years. In the central region of Africa, a marginal increase of the BS resulted a 1.8% increase in the TFPG after ten years. On the other hand, we found a significant association between the RS and the TFPG in all regions. The cumulative effect of the RS on the TFPG is 21.9%, -24.2%, -15.2%, and 25.6% in the Western, Eastern, Southern, and Central regions of the continent, respectively. These results show that West and Central Africa drive the positive and significant BS and RS effects on the TFPG at the aggregate level.

Table 1-1 Estimates of the Agricultural budget share (BS) effect on TFPG

Variables	(1) Without controls	(2) With controls	(3) With controls & lags
Time Trend	0.0001	0.0001	-0.0305
	(0.0003)	(0.0009)	(0.0315)
bs	0.0012*	0.0007	-0.0174
	(0.0006)	(0.0006)	(0.0203)
L.bs			0.0196***
			(0.0011)
L2.bs			0.0124
			(0.0131)
L3.bs			0.0183***
			(0.0009)
L4.bs			0.0011
			(0.0135)
L5.bs			0.0056
			(0.0066)
L6.bs			0.0080
			(0.0115)
L7.bs			0.0342**
			(0.0053)
L8.bs			-0.0109
			(0.0339)
L9.bs			0.0325
			(0.0199)
L10.bs			0.0011
			(0.0146)
L11.bs			0.0081
			(0.0109)
L12.bs			-0.0031
			(0.0078)
L13.bs			0.0091
			(0.0057)
L14.bs			0.0033
			(0.0060)
L15.bs			0.0000
			(0.0063)
L16.bs			0.0118
			(0.0101)
L17.bs			0.0030
			(0.0061)
L18.bs			0.0004
			(0.0149)
L19.bs			0.0012
			(0.0090)

Table 1.1 Estimates of the BS effect on TFPG (Continued)

Variables	(1) Without control	(2) With controls	(3) With controls & lags
Maputo Commitment (dummy)		-0.014	
		(0.009)	
Lagged food price index		-0.0016	-0.0019
		(0.0108)	(0.0659)
Precipitation		145.5119***	-348.6287
		(43.8085)	(527.9740)
Precipitation squared		-11.0657***	26.9152
		(3.3047)	(40.3360)
Minimum temperature		131.1301**	-467.4110
		(61.1855)	(559.0347)
Precipitation x mini temperature		-39.2868**	145.0405
		(18.1629)	(173.0734)
Precipitation squared x Minimum temperature		2.9777**	-11.2252
		(1.3532)	(13.2804)
Maximum temperature		163.4056***	-292.2568
		(42.7974)	(518.1872)
Precipitation x Maximum temperature		-49.4624***	89.8456
		(12.8307)	(159.9860)
Precipitation squared x Maximum temperature		3.7523***	-7.0204
		(0.9728)	(12.2343)
Minimum temperature x Maximum temperature		-46.4256**	121.4086
		(17.1719)	(168.6421)
Precipitation x Max temperature x Min temperature		13.9293**	-37.9859
		(5.1093)	(52.3133)
Precipitation squared x Max temperature x Min temperature		-1.0515**	2.9729
		(0.3824)	(4.0177)
Real GDP		-0.0087	0.1146
		(0.0082)	(0.1314)
Constant	0.0015	-481.209***	1,139.9980
	(0.0057)	(146.4982)	(1,712.9579)
Observations	638	588	84
R-squared	0.0020	0.0948	0.6509
Number of Countries	29	28	28

Notes: The dependent variable is the TFP growth rate. “bs” stands for Agricultural budget share. Regressions include country fixed effect, none of which are reported. Standard errors are clustered at country level and corrected for cross-sectional heteroscedasticity.
Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Table 1-2 Estimates of the RS effect on TFPG

Variables	(1) Without control	(2) With controls	(3) With controls & lags
Time trend	-0.000564	0.000891	0.00263
	(0.000398)	(0.00140)	(0.00566)
rs	-0.0110**	-0.00707	-0.00931
	(0.00469)	(0.00674)	(0.0393)
L.rs			-0.0134
			(0.0475)
L2.rs			0.0199
			(0.0436)
L3.rs			-0.0109
			(0.0291)
L4.rs			0.0141
			(0.0294)
L5.rs			-0.0100
			(0.0305)
L6.rs			0.0677***
			(0.0167)
L7.rs			-0.0365
			(0.0548)
L8.rs			-0.0353
			(0.0576)
L9.rs			0.0218
			(0.0301)
L10.rs			-0.0331
			(0.0502)
L11.rs			0.0532
			(0.0491)
L12.rs			0.00305
			(0.0442)
L13.rs			-0.0235
			(0.0280)
L14.rs			0.0283
			(0.0425)

Notes: The dependent variable is the TFP growth rate. "rs' stands for research share of Agricultural GDP. Regressions include country fixed effect, none of which are reported. Standard errors are clustered at country level and corrected for cross-sectional heteroscedasticity.
Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Table 1.2 Estimates of the RS effect on TFPG (continued)

Variables	(1) Without control	(2) With controls	(3) With controls & lags
Maputo Commitment (dummy)		-0.0226**	
		(0.0109)	
Lagged food price index		-0.00194	0.00299
		(0.0123)	(0.0207)
Precipitation		141.9*	-377.0
		(73.31)	(413.5)
Precipitation squared		-10.52*	28.42
		(5.627)	(35.36)
Minimum temperature		140.7	-391.2
		(90.17)	(387.3)
Precipitation x mini temperature		-40.58	124.3
		(27.26)	(135.0)
Precipitation squared x Minimum temperature		2.975	-9.630
		(2.070)	(11.48)
Maximum temperature		154.2**	-344.2
		(71.34)	(370.0)
Precipitation x Maximum temperature		-45.17**	104.9
		(21.84)	(129.6)
Precipitation squared x Maximum temperature		3.343*	-7.894
		(1.687)	(11.06)
Minimum temperature x Maximum temperature		-45.56*	109.5
		(26.07)	(120.7)
Precipitation x Max temperature x Min temperature		13.16	-34.72
		(7.943)	(42.06)
Precipitation squared x Max temperature x Min temperature		-0.963	2.688
		(0.608)	(3.578)
Real GDP		-0.00616	-0.0388
		(0.0105)	(0.0494)
Constant	0.0294***	-485.2*	1,232
	(0.00811)	(240.9)	(1,178)
Observations	477	455	144
R-squared	0.004	0.120	0.331
Number of Countries	29	28	18

Notes: The dependent variable is the TFP growth rate. “rs’ stands for research share of Agricultural GDP. Regressions include country fixed effect, none of which are reported. Standard errors are clustered at country level and corrected for cross-sectional heteroscedasticity.
Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Table 1-3 Estimates of the BS and RS effect on TFPG at regional levels

Variables	Budget share				Research Share			
	West	East	Southern	Central	West	East	Southern	Central
Time Trend	-0.00337	-0.0156	-0.000947	-0.0172	-0.00319	0.00918	-0.00426	0.00659
	(0.00485)	(0.0268)	(0.00439)	(0.0136)	(0.0118)	(0.00739)	(0.0107)	(0.00364)
Level	-0.00484	0.0229*	0.00853*	-0.000984	-0.0816	0.0295	0.0292	-0.00637
	(0.00383)	(0.00895)	(0.00424)	(0.00990)	(0.0727)	(0.0355)	(0.0244)	(0.116)
Lag 1	0.00763**	-0.0161*	-0.00909	-0.00515	0.102**	-0.0952	-0.0974***	0.0281
	(0.00324)	(0.00562)	(0.00675)	(0.00803)	(0.0387)	(0.0839)	(0.0118)	(0.792)
Lag 2	-0.00698	-0.000389	0.0102	0.00499	0.0677	0.201	0.0981***	-0.0139
	(0.00478)	(0.00898)	(0.00795)	(0.00805)	(0.0634)	(0.102)	(0.0108)	(0.267)
Lag 3	0.00849*	-0.00254	-0.00275	-0.0116	-0.0628	-0.160**	-0.0545***	0.133
	(0.00438)	(0.00878)	(0.00844)	(0.00882)	(0.0507)	(0.0422)	(0.0126)	(0.217)
Lag 4	-0.00294	0.0105	-0.00291	0.00126	-0.00947	0.0239	0.0201	-0.0595
	(0.00398)	(0.00724)	(0.00724)	(0.0100)	(0.0632)	(0.0280)	(0.0342)	(0.0736)
Lag 5	-0.00291	0.00465	0.00674	-0.000653	-0.0904	-0.0665	0.0120	0.0251
	(0.00468)	(0.0190)	(0.0108)	(0.0122)	(0.0807)	(0.0308)	(0.0105)	(0.120)
Lag 6	0.00588	0.00212	-6.81e-05	-0.00812	0.117***	0.114	-0.0163*	-0.190
	(0.00335)	(0.00849)	(0.0126)	(0.00479)	(0.0328)	(0.0569)	(0.00818)	(0.126)
Lag 7	-0.00136	-0.0162*	0.00441	0.00668*	0.0441	0.00693	0.0229	0.256*
	(0.00212)	(0.00654)	(0.00874)	(0.00304)	(0.0713)	(0.0479)	(0.0134)	(0.0743)

Notes: The dependent variable is the TFP growth rate. Regressions include country fixed effect, none of which are reported. Standard errors are clustered at country level and corrected for cross-sectional heteroscedasticity.
Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Table 1-3 Estimates of the BS and RS effect on TFPG at regional levels

Variables	Budget share				Research Share			
	West	East	Southern	Central	West	East	Southern	Central
Lag 8	-0.00194	0.0160	0.00465	-0.00332	-0.0972	-0.0859**	-0.0502	
	(0.00251)	(0.00906)	(0.00467)	(0.00686)	(0.0885)	(0.0233)	(0.0267)	
Lag 9	0.00249*	-0.0197	-0.000161	0.00241	0.0744	0.0403	0.0326	
	(0.00124)	(0.0214)	(0.00529)	(0.00241)	(0.0566)	(0.0460)	(0.0531)	
Lag 10	-0.000650	0.00657	-0.000969	0.00437	-0.0347	-0.0536	-0.0436	
	(0.00109)	(0.00861)	(0.00402)	(0.00612)	(0.0843)	(0.0615)	(0.0446)	
Maputo Commitment	-0.0323*	-0.0103	-0.0101	0.0185	-0.0199	0.0411	0.0238	0.00124
	(0.0155)	(0.0422)	(0.0282)	(0.0300)	(0.0232)	(0.0341)	(0.0695)	(0.141)
Climate, Price and GDP controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	1,751	319.4	-1,597	358.4	2,680	-1,676	-589.8	4,092
	(2,117)	(407.8)	(2,042)	(840.9)	(4,961)	(1,045)	(771.4)	(74,012)
Observations	132	48	96	60	98	48	56	31
R-squared	0.475	0.619	0.246	0.356	0.546	0.693	0.689	0.893
Number of Countries	11	4	8	5	9	4	7	3

Notes: The dependent variable is the TFP growth rate. Regressions include country fixed effect, none of which are reported. Standard errors are clustered at country level and corrected for cross-sectional heteroscedasticity.
Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

1.7 Robustness Check

We next assumed our approach to correct for autocorrelation and heteroskedasticity to be ineffective and inefficient. In such a case, our estimates might be biased or inefficient. We test the robustness of the estimates using two other estimation procedures aimed at correcting for autocorrelation and heteroskedasticity. We first used the Generalized Least Squares (GLS) procedure, which fits panel data using the feasible generalized least squares estimator. This procedure allows estimation in the presence of the first-order autoregressive autocorrelation within panels as well as cross-sectional correlation and heteroskedasticity across panels.

Second, we used the panel-corrected standard errors (PCSE) estimates for the linear cross-sectional time-series models. In this procedure, the parameters are estimated by either the ordinary least squares (OLS) or the Prais-Winsten regression. When computing the standard errors and the variance-covariance estimates, the PCSE assumes heteroskedastic and contemporaneously correlated disturbances across panels. Results are reported in Table 1-4.

Estimates from the feasible GLS and the PCSE are in line with those reported by the panel estimator with fixed effect, robust, and clustered standard errors (OLS). For the impact of the budget share, the OLS reported a 7.21% increase after eight years, while the feasible GLS reported 6.87% after ten years, and the PCSE reported 8.96% after eight years. Similarly, the three models yielded a cumulated impact of the research share on the TFPG of 6.77%, 6.37% and 6.60% after seven years for the OLS, and feasible GLS and PCSE, respectively. These results confirm the robustness of our estimated impact of budget share and research share on TFPG in Africa.

Table 1-4 Feasible GLS and Panel corrected standard errors estimates for robustness check

Variables	Budget share			Research Share		
	OLS	GLS	PCSE	OLS	GLS	PCSE
Time Trend	-0.0305	-0.0147	-0.0141	0.00263	-0.00318	-0.00204
	(0.0315)	(0.0679)	(0.0108)	(0.00566)	(0.00296)	(0.00326)
Level	-0.0174	-0.00378	-0.00390	-0.00931	-0.0139	-0.0168
	(0.0203)	(0.00387)	(0.00490)	(0.0393)	(0.0205)	(0.0170)
Lag 1	0.0196***	0.0207***	0.0336***	-0.0134	-0.0181	-0.00563
	(0.0011)	(0.00045)	(0.00453)	(0.0475)	(0.0328)	(0.0296)
Lag 2	0.0124	0.000279	-0.000214	0.0199	0.0318	0.0173
	(0.0131)	(0.00436)	(0.00518)	(0.0436)	(0.0337)	(0.0287)
Lag 3	0.0183***	0.0130***	0.0225***	-0.0109	-0.00455	-0.00404
	(0.0009)	(0.00320)	(0.00388)	(0.0291)	(0.0315)	(0.0236)
Lag 4	0.0011	-0.0164	-0.0163	0.0141	-0.0179	-0.00619
	(0.0135)	(0.02353)	(0.05396)	(0.0294)	(0.0310)	(0.0240)
L5.BS	0.0056	0.00965	0.0103	-0.0100	0.0197	-0.00477
	(0.0066)	(0.06363)	(0.02313)	(0.0305)	(0.0303)	(0.0220)
Lag 6	0.0080	-0.0109	-0.0117	0.0677***	0.0637***	0.0660***
	(0.0115)	(0.0351)	(0.0364)	(0.0167)	(0.018)	(0.0038)
Lag 7	0.0342**	0.0206***	0.0332***	-0.0365	-0.0360	-0.0431
	(0.0053)	(0.00508)	(0.00530)	(0.0548)	(0.0264)	(0.0313)
Lag 8	-0.0109	-0.00234	-0.00155	-0.0353	-0.0160	0.000472
	(0.0339)	(0.00696)	(0.00784)	(0.0576)	(0.0317)	(0.0367)
Lag 9	0.0325	0.00174	-0.00133	0.0218	0.0120	0.0102
	(0.0199)	(0.00603)	(0.00618)	(0.0301)	(0.0300)	(0.0336)
Lag 10	0.0011	0.0144***	0.0134	-0.0331	-0.00739	-0.00663
	(0.0146)	(0.00486)	(0.0486)	(0.0502)	(0.0285)	(0.0346)

Notes: The dependent variable is the TFP growth rate. Regressions include country fixed effect, Climate, Price and GDP none of which are reported. Standard errors are clustered at country level and corrected for cross-sectional heteroscedasticity for the OLS model.
Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Table 1-4 Feasible GLS and Panel corrected standard errors estimates for robustness check (continued)

Variables	Budget share			Research Share		
	OLS	GLS	PCSE	OLS	GLS	PCSE
Lag 11	0.0081	0.00770	0.00551	0.0532	0.0058	0.0358
	(0.0109)	(0.0350)	(0.00367)	(0.0491)	(0.028)	(0.0339)
Lag 12	-0.0031	-0.00727	-0.00413	0.00305	0.0118	0.0137
	(0.0078)	(0.0282)	(0.00272)	(0.0442)	(0.0281)	(0.0375)
Lag 13	0.0091	0.00279	-0.000278	-0.0235	-0.0443	-0.0304
	(0.0057)	(0.00325)	(0.00316)	(0.0280)	(0.0271)	(0.0378)
Lag 14	0.0033	-6.84e-06	0.00136	0.0283	0.00274	-0.00552
	(0.0060)	(0.00347)	(0.00297)	(0.0425)	(0.0214)	(0.0289)
Lag 15	0.0000	0.00323	0.00273			
	(0.0063)	(0.00245)	(0.00203)			
Lag 16	0.0118	0.00273	0.00217			
	(0.0101)	(0.0151)	(0.00158)			
Lag 17	0.0030	0.00518	0.00447			
	(0.0061)	(0.0219)	(0.0113)			
Lag 18	0.0004	-0.00178	-0.00275			
	(0.0149)	(0.00260)	(0.00299)			
Lag 19	0.0012	-0.00787	-0.00631			
	(0.0090)	(0.0282)	(0.0217)			
Climate, Price and GDP controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	1,145.5192	-191.2***		1,231.6567	233.1*	
	(1,701.9393)	(34.87)		(1,178.0730)	(124.2)	
Observations	84	84	84	144	144	144
R-squared	0.6509		0.463	0.3309		0.132
Number of Countries	28	28	28	18	18	18

Notes: The dependent variable is the TFP growth rate. Regressions include country fixed effect, Climate, Price and GDP none of which are reported. Standard errors are clustered at country level and corrected for cross-sectional heteroscedasticity for the OLS model.
Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

1.8 Conclusion

The study sets out to appraise the role of public expenditure in improving agricultural productivity in Africa. Our investigation was motivated by a void in the literature on the topic for many African countries, the necessity to assess the Maputo Commitment, and the need to provide policymakers with a metric of the impact of public spending on productivity growth. We achieved the objective using theoretical and empirical modeling of public expenditure and total factor productivity growth. The data was sourced from IFPRI, USDA, World Bank and CGIAR for forty-three African countries from 1991–2012.

The study found that Africa has not experienced much agricultural productivity growth, which might be traceable to low investment in irrigation and research activities. It was also established that there is a significantly positive association between public expenditure on agriculture and total factor productivity growth. Another finding was that the North Africa sub-region, with higher total factor productivity growth, did not experience the highest agricultural expenditure share. Yet, we found Northern African economies tend to invest more in soil productivity enhancement through irrigation, which might partly explain their higher productivity growth.

Over the period running from 1961–2014, the TFP grew at a pace of 0.97% per year, on average, in Africa. The five countries where the TFP grew the most rapidly include Morocco, Egypt, Tunisia, Swaziland, and South Africa. We also found that North Africa tops the continent in terms of TFP growth with 1.7% per year. Southern Africa, driven by Swaziland and South Africa follow with 0.5%. East Africa and West Africa have the lowest TFP growth rates of .3% and .1% per year, respectively. On average, the TFP decreases in the Central African region at a rate of -.025%.

On average, over the period running from 1980–2014, the continental average in terms of BS was 6.8%. Based on this three-decade average, Burkina Faso, Niger, Malawi, Madagascar, and Mali led all African economies in terms of BS allocation. The regional distribution of BS revealed that West Africa invested the most in agriculture. West Africa spends, on average, 9% on agriculture, while Central Africa invests only 4%. Meanwhile East, Southern, and North Africa spend 7.58%, 5.14% and 4.43%, respectively, on agriculture.

Over the period running from 1980–2016, the average African RS was about 1.06%, with the highest shares observed in Mauritius, Botswana, Namibia, South Africa, and Senegal. In these five countries, the average RS was beyond 1.5% of the agricultural GDP. The lowest average RS occurred in DR Congo, Ethiopia, Sierra Leone, Central African Republic (CAR), and Guinea-Bissau. In the latter countries, the RS did not exceed 0.3%. Overall, the continent has had a steadily-decreasing RS over the last four decades.

The fixed-effect panel data estimation revealed that a 1% increase in the agricultural budget share increased the TFPG by 1.96% for the following year, 1.83% on the third year, and 3.42% on year seven. Assuming a linear and non-compounding effect of the agricultural budget share on the TFPG, a 1% increase in BS results, ceteris paribus, in a cumulative TFPG of 7.21% after eight years. In regard to research share, we found that a 1% increase in the RS would result in a 6.77% TFPG after seven years. Put differently, increasing the research share of the agricultural GDP by 1% induces a 1% TFPG in each of the seven subsequent years, making up a 7% increase of the TFPG by the seventh year.

This investigation provides a general linkage between expenditures and productivity. Our findings show that research expenditure is key to fostering agricultural productivity in Africa. On average, African economies need to invest 14% of their annual budget in agriculture to double its productivity growth in the following eight years. On the other hand, a 15% of research share of agricultural GDP is needed to double the TFPG from its average 0.9% to 1.8%. We also found that the Maputo Commitment did not have a significant effect on the TFPG since several countries did not comply. Increasing the TFPG in order to trigger production that would contribute to food security and poverty alleviation requires a large increase in public spending towards applied research. Complying to the Maputo Commitment (10% BS) would have been a great step towards doubling agricultural productivity in the continent.

However, due to the lack of data, we could not disaggregate the expenditures further to uncover the mechanisms and causes of the inefficiencies. In addition, other factors like infrastructure and institutions (which are relevant for adequate technological diffusion) and adoption and products marketing should be taken into consideration in future studies. Hence, it is recommended that future studies examine the dynamics and determinant of agricultural expenditures with respect to institutional and infrastructural frameworks.

Chapter 2 - Modeling and Appraisal of Cereal Land Allocation Determinants in West Africa

2.1 Introduction

Poverty and land degradation make agricultural land use a central piece in geographic targeting of agricultural development interventions (Epprecht, 2006). Increasingly, researchers focus on land use in sustainable agriculture as it impacts smallholders' food security. It is well known that cropland has expanded to meet the food demands of a rapidly growing population (FAO, 2018). Yet, little is known about the spatial distribution of crops, especially in Sub-Saharan Africa (SSA). To the best of our knowledge, little research exists that studies the rationale of cropland allocation and the pattern of spatial crop distribution in Nigeria and Niger. Studies such as Braimoh and Onishi (2007), Gobin et al. (2002) Olaniran (1988), and Solagberu (2012) mainly focused on social and economic determinants of agricultural land allocation to crops and animal grazing in Nigeria.

The Ricardian theory focusing on the impact of climate on farmland productivity (Ricardo, 1821) triggered several studies on agricultural and forestry land use (Deressa, 2007; Golub et al., 2013; Mendelsohn, 2011; Mendelsohn & Dinar, 2009; Reinsborough, 2003; Sanghi & Mendelsohn, 2008). In most of the investigations, the impact of climate variables on land use was measured by accounting only for agronomic, climatic and limited spatial determinants. Nevertheless, Mendelsohn and Massetti (2017), in their seminal review paper, highlighted several shortfalls and provided empirical methods to ensure consistent estimation using Ricardian models. For example, they introduced the log linear functional form for climate variables to ensure proportional effect on farmland and the disaggregation between irrigated and non-irrigated subsamples to control for missing water markets. Mendelsohn and Massetti (2017) expressed the importance for Ricardian studies to carefully avoid omitted-variable bias by including spatial time-invariant variables, such as latitude, altitude, terrain, and soil characteristics.

Despite the classical farm-level framework that has been used to explore the determinants of land use, the literature has failed to provide an effective perspective on the strategic land allocation behavior that occurs at the household level. In fact, the widely used land use model itself has failed to account for the well-known household model (Ahn et al., 1981; Singh et al., 1986) as previous researches mostly explaned land use with climatic and agronomic variables. Therefore, the heterogeneity in strategy among specialized or diversified farmers, the signal provided by lagged market prices, the household food consumption decision, and their access to markets have not been fully examined to understand existing cropping patterns and to identify country-specific strategies, especially for staple production. We consider the model misspecification and omitted variables problems to go beyond spatial time-invariant factors and include consumption and trade characteristics of the households.

Based on the foregoing problem in the land-use literature, this research seeks to address the following question: To what extent do geography, climate, diversification, prices, consumption, and trade shape household cropland allocation? Our objective in addressing this research question is threefold. First, we theoretically refine the Ricardian land use model in the framework of the household model and mathematically show how market, behavioral, and geographic factors are intertwined in the household decision making. Second, we empirically demonstrate the importance of including diversification, prices, food consumption, and trade in the household cereal cropland allocation. Third and last, this study fills the gap in the SSA agricultural literature by providing a behavioral-spatial analysis of cropland allocation.

To achieve our research objectives, we use the World Bank Living Standard Measurement Survey for approximatively five thousand farming households in both Nigeria and Niger. In our methodological approach, we achieved our first objective by conceptually modeling household cropland allocation. Through modeling, we showed how price and trade expectations shape decision making, in combination with the cropping system used by a farming household. Next, we analyzed the spatial distribution of crops by mapping the household-level cereal acreage in Nigeria and Niger. By determining the crop-specific mean center for each survey year, we discovered that sorghum and millet are dominant in northern Nigeria and Niger. Additionally, we found maize and millet to be pervasive in both countries. Lastly, we achieved our empirical objective by employing the fractional regression model to test the effect of geography, climate variables, Simpson index of diversification, own and substitute prices, consumption, and trade on cereal acreage share.

Results of the fractional regression estimation revealed that prices, diversification, consumption, and trade play a major role in the household strategic cropland allocation decision. Using the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC) and the Ramsey RESET test, we showed that ignoring these economic factors produced misspecification and inconsistency in the geography and climate determinants of land use. In cases of monoculture, we illustrated that high own price drives up the acreage share of the crop. However, the effect of expected price on cropland allocation could not be determined unequivocally in cases where intercropping, relay-cropping, and mixed-cropping as biotic, abiotic, and other social characteristics overrode the price signal. Additionally, we found that access to irrigation infrastructure plays a significant role in crop acreage allocation. This led us to conduct disaggregated estimations for rainfed and irrigated farming households. Furthermore, our study showed that maize and rice shares of the cropland decrease as one moves north in both countries. Meanwhile sorghum and millet share larger cropland ratio in the northern regions.

Spatial analysis in the context of agriculture allows us to solve complex location-oriented problems and better understand where and what cropland is allocated to which crop. Understanding the variability in spatial cropland allocation is key to unlocking the benefits of precision agriculture (Wong & Asseng, 2006). This study goes beyond mere mapping and models the characteristics of households' acreage assignment and the relationships between them as one moves across regions in Nigeria and Niger. As a result, this study lends new perspectives to decision-making in relation to coping with climate change. Finally, our investigation provides evidence for effective household identification and targeting in agricultural geo-cooperatives formation.

The next sections of this essay include the background and the theoretical model of this investigation. We then present the methods, including the data description and the empirical model, and we summarize the main findings of the study. In the last section of the paper, we discuss the results and present policy recommendations.

2.2 Background

Effective farm policy-making requires a good knowledge of spatial and temporal cropland allocation (Wu et al., 2018). Up-to-date cropland mapping is required for tracking spatial and temporal patterns of cropland use. However, few studies have focused on understanding the dynamics of cropland in Africa. This limited literature is due to the difficulty of capturing seasonality, market failures, and diversified cropping systems. Meanwhile, there is a growing surge of interest in the literature for the impact of the global warming on crop land allocation.

Researchers are increasingly focusing on land use in sustainable agriculture as it impacts smallholders' food security (Xu et al., 2018).

The bulk of literature on land use carries the signature of Mendelsohn and tends to study agricultural land use under the lens of the effect of climate on agriculture. In their 1994 paper, Mendelsohn et al. evaluated the impact of global warming on agriculture using the Ricardian analysis. In this analysis, the authors used cross-sectional data on climate, farmland prices, and other economic and geophysical data for almost 3,000 counties in the United States and found that higher temperatures in all seasons, except autumn, reduce average farm values, while more precipitation outside of autumn increases farm values. They applied their model to global warming and found a significantly lower estimated impact of global warming on U.S. agriculture than the traditional production-function approach.

Later on, Mendelsohn (1998) published a review of studies aimed at assessing the impact of climate change on agriculture in developing countries and claimed that climate change would create considerable damage to agriculture in less-developed economies. In response to Mendelsohn's paper, Reilly (1999) argued for models aimed at forecasting the effects of climate change to account for adaptation practices. In order to define a comprehensive theoretical and empirical framework for cross-sectional data analysis for land use studies, Mendelsohn & Massetti (2017) published a review of methods useful to measure the impact of climate on agriculture, examining the strengths and weaknesses of all approaches and reporting guidelines for effective land use modeling. Our study builds upon Mendelsohn's research on issues concerning the cross-sectional analysis of land use. We aim to correct for those theoretical and empirical issues on competition for land and the omitted-variable bias in the empirical estimation.

The analysis of cropland allocation also relates to mapping and defining spatial patterns in agricultural land use. Wu et al. (2018) developed the first spatially-explicit approach to measure global cropping intensity. According to their findings, the global average cropping intensity around the year 2010 was 0.48% and 0.17% for the temperature- and temperature/precipitation-limited scenarios, respectively. Overall, their study indicated that reducing the cropping intensity gap (CIG), which represents the difference between the potential and actual cropping intensity, would provide a potential strategy to increase global food production without cropland expansion. Similarly, we aim to provide spatially-explicit information on the cropping intensity gap currently lacking in global croplands.

Wu et al. (2018) and Fritz et al. (2015) developed a global percentage map of cropland and farm size, integrating a number of individual cropland maps at global, regional, and national scales. They conducted their study using high-resolution satellite imagery via Geo-Wiki that has an overall accuracy of 82.4%. Their findings stand as critical inputs to global agricultural monitoring in the frame of spatial cropland study and serve as a guideline for improving land use models that require baseline cropland information.

Spatial cropland allocation investigations in Africa is at the inception level. A localized study conducted by Xu et al. (2018) proposed a new method of updating annual cropland mapping using a change-detection approach, in addition to post-classification, to improve the traditional bi-temporal change vector analysis. Egypt, Ethiopia, and South Africa were the three Landsat footprints selected based on their different cropping systems and field sizes. Overall, the study found a common trend of cropland expansion in all three sites, with a heterogeneous growth rate. The study pinpointed the potential application of time-series, Earth-observing satellite data in documenting and assessing food security in Africa.

You et al. (2009) proposed a spatial allocation model of crop production based on a cross-entropy approach using data from various sources. These authors merely mapped cropland allocation for the twenty major crops in Sub-Saharan Africa. In a slightly different vein, Dorosh et al. (2010) used geographic information systems data to examine the relationship between transport infrastructure and agriculture in Sub-Saharan Africa. They found low population densities and long travel times to urban centers to sharply constrain agricultural production.

In general, cropland allocation in several African countries has been addressed in only a few previous studies. For example, Ndhlovu (2010) and Chibwana et al. (2012) assessed the role of fertilizer input subsidies in cropland allocation in Malawi. Both studies uncovered a positive correlation between participation in the fertilizer subsidy program and the amount of land planted with maize and tobacco. Similarly, Porgo et al. (2018) examined farm households' cropland allocation decisions under credit constraints in rural Burkina Faso. These authors found a negative effect of credit constraints on farm households' decision to allocate land to maize and cotton. Using readily available geospatial data, Chamberlin et al. (2014) estimated the potentially available cropland for Africa with an emphasis on the returns to agricultural production under a variety of assumptions.

Although some research has been conducted in different countries in Africa, few studies have specifically evaluated the determinants of cropland allocation in Nigeria. Olaniran (1988) assessed the probability of attaining the climatic requirements for cereal (maize, rice), oil seed (groundnut), and industrial crop (sugar cane). The author used the estimated probabilities as a basis for evaluating the potential cropland for the cultivation of the specified crops from the climatological point of view. Similarly, Gobin et al. (2002) used logistic modeling to derive agricultural land use determinants in southeastern Nigeria. Using land cover characteristics, they found significant differences among the five local agricultural lands used in the region. The authors also found that the two most important land use determinants are landform and distance to the settlement, calculated along the road network. Enaruvbe & Atedhor (2015) used inter-temporal remote sensing to examine the agricultural land use change in Asaba between 1987–2013. Urban encroachment into the agricultural landscape and the pattern and rate of land use change determines the impact of the observed changes on agricultural land use. The study concluded that urban infringement into rural landscape should be controlled to minimize rural-urban migration and curb the loss of interest in agriculture.

African agriculture is made of many uneven spatially-distributed smallholders whose decision-making process is heterogeneous. As the African population continues to grow, enhanced crop productivity is a necessity. Thus, poverty and land degradation make agricultural land use information especially important in geographic targeting of interventions (Epprecht, 2006). While it is well known that croplands have expanded to meet the food demands of a rapidly-growing population, little if anything, is known about the spatial and temporal distribution of crops on the continent. For instance, food crops grown on the newly-tilled forest land can be of interest for evidence-based policymaking.

Building upon the global literature, and in order to contribute to the infant literature on African spatial cropland distribution, this study aims to assess spatial, social, and economic determinants of farmland allocation in Nigeria and Niger. We hypothesize that crop land allocation, throughout micro-level crop shifts, responds to both farmers' food preferences and their adaptation to climate change. Additionally, this study stands as a contribution to evidence-based policymaking in West Africa.

2.3 Theory: A Model of Agricultural Cropland Allocation

Combining utility and profit maximization theories, we model the farmer's cropland allocation behavior within the traditional household model. We consider a rural household with a given amount (F) of cropland to be allocated to two crops j and k. The two crops are each defined as sectors characterized by production functions with three fixed inputs per hectare: labor (L), capital (K), and land (W). The production functions for crop j and k are defined as follows:

$Y_j = f(L_j, K_j, W_j)$ and $Y_k = f(L_k, K_k, W_k)$ (1)

Both sectors compete for inputs, which are assumed to be perfectly mobile between the two sectors. The separability between consumption and production requires markets to be perfect. In such a case, the household economic behavior can be expressed as separate profit, maximizing the problem in both sectors. Nevertheless, in the case where markets are imperfect, (aka household consumption and production decisions are not separable), a technical change in crop j production can have an impact on land allocation for crops with magnitude and sign depending on the observed technical cropping system and climatic change. Following Deaton (1992), Ellis (1993), and Maertens et al. (2006), and based on the observation that most households in our sample in Nigeria and Niger have no off-farm employment opportunities, we use the Chayanov household model (Hunt, 1978) with missing off-farm labor markets and household trading off income and leisure.

We consider a representative household that maximizes utility U (R, Z) concave in income (R) and leisure (Z), which cannot be negative. The household derives the income (R) from selling outputs j and k from crop production at their expected prices P_j and P_k. Each crop is allocated a cropland A_i (i = j, k). We assume the labor and credit markets to be missing. Leisure and working time cannot exceed the total available time (T) and household income cannot be negative. The capital, labor, and land inputs (K, L and W) are purchased at price r, w, and e, respectively. We assumed a missing labor market, $w = 0$.

The price of land, e, can be understood as either the rental cost (which is rare in Nigeria and Niger) per hectare of cropland or the value attached to the specific land due to its characteristics, such as the distance to the farmer's house, soil features, and slope. In this second case, the more the cropland characteristics fit a crop $i = j$ or k based on the farmer's subjective perception, the higher the value of e. On the other hand, marginal lands with unsuitable characteristics to cereals trade for lower e.

Our model assumes a crop-specific cost of production due to specific tillage, seeding, and harvesting. Following Maertens et al. (2006), these additional costs are assumed as a convex function of cultivated cropland: αA_j^m for crop j and βA_k^n for crop k where $\alpha, \beta > 0, and\ m, n > 1$. We write the household constrained utility maximization model as follows:

$$\underset{A_j, A_k, Z}{Max}\ U(R, Z) \qquad (2)$$

Where:

$$R = A_j(P_j f(L_j;\ K_j, W_j) - rK_j - eW_j) + A_k(P_k f(L_k;\ K_k; W_k) - rK_k - eW_k) \qquad (3)$$

Subject to:

$$A_j \geq 0\ ;\ A_k \geq 0; Z \geq 0\ and\ R \geq 0 \text{ (Nonnegativity constraints)} \qquad (4)$$

$$T \geq Z + A_j L_j + A_k L_k + \alpha A_j^m + \beta A_k^n \text{ (Time constraint)} \qquad (5)$$

$$W \geq A_j + A_k \text{ (Land constraint)} \qquad (6)$$

$$Y_j = f(L_j, K_j, W_j) \text{ and} \qquad (7)$$

$$Y_k = f(L_k, K_k, W_k) \qquad (8)$$

The objective function of the maximization problem can be derived as follows:

$$\Psi = U\{A_j(P_jY_j - rK_j - eW_j) + A_k(P_kY_k - rK_k - eW_k), Z\} +$$

$$\lambda_1\big(T - Z - A_jL_j - A_kL_k - \alpha A_j^m - \beta A_k^n\big) + \lambda_2(W - A_j - A_k)$$

$$+ \lambda_3 A_j + \lambda_4 A_k + \lambda_5 Z + \lambda_6\{A_j(P_jY_j - rK_j) + A_k(P_kY_k - rK_k)\} \qquad (9)$$

From the objective function, we assume that the farmer chooses the leisure time (Z) and the acreage A_j *and* A_k allocated to each crop (j and k) to maximize their output $Y = Y_j + Y_k$ and subsequently their revenue R. We derive the following Kuhn-Tucker first-order conditions:

$$\frac{\partial\Psi}{\partial Z} = U_Z - \lambda_1 + \lambda_5 \leq 0 \,; Z\frac{\partial\Psi}{\partial Z} = 0 \qquad (10)$$

$$\frac{\partial\Psi}{\partial A_j} = U_R\big(P_jY_j - rK_j - eW_j\big) - \lambda_1\,(L_j + m\alpha A_j^{m-1}) -$$

$$\lambda_2 + \lambda_3 + \lambda_6\,\big(P_jY_j - rK_j\big) \leq 0\,;\ A_j\frac{\partial\Psi}{\partial A_j} = 0 \qquad (11)$$

$$\frac{\partial\Psi}{\partial A_k} = U_R(P_kY_k - rK_k - eW_k) - \lambda_1\,(L_k + n\beta A_k^{n-1}) -$$

$$\lambda_2 + \lambda_4 + \lambda_6\,(P_kY_k - rK_k) \leq 0\,; A_k\frac{\partial\Psi}{\partial A_k} = 0 \qquad (12)$$

We assume nonnegative constraints and considered the land constraint non-binding, implying $\lambda_2 = \lambda_3 = \lambda_4 = \lambda_6 = 0$. Conversely, we assume a binding time constraint ($\lambda_1 > 0$). We substitute (10) in (11) and (12) and solve for the following equilibrium cropland allocation between crops j and k:

$$A_j = \left\{\frac{U_R}{U_Z}\left(\frac{P_jf(L_j,K_j,W_j) - rK_j - eW_j}{m\alpha}\right) - \frac{L_j}{m\alpha}\right\}^{(1/m-1)} \qquad (13)$$

$$A_k = \left\{\frac{U_R}{U_Z}\left(\frac{P_kf(L_k,K_k,W_k) - rK_k - eW_k}{m\alpha}\right) - \frac{L_k}{m\alpha}\right\}^{(1/n-1)} \qquad (14)$$

$$R = A_j(P_jf(L_j;\ K_j,W_j) - rK_j) + A_k(P_kf(L_k;\ K_k;W_k) - rK_k) \qquad (15)$$

$$Z = T - A_jL_j - A_kL_k - \alpha A_j^m - \beta A_k^n \qquad (16)$$

We translate this theoretical set up into an empirical model to assess the effect of expected spatial localization (longitude and latitude), expected commodity price, expected weather, crop diversification experience, food expenditure, food trade and household size on cropland allocation to cereals. From equations (13) and (14), it can be inferred under monocropping that an increase in expected output price P_j and P_k induces higher land allocation A_j and A_k for crops j and k, respectively. The increase in the expected output price has two consequences: first, the marginal rate of substitution of leisure for income $\left({}^{U_R}/_{U_Z}\right)$ falls, and second, the farmer revenue (R) increases with output price.

The term $\left({}^{U_R}/_{U_Z}\right)$ represents the household's shadow labor wage or implicit wage rate. The reduction in $\left({}^{U_R}/_{U_Z}\right)$ leads to reduced A_j and A_k. This income effect implies that households enjoy a higher income, and therefore a higher level of utility, by producing less and allocating more time to leisure. Also, the reduction of a marginal rate of substitution of leisure for income, due to the increased output price, leads to the so-called substitution effect. Farmers react to more profitable production by substituting more labor for leisure and therefore increase cropland allocation. An increase in output price (P_i) has a positive substitution effect on land allocated to crop *i* and negative income effect on all crops' land allocation, assuming monocropping. The households' food preferences and markets determine the importance of both substitution and income effects.

Additionally, an increase in household size positively affect the shadow wage $\left({}^{U_R}/_{U_Z}\right)$, leading to an increase in cropland allocation for all commodities. Additional household members (active individual) increase, not only the total labor time (T) and leisure (Z), but also the preferences towards income (U_R) due to the causal effect on consumption. In this study, we assume household size to significantly affect land allocation to cereals, especially maize for Nigeria and millet and sorghum for Niger. We express the household size in adult-equivalence terms to account for both the labor supply and food demand.

Although we assumed a missing labor market, our model shows that migration (in) through an increased number of households reduces available cropland (W), which in turn impacts cropland allocation. Assuming j as a food crop and k as a cash crop, the binding land constraint implies $A_j = W$ in the context of subsistence farming, implying higher preferences for food. The expansion of cash crops is a very rare response to demographic pressure in such a framework. Because land market is mostly missing, we control for land adaptability to crops instead. Empirically, we include variables such as plot distance to the house, plot slope, and elevation whenever each of these variables are available.

A technical change relative to any of the inputs to crop j, for example, would increase its yield and therefore Y_j. Additionally, the output increase for crop j would improve the household income. Following equation (13), such a technical change relative to the inputs of crop j has a positive substitution effect on A_j. If the technology is labor-intensive, its adoption would reduce the substitution effect, but the income would be even stronger due to an increase in L_j and a reduction in Z. Conversely, a labor-saving technology would reduce L_j, produce an increase in A_j (eq. 13), and potentially increase Z (eq. 7) if the saved labor is not reallocated to crop k. This would hypothetically result in an increase in $\left({}^{U_R}/_{U_Z}\right)$, inducing agricultural expansion. However, we could not control for a technological change in our empirical model due to a lack of information.

Our model captures the spatial distribution of crops across regions through the value attached to water (w) for each specific crop j. For a drought tolerant crop i, the acreage A_i increases with respect to w. That is, households tend to allocate cropland to cereal, depending on their expectation of the rainfall and temperature defined by spatial and climatic conditions. We empirically test this spatial cropland allocation, including geo-variables (longitude and latitude in our models) and climatic variables (temperature and rainfall), in the empirical models.

Price Effect on Crop Acreage Share

We used crop acreage share as a dependent variable in the empirical model of this study. To theoretically assess the effect of price expectation on the crop j acreage share, we conducted additional mathematical analysis. Assuming the simple two crops model with households growing crops j and k, the acreage shares S_j of crop j is given by:

$$S_j = \frac{A_j}{A_j + A_k} \tag{17}$$

The change in acreage shares S_j, with respect to the expected price of crop j, is given by:

$$\frac{\partial S_j}{\partial P_j} = \frac{\frac{\partial A_j}{\partial P_j} - \frac{\partial A_j}{\partial P_j} - \frac{\partial A_k}{\partial P_j}}{\left[\frac{\partial (A_j + A_k)}{\partial P_j}\right]^2} = \frac{-\frac{\partial A_k}{\partial P_j}}{\left[\frac{\partial (A_j + A_k)}{\partial P_j}\right]^2} \tag{18}$$

Equation (18) implies that the sign of $\frac{\partial S_j}{\partial P_j}$ is determined by the sign of $\frac{\partial A_k}{\partial P_j}$.

In the case where households grow crops j and k in monocropping, with both crops competing for cropland, we derive $\frac{\partial A_k}{\partial P_j} < 0$ and resulting therefore in $\frac{\partial S_j}{\partial P_j} > 0$. That is, the change of crop $j's$ acreage share, with respect to its own price, is positive. This is in line with previous research by Chavas and Holt (1990), Choi and Helmberger (1993), Lin and Dismukes (2007), and Weersink et al. (2010) aimed at assessing the effect of own-price on acreage. These studies found that expected price is important in crop area allocation decisions. In the case of monoculture, Lin and Dismukes (2007) found that the magnitude of acreage-price elasticity determines the relative importance of price in the decision-making.

On the other hand, if households grow crops j and k in inter cropping, relay cropping, or mixed cropping (polyculture for more than two crops) the sign of $\frac{\partial A_k}{\partial P_j}$ is undefined, assuming a fixed total acreage. Therefore, one could not predict the sign of the change of crop $j's$ acreage share, with respect to its own price. In fact, intertwined factors determine the sign of $\frac{\partial A_k}{\partial P_j}$, including but not limited to, which crop takes the lead on the plot and the share of crop $j's$ plot planted with k. Another way to explain the case where the sign of $\frac{\partial A_k}{\partial P_j}$ might be undefined is the relative importance of self-produced food consumption in the household diet. Households that value food self-sufficiency mostly rely on the price signal (shadow price) of the most important food crop, maize in Nigeria and millet and or sorghum in Niger. To the best of our knowledge, this second case has not been addressed in previous literature.

2.4 Methods

We used two approaches to study the determinants of cropland allocation in Nigeria and Niger. The first approach focused on analyzing the spatial distribution of cereal cropland allocation. We used mapping to explore the spatial concentration of cereal acreage at the household level. Second, we used a statistical model to regress spatial, climatic, agronomic, household characteristics, food prices and trade on each cereal acreage ratio.

In this section, we first present the approach used to map acreage and determine mean centers for each country. Second, we present the fractional regression model used to estimate determinants of cropland allocation. In the last subsection, we describe the data used in this investigation.

2.4.1. Exploratory Mapping of Cereal Acreage

We mapped the per-household acreage in hectares for maize, sorghum, millet, and rice in Nigeria and Niger using ArcGis. This spatial analysis aims to visualize the spatial heterogeneity in the distribution of the cereals. Using the geo-referenced plot-level acreage, we were able to obtain the aggregated household acreage for each cereal.

Next, we used the mean center analysis to detect a change over time in acreage distribution. Computing the weighted acreage mean center for each survey year, we tracked the spatial and temporal shift in acreage allocation for each cereal. The weighted mean center is the average longitude ($\bar{X}_w$) and latitude ($\bar{Y}_w$) coordinate of all surveyed households weighted with their allocated cereal acreage in the country. It is useful for tracking changes in the distribution and for comparing the distributions of different types of features.

For each year (t), we computed the coordinates $\bar{X}_w$ and Y_w of the mean center C_{jt} $(\bar{X}_{wjt}, \bar{Y}_{wjt})$, weighted with household acreage (ω_i) for each cereal j as follows:

$$\bar{X}_{wjt} = \frac{\sum_{i=1}^{n} \omega_i x_i}{\sum_{i=1}^{n} \omega_i} \tag{19}$$

$$\bar{Y}_{wjt} = \frac{\sum_{i=1}^{n} \omega_i y_i}{\sum_{i=1}^{n} \omega_i} \tag{20}$$

where x_i and y_i are household latitude and longitude.

2.4.2 Empirical Model and Estimation Procedure

Following the derived theoretical model, we empirically estimated the acreage share A_{ijt}^{*} measured as a percentage of the household acreage allocated to the cereal $j = 1, 2, \dots 5$ using the panel data estimator of the fractional regression model with a year fixed effect. The fractional regression model is a maximum likelihood approach used to fit models with a dependent variable ranging from 0 to 1. This model was proposed by Papke and Wooldridge (1996) as a nonlinear panel data model that recognizes the bounded nature of the dependent variable. Several studies, including but not limited to, Papke and Wooldridge (2008), Ramalho and Silva (2009), Wicaksana (2010), Altman (2010), Ramalho et al. (2011), Ramalho et al. (2014), and Bhattacharya et al. (2019) used this model in health, nutrition, and market power analysis.

Additionally, we simultaneously estimated the likelihood model for cereal, maize, sorghum, millet, and rice shares. The log-likelihood function for fractional models is of the form:

$$lnL = \sum_{i=1}^{N} A_{ijt}^{*} * \ln\{G'(X'\beta\} + \left(1 - A_{ijt}^{*}\right) * ln\{1 - G'(X'\beta\} \tag{21}$$

where N is the sample size, A_{ijt}^{*} is the acreage share of crop j, lnL is the log-likelihood function, and G(.) is the link function that can be a probit, logit, or hetprobit approximation. We used the logit link function where $G'(X'\beta)$ is defined as:

$$G'(X'\beta) = \frac{\exp(X'\beta)}{1+exp(X'\beta)} \tag{22}$$

Additionally, we used clustered standard errors at the household level to attenuate the effect of idiosyncratic food preferences on estimates (Waldner et al., 2016). For each household i growing the crop $j = 1, 2, \dots 5$ in year t, the relation between A_{ijt}^{*} and the vector $X'\beta$ is as follows:

$$A_{ijt}^{*} = \beta_{0j} + \beta_{1j}\boldsymbol{Spatial} + \beta_{2j}\boldsymbol{Climate} + \beta_{3j}\boldsymbol{Irrigation} + \beta_{4j}\boldsymbol{Diversification} + \beta_{5j}\boldsymbol{Household} + \beta_{6j}\boldsymbol{Prices} + \beta_{7j}\boldsymbol{Consumption} + \beta_{8j}\boldsymbol{Trade} + \delta_t + \delta_j + \epsilon_i \tag{23}$$

where **Spatial** is a vector of spatial covariates that include geographic coordinates; **Climate** is the vector of temperature and rainfall; **Diversification** represents the lagged household crop diversification captured by the Simpson Index; **Prices** stands for the vector of lagged own and substitutes expected prices; **Consumption** includes household characteristics and food expenditures in the previous year; **Trade** is a vector of proximity, with infrastructure and market determining the household access to market; and **Irrigation** is a dummy variable capturing the lagged household access of irrigation. The vector of error term ϵ_i are residuals with logistic distribution while β are vectors of parameters to be estimated. We introduced δ_t and δ_j as the year and household fixed effects, respectively, to correct for temporal and spatial autocorrelation and get efficient estimates.

We conducted the estimation in three iterative steps. Each of the first two steps corresponds to a subset of equation (18). We first estimated the response of crop acreage ratio A^*_{ijt} to spatial, climate household characteristics, diversification, and irrigation access variables only. We called this the “traditional” land use model and expressed it as:

$$A^*_{ijt} = \beta_{0j} + \beta_{1j}\boldsymbol{Spatial} + \beta_{2j}\boldsymbol{Climate} + \beta_{3j}\boldsymbol{Irrigation} + \beta_{4j}\boldsymbol{Diversification} + \delta_t + \delta_j + \epsilon_i \quad (24)$$

Equation (24) is the approximation of the traditionally-estimated land use model. This first model fails the Ramsey RESET test of model specification. This reveals that traditionally estimated land use models at the plot level focused on spatial and climatic variables, providing inconsistent estimates.

The second model added price and household characteristics to the first model to account for their effect on cereal land use. We named this second model "Traditional + Price" and specified it as follows:

$$A_{ijt}^{*} = \beta_{0j} + \beta_{1j}\boldsymbol{Spatial} + \beta_{2j}\boldsymbol{Climate} + \beta_{3j}\boldsymbol{Irrigation} + \beta_{4j}\boldsymbol{Diversification} + \beta_{5j}\boldsymbol{Household} + +\beta_{6j}\boldsymbol{Prices} + \delta_t + \delta_j + \epsilon_i \quad (25)$$

Because the second model also failed the Ramsey's omitted variable test, we proceeded to the third model. In the latter, we added household food consumption, captured by their expected food expenditure and the access to trade, to account for the consumption and trade effects on cropland allocation.

Model (23) is selected based on the Akaike Information Criteria (AIC), the Bayesian Information Criterion (BIC), and the Wald test of equality between coefficients of the second and third model. The AIC and BIC penalize for irrelevant regressors but not relevant ones. Given that k is the number of regressors and N is the sample size, the AIC and BIC are defined as:

$$AIC = -2 * \ln(likelihood) + 2 * k \quad (26)$$

$$BIC = -2 * \ln(likelihood) + \ln(N) * k \quad (27)$$

The AIC and BIC include two components each. On one hand, the appropriateness of the fit of the model is measured by $-2 * \ln(likelihood)$, while the complexity of the model is measured by $2 * k$ or by $\ln(N) * k$ (Cameron & Trivedi, 2005). Because AIC and BIC were not significantly different for the second and third models, we relied on the Wald test to select the model in equation (23). These tests, along with the Ramsey specification test, revealed that controlling for diversification, irrigation, prices, consumption, and trade variables provides additional information and improves the estimates for spatial and climate covariates.

2.4.3 Data and Summary Statistics

This study uses the World Bank Living Standard Measurement Survey and Integrated survey for Agriculture (LSMS-ISA) for Nigeria and Niger. In Nigeria, the data were collected in a three-waved survey in 2010, 2012, and 2015. The panel component applied to 2,500 households, for which data on food production and consumption were collected. Two waves of the 2011 and 2014 survey data were compiled for Niger, making a panel of 2,100 households.

For each wave, two visits were carried out, one during the post-planting period and the other during the post-harvest period. Both datasets are nationally representative of urban and rural areas (NBS, 2016). The post-planting data were directly collected after the planting season, which includes information on plot preparation, inputs used, labor used for planting, and other issues related to the planting season.

In this study, we included several variables to control for specific factors and interactions affecting crop acreage allocation. We used acreage ratio as the outcome variable in the regression analysis. We explained the variability in households' acreage share with year-specific variability in geo-variables, climatic factors including expected temperature and rainfall, household characteristics, crop diversification, plot characteristics, irrigation access, expected food price, and food consumption and trade.

Geographic Variables

We controlled for the spatial distribution of crops using latitude and longitude provided for households (Nigeria) and clusters (Niger). Latitude and longitude variables were included in the

LSMS datasets. In Nigeria, sampled households' locations run from 4.69° to 13.71° north latitude, while their longitude runs from 2.97° to 13.63° east. The median latitude and longitude are 9.68° north and 7.78° east, respectively. In Niger, the latitude for the clusters runs from 11.87° to 18.71° north, while their longitude runs from 0.40° to 13.25° east. The median latitude and longitude in Niger are 13.87° north and 6.45° east, respectively

Weather and Climate Variables

We used the United States National Oceanic and Atmospheric Administration data (NOAA) to compute climate and weather variables. We assumed households' rainfall expectations to be based on short-term (weather) and or long-term (climate) temperature and rainfall observations. Using long-term (starting from 1960) daily averages for temperature and rainfall, we proxied household expectations on climate change. Daily means of the specific year, temperature, and rainfall for weather expectation variables were also included. On average, over the three years included in the panel, the mean daily temperature was 81° Fahrenheit and the average rainfall amounted to 0.09 inches in Nigeria. In Niger, the long-term average daily temperature was 84° Fahrenheit and the rainfall for both years was 0.04 inches.

Household Characteristics

In Nigeria, the average sampled household include six adult-equivalents, with the average household head being thirty-four years old. On average, 84% of the surveyed households were rural, while urban households accounted for 16% of the sample. Rural households tended to spend $480 per year for food, while urban dwellers spent $820. The sampled household food expenditure represented 42% of their annual income over the surveyed period, which is in line with the statistics reported by Ozughalu (2019).

In Niger, the typical sampled household included five adult-equivalents, mostly headed by a male (82.58%) about forty-seven years old. More than 75% of household heads did not have education higher than primary school. In addition, households had an average annual income of $2,675, about 40% of which went toward food expenditures. In general, urban, and rural households differed in terms of demographic and economic characteristics. While sampled urban households included four adult-equivalents, their rural counterparts included eight adult-equivalents where men were more likely to be the head of the household. Also, urban household heads completed higher education (> 5 years) and earned a relatively higher income ($3000). Overall, characteristics of the sampled households follow the general trends in Niger, as reported by Serra (2015).

Crop Diversification Index

We used the Simpson Diversity Index (SDI) to measure the crop diversification of the sampled households. The Simpson index is one of the most popular measures of crop diversification used in the literature (Arslan et al., 2018; Di Falco & Perrings, 2005). The SDI is the inverse of the Herfindahl index, calculated as $1 - \sum_{i=1}^{k} p_i^2$ where P_i represents the acreage share of each crop i. Like the Herfindahl index, it is based on the number of cereals grown and their relative abundance in the crop portfolio. The value of SDI ranges between 0 and 1 with 1 representing infinite diversity and 0, no diversity. On average, the Simpson index is 0.51 and 0.56 in Nigeria and Niger, respectively. The SDI compares two farmers to find who has the more diverse farming. For example, if one has an SDI of 0.5 and another has an SDI of 0.35, then the farmer with the SDI of 0.5 is has more diverse farming.

Access to Irrigation

Very few households reported partial or full access to irrigation on their farmland. In Nigeria 2.30% of the surveyed households (130) reported access to irrigation. This number is lower in Niger where only 1.25% of the surveyed households (61) reported access to water (other than rainfall on their cropland). Access to irrigation in Nigeria and Niger is lower than the continent average of 4% reported by Burney et al. (2013). Because we estimated the effect of expected temperature and rainfall on cropland acreage allocation, controlling for access to irrigation is required to identify the weather variables coefficient.

Expected Food Prices

Own and competing crop prices have been the fundamental variables used in previous analyses to explain acreage response (Chavas & Holt, 1990). First, there is the question of a suitable measure of price expectations. Several studies suggested using the commodity future price as a proxy for the expected price at planting time (Choi & Helmberger, 1993). However, such prices are not readily available for Nigeria and Niger. Other studies recognized that effective production estimation necessitated the modeling of price expectations, and from the beginning to the present time, researchers have relied on simple cobweb theory, taking the price in period $t - 1$ as a proxy for the expected price in period t (Chavas & Holt, 1990; Choi & Helmberger, 1993). We used this second approach in our study.

Using cereal prices from the Famine Early Warning Systems Network (FEWS NET) for each production year in Nigeria, we approximated the expected cereal price with the monthly average price until the planting month of the previous year. Because FEWS NET price data are not available for Niger, we used the adjusted cluster mean unit values to approximate household level prices. Following Deaton and Muellbauer (1981) and Cox and Wohlgenant (1986), a model was estimated for each of the four cereals to obtain the Niger household adjusted prices that are immune to the quality and quantity bias, assuming homogeneous food products for each commodity:

$$lnP_{ki} = \alpha_{ko} + \alpha_{k1} lnx_i + \alpha_{kz} Z' + \alpha_{kv} V_i + \alpha_{ku} U_i + \varepsilon_{ki} \qquad (28)$$

where, lnP_{ki} is the logarithmic unit value of item k reported by household i; lnx_i is the logarithm of household i's per capita real expenditure; Z' is the vector of household socio-demographic variables: household size, gender and marital status, age, education of household-head. Vectors V and U represent binary variables that control for price differences between two visits and between clusters, and ε_{ki} are residuals.

The quality-adjusted prices derived from utilizing equation (28) are inconsistent with the hypothesis that households in the same market face the same prices. Therefore, the communal median quality-adjusted prices are used as corrected prices in the cropland allocation model. We used the lagged median, instead of the averaged contemporaneous communal price, to purge potential outlier price effects. On average, rice was the most expensive cereal in both Nigeria and Niger over the period of this study. Millet was the second most expensive cereal in both nations. While maize was more expensive than sorghum in Niger, the two cereals had the same averaged prices in Nigeria.

Table 2-1 Summary statistics of socio demographic covariates

Variable	Niger		Nigeria	
	Mean	Std. Dev.	Mean	Std. Dev.
Spatial variables				
Latitude (degree)	13.89	0.82	9.50	2.49
Longitude (degree)	6.09	3.21	8.06	2.11
Socioeconomics				
Equivalent adult (unit)	5.28	1.29	6.12	3.35
Average education years (year)	1.28	0.51	4.28	1.22
Annual food expenses ($ USD)[d]	1,893.37	689.13	714.28	194.46
Weather/Climate variables				
Average daily temperature (Planting month -°F)	76.45	2.23		
Average daily temperature (Planting year- °F)	86.34	0.70		
Average daily temperature (1960 to planting year-°F)	84.89	0.06	81.07	1.47
Average daily rainfall (Planting month -inch)	0.00	0.00		
Average daily rainfall (Planting year-inch)	0.05	0.01		
Average daily rainfall (1960 to planting year-inch)	0.04	0.00	0.09	0.03
Cereals price ($ USD /Kilogram)[d]				
Maize	1.078	3.127	0.121	0.039
Sorghum	0.867	2.479	0.121	0.043
Millet	1.138	2.932	0.130	0.042
Rice	1.436	2.997	0.281	0.039
Simpson Diversification Index (0 to 1)	0.56	0.20	0.51	0.39
Averaged distance to farm plots	3.80	1.57	2.76	1.75
Households having access irrigation (dummy)	1.25%		2.30%	
Observation # (Panel)	4844.00		5507.00	

Source: Author
Note: [a] Computed from LSMS-ISA dataset for both countries. [b] Obtained and computed from NOAA website. [c] Obtained from FEWS NET for Nigeria and estimated from unite values for Niger. [d] Approximated 1$USD with 500 Naira or CFA

Plot Characteristics

The average plot acreage for the sampled households was 2.26 hectares (ha) in Nigeria. This is higher than the national average of smallholder farm plot acreage, which is 0.85 hectares (FAO, 2018). While 60% of the plots were monocropped, 40% were under inter or mixed cropping. In most households, a minimum of two crops were cultivated on the same plot.

The average cereal acreage per household was 1.53 ha in Nigeria, which represents 68% of the average household cropland. Maize was the most-produced cereal in Nigeria, sharing an average of 26% of the household food cropland and 47% of the cereal cropland. Sorghum and millet were allocated 29% and 18% of the households' cereal farmland, while rice shared only 6%. The remaining 32% of households' food cropland allocations went to cassava, cowpeas, yams, potatoes, and vegetables (tomatoes, okra, pumpkins, and peppers). These statistics are in accordance with the reported national cereal acreage, which represents more than 60% of the agricultural farmland (Ismaila et al., 2010).

In Niger, maize occupies only 2% of households' farmland. Most of the food cropland goes to millet (46%), followed by sorghum (21%), and cowpeas (12%). Rice occupies 2% of farming households' cropland on average. Other crops, including cassava, yams, potatoes, and vegetables are grown on the remaining 19% of the food cropland. The average plot acreage is 0.98 hectares, which is higher than the national average, 0.7 hectare reported by Manssour et al. (2014). However, the average household farms 2.47 hectare of land. Cereals occupy 91% of the farmland, with millet and sorghum being the most widely-grown cereals.

Table 2-2 Summary statistics of acreage and acreage ratios [a]

Variable		Niger		Nigeria	
		Mean	Std. Dev.	Mean	Std. Dev.
Farm acreage (hectare)					
Total farm acreage [b]		2.47	1.03	2.26	1.01
Cereals Acreage [b]		2.25	1.67	0.66	0.26
Maize		1.54	1.56	0.39	0.87
Sorghum		2.28	1.53	0.51	1.06
Millet		2.40	1.81	0.32	0.83
Rice		1.69	1.96	0.09	0.45
Cereals Acreage ratio					
Maize household acreage ratio					
	Panel	0.03	0.14	0.47	0.43
	2010			0.46	0.44
	2011	0.02	0.10		
	2012			0.47	0.43
	2014	0.04	0.17		
	2015			0.49	0.43
Sorghum household acreage ratio					
	Panel	0.29	0.18	0.29	0.31
	2010			0.29	0.33
	2011	0.29	0.17		
	2012			0.31	0.31
	2014	0.30	0.19		
	2015			0.28	0.30
Millet household acreage ratio					
	Panel	0.66	0.20	0.18	0.28
	2010			0.18	0.29
	2011	0.67	0.19		
	2012			0.17	0.26
	2014	0.64	0.22		
	2015			0.18	0.28
Rice household acreage ratio					
	Panel	0.03	0.12	0.06	0.19
	2010			0.08	0.22
	2011	0.03	0.11		
	2012			0.06	0.19
	2014	0.02	0.12		
	2015			0.05	0.17
Observation # (Panel)		1219		5663	

Source: Author computation

Note: [a] Computed from LSMS-ISA dataset for both countries; b the averaged total farm acreage and cereals acreage are smaller than some averaged specific crops acreage due since all households do not grow all crops and in the same proportions.

2.5 Results

This section summarizes our results for the exploratory mapping and the fractional regression model estimation.

2.5.1 Exploratory Map

We mapped acreage for each cereal and computed the mean center to track spatial and temporal shifts for Nigeria and Niger. We combined LSMS data to shapefiles retrieved from online data repositories using ArcGIS. In the following paragraphs, we report the maps and mean centers for each country.

2.5.1.1 Cereal Acreage Distribution in Nigeria

Food production data were collected in Nigeria for 2010, 2012, and 2015. On the following maps, we show the cereals' acreage for 2015, along with the mean centers for 2010, 2012, and 2015. We report the mean centers to uncover the spatial shift that occurred in between the two survey periods. Figure 2.1 shows the mean centers for cereal acreage per household in Nigeria. We observe that millet and sorghum are northern crops, while maize and rice are southeastern crops in Nigeria. On a gradient from the south to the north, one could order rice, maize, sorghum, and millet.

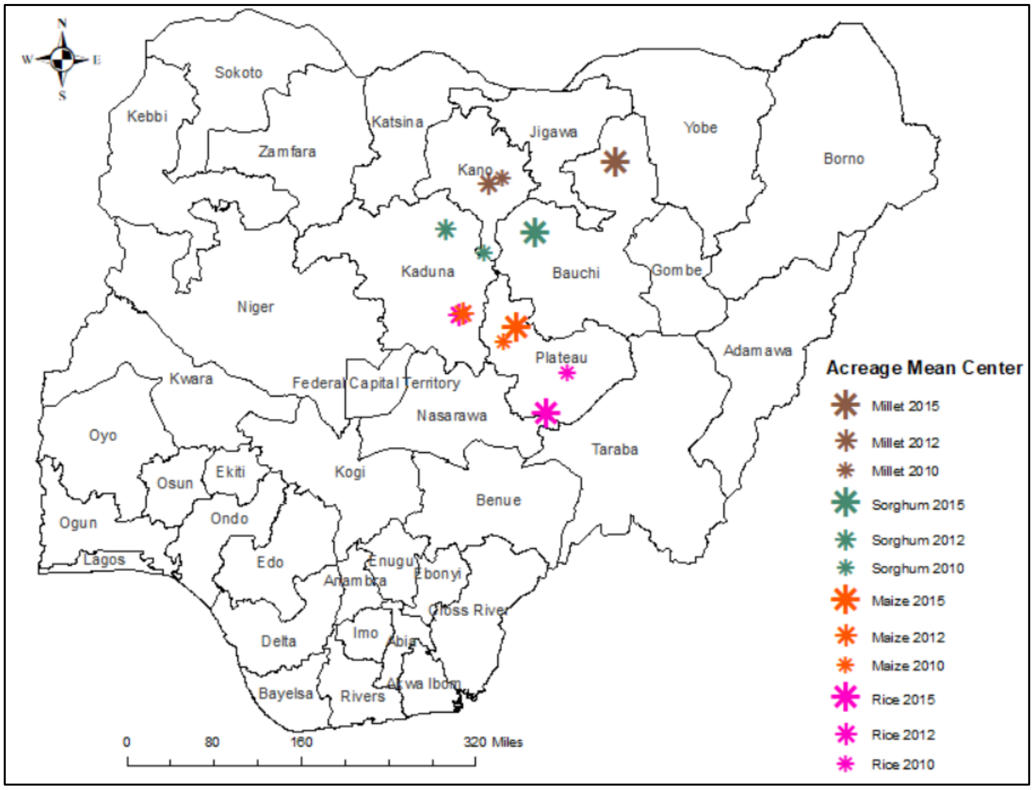

Figure 2-1 Mean centers of cereals per household acreage in Nigeria

Source: Author computation

Figure 2.2 shows the spatial distribution of rice in 2015 with the mean centers of the crop acreage for 2010, 2012, and 2015. Rice production is concentrated in the southeast of Nigeria in Benue, Taraba, and Adamawa. In Benue and Taraba, on average, households allocate more than 0.5 hectare to rice. Except for Adamawa, households in Nigeria allocate less than a quarter hectare to rice production. The mean centers do not describe any clear temporal and spatial shift for rice cultivation. In seventeen out of the thirty-seven states of the country, the household crop acreage allocated to maize is very small (< 0.15 hectare). Maize is produced almost everywhere in the center and northeast Nigeria, with an average greater than a quarter hectare per household (see Figure 2.3). In 2010, the mean center of maize production was in the state Plateau. It moved northwest and localized in the state of Kaduna in 2012 then shifted back to Plateau in 2015, which is an apparent northern shift. The map illustrates a per household maize acreage reduction in the southern states, along with an increased acreage of the crop per household in the northern states. In general, maize production remains in the eastern regions, especially in Adamawa, Taraba, Bauchi, Kaduna, Zamfara, and Borno. While states such as Zamfara, Ebonyi, and Niger have witnessed an increased maize acreage per household, others states such as Edo and Delta have witnessed a decrease in per household maize acreage.

Figure 2.4 reproduces the per-household acreage allocated to millet. Millet cultivation moved north between 2010 and 2015, and in 2010, the central and eastern regions (including Taraba, Plateau, and Nasarawa) had the highest concentration of per–household acreage of millet. Thus, in 2010 millet and maize had the same hotspot of per-household acreage. However, the maize acreage hotspot moved to the northeast in 2015 to Jigawa, Yobe, and Bauchi, while the millet acreage mean center shifted north but remained within the state of Kaduna. In general, millet is absent from southern states.

The spatial distribution of sorghum represented in Figure 2.5 shows that the crop is cultivated in dryer states of the country. Overall, 90% of the sorghum production is concentrated in the northern states of Yobe, Jigawa, Bauchi, Kano, Plateau, and Kebbi. In these states, households allocate an average of 1.8 hectares of their farmland to the crop. The states of Borno and Kano witnessed a reduction in the household land allocation to millet between 2010 and 2015. Similar to millet, sorghum is produced in all northern states except Borno. Central states, such as Benue and Niger and eastern states like Adamawa, have the highest concentration of sorghum cropland in the country. The sorghum mean-centers in between Kaduna and Bauchi, with a slight northern shift between 2010 and 2015.

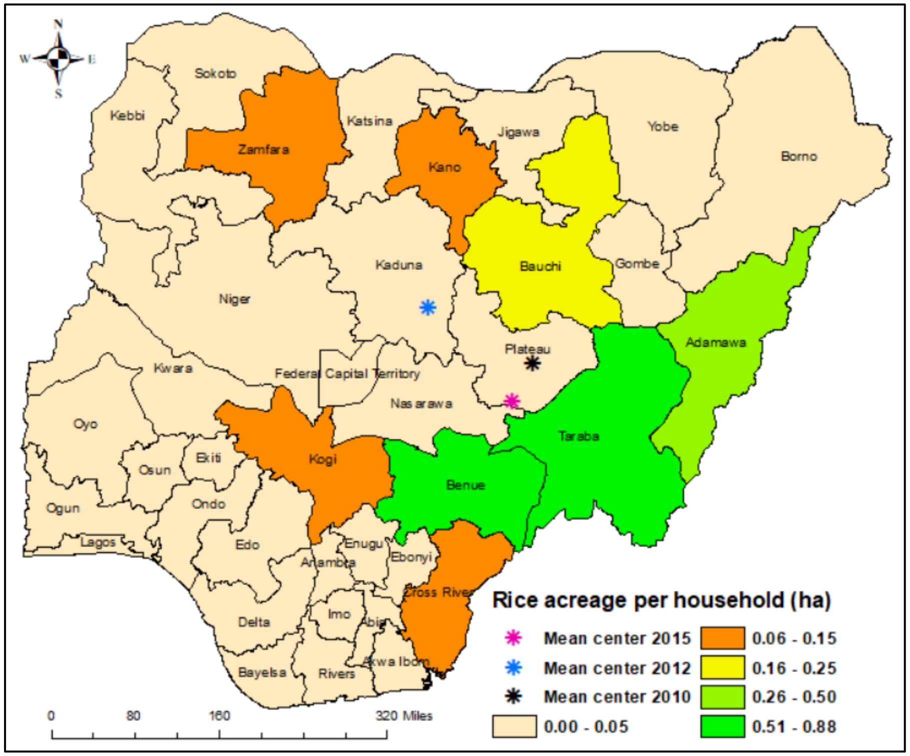

Figure 2-2 Shift in per-household rice acreage (in hectare) mean center represented on 2015 maize acreage allocation in Nigeria

Source: Author

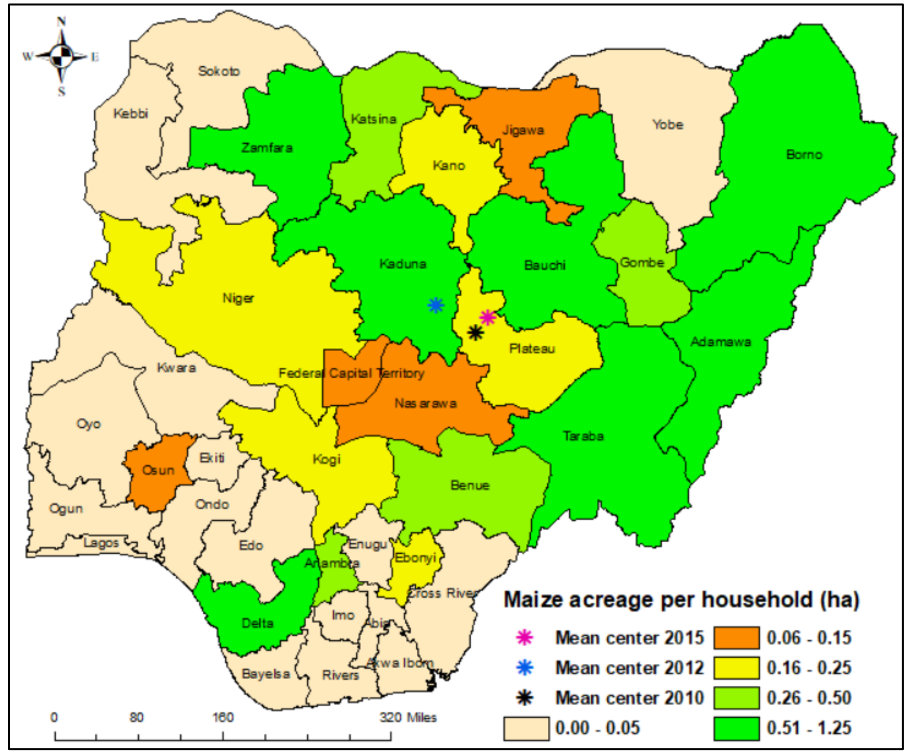

Figure 2-3 Shift in per-household maize acreage (in hectare) mean center represented on 2015 rice acreage allocation in Nigeria

Source: Author

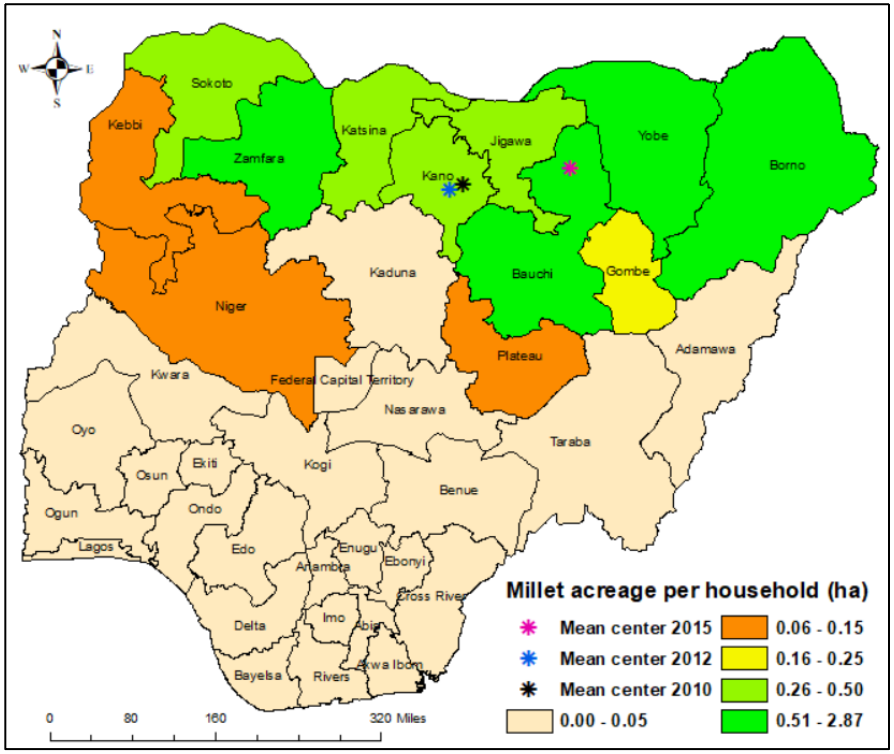

Figure 2-4 Shift in per-household *S*orghum acreage (in hectare) mean center represented on 2015 sorghum acreage allocation in Nigeria

Source: Author

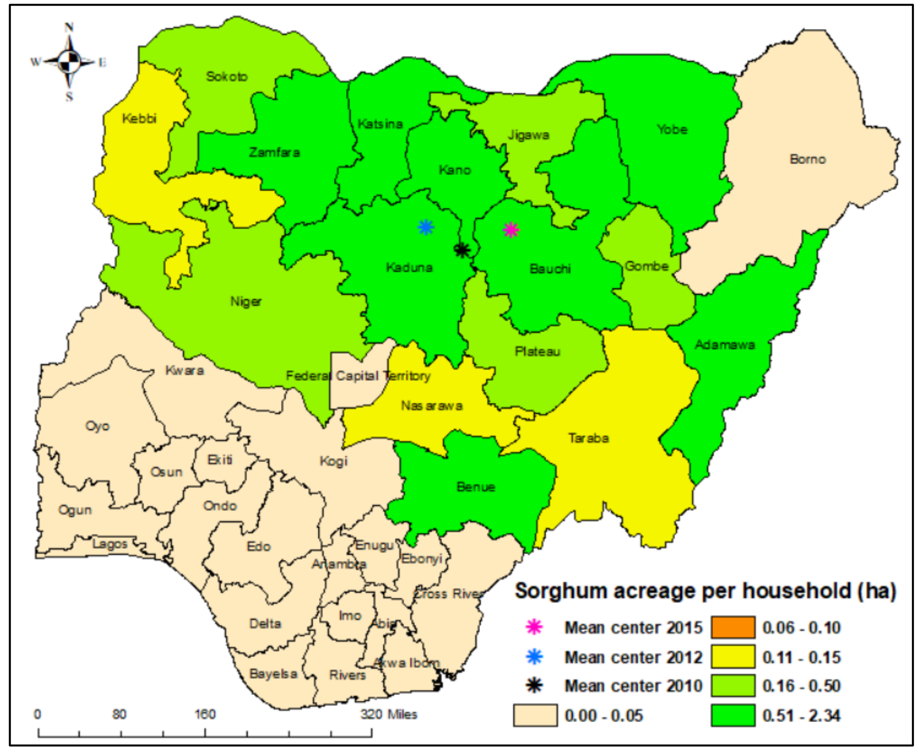

Figure 2-4 Shift in per-household *S*orghum acreage (in hectare) mean center represented on 2015 *sorghum* acreage allocation in Nigeria

Source: Author

2.5.1.2 Cereal Acreage Distribution in Niger

Niger data include two panels collected in 2011 and 2014, which offer two spatial distributions with a three-year lag. The region of Agadez, which accounts for 52% of Niger's territory is mostly desertous (IOM, 2017), which makes the southern part of the country the most suitable agricultural land. Figure 2.6 shows that the mean centers for the four cereals are clustered in Tahoua and Maradi. While the sorghum acreage mean center did not shift between 2011 and 2014, other cereals exhibit an east-west and north-south shift.

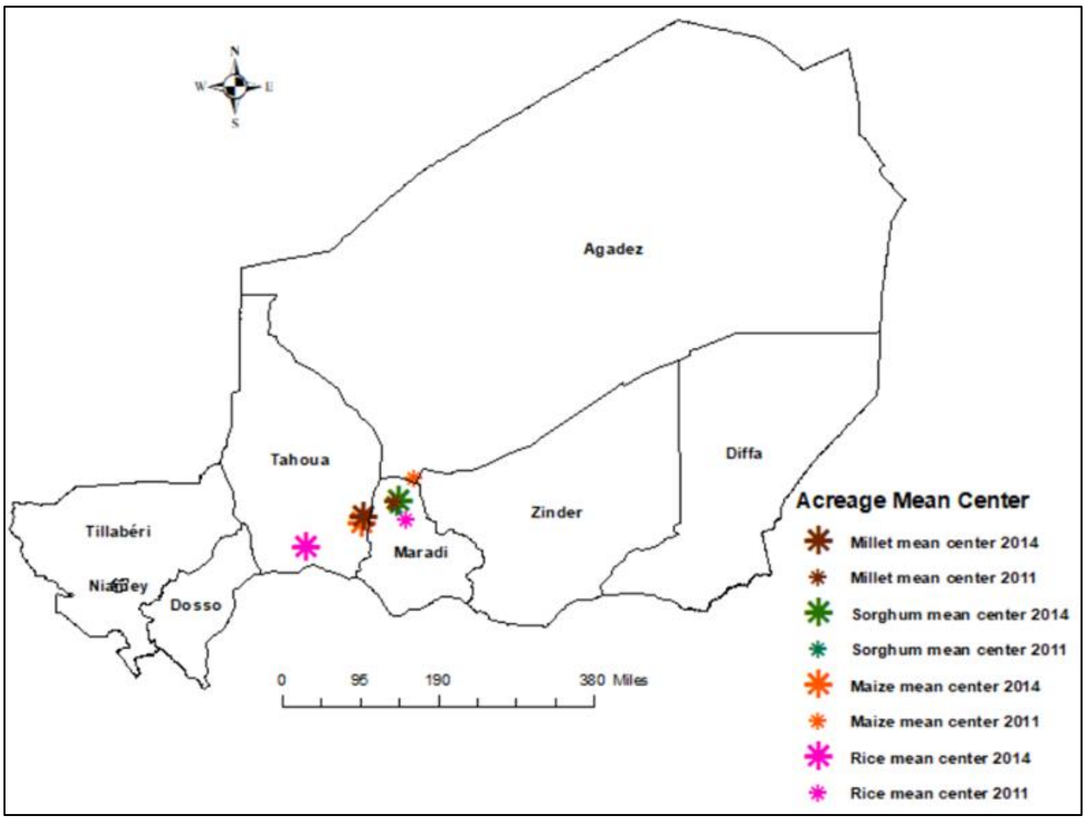

Figure 2-6 Mean centers of cereals per household acreage in Niger

Source: Author

Figures 2.7 and 2.8 map rice and maize, which requires more water. While rice is mostly grown in Dosso, Tillaberi, and Maradi, maize production is dominant in Dosso. In 2014, farmers in Dosso allocated 0.40 hectare to maize, while the national average is 0.15 ha. Meanwhile, Dosso, Tillaberi, and Maradi are regions where rice received the higher per household acreage (1.51-2.30

ha). For both maize and rice, Agadez shows the lowest per household acreage allocation (< 0.04 ha).

In Niger, the cropland distributions are similar for both millet and sorghum (see Figures 2.9 and 2.10). Both crops are drought-tolerant cereals and are therefore produced even in the Agadez region with an average of 0.80 hectare per household. In the other regions of the country, households allocate on average 1.5 hectare to sorghum and/or millet. Between 2011–2014, the mean center of millet shifted from Maradi to the neighboring Tahoua region.

Agadez is a desertous region where cereal production is the lowest in Niger. In terms of proportion of households allocating cropland to cereals, this region is a kind of outlier. Out of the sixty-one surveyed households in this region, none produces rice and only five households (8%) produce maize. Millet and sorghum are the most produced cereal in Agadez with 91% and 80% of households, respectively. In 2014, 51% of the surveyed households in Agadez reported using irrigation on part or all their farmland. This makes Agadez the most irrigated region. Based on the sample statistics, only 1.2% reported using irrigation on at least one plot.

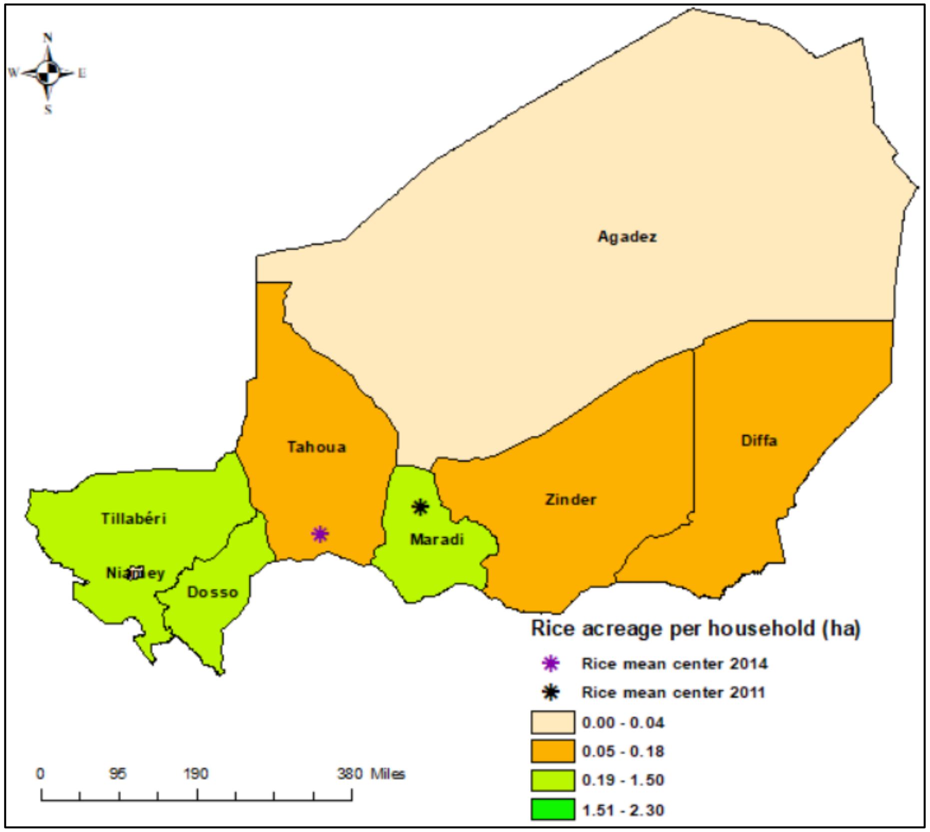

Figure 2-7 Shift in per-household rice acreage (in hectare) mean center represented on 2014 rice acreage allocation in Niger

Source: Author

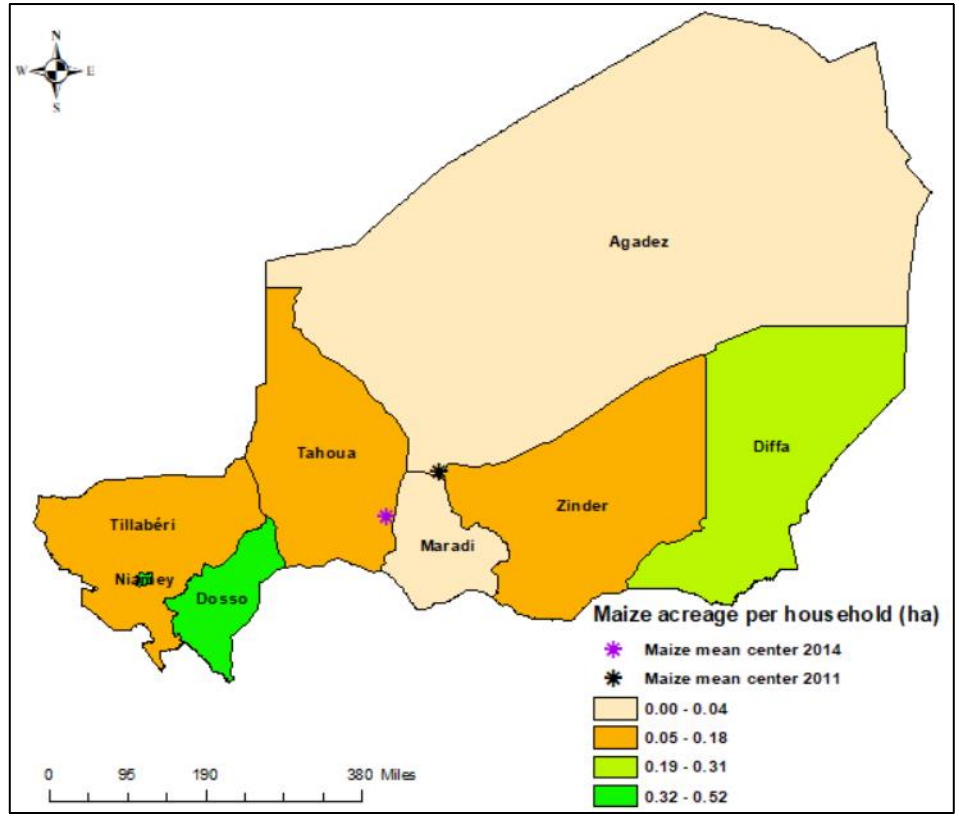

Figure 2-8 Shift in per-household maize acreage (in hectare) mean center represented on 2014 maize acreage allocation in Niger

Source: Author

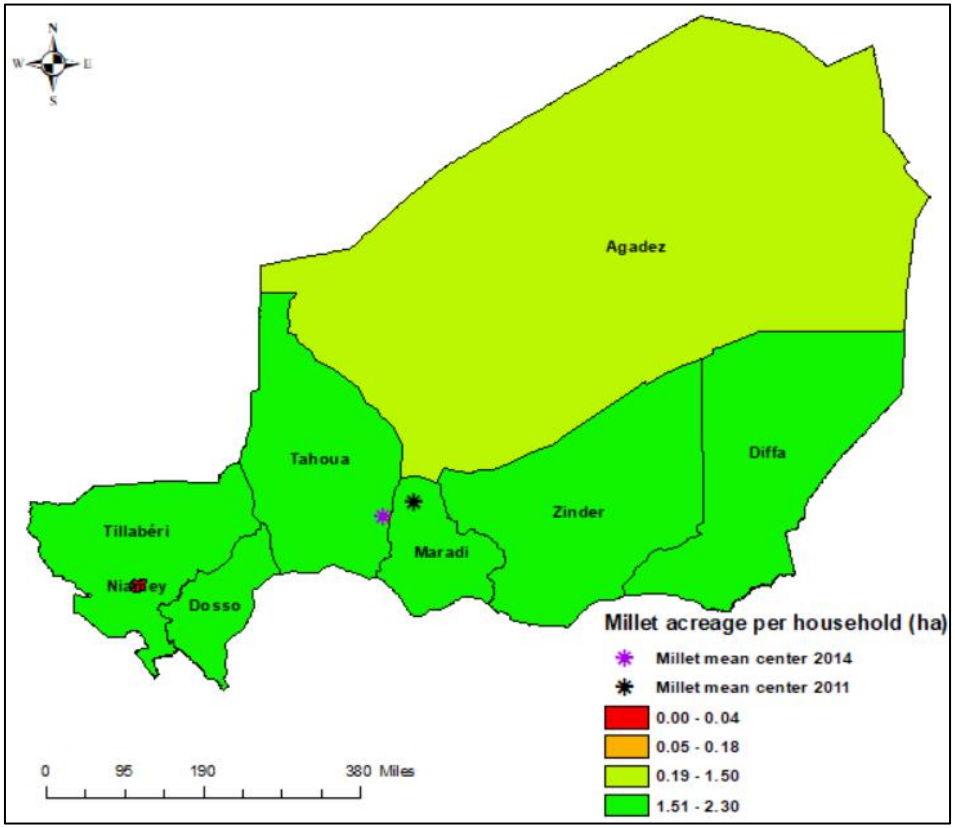

Figure 2-9 Shift in per-household millet acreage (in hectare) mean center represented on 2014 millet acreage allocation in Niger

Source: Author

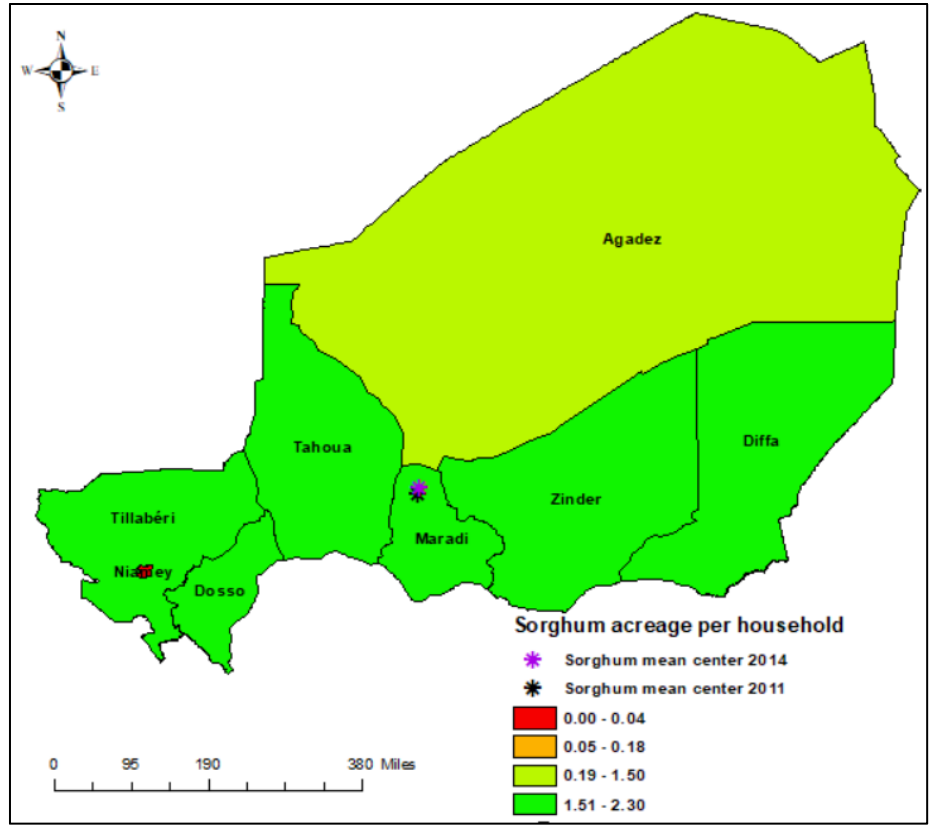

Figure 2-10 Shift in per-household sorghum acreage (in hectare) mean center represented on 2014 sorghum acreage allocation in Niger

Source: Author

2.5.2 Determinants of Cereal Cropland Allocation

In the previous section, we mapped the spatial cropland distribution in Nigeria and Niger using household-level acreage. The maps were purely descriptive and provided patterns on acreage allocation to each cereal in both countries. To make positive statements on the spatial distribution of cereals, we estimate cropland allocation drivers using the panel data estimator. In the current section, we use the fractional regression model to estimate factors that affect cropland allocation. Our empirical strategy is based on a two-stage stepwise estimation of the acreage ratios. In the first stage, we estimated the determinants of farmland allocation to cereals as a group. In the second stage, we estimated the causes of cropland allocation to maize, sorghum, millet, and rice. We used each cereal acreage ratio as an outcome variable to track the potential effect of space, climate, household characteristics, crop diversification, access to irrigation, prices, and food consumption and trade. Using the AIC, the BIC, the Ramsey test of omitted variable bias, and the Wald test of difference among nested models, we specified and selected the model that best fit the data.

After testing the estimated model for heteroscedasticity using the Breusch-Pagan test and the White test, both tests revealed the existence of heteroskedastic standard errors. Under heteroscedasticity, estimates are unbiased but inefficient, inducing potentially inaccurate hypothesis tests (t-tests and F-tests). White's robust standard errors were used to correct for heteroscedasticity.

We used the Wu-Hausman test for endogeneity to test for a potential endogenous Simpson index, irrigation dummy, and prices, although all these variables are based upon lagged observations. Endogeneity reveals a correlation between the explanatory variable and the error term. This correlation could arise from omitted variable bias, simultaneity, and/or errors in variables measurement. The Ramsey test of omitted variable bias revealed the absence of an omitted variable. We excluded the simultaneity cause of endogeneity using lagged covariates for prices, Simpson index and irrigation dummy. To check measurement error related endogeneity, we regressed the potential endogenous variables on the instrumental variables, such as plot wetness and distance to plot. Adding the residuals from this estimation as another explanatory variable in the regression of the main model, we found a non-statistically significant coefficient on the residual, which confirms the absence of endogeneity.

Our model specification assumed a quadratic relationship between acreage ratio and climatic variables to reflect the nonlinear relationship between cropland allocation and climate that is consistent with Ricardian studies applied elsewhere (Mendelsohn, 2000; Mendelsohn & Dinar, 2009; Mendelsohn & Massetti, 2017; Schueller, 1992). The quadratic term reflects the response of the acreage ratio as a function of climate variables. While positive quadratic terms indicate that the acreage ratio function is U-shaped, the negative quadratic terms reveal a hill-shaped function. Based on previous agronomic and cross-sectional analyses, we expect the relationship between the acreage ratio and temperature to hill-shape for sorghum and millet, and U-shape for maize and rice. Conversely, we expect the relationship between the acreage ratio and rainfall to be hill-shaped for maize and rice, and U-shaped for sorghum and millet.

As a way of ascertaining which model best describes the relationship between the cereal acreage ratio and the spatial determinants in the presence or absence of irrigation in Nigeria and Niger, we estimated three specifications for each regression model. The first estimation includes all the sample farming households; we called this the "pooled model." The second model approximates the estimation for rainfed farming households only based on lagged irrigation access information. The last model runs a separate regression for households using irrigation. It is important to highlight that farming households using irrigation in the study might have some rainfed areas as the irrigation question included in the survey was plot specific.

In the following paragraphs, we report and discuss elasticities of the most efficient model for each country, namely, Nigeria and Niger. In each case, we report two tables. The first table includes the estimates for the pooled model. The second table reports side-by-side elasticities for households using rainfed farming and those using irrigated farming. We report the three-stage estimation results for each crop in the appendices.

2.5.2.1 Empirical Estimation Results and Discussions for Nigeria

We present the results of the three-stage estimation approach used to improve the traditional Ricardian land use model. Table 2.3 reports results for the pooled sample and for the aggregated cereal group. The first column includes estimates of the traditional model, which include spatial and climatic covariates. The second column adds household characteristics and price covariates to the traditional model. The third and last column reports the full model, which satisfies specification and robustness tests.

Table 2-3 Alternative model selection for cereal cropland use in Nigeria

Variables	Pooled sample		
	Traditional	Traditional + Prices	Traditional + Price+ Consumption + Trade
Longitude	0.19***	0.16**	0.13*
	(0.07)	(0.08)	(0.08)
Longitude Squared	0.01*	2.3e-3	2.20e-3
	(0.001)	(0.001)	(4e-3)
Latitude	1.65***	1.37***	1.30***
	(0.09)	(0.09)	(0.09)
Latitude Squared	-0.07***	-0.06***	-0.05***
	(3.2e-3)	(e-3)	(2.1e-3)
Daily average temperature (Long run average)	0.35	0.21	0.15
	(0.31)	(0.32)	(0.32)
Daily average temperature (Long run average) Squared	-2.12 e-3	-1.26e-3	-8.6e-4
	(2.3e-3)	(1.5e-3)	(3.2e-4)
Daily average rainfall (Long run average)	0.70	2.50	3.15***
	(1.77)	(2.00)	(1.02)
Daily average rainfall (Long run average) Squared	-17.57**	-19.98**	-23.34**
	(8.85)	(9.11)	(9.23)
Diversification Index	0.21***	0.19***	0.19***
	(0.06)	(0.06)	(0.06)
Averaged distance to farm	2.6.e-4	2.3.e-4	2.6e-4
	(2.5e-4)	(1.3e-4)	(1.2e-3)
Averaged household farm slope	-0.05***	-0.04***	-0.04***
	(0.01)	(0.01)	(0.01)
Averaged household farm Elevation	1.13 e-3***	1.21 e-3***	1.2e-3***
	(2.3e-4)	(3.4e-4)	(2.4e-4)
Adult Equivalent		0.01**	0.01
		(0.01)	(0.01)
Household Head Age		-1.43e-3	-1.5e-3
		(e-3)	(3e-3)
Maize Price		0.01***	0.01***
		(2e-3)	(0.001)
Sorghum Price		0.02***	0.01***
		(e-3)	(0.001)
Millet Price		-0.03***	-0.03***
		(0.01)	(0.01)
Rice Price		-6.3e-4	-7.3e-4
		(0.001)	(0.001)

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

2.3 Alternative model selection for cereal cropland use in Nigeria (continued)

Variables	Pooled sample		
	Traditional	Traditional + Prices	Traditional + Price+ Consumption + Trade
Distance to market			1.04e-3*
			(e-3)
Per capita Food Expenditure			1.3e-4
			(0.001)
Per Capita Income			-1.2e-5**
			(0.5e-5)
2012.year	1.3e-3	0.10	0.07
	(0.04)	(0.08)	(0.09)
2015.year	0.01	0.25***	0.22***
	(0.03)	(0.05)	(0.05)
Using Irrigation	0.61***	0.63***	0.65***
	(0.15)	(0.15)	(0.15)
Total Farm Acreage	-0.02***	-0.03***	-0.03***
	(0.001)	(0.001)	(0.001)
Longitude x Latitude	-0.03***	-0.02***	-0.02***
	(0.01)	(0.01)	(0.01)
Constant	-23.04*	-15.54	-12.89
	(12.50)	(12.83)	(12.87)
Observations	5,507	5,504	5,504
AIC	6371	6363	6345
BIC	6490	6521	6503
Pseudo R2	0.106	0.108	0.108
Likelihood-ratio test of rho=0	2537	2815	2859
Prob > chi2	0	0	0

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

Spatial Variability in Cereal Acreage Shares

We expected acreage ratio to vary across spatial scales. In general, each spatial scale covers more than one agro-climatic zone, which generally exhibits spatial differences in climatic and soil-related variables. Table 2.4 includes elasticities of latitude and longitude, which enable the assessment of the variability in acreage shares across spatial scales.

Estimates for longitude confirm spatial heterogeneity in sorghum, millet, and rice acreage allocation in Nigeria. As one moves one-degree east, the per-household acreage allocated to cereals, maize, sorghum, millet, and rice significantly increases by0.13%, 0.17%, 1.29%, 0.68%, and 1.56%, respectively. On the other hand, elasticities for latitude reveal that cereals are mostly produced in the northern regions of Nigeria. One-degree north, the acreage shares for cereals increase on average by 1.30%. Also, millet, sorghum and rice acreage share increase more proportionally than maize.

The same trends are observed for households practicing rainfed farming but are unobserved for households having access to irrigation. Based on rainfed farming households' estimates, millet and sorghum can be characterized as northerner cereals. Overall, the results show great variability in acreage share across the space, indicating that acreage allocation to cereals may be influenced by differences in climatic conditions in the various agro-climatic zones. The empirical analysis therefore tried to find climatic, soil, socioeconomic, and other variables that would help explain this variability.

Impact of Climate Variables on Cereal Acreage Shares

Weather variables are diversely associated with acreage allocation to cereals. In general, the effect of temperature and rainfall on farmland attribution to crop is a nonlinear function of a farmer's expectation of these weather variables. Also, we found the same climatic variables effect for both the pooled sample and for households using only rainfed farming. This implies that farmers in Nigeria mostly base their allocation decisions on their expectations of temperature and rainfall.

For rainfed farmers, higher expected temperature is associated with lower millet acreage share and higher rice, sorghum and maize acreage share. When the expected temperature increases by one degree Celsius, millet acreage share decreases by 3.06%, while the rice share of cropland increases by 5.03%. However, the effect of temperature on farmers using irrigation is different. An increase in temperature induces an increase in acreage share for sorghum and a decrease in acreage share for rice. In general, change in temperature does not affect the overall acreage share for cereals in Nigeria.

Additionally, rainfall expectations positively impact the acreage ratio for cereals, especially sorghum and rice. For an increase in a rainfall expectation of one millimeter of water, the cereal acreage ratio increases on average by 3.15%. This elasticity is 4.04% and 3.13% for rainfed and irrigated farm owners, respectively. Also, following an increase of rainfall expectation of one millimeter, an average farming household increases the sorghum acreage ratio by 1.77%. Rice acreage has the highest response to rainfall expectation with an expectation of a 22.97% marginal increase.

Acreage of maize and millet, the main cereal in the country, is unresponsive to temperature and rainfall. This finding, especially for maize, is in line with Mano & Nhemachena's (2006) findings in Zimbabwe for maize. Overall, climate variable elasticities are important given that much of agricultural production in Nigeria is rainfed. On the other hand, other cereals, especially sorghum and rice acreage shares, increase at a decreasing rate with rainfall. This is consistent with the dominance of sorghum in Northern Nigeria where rainfall is less frequent.

Impact of Household Social and Production Characteristics on Acreage Allocation

Household characteristics influence food consumption patterns. This has a potential effect on crop choice and acreage assignment. Our estimation reveals that older household heads produce more millet and less rice in Nigeria. For a 1% increase in the age of the head of household, the acreage allocated to millet slightly increases by 0.01%, while that of rice decreases by the same magnitude. We found no effect of household size on the cereal acreage ratios.

Farm plot characteristics resulting from soil features, topography, and environmental interactions affect cropland allocation as well. While millet is preferably planted in steeper plots, the other cereals are less likely to be assigned sloping farmlands. We also found that the distance from the house to the farm does not affect acreage allocation to cereals. Conversely, access to irrigation increases cereal production, especially rice. However, households having access to irrigation reduce their farmland allocation to sorghum.

In a monoculture agricultural system, one would expect a one-to-one relationship between the Simpson diversity index and acreage share for cereals. This is not the case in most of Sub-Saharan Africa's agricultural systems (Fritz et al., 2015; Porgo et al., 2018). In Nigeria, we found that 80% of farm plots carry at least two crops. Among these, 65% of plots are occupied by at least two cereals. Accordingly, our estimation uncovered that a 1% increase in the Simpson diversification index is associated with a significant but inelastic overall cereal acreage ratio. However, individual acreage ratios are highly elastic to diversification. While maize acreage share decreases, sorghum, millet, and rice are associated with increased crop diversification.

Impact of Expected Prices of Acreage Shares on Cereals

As derived in the conceptual framework, the sign of the marginal effect of the expected own- or cross-price on the acreage ratio can be positive or negative depending on the cropping system of the farmer. In a case where the crop is grown on monoculture or planted earlier, one could objectively expect a positive effect of own price on the acreage share. Another important economic behavior in relation to price effect on acreage allocation is the consumption or market orientation of the cereal production. One would expect more responsive acreage to prices in cases where the cereal production is mostly market oriented.

We found the maize price to be a positive signal for all cereals. That is, acreage allocation to cereals responds positively to higher expectations in maize price. However, sorghum and millet price expectations are negatively related to their own acreage ratios. We explain this finding with two reasons. First, maize is the most popular food crop in Nigeria. As such, maize is mainly produced for food and in this mostly subsistence agricultural system, farmers produce first to secure enough food for their households. We consider the maize price to reinforce the food self-sufficiency behavior of farmers. Second, we found maize to be mostly produced in a monoculture. Overall, 85% of surveyed farmers declared growing maize under a monoculture, while 45% of farmers reported growing sorghum, millet, and rice under either inter-cropping, mixed cropping, relay cropping, or alley cropping. In such a setting, cross-price effects play a major role in the effect of own price on acreage ratio (see equation 18).

Trade Impact on Cereals Acreage Shares

One key novelty of this study consisted of adding trade and expected food demand proxies to the traditional Mendelsohn land use model. Several statistical tests showed that adding these components improved the model for cereal production. Tables 2-5 and 2-6 report estimates for distance to the nearest market, the expected food expenditure, and the expected per capita household income.

We used distance to the nearest market as a proxy for market accessibility. As such, we expected this variable to reveal how market proximity affects cropland allocation. We found that sorghum acreage share decreases with market proximity while maize and rice acreage share increases. Overall, we found that market proximity significantly determines cereal acreage share.

Using the lagged food expenditure, we approximated the household trade and expected food demand pattern. We anticipated that lagged food expenditure would reveal how the share of income spent on food determines the household's cropland allocation for cereals. In general, we found that the increase in expected food expenditure causes the acreage share for maize and rice to increase. This is in line with the importance of maize and rice in household food consumption, maize being consumed nationwide in Nigeria. However, higher food expenditure lowers millet acreage shares.

Lastly, we used the lagged per capita household income to assess how expected income relates to farmland allocation to staples. The higher the income expected for the household, the lower the acreage allocated to all cereals. In other words, higher income expectation caused cropland allocation to non-cereal crops.

In summary, adding the household expected demand for food improved the appropriateness of fit and brought some additional explanatory power to the cropland allocation decision-making process. Also, Table 2-5 reports that the overall cereal acreage share increased between 2012 and 2015 in Nigeria. It is also notable that maize, sorghum, and millet acreage shares increased in 2015 in comparison to their 2012 levels.

Table 2-4 Spatial and Climatic determinants of cereal acreage land use in Nigeria

Variables	All Households				
	Cereals	Maize	Sorghum	Millet	Rice
Longitude	0.13*	0.17***	1.29***	0.68***	1.56***
	(0.08)	(0.06)	(0.17)	(0.23)	(0.32)
Longitude Squared	2.20e-3	1.9e-3	-0.02***	-0.04***	-0.04***
	(1.3e-3)	(1.2e-3)	(0.01)	(0.01)	(0.01)
Latitude	1.30***	0.98***	3.34***	4.49***	4.40***
	(0.09)	(0.08)	(0.20)	(0.41)	(0.45)
Latitude Squared	-0.05***	-0.05***	-0.13***	-0.17***	-0.21***
	(0.001)	(0.001)	(0.01)	(0.02)	(0.02)
Daily average temperature (Long run average)	0.15	0.73*	0.74**	-2.98***	4.16***
	(0.32)	(0.39)	(0.29)	(0.43)	(1.15)
Daily average temperature (Long run average) Squared	-8.6e-4	-4.17e-3*	-1.5e-3**	0.02***	-0.03***
	(7.5e-4)	(3.7e-3)	(0.5e-3)	(0.001)	(0.01)
Daily average rainfall (Long run average)	3.15***	0.29	1.71***	10.19	22.97**
	(1.02)	(1.61)	(0.38)	(11.20)	(9.16)
Daily average rainfall (Long run average) Squared	-23.34**	-1.86	-23.73	-78.59	-161.65***
	(9.23)	(6.63)	(23.37)	(90.02)	(59.04)
Diversification Index	0.19***	-5.63***	2.11***	1.31***	2.42***
	(0.06)	(0.10)	(0.09)	(0.10)	(0.16)
Averaged distance to farm	2.6e-4	2.2e-4	1.8e-4	-3.9e-4	-7.7e-4
	(1.2e-3)	(2e-4)	(3e-4)	(3.6e-3)	(5e-4)

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

Table 2.4. Spatial and Climatic determinants of cereal acreage land use in Nigeria (continued)

Variables	All Households				
	Cereals	Maize	Sorghum	Millet	Rice
Averaged household farm slope	-0.04***	-0.02***	-0.03***	0.03**	-0.04
	(0.01)	(0.001)	(0.01)	(0.01)	(0.04)
Averaged household farm Elevation	1.2e-3***	1.2e-3***	6.5e-4***	-5.0e-3***	-2.02e-3***
	(2e-4)	(1.4e-4)	(e-4)	(1.1e-3)	(0.2e-3)
Adult Equivalent	0.01	1.6e-3	-0.01	-3.2e-3	0.01
	(0.01)	(e-3)	(0.01)	(0.01)	(0.02)
Household Head Age	-1.5e-3	-7.9e-4	-1.25e-3	0.01***	-0.01***
	(e-3)	(2.3e-3)	(1.2e-3)	(0.001)	(0.001)
Total farm acreage	-0.03***	-0.01*	0.03***	0.02***	-0.02
	(0.001)	(0.001)	(0.01)	(0.01)	(0.02)
Longitude x Latitude	-0.02***	-0.02***	-0.08***	4.07e-3	-0.09***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Constant	-12.89	-32.60**	-57.53***	89.18***	-197.98***
	(12.87)	(15.70)	(11.59)	(17.65)	(45.84)
Observations	5,504	5,504	5,504	5,504	5,504
AIC	6345	4427	4580	3035	1666
BIC	6503	4606	4759	3214	1845
Pseudo R2	0.108	0.309	0.223	0.285	0.228
Likelihood-ratio test of rho=0	2859	4918	2330	1075	995
Prob > chi2	0	0	0	0	0

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

Table 2.4. Spatial and Climatic determinants of cereal acreage land use in Nigeria (continued)

Variables	Households with rainfed plots					Households with irrigated plots				
	Cereals	Maize	Sorghum	Millet	Rice	Cereals	Maize	Sorghum	Millet	Rice
Longitude	0.16**	0.18***	1.30***	0.59***	1.81***	-2.87***	-0.31	0.44	-0.54	-0.87
	(0.07)	(0.06)	(0.17)	(0.23)	(0.34)	(1.03)	(0.45)	(1.55)	(2.42)	(1.63)
Longitude Squared	1.46e-3	1.34e-3	-0.02***	-0.04***	-0.04**	0.17***	-0.03	-0.01	0.07	-0.03
	(1.3e-3)	(e-3)	(0.01)	(0.01)	(0.02)	(0.06)	(0.03)	(0.06)	(0.09)	(0.10)
Latitude	1.31***	1.02***	3.39***	4.42***	1.90***	0.36	-0.21	4.33*	5.34	-2.45
	(0.09)	(0.08)	(0.20)	(0.41)	(0.15)	(1.60)	(0.90)	(2.63)	(4.36)	(2.28)
Latitude Squared	-0.05***	-0.05***	-0.13***	-0.17***	-0.22***	-0.04	-0.02	-0.18*	-0.19	0.07
	(0.001)	(0.001)	(0.01)	(0.02)	(0.02)	(0.07)	(0.05)	(0.11)	(0.18)	(0.10)
Daily average temperature (Long run average)	0.23	0.68*	0.70**	-3.06***	5.03***	-16.74	10.11	5.97***	22.31	-24.81***
	(0.32)	(0.39)	(0.29)	(0.44)	(1.25)	(19.15)	(6.40)	(2.24)	(25.97)	(5.79)
Daily average temperature (Long run average) Squared	-1.40e-3	-3.84e-3	-3.94e-3**	0.02***	-0.03***	0.10	-0.06	-0.04***	-0.14	0.15***
	(e-3)	(2.5e-3)	(1.3e-3)	(0.001)	(0.01)	(0.12)	(0.04)	(0.01)	(0.16)	(0.04)
Daily average rainfall (Long run average)	4.04**	0.13	0.61	12.71	20.19**	3.13***	72.19	85.13	-38.19	5.27
	(0.96)	(1.62)	(3.23)	(11.30)	(9.35)	(0.88)	(52.16)	(55.07)	(169.92)	(56.03)
Daily average rainfall (Long run average) Squared	-19.14**	-0.97	-15.01	-93.85	-152.19**	-1,037.64***	-512.46	-737.80*	149.68	129.88
	(9.06)	(6.68)	(21.95)	(90.93)	(59.84)	(314.66)	(418.85)	(437.31)	(1,341.08)	(428.02)
Diversification Index	0.20***	-5.60***	2.16***	1.25***	2.45***	1.34***	-6.14***	2.03***	2.17***	2.43***
	(0.06)	(0.10)	(0.10)	(0.11)	(0.17)	(0.42)	(0.59)	(0.37)	(0.52)	(0.58)
Averaged distance to farm	3.2e-4	2.6e-4	1.4e-4	-4.3e-4	-3.8e-4	-0.04*	-2.07e-3	0.01	0.08	0.08*
	(1.8e-3)	(2.1e-4)	(e-4)	(2.3e-4)	(1.5e-4)	(0.02)	(0.03)	(0.02)	(0.06)	(0.04)

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, *p<0.1, significance levels.

Table 2.4. Spatial and Climatic determinants of cereal acreage land use in Nigeria (continued)

Variables	Households with rainfed plots					Households with irrigated plots				
	Cereals	Maize	Sorghum	Millet	Rice	Cereals	Maize	Sorghum	Millet	Rice
Averaged household farm slope	-0.04***	-0.02***	-0.03***	0.03**	-0.04	-0.16**	-0.16*	0.10	0.06	-0.13
	(0.01)	(0.001)	(0.01)	(0.01)	(0.04)	(0.07)	(0.09)	(0.07)	(0.11)	(0.09)
Averaged household farm Elevation	1.20e-3***	1.18e-3***	6.1e-4***	-5.0e-3***	-1.7e-3***	3.47e-3***	1.82e-3**	2.38e-3*	-4.32e-3	-0.01***
	(e-4)	(e-4)	(3.1e-4)	(3.2e-3)	(1.2e-4)	(0.5e-3)	(e-4)	(1.3e-3)	(3.2e-3)	(0.001)
Adult Equivalent	0.01	1.62e-3	-0.01	0.8e-3	0.01	0.05	-0.01	0.17***	-0.18**	-0.01
	(0.01)	(0.00)	(0.01)	(0.01)	(0.02)	(0.05)	(0.04)	(0.04)	(0.08)	(0.08)
Household Head Age	-1.22e-3	-0.9e-3	-1.62e-3	0.01***	-0.01***	0.02	0.02**	0.01	0.03	-0.02
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Total farm acreage	-0.03***	-0.01	0.03***	0.02***	-0.01	-0.15**	-0.05	0.24***	0.11	-0.27*
	(0.00)	(0.00)	(0.00)	(0.01)	(0.02)	(0.07)	(0.06)	(0.09)	(0.07)	(0.16)
Longitude x Latitude	-0.02***	-0.03***	-0.08***	0.01	-0.12***	0.06	0.09**	-0.04	-0.05	0.16***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.05)	(0.04)	(0.07)	(0.12)	(0.06)
Constant	-15.94	-30.70*	-56.23***	93.02***	-235.42***	68.39	-39.12	-27.16***	-90.88	1,02.59***
	(12.82)	(15.78)	(11.59)	(17.83)	(49.84)	(792.83)	(242.96)	(87.09)	(1,064.55)	(238.13)
Observations	5,375	5,375	5,375	5,375	5,375	129	129	129	129	129
AIC	6244	4360	4459	2947	1567	152	110.3	151.6	121.5	119.6
BIC	6415	4531	4630	3118	1739	226.3	184.7	226	193	193.9
Pseudo R2	0.108	0.303	0.226	0.285	0.221	0.179	0.613	0.243	0.402	0.418
Likelihood-ratio test of rho=0	2810	4860	2387	1078	924	110.8	1849	92.87	122.5	116
Prob > chi2	0	0	0	0	0	0	0	9.68e-10	0	0

Table 2-5 Expected Price and food demand effect on cereal land use in Nigeria

Variables	All Households				
	Cereals	Maize	Sorghum	Millet	Rice
Maize Price	0.01***	0.02***	0.01*	0.02***	0.01
	(0.001)	(0.001)	(0.01)	(0.01)	(0.01)
Sorghum Price	0.01***	0.02***	-0.02***	0.001	0.01
	(0.001)	(0.01)	(0.01)	(0.01)	(0.02)
Millet Price	-0.03***	-0.03***	0.01	-0.01**	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Rice Price	-7.3e-4	2.8e-3***	1.53e-3	-3.2e-3*	-0.01
	(0.001)	(1.2e-4)	(0.001)	(0.001)	(0.01)
Distance to market	1.04e-3*	-1.05e-3**	3.2e-3***	-9.6e-4	-8.5e-3***
	(e-3)	(e-4)	(e-4)	(0.001)	(0.001)
Per capita Food Expenditure	1.3e-4	2.3e-4***	1.5e-4	-1.2e-4***	1.02e-3***
	(0.001)	(e-4)	(0.001)	(e-5)	(e-4)
Per Capita Income	-1.2e-5**	-2.4e-5***	-5.01e-3***	1.3e-5	-2.03e-4*
	(0.5e-5)	(1.2e-6)	(e-4)	(e-5)	(e-4)
2012.year	0.07	0.15**	0.05	0.49***	-0.56**
	(0.09)	(0.07)	(0.09)	(0.13)	(0.24)
2015.year	0.22***	0.31***	0.13*	0.24***	-0.13
	(0.05)	(0.04)	(0.07)	(0.09)	(0.18)
Using Irrigation	0.65***	0.06	-0.43**	-0.20	0.85***
	(0.15)	(0.12)	(0.17)	(0.17)	(0.26)
Constant	-12.89	-32.60**	-57.53***	89.18***	-197.98***
	(12.87)	(15.70)	(11.59)	(17.65)	(45.84)
Observations	5,504	5,504	5,504	5,504	5,504
AIC	6345	4427	4580	3035	1666
BIC	6503	4606	4759	3214	1845
Pseudo R2	0.108	0.309	0.223	0.285	0.228
Likelihood-ratio test of rho=0	2859	4918	2330	1075	995
Prob > chi2	0	0	0	0	0

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

Table 2.5. Expected Price and food demand effect on cereal land use in Nigeria (continued)

Variables	Households with rainfed plots					Households with irrigated plots				
	Cereals	**Maize**	**Sorghum**	**Millet**	**Rice**	**Cereals**	**Maize**	**Sorghum**	**Millet**	**Rice**
Maize Price	0.01***	0.02***	0.1	0.01**	0.02	0.10**	0.06*	0.09***	3.8e-3	0.05
	(0.001)	(0.001)	(0.01)	(0.01)	(0.01)	(0.04)	(0.04)	(0.03)	(0.11)	(0.06)
Sorghum Price	0.02***	0.02***	-0.02***	4.9e-3	0.01	-0.06	-0.08*	-0.10*	-0.04	0.05
	(0.001)	(0.01)	(0.01)	(0.01)	(0.02)	(0.05)	(0.05)	(0.06)	(0.13)	(0.08)
Millet Price	-0.03***	-0.04***	0.01	-0.01***	-0.01	-0.05	0.02	-0.06	0.03	-0.11*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.06)	(0.04)	(0.04)	(0.05)	(0.06)
Rice Price	-2.3e-3*	2.6e-3**	1.9e-3	-2.4e-3	-0.01*	0.05***	7.8e-4	-0.01	-0.05	-4.2e-3
	(1.1e-3)	(0.001)	(0.5e-3)	(1.4e-3)	(7e-3)	(0.02)	(0.01)	(0.01)	(0.03)	(0.01)
Distance to market	8e-4	-1.2e-3***	3e-3***	-2e-4	-0.01***	0.02**	4.4e-3	0.01**	-0.01*	0.01
	(7e-4)	(e-4)	(e-3)	(1.2e-4)	(0.001)	(0.01)	(35e-3)	(0.01)	(0.01)	(0.01)
Per capita Food Expenditure	3e-5	4e-5***	4e-5	-1.2e-5**	3.1e-5***	e-5***	e-5*	e-5***	-2e-5*	1.3e-5
	(e-4)	(e-5)	(1.6e-4)	(0.5e-5)	(e-6)	(e-6)	(2.1e-6)	(e-5)	(1.2e-5)	(e-5)
Per Capita Income	-4e-5***	-3e-5***	-2e-5***	3e-4	-4.1e-5*	e-5	1.2e-5	-2.3e-5**	-2.4e-4	-2.1e-4
	(1.3e-6)	(1.2e-5)	(0.5e-5)	(2.5e-4)	(2.7e-5)	(1.2e-5)	(2e-5)	(e-6)	(2.2e-4)	(2e-4)
2012.year	0.07	0.15**	0.03	0.49***	-0.50*	0.84	1.02	0.60	1.68	-1.11
	(0.09)	(0.07)	(0.10)	(0.13)	(0.25)	(0.73)	(0.75)	(0.77)	(1.36)	(0.87)
2015.year	0.22***	0.32***	0.12*	0.22**	-0.09	0.17	-0.54	1.04*	1.31	-0.22
	(0.05)	(0.04)	(0.07)	(0.09)	(0.19)	(0.76)	(0.61)	(0.58)	(1.34)	(0.96)
Constant	-15.94	-30.70*	-56.23***	93.02***	-235.42***	68.39	-39.12	-27.16***	-94.88	1,02.59***
	(12.82)	(15.78)	(11.59)	(17.83)	(49.84)	(792.83)	(242.96)	(87.09)	(1,064.55)	(238.13)
Observations	5,375	5,375	5,375	5,375	5,375	129	129	129	129	129
AIC	6244	4360	4459	2947	1567	152	110.3	151.6	121.5	119.6
BIC	6415	4531	4630	3118	1739	226.3	184.7	226	193	193.9
Pseudo R2	0.108	0.303	0.226	0.285	0.221	0.179	0.613	0.243	0.402	0.418
Likelihood-ratio test of rho=0	2810	4860	2387	1078	924	110.8	1849	92.87	122.5	116
Prob > chi2	0	0	0	0	0	0	0	9.68e-10	0	0

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

2.5.2.2 Empirical Estimation Results and Discussions for Niger

In this section, we present the estimates of the cereal land use model in Niger. We show how spatial, climatic, consumption, production, prices, and trade factors affect cropland allocation to cereal, maize, sorghum, millet, and rice. We also draw a comparison with the case of Nigeria. We follow the same outline as in the previous section and highlight results for the pooled sample, followed by estimates for the subsamples of households using rainfed and irrigated farming.

As was the case of Nigeria, we first report the results of the three-stage estimation approach used to improve the traditional Ricardian land use model for Niger. The three columns of Table 2-6 report result for the “traditional model,” the “traditional + Price” model, and the full model for pooled households’ sample. The model in column 3 of Table 2-6 is the selected model regress acreage shares on the spatial, climatic, household characteristics, prices, trade, and cropping system.

Table 2-6 Alternative model selection for cereal cropland use in Niger

Variables	Pooled sample		
	Traditional	Traditional + Prices	Traditional + Price+ Consumption + Trade
Longitude (degree)	-0.38*	-0.32*	-0.26
	(0.20)	(0.19)	(0.23)
Longitude Squared	0.01*	4.88e-3	4.68e-3
	(0.001)	(3.4e-3)	(4.5e-3)
Latitude (degree)	-1.14	0.56	1.13
	(1.51)	(2.02)	(2.25)
Latitude Squared	0.03	-0.03	-0.05
	(0.06)	(0.07)	(0.08)
Daily average temperature (Planting year)	-35.51***	189.23**	219.81**
	(7.62)	(82.23)	(92.43)
Daily average temperature (Long run average)	14.79***	-146.37**	-167.71**
	(5.65)	(60.81)	(68.71)
Daily average rainfall (Planting year)	183.85***	-931.15**	-1,077.80**
	(36.67)	(407.31)	(455.83)
Daily average rainfall (Long run average)	42.01***	-315.07**	-362.76**
	(11.93)	(134.48)	(150.62)
Daily average temperature (Planting year) Squared	0.21***	-1.11**	-1.29**
	(0.04)	(0.48)	(0.54)
Daily average temperature (Long run average) Squared	-0.09***	0.86**	0.99**
	(0.03)	(0.36)	(0.40)
Daily average rainfall (Planting year) Squared	-1,667.25***	8,044.27**	9,322.99**
	(341.13)	(3,541.71)	(3,962.86)
Diversification Index	9.28***	9.32***	9.35***
	(0.36)	(0.36)	(0.36)
Soil wetness	-1.26e-3	-1.71e-3	-4.79e-3
	(0.001)	(0.001)	(0.001)
Soil nutrient	0.06	0.05	0.04
	(0.04)	(0.04)	(0.04)
Household Equivalent adults		-2.3e-3	0.01
		(1.5e-3)	(0.01)
Household head age		-4.03e-3	-6.22e-3
		(0.00)	(0.00)
Millet Price		-0.11	-0.24
		(0.91)	(0.91)
Sorghum Price		-0.53	-0.58
		(0.78)	(0.76)
Rice Price		-7.62***	-8.59***
		(2.87)	(3.13)
Maize Price		-0.64	-1.30
		(0.84)	(0.83)

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

Table 2-6. Alternative model selection for cereal cropland use in Niger (continued)

Variables	Pooled sample		
	Traditional	Traditional + Prices	Traditional + Price+ Consumption + Trade
Distance to nearest market			4.6e-4
			(0.001)
Distance to nearest asphalted road			3.79e-3*
			(1.7e-3)
Per Capita Food Expenditure			-1.01e-3*
			(0.001)
Per capita Income			2.3e-4**
			(e-5)
Female Head of household (Male = 0)		-0.04	-0.04
		(0.03)	(0.03)
Access to Irrigation	1.34***	0.63	0.63
	(0.50)	(0.46)	(0.46)
Total Farm Acreage	2.02e-3**	2.15e-3**	2.14e-3**
	(e-3)	(e-3)	(e-3)
Longitude x Latitude	0.02	0.02	0.01
	(0.01)	(0.01)	(0.02)
Constant	879.43***	-1,777.61*	-2,163.37**
	(326.02)	(957.10)	(1,052.18)
Observations	4,844	4,844	4,844
AIC	4142	4150	4054
BIC	4252	4299	4123
Pseudo R2	0.239	0.240	0.240
Likelihood-ratio test of rho=0	2917	2971	2772
Prob > chi2	0	0	0

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

Spatial Variability in Cereal Acreage Shares

Table 2.7 includes elasticities of latitude and longitude for cereal acreage ratios. Estimates for longitude show a reduced rice acreage ratio as one moves east. This trend is the same for both rainfed and irrigated farmers. The estimates for the irrigated farming household show an increase in cereal acreage by 8% when one moves 1° east, due mainly to increase in millet and sorghum acreage share.

We found the cereal acreage ratio to be generally elastic to the marginal change in latitude. For a 1% increase in latitude, which is moving from south to north, the cereal acreage ratio increases by 1.75% for rainfed farmers and by 5.10% for irrigation users. Overall, the acreage ratio for maize and rice shrinks as one moves north. However, the acreage ratio for millet increases, on average, by 5% as the latitude increases by 1%, especially for rainfed farmers. We observe the same trend with a smaller magnitude for sorghum acreage share. We identify millet and sorghum as northeast crop in Niger.

Impact of Climate Variables on Cereals Acreage Shares

Temperature and rainfall estimates in Niger reveal that farmers base their weather expectations on both the long- and short-term records. However, we found long-term expectations produce a lower response in comparison to short-term expectations. Table 2-7 reports estimates for climatic variables.

While higher temperature reduces the acreage shares for cereals, increasing expectations of rainfall causes households to assign more cropland to cereals. Expected high temperature causes farmers to reduce the maize (5%) and rice (3%) acreage share more than sorghum (1.80%) and millet (1.80%), based on the planting year observations.

In addition, based on their short-term and long-term expectations of rainfall, farmers more proportionally increase their cereal acreage share. For an expected 1% increase in rainfall, an average farmer increases the cereal acreage share by 1.29% (sort-run) and 9.32% (long-term). Millet (5%) acreage share is the most responsive to rainfall, followed by sorghum (1.13%) acreage while maize and rice are the least responsive. The response to rainfall expectations is higher rainfed farmers while less-responsive irrigation users significantly increase their cereal acreage share as their rainfall expectations increase.

Impact of Household Social and Production Characteristics on Acreage Allocation

We found that female heads of households allocate less cropland to cereals. In addition, the pooled sample estimate shows that female heads of households tended to produce maize more than male head of households. Except for maize, previous crop diversification experience causes the acreage share of other cereals to increase. For a 1% increase in the Simpson index, the average cereal acreage share increased by 9.35%, with the highest increase observed for millet (9%). Furthermore, we found the diversification impact on acreage shares to be more important for rainfed farmers for all cereals but rice.

Soil wetness and its nutrient content positively affect acreage allocation to rice for rainfed farmers. However, wetter soils are preferably allocated to maize and millet and retracted from sorghum. Also, we found older household heads to allocate lower acreage share to millet.

Impact of Expected Prices on Cereals Acreage Shares

Price elasticities for acreage shares estimated for Niger exhibit the same theoretical and empirical patterns as those estimated for Nigeria. That is, consumption and cropping systems interplay to determine the relationship between expected price and the acreage ratio assigned to a cereal. While maize is the major cereal in Nigeria, millet is the most-produced and most-consumed staple in Niger. Also, descriptive statistics reveal that millet and sorghum are overwhelmingly grown under monoculture by 86% and 82% of the farmers, respectively. For these two cereals, and based on the theoretical analysis made previously, we anticipated that higher own price expectation would cause higher acreage ratios.

Estimates in Table 2-8 reveal expected millet and sorghum prices to induce high and positively elastic acreage increases for these crops. As a consequence, the overall cereal acreage share increases as millet or sorghum expected price increases. For a 1% increase in expected millet and sorghum prices, the acreage shares of these cereals increase by 8.59% and 0.58%, respectively. Since millet is the most consumed cereal nationwide, higher expected millet price drives up the cereal acreage share. Meanwhile, the acreage share price elasticity for maize is negative and estimated at 16.68%. Furthermore, we found a competition between millet and sorghum because millet acreage decreases as the expected price for sorghum increases and vice versa. This reveals that there is cropland substitution between these two crops as only 2.3% of farmers declared growing both crops during the 2014 production season. In addition, we found the increase in expected rice price to induce an increase in its acreage share for farmers using irrigation. This implies that control for water increases farmers' response to the rice price.

In general, we found greater acreage share is allotted for important food crops, namely millet and sorghum in Niger. Consequently, millet and sorghum price expectations determine the acreage assigned to cereals, specifically millet and sorghum. The maize price does not give a significant signal to its acreage share but encourages farmers to increase the acreage share for sorghum, probably to secure food for the household. In addition, as control for water reduces uncertainty in rice production, irrigated farmers have an elastic response to the rice price increase.

Trade Impact on Cereals Acreage Shares

We found percapita food expenditure to significantly affect cereal cropland allocation to millet. Also, we found that a longer distance to the nearest market tended to induce cropland allocation towards millet. That is, farmers far from nearest markets are more food-self-sufficiency oriented. Also, farmers closer to an asphalt road tend to grow less rice, while farmers living far from improved road infrastructure grow more millet and sorghum. This finding illustrates that farmers who live far from trading centers and transport infrastructures tend to focus on self-sufficiency, so they grow millet and sorghum to secure enough food for their household. Furthermore, results in Table 2-8 show that wealthier farmers (with higher income) allocate less farmland to cereals. In general, estimates in the case of Niger also show that controlling trade-related variables improves cropland use modeling.

Table 2-7. Spatial and Climatic determinants of cereal acreage land use in Niger

Variables	All Households				
	Cereals	Maize	Sorghum	Millet	Rice
Longitude (degree)	-0.26	-3.58**	-0.71**	0.20	-4.63**
	(0.23)	(1.44)	(0.30)	(0.18)	(2.21)
Longitude Squared	4.7e-3	0.05	0.01	-0.01***	0.27***
	(0.00)	(0.05)	(0.01)	(0.00)	(0.03)
Latitude (degree)	1.88***	-6.20*	0.06	4.95***	-22.77**
	(0.52)	(3.17)	(1.62)	(1.43)	(10.58)
Latitude Squared	-0.05	0.15	-0.02	-0.18***	0.80**
	(0.08)	(0.12)	(0.06)	(0.05)	(0.39)
Daily average temperature (Planting year)	2.81**	-4.82***	-1.87***	-1.83***	-2.70***
	(1.43)	(1.28)	(0.56)	(.37)	(1.03)
Daily average temperature (Planting year) Squared	-167.71**	266.04**	158.94**	597.57***	-321.34*
	(68.71)	(108.39)	(67.15)	(158.83)	(173.03)
Daily average temperature (Long run average)	-1.80**	-2.91***	1.52***	4.18***	-3.28***
	(0.83)	(0.28)	(0.11)	(0.37)	(0.61)
Daily average temperature (Long run average) Squared	-36.76**	-73.95***	-58.23***	-130.02***	-1,20.50***
	(15.62)	(22.63)	(13.05)	(35.44)	(42.16)
Daily average rainfall (Planting year)	1.29**	0.78***	1.13***	5.00***	0.25***
	(0.54)	(0.004)	(0.40)	(1.30)	(0.01)
Daily average rainfall (Planting year) Squared	0.99**	1.57**	-0.94**	-3.52***	1.91*
	(0.40)	(0.64)	(0.39)	(0.93)	(1.01)
Daily average rainfall (Long run average)	9.32**	18.02***	-11.96***	-36.71***	31.55***
	(3.86)	(6.32)	(2.06)	(9.09)	(8.67)

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

Table 2-7 Spatial and Climatic determinants of cereal acreage land use in Niger (continued)

Variables	All Households				
	Cereals	Maize	Sorghum	Millet	Rice
Diversification Index	9.35***	-16.30***	0.79***	9.42***	3.39***
	(0.36)	(4.36)	(0.17)	(0.46)	(0.68)
Soil wetness	-1.2e-3	-4.8e-3	-1.25e-3	-0.01	0.02
	(0.001)	(0.05)	(0.01)	(0.00)	(0.02)
Soil nutrient	0.04	-0.04	-0.09**	-5.4e-4	0.93***
	(0.04)	(0.36)	(0.04)	(0.03)	(0.27)
Household Equivalent adults	0.01	0.09	0.01	-3.3e-3	0.04
	(0.01)	(0.08)	(0.01)	(0.01)	(0.10)
Household head age	-1.3e-4	-2.5e-3	2.24e-3	-2.9e-3***	0.02
	(0.00)	(0.02)	(0.00)	(0.00)	(0.02)
Total farm acreage	2.14e-3**	-0.03	2.04e-3**	1.8e-3**	-0.01
	(0.001)	(0.02)	(0.00)	(0.00)	(0.03)
Longitude x Latitude	0.01	0.25**	0.04**	-0.01	-0.50***
	(0.02)	(0.12)	(0.02)	(0.01)	(0.15)
Constant	-2.37**	-8.09	1.40	10.41***	-31.13
	(1.18)	(5.30)	(1.02)	(2.53)	(20.60)
Observations	4,844	4,844	4,844	4,844	4,844
AIC	4054	107	2448	3135	160.1
BIC	4123	282.1	2623	3297	335.3
Pseudo R2	0.240	0.726	0.0284	0.297	0.586
Likelihood-ratio test of rho=0	2772	1.921e+06	58564	1343	4.988e+06
Prob > chi2	0	0	0	0	0

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

Table 2-7. Spatial and Climatic determinants of cereal acreage land use in Niger (continued)

Variables	Households with rainfed plots					Households with irrigated plots				
	Cereals	Maize	Sorghum	Millet	Rice	Cereals	Maize	Sorghum	Millet	Rice
Longitude (degree)	-0.20	-3.66	-0.77**	0.20	-0.55	7.96***	-16.63	15.17***	7.49***	-19.20
	(0.13)	(5.96)	(0.30)	(0.18)	(2.73)	(3.07)	(83.71)	(3.92)	(1.05)	(40.14)
Longitude Squared	e-3	-0.04	0.01*	-0.01**	0.20***	-1.45***	0.76	-6.02***	-0.05	2.55***
	(e-3)	(0.10)	(0.01)	(0.00)	(0.04)	(0.34)	(1.78)	(0.91)	(1.63)	(0.55)
Latitude (degree)	1.75***	-8.90	1.29***	5.24***	-26.79**	5.10***	-38.82	5.59**	6.03**	-53.03
	(0.66)	(45.75)	(0.53)	(1.45)	(13.50)	(2.07)	(170.81)	(3.02)	(2.10)	(52.15)
Latitude Squared	-0.07***	0.27	0.03	-0.19***	0.92*	-2.24***	0.93	-15.17***	-0.26**	1.65
	(0.02)	(1.70)	(0.06)	(0.05)	(0.52)	(0.66)	(5.38)	(0.73)	(0.01)	(1.23)
Daily average temperature (Planting year)	-57.12	-63.65	-31.90***	-84.51***	121.18*	37.16***	-13.47	126.82***	5.02	-29.69
	(82.79)	(56.95)	(9.35)	(30.53)	(66.66)	(13.56)	(70.40)	(1.60)	(0.00)	(20.09)
Daily average temperature (Planting year) Squared	45.76	598.13	246.55***	590.97***	-599.66					
	(59.85)	(663.67)	(48.92)	(164.87)	(663.04)					
Daily average temperature (Long run average)	0.34	3.73	1.85***	4.96***	-7.11*	-114.79***	78.53	-533.26	7.18***	149.45***
	(0.49)	(3.90)	(0.29)	(1.35)	(3.93)	(18.89)	(68.36)	(0.00)	(1.39)	(29.20)
Daily average temperature (Long run average) Squared	-0.27	-3.51	-1.46***	-3.48***	3.52					
	(0.35)	(3.90)	(0.29)	(0.97)	(3.90)					
Daily average rainfall (Planting year)	29.24***	29.27	17.78***	4.37***	-5.24	19.07***	20.53	4.00***	-288.84	2.19***
	(4.08)	(36.15)	(2.62)	(1.55)	(3.48)	(3.66)	(33.84)	(1.54)	(168.00)	(0.05)
Daily average rainfall (Planting year) Squared	-262.23	-254.16	-162.00***	-360.68***	414.88					
	(359.40)	(319.14)	(22.67)	(109.15)	(299.45)					
Daily average rainfall (Long run average)	108.43	199.97	58.02***	289.11***	289.31	35.46***	-783.69	88.76***	49.87	6.17*
	(92.89)	(120.71)	(11.72)	(67.34)	(170.02)	(20.95)	(847.31)	(36.43)	(36.11)	(4.26)

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

Table 2-7. Spatial and Climatic determinants of cereal acreage land use in Niger (continued)

Variables	Households with rainfed plots					Households with irrigated plots				
	Cereals	Maize	Sorghum	Millet	Rice	Cereals	Maize	Sorghum	Millet	Rice
Diversification Index	10.30***	-18.42***	0.72***	9.56***	2.91***	-0.28	-8.98***	32.60	0.07	10.85***
	(0.18)	(4.17)	(0.17)	(0.47)	(0.93)	(1.72)	(0.88)	(32.32)	(4.00)	(1.00)
Soil wetness	-2.7e-3	0.04**	-2.3e-4***	-0.01	-0.01	-0.03	0.22***	-0.45***	0.42	0.39***
	(0.001)	(0.005)	(1.2e-5)	(0.00)	(0.04)	(0.07)	(0.05)	(0.07)	(0.36)	(0.08)
Soil nutrient	-0.02	-0.05	-0.06	0.01	0.50*	0.28	0.75	-0.84	-1.86	-0.32
	(0.02)	(0.47)	(0.04)	(0.03)	(0.26)	(1.05)	(2.26)	(1.49)	(7.53)	(1.87)
Household Equivalent adults	0.01	0.05	0.01	-0.00	0.02	0.21	0.30	-1.22	1.49	-0.07
	(0.01)	(0.13)	(0.01)	(0.01)	(0.10)	(0.13)	(0.23)	(0.99)	(1.03)	(0.08)
Household head age	-1.4e-3	0.01	2.3e-3	-2.8e-3**	0.02	-1e-3	0.01	-0.18*	-0.15	0.02**
	(0.001)	(0.02)	(0.001)	(0.001)	(0.02)	(0.02)	(0.01)	(0.10)	(0.12)	(0.01)
Total farm acreage	e-3**	-0.02	2.3e-3**	3.5e-4**	6.2e-3	-0.05	0.10	-2.29***	0.69***	-0.20
	(e-4)	(0.02)	(3.1e-4)	(1.2e-4)	(0.01)	(0.03)	(0.14)	(0.23)	(0.17)	(0.15)
Longitude x Latitude	0.01	0.33	0.04**	-0.01	-0.18	-1.32	0.83	-6.18**	-0.33	-0.56
	(0.01)	(0.40)	(0.02)	(0.01)	(0.21)	(1.56)	(5.08)	(2.75)	(1.78)	(1.86)
Constant	454.67	165.90	278.53	106.67***	-260.07	56.71	-53.93	28.95	-423.53	-93.07
	(386.49)	(160.00)	(250.00)	(27.50)	(245.00)	(50.01)	(48.30)	(20.00)	(396.00)	(80.00)
Observations	4,783	4,783	4,783	4,783	4,783	61	61	61	61	61
AIC	3996	55.30	2433	3097	137.4	96	60.50	35.10	32.80	46.70
BIC	4165	139.4	2595	3220	292.7	144.6	102.8	71	62.40	89
Pseudo R2	0.256	0.524	0.0246	0.297	0.334	0.400	0.631	0.941	0.800	0.879
Likelihood-ratio test of rho=0	3689	523.3	306851	1192	19809	7.470e+08	1731	4.370e+07	4.363e+06	9.750e+08
Prob > chi2	0	0	0	0	0	0	0	0	0	0

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

Table 2-8. Expected Price and food demand effect on cereal land use in Niger

Variables	All Households				
	Cereals	Maize	Sorghum	Millet	Rice
Maize Price	-0.24	-16.68***	2.98***	-0.63	3.92
	(0.91)	(5.79)	(1.09)	(0.63)	(4.73)
Sorghum Price	0.58***	-9.85***	18.32***	-1.89***	-4.19
	(0.10)	(3.80)	(2.24)	(0.50)	(5.18)
Millet Price	8.59***	-2.52	-5.13*	30.67***	-3.81
	(3.13)	(4.29)	(2.83)	(7.92)	(6.87)
Rice Price	-1.30	-11.03	-4.71***	0.04	8.89
	(0.83)	(10.98)	(1.26)	(0.86)	(7.99)
Distance to nearest market	4.6e-4	-0.6e-3	0.9e-3	0.5e-3	0.01
	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)
Distance to nearest asphalted road	3.8e-3*	-0.02	2.8e-3	0.6e-3	-0.03*
	(0.00)	(0.02)	(0.00)	(0.00)	(0.02)
Per Capita Food Expenditure	-1.2e-3	-2e-3	3.2e-4	3.6e-4	1.4e-4
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Per capita Income	3.5e-5**	2.4e-5**	-2.6e-4	-1.3e-3	2.3e-4
	(e-5)	(0.00)	(0.00)	(0.00)	(0.00)
Female Head of household (Male = 0)	-0.04***	0.42***	0.03	-0.07**	-0.25
	(0.001)	(0.02)	(0.07)	(0.03)	(0.66)
Access to Irrigation	0.63	-0.42	0.25	-6.45***	3.29***
	(0.46)	(0.74)	(0.75)	(0.92)	(0.70)
Constant	-2.37**	-8.09	1.40	10.41***	-31.13
	(1.18)	(6.06)	(0.89)	(2.53)	(30.10)
Observations	4,844	4,844	4,844	4,844	4,844
AIC	4054	107	2448	3135	160.1
BIC	4123	282.1	2623	3297	335.3
Pseudo R2	0.240	0.726	0.0284	0.297	0.586
Likelihood-ratio test of rho=0	2772	1.921e+06	58564	1343	4.988e+06
Prob > chi2	0	0	0	0	0

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

Table 2.8. Expected Price and food demand effect on cereal land use in Niger (continued)

Variables	Households with rainfed plots					Households with irrigated plots				
	Cereals	**Maize**	**Sorghum**	**Millet**	**Rice**	**Cereals**	**Maize**	**Sorghum**	**Millet**	**Rice**
Maize Price	0.27	-27.78***	3.29***	-0.81	8.76	-66.14*	4.76	120.04	-22.26	-82.10***
	(0.63)	(8.67)	(1.14)	(0.63)	(5.69)	(37.03)	(42.90)	(118.23)	(20.6)	(29.12)
Sorghum Price	1.14***	0.27	16.98***	-1.98***	29.14	-2.54	-10.55***	43.06***	0.37	-13.40
	(0.39)	(19.48)	(2.38)	(0.47)	(32.60)	(4.19)	(2.96)	(7.29)	(0.00)	(13.04)
Millet Price	1.59***	26.15	-0.24	30.47***	-44.02**	2.88	10.47	-14.91	-15.38	7.12*
	-0.05	(30.01)	(1.74)	(8.25)	(21.05)	(7.45)	(283.65)	(12.3)	(13.14)	(4.17)
Rice Price	-1.21**	-0.48	-4.32***	0.03	8.36	56.64**	29.29	30.36	-75.96	27.46**
	(0.57)	(10.51)	(1.24)	(0.80)	(9.83)	(25.12)	(337.90)	(26.3)	(60.3)	(13.07)
Distance to nearest market	6.6e-3**	0.01	1.14e-3	1.4e-3***	0.01	0.04***	-0.04	0.34***	-0.33	-0.07***
	(3.1e-4)	(0.02)	(2e-4)	(1.2e-4)	(0.01)	(0.01)	(0.08)	(0.05)	(0.54)	(0.02)
Distance to nearest asphalted road	4.2e-3***	-0.01	1.4e-3	2.2e-3	-0.03*	0.07**	-0.07	0.21***	0.46	-0.07***
	(3.1e-4)	(0.03)	(2.1e-4)	(1.8e-3)	(0.02)	(0.03)	(0.06)	(0.07)	(0.74)	(0.02)
Per Capita Food Expenditure	1.3e-3***	-3.1e-5	-6.1e-3	3.7e-3***	0.03	-0.4e-3	-0.5e-4	-1.2e-3***	3.3e-3	3e-3
	(2.2e-5)	(2.4e-4)	(5.1e-3)	(2.4e-4)	(0.02)	(0.3e-3)	(0.1e-3)	(3.2e-4)	(3.2e-3)	(2.7e-3)

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

Table 2.8. Expected Price and food demand effect on cereal land use in Niger (continued)

Variables	Households with rainfed plots					Households with irrigated plots				
	Cereals	Maize	Sorghum	Millet	Rice	Cereals	Maize	Sorghum	Millet	Rice
Per capita Income	-2.3e-3***	1.3e-3	-4.5e-3	3.1e-4	8.1e-3	4.1e-3**	5.2e-3**	-2.3e-3***	-3.1e-3	1.5e-3**
	(1.2e-4)	(1.2e-3)	(4.2e-3)	(2.3e-4)	(7.5e-3)	(3.1e-3)	(3.8e-3)	(1.2e-3)	(1.4e-3)	(0.6e-3)
Female Head of household (Male = 0)	-0.06**	-131.52	0.01	-0.07	-0.21	-0.57	0.12	3.15*	-8.87***	-140.28
	(0.03)	(125.2)	(0.07)	(0.05)	(0.64)	(0.64)	(0.45)	(1.68)	(2.03)	(0.00)
Constant	4.46	-6.9	21.58	10.78***	-25.34	7.6	-4.25	18.,27	-12.05	-8.97
	(5.1)	(5.05)	(15.40)	(4.23)	(17.33)	(6.1)	(3.05)	(17.30)	(10.23)	(7.22)
Observations	4783	4783	4783	4783	4783	61	61	61	61	61
AIC	3992	56.4	2432	3108	134.2	94.3	62.5	27.1	36.9	46.8
BIC	4141	147	2588	3263	276.6	140.8	106.8	54.6	70.7	89
Pseudo R2	0.256	0.538	0.024	0.297	0.328	0.396	0.632	0.94	0.796	0.878
Likelihood-ratio test of rho=0	3622	956.2	145827	1340	8173	5370	4096	1270	3370	7950
Prob > chi2	0	0	0	0	0	0	0	0	0	0

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

2.6 Discussion and Conclusion

In this paper, we sought to uncover factors influencing farmers' cereal cropland allocation. We brought three key novelties to the land use literature. First, we made a theoretical contribution by modeling the cropland allocation using the household model framework to show how expectations of prices, rainfall, food demand, and trade are important in the decision-making process. Second, we analytically and empirically showed that the effect of expected price on acreage allocation is a function of cropping system. Third, we empirically added expected prices, trade and expected food demand proxies to the traditional Mendelsohn land use model to improve efficiency of estimates for spatial and climatic variables. We conducted several statistical tests to prove that adding these components improved the Mendelsohn land use model for cereal production.

We used a series of survey waves conducted by World Bank under the Living Standard Measurement Survey, Integrated Survey for Agricultural scheme. The data included three waves for Nigeria (2011, 2013, and 2016) and two waves for Niger (2011 and 2014). Overall, data on 2,500 and 2,100 households were used in this analysis for Nigeria and Niger, respectively. We included climate and price data from external sources in our empirical analysis.

We theoretically derived a model of agricultural cropland allocation to identify factors affecting farmers' cropland allocation. This model combines utility and profit maximization in the household model framework. We analytically derived the effect of weather and price expectations on cropland allocation between two competitive crops. Next, we conceptually explained the ambivalence that can occur when estimating the effect of own price on acreage ratio, due to cropping system and the separability within the household budget model.

Empirically, we used mapping and statistical approaches to uncover the spatial distribution of cereals in both countries. We mapped household average cereal acreage and reported the year-specific mean center for each cereal. In the second step, we statistically used the fractional regression model to estimate spatial and economic determinants of cropland allocation with a fixed-effect panel estimator. We tested and corrected for heteroskedastic error terms to ensure unbiased and efficient coefficients.

Three main findings resulted from our analysis. First, the exploratory maps revealed a geographically heterogeneous distribution of cereal cropland in Nigeria and Niger. Overall, we found millet and sorghum to be northern crops, while maize is cultivated nationwide in Nigeria. Rice is sparsely distributed across the country with some concentration in southeast Nigeria. On a gradient from the south to the north, one could see rice, maize, sorghum, and millet in Nigeria. In Niger, on the other hand, acreage mean centers revealed an east-west distribution since the Agadez region is mostly desert. In Niger, we identified sorghum as a northeast crop.

Second, the estimation of spatial variables revealed sorghum and millet to be northern crops in both Nigeria and Niger. We also found the acreage ratio for maize and rice to decrease as one moves north in both countries, especially for households using rainfed farming. Furthermore, expectations of temperature and rainfall are revealed to partly determine crops acreage ratios. As farmers expect higher heating conditions, cereal acreage allocation drops. However, we found that a higher rainfall expectation tended to cause an increase in the cereal acreage ratio in both rainfed and irrigated farming conditions. In general, we derive from our climatic variables' estimations in Nigeria and Niger that maize and rice are prevalent in wetter regions or under irrigated farming. On the other hand, farmers in both countries mostly substitute maize for sorghum and millet when wetter and hotter conditions are expected. Consequently, the drought and heat tolerance features of sorghum and millet are reflected in the household cropland allocation.

We found the cropping system and crop dominance to confound the effect of price expectations on land use. Our theoretical and empirical models for both countries concur that farmers' response to price expectations depends not only on the household consumption pattern but also on the cropping system that optimally guides crop production. While maize, millet, sorghum, and rice are grown in both countries, maize and millet are dominant because they respond to the subsistence feature of most farming households. This is in accordance with Ekpo (2007) and FAO (2018), who reported that maize, millet, and sorghum are mostly produced in West Africa for subsistence, while rice is grown both for food and cash. Also, our investigation uncovered maize as the most mono-cropped food plant in Nigeria. On the other hand, we found millet and sorghum to be the main food crops competing for monoculture in Niger. Consequently, expected maize price in Nigeria, and millet and sorghum prices in Niger, positively drive cereal acreage share in both countries. This is in accordance with the findings of Chavas and Holt (1990) and Lin and Dismukes (2007) in the case of maize and soybeans grown under monocropping in the United States. Because Nigeria and Niger are predominantly subsistence farming economies, these results show that farmers respond primarily to the prices of the dominantly-consumed cereal.

Furthermore, our findings imply that land use modeling in the household economic framework is relevant to uncovering the decision-making process. Prices, household characteristics, demand, and access to trade are additional factors to control for an efficient estimation of acreage allocation to crops. Expected household food expenditures, the proximity to a market or an asphalted road, and household income or purchasing power are important factors that determine the weight of consumption and food price signals. One caveat here is the necessity for future studies to include producer prices instead, especially if these prices are available.

In summary, our findings contribute to crop suitability geo-mapping and can help improve farm productivity with crop-specific targeting programs. More specifically, the introduction of more drought-tolerant sorghum and millet varieties may enhance efficiency in cropland allocation in northern and eastern Nigeria and Niger. Efforts for maize production enhancement in Nigeria may focus on the southern and central regions to account for the climate-induced regional comparative advantage. Furthermore, our findings could be incorporated into a land use framework for planning, environmental monitoring, scenario analysis, and impact assessment. More specifically, this investigation provides key evidence for the Nigerian incentive-based risk sharing system for agricultural lending (NIRSAL) in its geo-referenced cooperative approach (NIRSAL, 2020). The evidence for the nationwide cereal land use provided by our investigation serves the NIRSAL's goal to foster farmers' cooperatives based on spatial and cropping features for maize, sorghum, millet, and rice. Based on the spatial distributions of the studied staples, NIRSAL may build region or district-specific agribusinesses based on crop-specific niches.

With these findings, future work should further examine cropland use under a broader production scope. That is, it will be important to consider all crop combinations in effect in order to assess production efficiency. The goal of such an investigation could be to uncover alternative methods of more effective geographically-referenced production land allocation. Future research could also track crop productivity through yield and under heterogeneous climatic, economic, and social conditions. Finally, this analysis highlights the need for additional research estimating the cost differentials of different land use scenarios, especially in Sub-Saharan Africa.

Chapter 3 - Staple Foods Demand and the Impact of Food Price Change on Welfare

3.1 Introduction

Aggregate consumption responsiveness to price and income changes is measured using the price and the income elasticities of demand. Knowing the elasticities of demand is essential to anticipating the welfare impact of price shocks and financial instruments of policy, such as subsidies, cost sharing schemes, and taxation. Also, understanding household demand for food staples is essential to addressing the introduction of new agricultural technologies and their implications for food security (Mittal, 2010).

In this third chapter, we first conduct demand analyses for maize, millet, rice, sorghum, and cassava flour to shed light on household-level tradeoffs among grains and starchy foods in Niger. Second, we conduct a budget share analysis for each staple to provide insight into how households allocate their food budget across staples. Third and last, we simulate a short-term welfare effect of a millet and sorghum price shock. Overall, this study aims to identify household food consumption behavior and fill in the knowledge gap in the cereal demand and welfare analysis literature for Niger.

We empirically conducted our analysis using the 2011 and 2014 LSMS-ISA data, a nationally-representative sample of households in Niger. Our analysis revealed that maize, rice, and sorghum are luxuries, while millet is a necessity for an average national consumer. We found rice demand to be the most sensitive to income changes in rural areas. Our results also show that additional income for both urban and rural households will be mainly spent on either rice or sorghum. The demand responsiveness is greater for rural households, which is consistent with the higher poverty rate in rural areas of the country.

Based on own-price elasticity estimation, we found both urban and rural consumers to be more price-responsive to cassava flour, maize, and millet. Furthermore, cross-price elasticities, in combination with a budget share analysis, revealed millet as the most consumed grain. Compensated and uncompensated cross-price elasticities reveal sorghum as the closest substitute for millet. In addition, we found urban households to have a more diversified cereal diet in comparison to their rural counterparts.

The welfare analysis showed that millet price change affects households more than sorghum price change since millet is the most consumed staple. A 20% increase of the millet price produces a 5.88% overall welfare loss. We also found an increase in millet price to adversely affect 97% of households, with the majority living in urban areas. Farming households that are net sellers of the crop, and who make 5% of the farming households, are the only beneficiaries of such a price increase. On the other hand, a change in sorghum price of the same magnitude reduces the welfare by only 4.38% making 57% of households worse off. In general, most urban households are negatively affected by the millet and sorghum price shock.

The remainder of the paper is organized as follows. In Section 2, theoretical underpinnings of the model are discussed, and the model is delineated. Estimation strategies are also considered. Section 3 describes the data and summarizes food consumption patterns in Niger. Results of the estimation procedures are presented and discussed in Section 4. Section 5 presents the welfare impact of a millet and sorghum price change. The last section, Section 6, provides concluding remarks.

3.2 Background

Previous empirical studies on household food demand in African countries are rather narrow. Differences in dietary patterns and food supply structures across regions induce heterogeneous relationships between income, price, and food demand across the continent. Though several studies have focused on food item elasticity estimation at continental level (Abdulai and Aubert 2004; Case, 1998; Colen et al., 2018; Dockel and Groenewald, 1970; and Melo et al., 2015), In addition, the studies of household food demand in Niger are limited. To the best of our knowledge, only a working paper by Cheng and Larochelle (2017) used the 2011 World Bank Living Standard Measurement Study data to compute expenditure, own-price, and cross-price elasticities for food groups and staples in Niger and Nigeria. These authors found that when cross-price elasticities are significant millet, sorghum, rice, and maize are substitutes.

Whereas Zheng and Larochelle (2017) used a three-stage demand model on the aggregated food categories and food staples, our investigation focused on the food staples demand system and welfare analysis. We sought to estimate the effects of price and income changes on consumer demand for major cereals. We incorporated household characteristics into the demand system to account for heterogeneous demographic and economic characteristics. Previous demand analysis by Theil (1952) and Cox and Wohlgenant (1986) revealed that larger families generally pay lower average prices because of economies of size in purchasing and household economic activities. We fit a Linear approximation of the Almost Ideal Demand System (LA-AIDS) model to consistently estimate income and price elasticities for each commodity. We used the estimated elasticities to conduct a welfare analysis of millet and sorghum price change.

Staple foods in Niger include cereals: millet, maize, sorghum, rice, and also starchy foods, especially cassava flour. These staples are the main source of calories for both urban and rural households. Based on Food and Agricultural Organization of the United Nations data, millet is the most-consumed cereal in Niger, followed by sorghum. In 2013, the per capita annual consumption was 313.6 kg and 115.7 kg for millet and sorghum, respectively. After millet and sorghum, rice, cassava, and maize are the next most-consumed cereal with 27.3 kg, 16.5 kg, and 7.5 kg, respectively (Faostat, 2020). Figure 3.1 shows the growth in per capita consumption of these staples. One can observe a constant trend in millet and sorghum consumption.

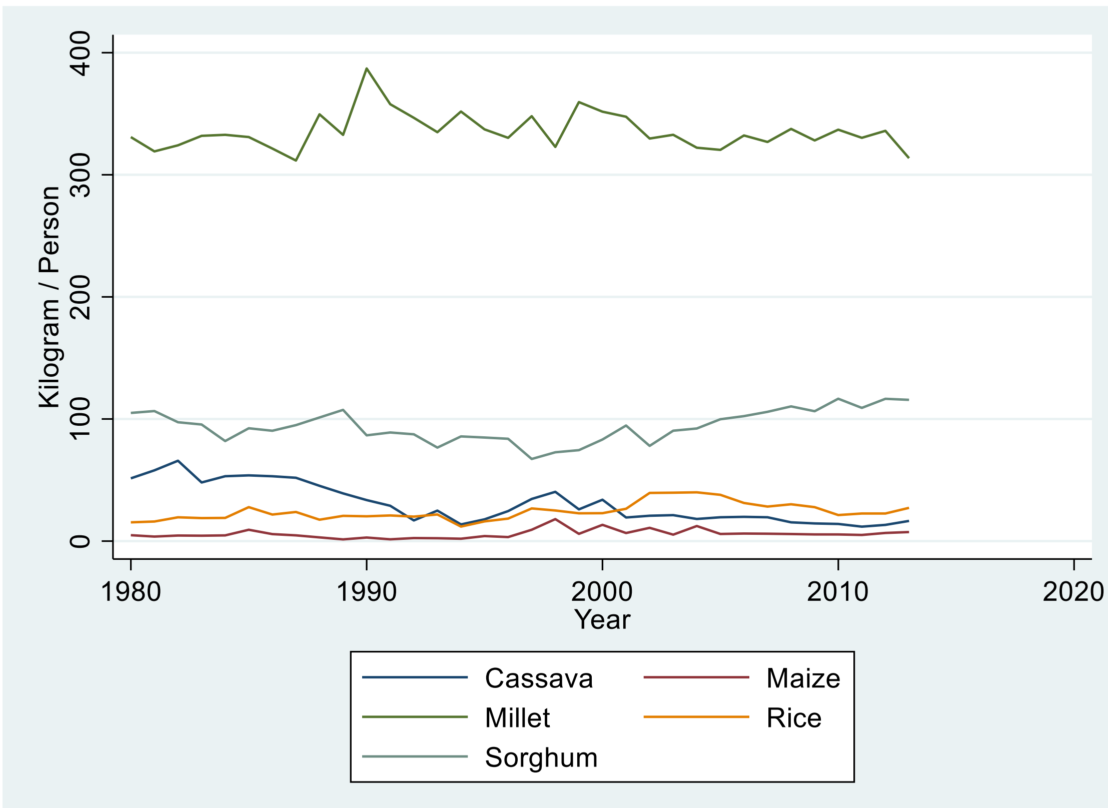

Figure 3-1 Per capita staple consumption in Niger over the period 1980-2013

Source: Faostat, 2020

Cereals account for 61% of the caloric intake in Niger, with millet and sorghum as the most-consumed cereals (Internationale, 2009). However, with urban population growth, household spending on grains other than millet and sorghum is increasing. Urban households spend more on rice, maize, and wheat than millet and sorghum (MAE NIGER, 2016). Conversely, in rural areas, where households live upon agriculture, they mainly grow millet, sorghum, and rice for self-consumption (FAO, 2014). Estimating cereal demand elasticities is relevant from consumption, production, and welfare analysis perspectives.

3.3 Linear Approximated Almost Ideal Demand System (LA-AIDS) Model

A complete demand system is required for a robust estimation of demand for food grains that generally compete with other foods and consumer items for household budget allocations. An important factor to consider in such an investigation on demand systems is the choice of a consistent functional form that accounts for specific observed consumer behavior. The principles of demand theory, such as adding up homogeneity and symmetry restrictions, along with practical criteria of fit determine the functional form selection. A widely-used model in applied demand analysis is the Linear approximation of the Almost Ideal Demand System (LA-AIDS) of Deaton and Muellbauer (1980). Because of this model's theoretical consistency, we use it for this study, assuming weak separability of demand that allows removing non-food commodities from the estimation. The estimates derived were cross-checked with the Quadratic AIDS (QUAIDS) and the Rotterdam models for robustness.

Often, analyses of household food demand using cross-sectional survey data have faced criticism about whether using cross-sectional price variations to identify a demand system and derive consistent elasticities is appropriate. Prais and Houthakker (1955) suggested that variation in region, price discrimination, seasonality, and quality effects are main drivers of the cross-sectional variations in prices. Since this paper deals with staple foods, we assume relatively little quality variation for maize, millet, rice, sorghum, and cassava in Niger. Other seminal papers on demand analysis argue that price variations from regional and seasonal differences allow for a more accurate estimation of price elasticities and are thus desirable for demand analysis (Cox & Wohlgenant, 1988; Deaton, 1988). The seasonal and regional dummies were included in the model specification following Deaton (1997).

Empirically, the LA-AIDS is based on the Seemingly Unrelated Regression (SURE) specification since the shares of the expenditure sum to one (adding up restriction). As a result, the variance-covariance matrix is singular (Gostkowski, 2018; Poi, 2012; Wolak, 2008). In such a case, one equation is dropped, and the model is estimated. The coefficients of the dropped commodity are then recovered indirectly. The Iterative Feasible Generalized Least Squares approach was used for estimation.

Since the households' choice to purchase a food item is endogenous due to self-selection, income and price elasticities cannot be consistently estimated. To correct for such endogeneity in the LA-AIDS demand system, inverse Mills ratios (IMR) were constructed following Saha et al. (1997). A reduced-form purchase choice equation for each cereal food was estimated using the Probit model to obtain an unbiased estimate of the inverse Mills ratios. With these estimates in hand, sample selection-corrected performance equations were estimated using the Seemingly Unrelated Regression estimation approach.

It is assumed that cereal grain consumers in Niger maximize their utility subject to a linear budget constraint. The consumer's expenditure function is consistent with utility maximization and defined by Deaton and Muellbauer (1980) as follows:

$$\ln C(U,P) = \alpha_0 + \sum_i \alpha_i \, lnP_j + \frac{1}{2}\sum_i \sum_j \alpha_{ij} \, lnP_i lnP_j + U \prod_i P_i^{bi} \quad (1)$$

Where P is a price vector and C (U, P) is concave in P, non-decreasing in P, homogeneous of degree one in P, and increasing in U; C is the expenditure function concave and homogeneous of degree one in P, continuous in P and U, strictly increasing in U and non-decreasing in P_i for any commodity i; and U is the continuous utility function representing a locally-nonsatiated preference relation.

Employing Shepard's Lemma, we derive the consumer's budget shares from the cost function and specify the Almost Ideal Demand System (Deaton, 1980), which can be written as:

$$W_i = \alpha_i + \sum_j \gamma_{ij} \, lnP_j + \beta_i \ln(x/P) \quad (2)$$

where, W_i is the budget share of good i, P_j is price of good j, and X is the total expenditure. In addition, P is the price index of all goods in the model defined by:

$$lnP = \alpha_0 + \sum_k \alpha_k \, lnP_k + 1/2 \sum_k \sum_l \alpha_{kl} \, lnP_k lnP_l \quad (3)$$

In order to address the nonlinearity in the model estimation, Deaton and Muellbauer (1980) proposed the use of Stone's index as a linear approximation of the P in (3). It follows that P takes the form:

$$lnP = \sum_i w_i lnP_i \quad (4)$$

In this model, the adding-up restrictions are defined as:

$$\sum_k \alpha_k = 1 \, ; \sum_k \beta_k = 0 \, ; \; \sum_k \gamma_{kj} = 0 \quad (5a)$$

Homogeneity requires:

$$\sum_k \gamma_{kj} = 0 \quad (5b)$$

And symmetry is satisfied if

$$\gamma_{ij} = \gamma_{ij} \quad (5c)$$

The LA-AIDS model satisfies the axioms of choice exactly. It allows consistent aggregation of individual consumers' demand functions at the market level. In addition, the model does not require additive preferences (Eales & Unnevehr, 1988). Using the Stone's price index, defined in equation (3), together with restrictions (5a), (5b), and (5c), we write the equation (2) as linear in parameters.

The LA-AIDS provides a good approximation of the food grain demand based on its flexibility and previously-mentioned proprieties. In addition, the model allows for the addition of the socio-demographic, economic, and geographic characteristics that matter in the context of the food demand analysis in Niger (Nakelse et al., 2018). Including the socio-demographic characteristics of the household in the LA-AIDS yields:

$$W_i = \alpha_i + \sum_j \gamma_{ij} \, lnP_j + \beta_i \ln(x/P) + \beta F + \mu_i \tag{6}$$

Where F is the vector of socio-demographic, economic, and geographic and μ_i is the staple specific residual term.

Elasticities Estimation

The expenditure elasticity of the LA-AIDS model is given by:

$$e_i = \frac{\beta_i}{w_i} + 1 \tag{7}$$

The uncompensated price elasticity is computed as:

$$e_{ij} = \frac{\gamma_{ij} + \beta_i w_j}{w_i} - \delta_{ij} \tag{8}$$

where δ_{ij} is the Kronecker delta that is set equal to one for the own-price elasticity (i.e i=j) and zero for the cross-price elasticity (i.e. $i \neq j$). The elasticities are computed at the mean values of the expenditures shares (Gustavsen & Rickertsen, 2014).

Adjusting Unit Values

The current analysis is based on survey data where clusters of households in each community are surveyed within a short period. The information requested was to recall the consumption of a wide variety of food items (125) in the seven days prior to each visit. The community survey includes a food price module that collected the prices of thirty-seven items from three sales locations in each community. However, because the commodity prices collected the at community level are based on varieties, while the household-level consumption does not identify varieties, we grounded the analysis on unit values. A common practice for calculating values is to divide commodity expenditures by the corresponding quantities purchased.

Observed differences in unit values are due to choices of quality by each household, which in turn depends on household income and preferences (Deaton & Muellbauer, 1981). Unit values can also be influenced by quantity since households that buy in large quantities usually receive lower prices. According to Deaton (1988), inferior quality products having lower prices crowd out substitutes of superior quality and higher prices. That action leads to lower variability in unit values compared to exogeneous market price variabilities. As a result, use of unit values in the demand model exaggerates household responses to prices. Based on these claims, Deaton (1988) addressed the endogeneity of unit values by regressing the logarithmic unit value on the logarithmic total household expenditure and other household characteristics.

In addition, high transaction costs in Niger lead to important spatial price differences (Shin, 2010). In the case of stratified and clustered surveys of households interviewed within a short period of time, it is reasonable to expect that all households in the same cluster face the same price. Based on this assumption, community dummy variables are included as covariates and their coefficients are taken as a proxy for the market prices for households reporting zero consumption of any of commodities.

Following Deaton and Muellbauer (1981) and Cox and Wohlgenant (1986), a model was estimated to obtain household adjusted prices for each of the five staple food items that are immune to quality and quantity bias:

$$lnP_{ki} = \alpha_{ko} + \alpha_{k1} lnx_i + \alpha_{kz} Z' + \alpha_{kv} V_i + \alpha_{ku} U_i + \varepsilon_{ki} \qquad (9)$$

where, lnP_{ki} is the logarithmic unit value of item k reported by household i; lnx_i is the logarithm of household i's per capita real expenditure; Z' is the vector of household socio-demographic variables: household size, gender, marital status, age, and education of household-head. Vectors V and U represent binary variables that control for price differences between two visits and between clusters, and ε_{ki} are residuals.

The quality-adjusted prices derived from utilizing equation (9) are inconsistent with the hypothesis that households in the same market face the same prices. Therefore, the communal median quality-adjusted prices are used as corrected prices in the LA-AIDS model. Instead of finding averaged communal price, the median was used to purge potential outlier price effects.

3.4 Data and Data Processing

We used data collected under the Living Standards Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA) of the World Bank for model estimation. Two waves of the 2011 and 2014 survey data were compiled. During each wave of the survey, data were collected on the weekly recall of food purchases for each household. The 2011 survey included 3,859 households: 2,343 rural and 1,516 urbans. The 2014 survey included 2,143 rural and 1,219 urban households, a total of 3,362. Both 2011 and 2014 data are representative of urban and rural areas. For each survey year, household heads were interviewed at post-planting and post-harvest periods in order to capture any potential seasonality of food consumption patterns.

The typical sampled household has a 47-year-old male head of household (82.58%) and includes 5.42 adult equivalents. More than 75% of household heads have not attended school higher than the primary level. The average income is 33,8431 CFA francs ($675), about 40% of which goes toward food expenditures. In general, urban, and rural households differ in terms of demographic and economic characteristics. On average, while sampled urban households are larger than their rural counterparts, rural household heads are more likely to be male. Also, urban household heads tend to have completed higher education and tend to earn a relatively higher income. Overall, characteristics of the sampled households follow the general trends in Niger as reported by Serra (2015).

At the national level, 85.5% of households have reported millet consumption, followed by rice (75%) and maize (45%). Millet is also the most-consumed cereal in rural areas (97% of households), while in urban areas rice is the most-consumed cereal (93% of households). While 33% of rural households reported having consumed sorghum, only 8% of urban households reported having done so.

About half of the food budget is spent on staples, and the consumption of those staples differs between rural and urban areas. Among the five staples, millet has the largest food budget share in rural Niger (18.41%). However, rice shares the largest part of the urban household food budget (14.10%). Sorghum is consumed more often in rural households (7.96%) than in urban households (4.70%). Overall, the structure of consumption of the sampled households is consistent with the national agricultural production of the staple crops. According to Serra, (2015) millet occupies almost one-third of cultivated land.

Table 3-1 Staples share of food Budget and Prices in Niger

Food items	National				Urban				Rural			
	% HHs consuming	Budget shares (%)			% HHs consuming	Budget shares (%)			% HHs consuming	Budget shares (%)		
		Mean	Median	SE		Mean	Median	SE		Mean	Median	SE
Maize	45.72	12.7	10.21	8.75	59.18	10.07	7.9	7.53	37.11	14.47	12.67	9.11
Millet	85.51	14.7	11.31	12.98	67.48	9.17	7.23	7.76	97.01	18.41	15.29	14.42
Rice	70.57	13.61	12.96	7.44	92.74	14.10	12.89	6.79	56.28	13.28	13.00	7.88
Sorghum	23.77	6.65	5.16	5.77	8.35	4.70	4.02	3.17	33.34	7.96	6.13	6.71
Cassava flour	40.06	3.31	2.79	2.60	47.82	2.71	2.29	1.93	35.21	3.72	3.13	2.91
		Prices (FCFA/Kg)				Prices (FCFA/Kg)				Prices (FCFA/Kg)		
Maize		181	167	46		178	167	29		183	170	54
Millet		176	167	72		185	167	74		169	167	70
Rice		479	500	116		502	500	49		464	500	143
Sorghum		151	150	62		159	150	69		147	133	58
Cassava flour		441	300	274		477	350	280		417	300	270

Table 3-2 Summary statistics of demographic and economic covariates

Variables	National			Urban			Rural		
	Mean	**Median**	**SE**	**Mean**	**Median**	**SE**	**Mean**	**Median**	**SE**
Equivalent adult (unit)	5.42	4.55	3.04	6.58	5.62	3.46	4.65	3.93	2.46
Household age (Year)	47.21	47.50	13.71	50.17	49.00	12.38	45.23	42.00	14.27
Gender of household head									
Male (%)	82.58			75.47			87.34		
Female (%)	17.42			24.53			12.66		
Household head education									
Maximum primary school (%)	75.76			64.15			83.54		
Higher than primary school (%)	24.24			35.85			16.46		
Annual food expenditure (FCFA)	134101	119697	73948	152801	129446	84174	121555	108958	63747
Annual nonfood expenditure (FCFA)	80563	55646	76202	125315	94362	96458	50538	41614	35715
Income (FCFA)	338432	316973	173930	368532	329820	223897	318238	290581	127902

Note*:* 1 USD equals 452.64 and 478.88 CFA francs in July 2011 and 2014, respectively (based on estimation by x-rates.com/historical)

3.5 Results and Discussion

In this section, we first report and discuss the demand model specification. Second, we present the estimated income, own price, and cross-price elasticities for maize, millet, rice, sorghum, and cassava flour in tabular form (see Tables 3.3 – 3.6). Separate models defined for rural areas, urban areas, regions, and income quintiles, based on the assumption that food consumption patterns are heterogeneous due to differences in food preferences and food availability, were estimated. Third, we report and discuss the marginal effects of household characteristics on budget shares. And last, we report, discuss, and draw policy recommendations of welfare effects of millet and sorghum price change.

3.5.1. Model Specification Tests

The Wald test for joint significance of the lambda (λ) parameters was conducted in order to choose from among the model specifications initially considered. Based on the test results, the λ parameters are jointly significant at the 1% level for all the five food items in the LA-AIDS model. However, the λ parameters are jointly significant only for maize, rice, and millet in the QUAIDS model. The linear AIDS specifications offer good flexibility in accounting for socio-demographic, economic, and geographic variables in the estimation. These findings support using an LA-AIDS specification over the others. The LA-AIDS model uses the seemingly unrelated estimation approach provided by the reported estimates shown in the tables. Both the QUAIDS and Rotterdam models were used to obtain estimates as a check of robustness.

3.5.2 Expenditure Elasticities

The expenditure elasticities are positive and significant at the 1% level in all cases. Based on their magnitudes, the expenditure elasticities reveal that maize, rice, and sorghum are luxuries (expenditure elasticity > 1) for a typical national consumer. That is, the demand for these commodities increases more proportionally than an income increase. Millet and cassava are necessities (expenditure elasticity < 1) for households. Millet, the main staple in Niger, is a normal good for all consumers.

Households in rural areas have higher expenditure elasticities than those in urban areas for the selected food commodities, except for sorghum. Thus, as income rises, rural households are likely to purchase more maize, millet, rice and cassava and less sorghum than are urban households. While maize, rice, and sorghum are luxuries for rural consumers, only rice and sorghum are revealed as luxury items for their urban counterparts. Maize and millet are necessities for urban consumers while only millet is shown to be a necessity for rural consumers. In both urban and rural areas, future growth in per capita income will generate an increase in demand for all staples. In urban areas, the growth in demand is expected to be higher than the income growth for sorghum and rice. In rural areas, the growth in demand is expected to be higher than the income growth for rice, sorghum, and maize.

The food demand and consumption patterns are also shown to be somewhat different across regions. The income elasticities of maize, millet, rice, sorghum, and cassava are the highest in Tahoua, Niamey, Diffa, and Dosso, respectively. Millet is found to be a necessity in all regions, while sorghum is found to be luxury in all regions. We found rice to be a necessity only for a Niamey consumer, while cassava is shown as a luxury in Tillaberia and Niamey. The general pattern shows millet and cassava demands to be relatively income-inelastic, while rice and sorghum have income-elastic demands in most regions. Overall, households in all regions tend to prefer to buy more rice and/or sorghum rather than millet as their incomes rise.

Regarding the expenditure quintiles, the poorest 20% of rural and urban households have relatively higher expenditure elasticities for rice and sorghum than other groups. Interestingly, the mean expenditure elasticity for rice and maize of the poorest group is higher than that of the richest group. Poorer households in rural and urban areas tend to increase their consumption of rice, sorghum, and cassava when their incomes rise more so than wealthier households. In fact, except for maize and millet, the expenditure elasticities of the poorest 40 % of households are greater than one for all the other staples. Meanwhile, for the richest 20%, only sorghum has an expenditure elasticity that is greater than unity. Also, farmers have a higher income elasticity of demand for maize and rice than non-farmers.

The findings presented, with respect to observed differences across groups and areas, are consistent with the concentration of chronic poverty and impoverishment in rural areas as reported by USAID (2018). On the other hand, the income elasticity for sorghum is higher for urban consumers. Because sorghum is gluten free and rich in phosphorus and potassium, households may increase their demand for this cereal as their incomes increase.

Our estimated expenditure elasticities are consistent with those found in the literature. Cheng and Larochelle (2016) used the 2011 LSMS data to estimate income elasticities in Niger and found that sorghum (1.13), rice (1.06), and maize (1.04) are luxuries for rural consumers. Nevertheless, these authors found all staples to be necessities for urban consumers.

Based on these previous findings, poverty levels, and given that diets in Niger are highly based on starchy foods, we argue that the reported expenditure elasticities capture staple demand patterns of households. Engel's Law suggests that consumers tend to allocate proportionally more of their additional income to non-food items as they become richer, although the reduction in the food budget share is not linear and occurs when households have reached a saturation point in calorie consumption (Colen et al., 2018; FAO, 2015; Norwood & Lusk, 2008). Studies have also reported significant differences in dietary patterns and food supply as well as demand structures across regions in Africa, supporting the heterogeneity in the reported income elasticities (Fabiosa, 2012).

Table 3-3 Expenditure elasticities of staple foods in Niger

Food items	Maize	Millet	Rice	Sorghum	Cassava flour
National (LA AIDS)	1.017***	0.834***	1.274***	1.120***	0.961***
National (QUAIDS)	1.106***	0.701***	1.143***	1.025**	0.563**
National (Rotterdam)	1.08***	0.729***	1.221***	1.045***	0.621***
Urban vs Rural					
Urban	0.801***	0.850***	1.097***	1.223***	0.610***
Rural	1.016***	0.904***	1.319***	1.107***	0.950***
Region					
Agadez	1.155***	0.924***	1.272***	1.178***	0.924***
Diffa	1.113***	0.805***	1.390***	1.206***	0.949***
Dosso	0.870***	0.873***	1.354***	1.260***	0.973***
Maradi	1.067***	0.806***	1.355***	1.030***	0.948***
Tahoua	1.228***	0.783***	1.370***	1.005***	0.961***
Tillaberi	0.970***	0.714***	1.322***	1.183***	1.002***
Zinder	1.079***	0.721***	1.342***	1.055***	0.976***
Niamey	0.826***	0.992***	0.998***	1.226***	1.018***
Rural Income quintiles					
Quintile 1	1.072***	0.431***	1.421***	1.218***	1.068***
Quintile 2	0.908***	0.499***	1.436***	1.223***	1.070***
Quintile 3	0.910***	0.543***	1.463***	1.167***	1.061***
Quintile 4	0.907***	0.611***	1.390***	1.194***	1.050***
Quintile 5	0.880***	0.626***	1.315***	1.139***	1.060***
Urban Income quintiles					
Quintile 1	0.783***	0.718***	1.169***	1.247***	1.030**
Quintile 2	0.743***	0.737***	1.154***	1.451***	1.012***
Quintile 3	0.691**	0.727***	1.084***	1.354***	0.998***
Quintile 4	0.746***	0.929***	0.957***	1.301***	0.978***
Quintile 5	0.778**	0.924***	0.929***	1.262***	0.905**
Profession					
Farmer	1.107***	0.733***	1.377***	1.135***	0.986***
Non-farmer	1.038***	0.921***	1.270***	1.134***	0.921***

Note: LA-AIDS is the base model. Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Number of observations: 14,419 Log-likelihood = 663.76. The QUAIDS and Rotterdam models are used for robustness check.

3.5.3 Compensated and Uncompensated Elasticities of Own-price and Cross-prices

Uncompensated (Marshallian) demand functions describe the link between utility and prices, given wealth. Marshallian elasticities describe how demand responds when prices change, holding money income constant. On the other hand, the compensated (Hicksian) demand function focuses on the link between expenditure and price, while keeping utility constant. Thus, Hicksian highlights how demand reacts when prices change, holding "real income" or utility constant. The compensated elasticities capture only the substitution effects of changes in prices; the uncompensated elasticities encompass both the substitution and the income effects induced by the changes.

Table 3-4 summarizes the Marshallian and Hicksian price elasticities at the national level. Recall that the own-price elasticity reflects changes in the purchased quantity of a commodity, with changes in that commodity’s price, while a cross-price elasticity reflects changes in demand for a commodity when the price of another product fluctuates. All own-price elasticities are negative, so the implication is that staple demand in Niger follows demand theory. The quantity demanded decreases as the commodity’s own price increases. The absolute values of estimates are utilized when discussing own-price elasticities magnitudes. For the five products studied, we consider both own-price elasticity and cross-price elasticity of demand.

Holding the utility constant when prices increase, sorghum is the most inelastic staple. On the other hand, when prices increase when household income is held constant, sorghum is the least elastic staple. The compensated and uncompensated own-price elasticity of rice and cassava are greater than 1, indicating that these staples have elastic demand in Niger. That is, for a 1% increase in the rice or cassava price, household demand for the commodity decreases by more than 1%.

Based on estimated compensated and uncompensated cross-price elasticities, millet, sorghum, and cassava flour are substitutes for maize when the cross-price elasticities are significant. Households in Niger consume a large quantity of millet, and they switch from millet to either maize or sorghum when the millet price increases. In addition, most of the significant cross-price elasticities for sorghum and rice are close to zero. That result suggests the demands for sorghum and rice are mainly influenced by their own price since substitution or complementarity relationships with other items is weak.

Table 3-4 Marshallian and Hicksian price elasticities for staple food items in Niger

	With respect to the price of				
	Maize	Millet	Rice	Sorghum	Cassava flour
	Uncompensated (Marshallian) price elasticities				
Maize	-0.665***	0.00680***	-0.493***	-0.122***	0.190***
	(0.0174)	(0.00243)	(0.0274)	(0.00696)	(0.00998)
Millet	0.00510	-0.685***	-0.299***	0.0132***	-0.124***
	(0.00510)	(0.0164)	(0.0186)	(0.00194)	(0.00682)
Rice	-0.427***	-0.272***	-1.145**	-0.126***	-0.0276***
	(0.0343)	(0.0226)	(0.0684)	(0.0100)	(0.00219)
Sorghum	-0.183***	0.106***	-0.235***	-0.455***	-0.0448***
	(0.0110)	(0.00615)	(0.0142)	(0.0306)	(0.00270)
Cassava flour	1.006***	-0.587***	-0.0986***	-0.113***	-1.025***
	(0.0885)	(0.0526)	(0.00949)	(0.00972)	(0.00236)
	Compensated (Hicksian) price elasticities				
Maize	-0.408***	0.300***	-0.177***	0.0181**	0.266***
	(0.0117)	(0.0134)	(0.0262)	(0.00815)	(0.0119)
Millet	0.268***	-0.401***	0.0261**	0.154***	-0.0475***
	(0.00985)	(0.0106)	(0.0106)	(0.00669)	(0.00727)
Rice	-0.184***	-0.00227	-1.143**	0.00187	0.0414***
	(0.0324)	(0.0200)	(0.0616)	(0.0117)	(0.00491)
Sorghum	0.0136	0.321***	0.000237	-0.346***	0.0116**
	(0.0138)	(0.00968)	(0.0175)	(0.0264)	(0.00489)
Cassava flour	1.205***	-0.371***	0.142***	-0.0128	-0.963***
	(0.0856)	(0.0558)	(0.0172)	(0.0123)	(0.00583)

Note Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

To have a better understanding of the demand of staple foods in Niger, we examine the price elasticities for different geographic and income groups by estimating separate regressions for these groups. This information is important for policymakers as they consider how potential food policies might affect different groups. Tables 3-5 and 3-6 present the Marshallian and Hicksian price elasticities for different household groups, respectively.

The Marshallian own-price elasticities indicate that urban demand is more price-elastic for maize, millet, rice, and cassava flour but less price-elastic for sorghum. Geographically, households in Maradi have the highest price elasticity for rice, while Niamey, the capital city, exhibits the lowest. In general, households in Agadez (maize), Tahoua (millet), Tillaberi (rice and cassava), and Zinder (sorghum) are the most price inelastic.

In both rural and urban areas, when the prices of staple foods increase, the poorest quintile is most likely to cut their corresponding food consumption since their demand for such foods is the most price-elastic. Because the staple foods are the basic diet for most households in Niger, poor households are vulnerable to food price increase. Similarly, farmers tend to reduce their share of staple foods consumption (more so than non-farmers) as the prices of these foods increase.

Table 3-5 Disaggregated Marshallian own-price elasticities for staple food items in Niger

Food items	Maize	Millet	Rice	Sorghum	Cassava flour
Urban vs Rural					
Urban	-2.073***	-2.416**	-1.262**	-0.552***	-1.925***
Rural	-0.465**	-0.568***	-1.156**	-0.708***	-0.993**
Regions					
Agadez	0.602	-2.674***	1.05**	-0.987***	-2.702*
Diffa	1.324**	-1.717**	-1.572*	-.823*	-1.915***
Dosso	-2.290***	-3.415***	.886**	-1.695***	-1.659**
Maradi	-3.650***	-1.887***	2.339***	-1.87***	-4.017***
Tahoua	-.413***	-1.046***	-0.709*	-2.442***	-2.275**
Tillaberi	-1.508**	-2.909***	-.475	-1.195***	-1.164***
Zinder	-1.947***	-4.998***	2.164***	0.805	-2.624***
Niamey	-1.387***	-1.526***	-0.629**	-0.511***	-2.040***
Rural Income quintiles					
Quintile 1	-0.990**	-.820***	-2.344***	-1.356	-2.812***
Quintile 2	-0.987	-0.745*	-2.182***	-1.204***	-2.383***
Quintile 3	-0.880**	-0.626*	-1.517***	-0.661	-1.946***
Quintile 4	-0.675**	-0.383***	-1.249***	0.012	-1.345***
Quintile 5	-0.560*	-0.376**	-1.650***	-0.523**	-1.257***
Urban Income quintiles					
Quintile 1	-3.001***	-4.716***	-4.289***	-.575***	-2.286***
Quintile 2	-2.939***	-5.406***	-2.714***	-.529***	-1.567***
Quintile 3	-3.079***	-4.924***	-2.197**	-.497***	-1.381***
Quintile 4	-1.057	-2.979***	-1.380***	-.479***	-1.330***
Quintile 5	-.182	-1.045	-.708	-.373***	-0.853***
Profession					
Farmer	-1.658***	-2.45***	-1.708**	-1.339***	-2.292***
Non farmer	-1.242**	-1.964***	0.123**	-0.578**	-2.127***

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Quintiles are in increasing order. That is, the 1st quintile includes the poorest 20% of households, while the 5th quintile encompasses the 20% of wealthier households

Table 3-6 Disaggregated Hicksian own-price elasticities for staple food items in Niger

Food items	Maize	Millet	Rice	Sorghum	Cassava flour
Urban vs. Rural					
Urban	-1.878***	-2.233**	-0.901**	-0.428**	-0.789***
Rural	-0.261**	-0.378***	-0.888***	-0.55**	0.185
Regions					
Agadez	0.784	-2.302***	1.351	-0.866**	-1.679*
Diffa	1.55	-1.416**	-1.855	-0.698*	-1.850***
Dosso	-2.001***	-3.213***	-1.144**	-1.542***	-1.562***
Maradi	-3.386***	-1.666***	2.622***	-1.718***	-2.935***
Tahoua	-.208	-2.770***	0.992**	-2.285***	-2.196***
Tillaberi	-1.247***	-1.702**	-.228	-1.042***	-1.032**
Zinder	-1.730***	-4.791**	-2.480***	0.958*	-3.516***
Niamey	-1.201***	-1.339***	-0.259**	-0.386***	-.907***
Rural Income quintiles					
Quintile 1	-0.787	-0.676***	-2.086***	-1.172	-2.601***
Quintile 2	-0.601	-.980	-1.913***	-1.025***	-2.182***
Quintile 3	-0.583*	-0.444	-1.839**	-0.500	-1.764**
Quintile 4	-0.471	-0.430**	-1.770***	0.163	-1.582***
Quintile 5	-0.355	-0.385*	-1.363***	-0.381***	-1.481***
Urban Income quintiles					
Quintile 1	-2.818***	-4.539***	-3.962***	-0.425**	-2.121
Quintile 2	-2.755***	-5.246***	-2.336***	-.283*	-1.435***
Quintile 3	-2.905***	-4.775***	-2.798	-.365***	-1.335***
Quintile 4	-.868	-2.783***	-1.027***	-.354***	-1.293***
Quintile 5	-.002	-.866	-.327	-.254*	-.712**
Profession					
Farmer	-1.428***	-2.227**	-1.434***	-1.181**	-2.179***
Non farmer	-1.012**	-1.719***	0.485**	-0.453***	-2.091***

Note: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. Quintiles are in increasing order. That is, the 1st quintile includes the poorest 20% of households, while the 5th quintile encompasses the 20% of wealthier households

3.5.4. Marginal Effects of Household Demographics on Budget Shares

With the exception of cassava flour, the R-squared of the first-stage regressions of other staple food demand systems are over 80 percent. This result indicates that geographic, demographic, and economic variables explain much of the variation in budget shares across households. It is also observed that most of the demographic variables exhibit small or insignificant marginal effects on the staple food budget shares.

A larger family will naturally have a larger budget share of millet and maize. For an additional household member, the maize budget share increases (0.007) less than the millet budget share (0.01). Female heads of household allocate a larger share of the food budget to rice. Also, the older the head of household, the larger the food budget share for maize, rice, and sorghum. Furthermore, households in rural areas have higher budget shares for maize, millet, and sorghum while having a small cassava budget share.

Education and regional location are associated with heterogeneity in budget shares. Having attended higher than primary school is positively associated with higher rice and sorghum budget shares. Living in Diffa, Maradi, Tahoua, and Zinder is associated with increased maize and millet budget shares compared to Agadez. However, those households in Tahoua and Zinder are associated with lower rice budget shares compared to their counterparts living in Agadez. Households living in Niamey, the capital city, have the highest rice budget share. Living in Dosso, Maradi, Tahoua, Zinder, and Niamey are associated with a lower cassava flour budget share, compared to those living in Agadez.

Overall, there is weak seasonal heterogeneity in sampled households' staple food demand schedules. Households had a higher sorghum budget share in the post-harvest period of 2011 compared to the planting season of the same year. Also, households allocated a significantly lower budget share to millet in the 2014 post-harvest season compared to their budget allocation to this same food item in the 2011 planting period.

Table 3-7 Marginal effects of household demographic characteristics on budget shares

Variables	Shares of food expenditures				
	Maize	Millet	Rice	Sorghum	Cassava Flour
Region (Reference = Agadez)					
Diffa	0.119	0.153*	-0.0650	-0.0284	-0.0319
	(0.0727)	(0.0811)	(0.0751)	(0.0467)	(0.0446)
Dosso	0.136***	0.0441	0.00507	-0.0106	-0.0437**
	(0.0378)	(0.0422)	(0.0390)	(0.0243)	(0.0210)
Maradi	0.114***	0.106***	-0.0115	0.00822	-0.0742***
	(0.0328)	(0.0368)	(0.0346)	(0.0211)	(0.0185)
Tahoua	0.101***	0.126***	-0.0575*	0.00442	-0.0762***
	(0.0302)	(0.0342)	(0.0317)	(0.0193)	(0.0221)
Tillaberi	0.0827**	0.0660*	-0.00400	-0.0294	-0.0273
	(0.0350)	(0.0391)	(0.0362)	(0.0225)	(0.0193)
Zinder	0.0813***	0.0653*	-0.0590*	0.0258	-0.0402**
	(0.0306)	(0.0343)	(0.0320)	(0.0196)	(0.0168)
Niamey	0.0368	0.0458	0.119***	-0.0148	-0.0949***
	(0.0355)	(0.0394)	(0.0366)	(0.0227)	(0.0215)
Living in rural area	0.0374**	0.140***	-0.00250	0.0528***	-0.0617***
	(0.0166)	(0.0184)	(0.0172)	(0.0106)	(0.0110)
Adult equivalent (unit)	0.00702**	0.00957***	-0.00105	-0.000807	-0.00333
	(0.00296)	(0.00330)	(0.00305)	(0.00190)	(0.00221)
Age of the household head	0.00171***	-0.000119	0.00156**	0.000824**	-0.000388
	(0.000597)	(0.000667)	(0.000621)	(0.000383)	(0.000399)
Female Head of household	0.00262	0.000918	0.0609**	0.000566	-0.0168
	(0.0237)	(0.0266)	(0.0239)	(0.0153)	(0.0131)
Attended higher than primary school	-0.0235	-0.0108	0.0490**	0.0466***	-0.0202
	(0.0218)	(0.0243)	(0.0225)	(0.0140)	(0.0125)
Survey waves (Reference 1st wave 2011)					
2011 Second wave	0.00697	-0.0254	0.0289	0.0419***	-0.0162
	(0.0235)	(0.0263)	(0.0242)	(0.0151)	(0.0129)
2014 Second Wave	-0.00706	-0.0496*	0.0352	0.0119	0.00345
	(0.0235)	(0.0262)	(0.0242)	(0.0151)	(0.0129)
Observations	10232	10232	10232	10232	10232
R-squared	0.869	0.869	0.903	0.820	0.633

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

3.6. Short-term Impact of a Food Price Shock on Household Welfare

In this section, we used the estimated price elasticities to examine the impacts of changing a single commodity price on household welfare. We applied the method proposed by Deaton (1989) and modified by Vu (2020) to assess the welfare effect of a millet and sorghum price change. Conducting the welfare analysis in two steps, we first focus on the impact of a hypothetical 20% increase in a single staple -millet or sorghum- price on consumer welfare. Second, we simulated the welfare effect of a price change ranging from -50% to + 50% for millet and sorghum.

The assessed hypothetical price changes were assumed to originate from demand shock, such as a drastic change in population, income, food preferences, expectations on future prices, or price for substitutes or complements similar to Gagnon and López-Salido (2020). Such a price change can originate from a supply shock induced by drought, flood, introduction of high-yielding varieties of sorghum or millet, or insect infestation (Ball & Mankiw, 1995; Bren D'Amour et al., 2016; Mawejje & Lwanga, 2016).

Prices changes can also be the result of both supply and demand shocks as they occur now with COVID-19 (FAO, 2020) or in the past with the 130% increase in the global prices of major cereal from mid-2007 until mid-2008. The latter was mostly passed on to domestic markets in small economies, such as Niger (Baquedano & Liefert, 2014; Ivanic & Martin, 2014; Nakelse et al., 2018). Such dramatic changes in food prices may adversely affect welfare in developing countries (Headey & Martin, 2016).

Following Deaton's (1989) seminal study and its extension by Vu & Glewwe (2011) and (Nakelse et al., 2018), we measure the impact of price changes on households using the compensating variation (the amount of money required to keep a household's utility at a level enjoyed before the change in price). We derive the compensating variation using both the household profit and from indirect utility functions. Overall, the implicit profit increases for net suppliers when food prices increase. For net buyers, the profit decreases when food prices increase (Vu & Glewwe, 2011). We therefore express the change in the household income (ΔB) as a fraction of household expenditure (X):

$$\frac{\Delta B}{X} = \sum_{i=1}^{n}\left(w_i \Delta \ln(P_{ci}) - \frac{P_{pi}y_i}{X}\Delta \ln\left(P_{pi}\right)\right) \tag{10}$$

Where:

w_i is commodity i budget share,

P_{ci} is the consumer price of commodity i,

P_{pi} is the producer price of commodity i,

y_i is the quantity of commodity i sold by the household,

$\frac{P_{pi}y_i}{X}$ is the sales of commodity i as a fraction of household expenditure X.

Intuitively ΔB is a proxy for welfare change, which is the difference between the change in the cost of maintaining current consumption and the change in income from current production, accounting for both income and substitution effects. Equation (10) expresses the welfare change as determined by the flexible change in the consumer and producer price of commodity i. The welfare change measure in equation (10) is the immediate effect of price changes. However, the consumer can shift away from commodity i when its price rises.

By applying a second-order Taylor's expansion to the expenditure function in equation (10), while allowing for substitution behavior, the following expression (11) for the change in expenditure needed to maintain the household utility after the price shock is revealed:

$$\Delta C = \sum_{i=1}^{n} q_i \Delta p_{ci} + \left(\frac{1}{2}\right)\sum_{i=1}^{n}\sum_{j=1}^{n} s_{ij}\Delta p_{ci}\Delta p_{pj} \tag{11}$$

here, s_{ij} is the Slutsky derivative of the Walrasian demand function. Equation (11) can be expressed in terms of budget shares and proportional price changes as follows:

$$\Delta \ln(C) = \sum_{i=1}^{n} w_i \Delta \ln(P_{ci}) + \left(\frac{1}{2}\right)\sum_{i=1}^{n}\sum_{j=1}^{n} w_i \varepsilon_{ij}\Delta \ln\,(p_{ci})\Delta ln(p_{pj}) \tag{12}$$

ε_{ij} is the compensated price elasticity of food item i with respect to the price of food item j. We can use equations (10) and (12) to rewrite the short-term effect of an increase in prices with substitution among food items as follows:

$$\Delta \ln(B^{sr}) = \sum_{i=1}^{n} \left[w_i \Delta\, ln(P_{ci}) - \frac{P_{pi} y_i}{X} \Delta\, ln\big(P_{pi}\big)\right] + \left(\frac{1}{2}\right) \sum_{i=1}^{n} \sum_{j=1}^{n} w_i \varepsilon_{ij} \Delta ln\ (p_{ci}) \Delta ln(p_{pj}) \qquad (13)$$

Equation (13) expresses the short-term welfare impact of the price change of multiple items. To assess the impact of a change in the price of a single food item i, such as millet or sorghum, Equation (13) can be simplified to the following expression:

$$\Delta \ln(B^{sr}) = w_i \Delta\, ln(P_{ci}) - \frac{P_{pi} y_i}{X} \Delta\, ln\big(P_{pi}\big) + \left(\frac{1}{2}\right) \sum_{i=1}^{n} w_i \varepsilon_{ij} \Delta ln\ (p_{ci}) \Delta ln(p_{pj}) \qquad (14)$$

Now, making use of the procedure by Dawe and Maltsoglou (2009), in combination with the procedure developed by Nakelse et al. (2018), we consider first that consumer prices p_c are equal to producer prices p_p plus a marketing margin M:

$$P_c = P_p + M \qquad (15)$$

Taking total differentials of equation (6) yields:

$$dP_c = dP_p + dM \qquad (16)$$

Assuming a constant marketing margin[2], Equation (16) can be rewritten as:

$$dP_c = dP_p \qquad (17)$$

Equation (17) can be rewritten as:

$$dP_c \frac{P_c}{P_c} = dP_p \frac{P_p}{P_p} \qquad (18)$$

Which can be transformed as:

[2] Assuming constant marketing margin ignores the fact that some producers and consumers may also receive some trading income that has increased as a result of the increases in farm and retail prices

$$\frac{dP_p}{P_p} = \frac{dP_c}{P_c} * \frac{P_c}{P_p} \tag{19}$$

Which yields:

$$dlnP_f = dlnP_f * \frac{P_c}{P_p} \tag{20}$$

Inserting Equation (20) in Equation (14) results in the following equation:

$$\Delta \ln(B^{sr}) = \Delta\, ln(P_{ci}) \left[w_i - \frac{P_{ci}y_i}{X}\right] + \left(\frac{1}{2}\right) \sum_{i=1}^{n} w_i \varepsilon_{ij} \Delta ln\,(p_{ci}) \Delta ln(p_{cj}) \tag{21}$$

First, the analysis of the welfare effect consists of estimating Equation (21), assuming a 20% increase in the millet or sorghum price, while other food prices are assumed to be affected only through the price transmission mechanism. The results are given in Table 3.8. Second, we simulated a wider range of price changes for each commodity. The welfare change that follows can be called the short-term effect of price changes since one change is considered at a time - for instance, supply and producer behavior is fixed during demand shock.

3.6.1 Effect of Millet Price Change on Welfare

The average household welfare in Niger decreases by 5.88% when millet prices increase by 20%. This is not surprising since millet is the most-consumed cereal in Niger (Ouendeba & Sogoba, 2016). Although the country witnessed increased millet production over the period running from 2010–2015 (MAN-DS, 2013, 2015), 85% of the average household production goes to own-consumption. At the household level, and based on the computed average for 2011 and 2014, the net supplier represented 3% of the sample, selling 92 kilograms of millet, while the net buyer represented 97% of the sample, purchasing 280 kilograms of millet. From the demand analysis in the previous section, we found that urban households allocate 9.17% of their food staples budget to millet. Meanwhile, rural households assign double (18.41%) to the same grain.

Therefore, a price increase produces a loss in consumer surplus that outweighs the gain in producer welfare, resulting in an overall welfare loss. In rural areas, household welfare decreases by 6%, while it falls by 5% in urban areas. In fact, urban households are mostly net buyers; they purchase 120 kilograms of millet per year, while rural net buyers purchase 326 kilograms of the grain per year, on average. This is in line with our findings on demand analysis suggesting that urban consumers have a more diversified diet than their rural counterparts.

Whereas more households are worse off in Agadez and Niamey, the average welfare loss in these regions is lower, 3.73% and 4.97%, respectively. More than 99% of households purchase, on average, 130 kilograms of millet per year in these two regions, which is below the national average of 260 kilograms per year. Therefore, the average household in these regions witnesses lower welfare loss, whereas Diffa, Tahoua, and Maradi are the regions that exhibit the highest welfare loss (see Figure 3a, Appendix C) following a millet price increase.

We provide a more detailed analysis using income quintiles in both urban and rural areas. In general, the welfare loss reduces as the income increases. In rural areas, the fifth quintile households have a welfare loss of 5.46%, while their urban counterparts have a welfare loss of 4.28%.

In Table 3.8, we also reported the percentages of households whose welfare dropped following the millet price increase. Overall, when social welfare decreases, 97.63% of households are negatively impacted by the millet price increase. Those households hit the hardest tend to live in urban areas. On a regional basis, Diffa has the lowest percentage of households faced with welfare loss. Furthermore, while households headed by farmers face higher welfare loss, some of them are better off. In addition, while the majority of households are worse off in both rural and urban areas, the relative number of households made worse off decreases as one moves from the first of the fifth income quintiles.

In general, and as it can observed in Figure 3.2, a positive change in millet price produces an overall welfare loss in Niger. Conversely, a reduction in millet price results in a welfare gain, since the gain in consumer surplus outweighs the loss in producer surplus. Most of the welfare benefit goes to rural dwellers, especially millet net sellers (farmers). Only 32% of farmers are net millet sellers. Therefore, most of the welfare loss is faced by 68% of farmers and most of the non-farming urban households (see Figure 3.3). A hypothetical 50% increase (decrease) in millet price negatively (positively) affects the total welfare by 20% (14%). However, most households are worse off when millet prices increase.

3.6.2 Effect of Sorghum Price Change of Welfare

An increase in the sorghum price induces a welfare loss for an average Niger household (see Figure 3.2). Conversely a price reduction positively affects the average household's welfare. For a 20% sorghum price increase, the welfare reduction is 4.38% (see Table 3.8). This represents 59,670 FCFA ($108 USD). Such a sorghum price increase makes 57% of households worse off, most of whom live in urban areas. On the other hand, a 20% reduction in sorghum price induces a 6.40% welfare gain, which represents 87,075 FCFA ($158 USD). The gap between the average household supply and demand for the commodity sheds light on these findings. While net buyers purchase 45 kilograms of the grain per year, net suppliers sell 61 kilograms of the commodity per year, on average. On average, the change in sorghum price affects farmers and non-farmers the same way (in general) since only 38% of sorghum growers are net sellers (see Figure 3.3).

The largest welfare effect of a sorghum price increase is observed in Niamey because demand for sorghum is the highest in this capital city. While the average national household purchases 45 kilograms of sorghum per year, an average Niamey household purchases 113 kilograms of the commodity per year, on average. This makes Niamey households more adversely affected by a sorghum price increase. Conversely, a reduction in sorghum price represents a welfare gain for the average Niamey household. Hence, the highest proportion of worse-off households is observed in Niamey when sorghum prices increase (see Figure 3.4).

Based on income quintiles, the loss of welfare induced by a 20% increase in the sorghum price grows as one moves from the first to the fifth quintile in rural and urban areas. This is in line with sorghum being a luxury food in Niger. For each corresponding quintile, the welfare loss for an average urban household is at least 1.3 times that of a rural household. Whereas the fifth quintile exhibits the highest proportion of worse off households in the rural areas, the third quintile tops the ranking in urban areas. Also, the disaggregation based on professional affiliation revealed that, non-farmers lose 5.13% of their welfare while farmers only lose 4% of theirs.

3.6.3 Partial Conclusion on Welfare Analysis

Overall, the change in millet price affects households' welfare more than that of sorghum. While a 50% increase in sorghum price reduces the average welfare in Niger by less than 12%, the increase in the millet price of the same magnitude induces a welfare loss of about 20%. The supply and demand of the two commodities help explain these findings. Millet is the most-produced and most-consumed cereal in the country, making it a necessity, while sorghum is a luxury for most households.

While the average household purchases 286 kilograms of millet per year, their sorghum counterparts demand only 80 kilograms. In addition, millet represents, on average, 15% of the household budget share, while sorghum represents only 7%. On the other hand, the average quantities sold by net sellers of millet and sorghum are 88 and 61 kilograms, respectively. Furthermore, the price difference may be another cause for the difference in welfare effect. Table 3.1 in the summary statistics indicates a slight difference in prices for both cereals with 176 and 151 CFA francs per kilogram of millet and sorghum, respectively.

Lastly, household preferences for millet and sorghum, along with market prices, determine the substitution mechanism that occurs when prices change for both cereals. The variability in preferences induces heterogeneity in the substitution effect that occurs when each cereal price changes. The combination of preferences, price, and substitution mechanisms determine the income transfer from urban net buyers to rural net suppliers when millet or sorghum prices change.

For a 20% increase in the millet price, net sellers gain on average 16,739 FCFA ($30), which represents a 1.23% welfare improvement. Meanwhile, net buyers lose 107,509 FCFA ($195), which is equivalent to a 7.94% welfare loss. Net suppliers receive 16% of the income lost by net buyers, which results an overall welfare loss of 5.88% following a 20% increase in the millet price. Conversely, a millet price decrease of 20% induces a 6.92% of welfare gain for net buyers and a 2% welfare loss for net sellers. In the latter case, net sellers' welfare losses represent 30% of the net buyers' welfare gain.

Following a 20% increase in the sorghum price, net sellers receive an average of 62,419 FCFA ($113), and net buyers lose an average of 40,889 FCFA ($74). On an individual basis, the average welfare loss for net buyers represents 65% of the average welfare gain; however, because sorghum net sellers represent 19% of the sorghum net buyers in terms of number, the overall welfare effect following a sorghum price increase is negative and amounts to 4.38%. Accordingly, when the sorghum price decreases by 20%, net buyers gain 3.35% of their welfare, while net sellers lose 4.37% of their welfare, yielding an overall welfare gain of 4%.

Table 3-8 Percentage of household welfare change due to millet price increases

	Millet			Sorghum		
	Welfare Change (%)	**Welfare change (FCFA)**	**Worse off (%)**	**Welfare Change (%)**	**Welfare change (FCFA)**	**Worse off (%)**
All	-5.88	-80,019	96.63	-4.38	-59,670	57.47
Urban vs. Rural						
Urban	-4.95	-67,411	98.49	-6.28	-85,419	68.01
Rural	-6.08	-82,683	94.57	-3.99	-54,250	51.1
Region						
Agadez	-3.73	-50,742	99.04	-5.35	-72,785	63.80
Diffa	-10.20	-138,827	81.81	-4.43	-60,331	57.28
Dosso	-6.24	-84,881	97.63	-3.83	-52,092	44.05
Maradi	-7.49	-101,925	98.08	-3.89	-52,889	54.65
Tahoua	-9.36	-127,439	98.84	-4.18	-56,830	55.19
Tillaberi	-6.57	-89,460	94.75	-3.84	-52,315	45.48
Zinder	-6.42	-87,343	94.82	-4.57	-62,135	40.84
Niamey	-4.97	-67,568	98.79	-7.63	-103,848	68.29
Rural Income quintiles						
Quintile 1	-6.48	-88,136	95.31	-3.38	-46,052	77.05
Quintile 2	-6.22	-84,591	94.53	-3.59	-48,837	76.94
Quintile 3	-6.20	-84,357	94.4	-3.96	-53,824	75.65
Quintile 4	-6.02	-81,941	94.23	-3.62	-49,256	75.56
Quintile 5	-5.46	-74,276	92.38	-4.07	-55,423	73.60
Urban Income quintiles						
Quintile 1	-5.83	-79,322	99.48	-4.55	-61,908	97.32
Quintile 2	-5.10	-69,425	98.3	-5.15	-70,043	96.88
Quintile 3	-4.71	-64,077	98.29	-6.28	-85,490	96.78
Quintile 4	-4.59	-62,422	98.22	-5.28	-71,839	94.78
Quintile 5	-4.28	-58,312	97.21	-5.61	-76,314	88.57
Profession						
Farmer	-6.04	-82,143	94.67	-3.97	-54,069	53.98
Non farmer	-5.60	-76,221	97.17	-5.13	-69,750	60.32

*Welfare change level is calculated with respect to the average annual income of 1360871 FCFA or $2475 USD

Figure 3-2 Simulation of relative welfare change based on millet and sorghum consumer price variation

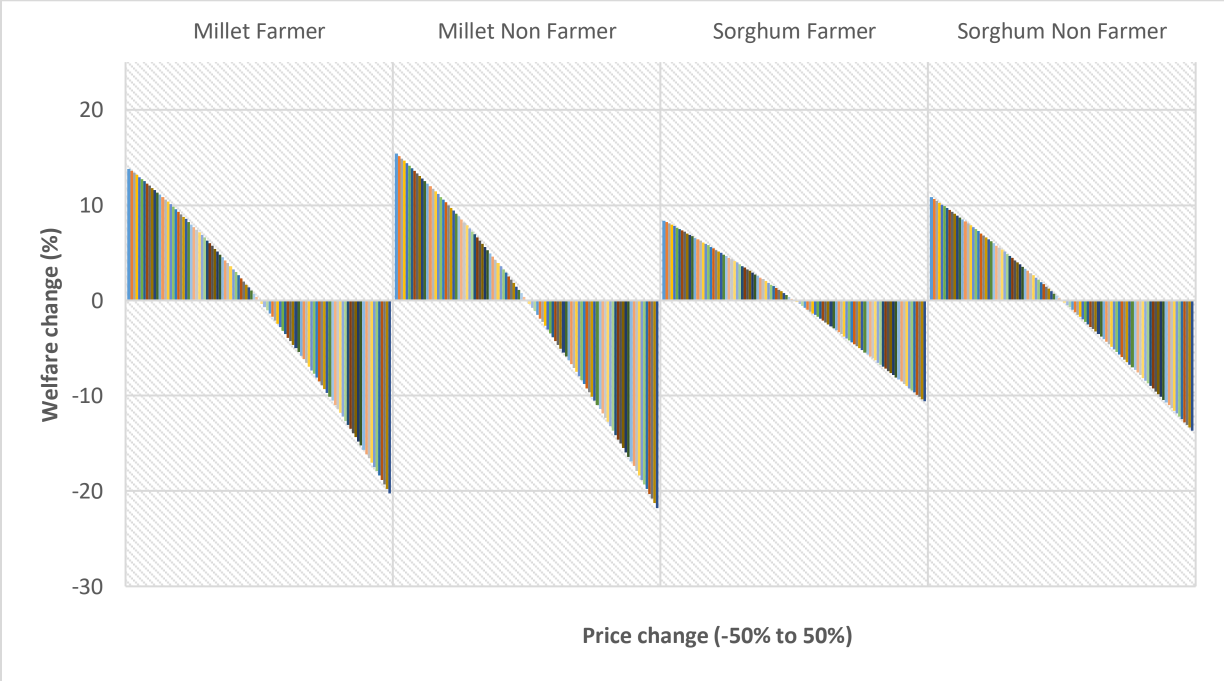

Figure 3-3 Simulation of relative welfare change based on millet and sorghum consumer price variation for farmers and Non-farmers

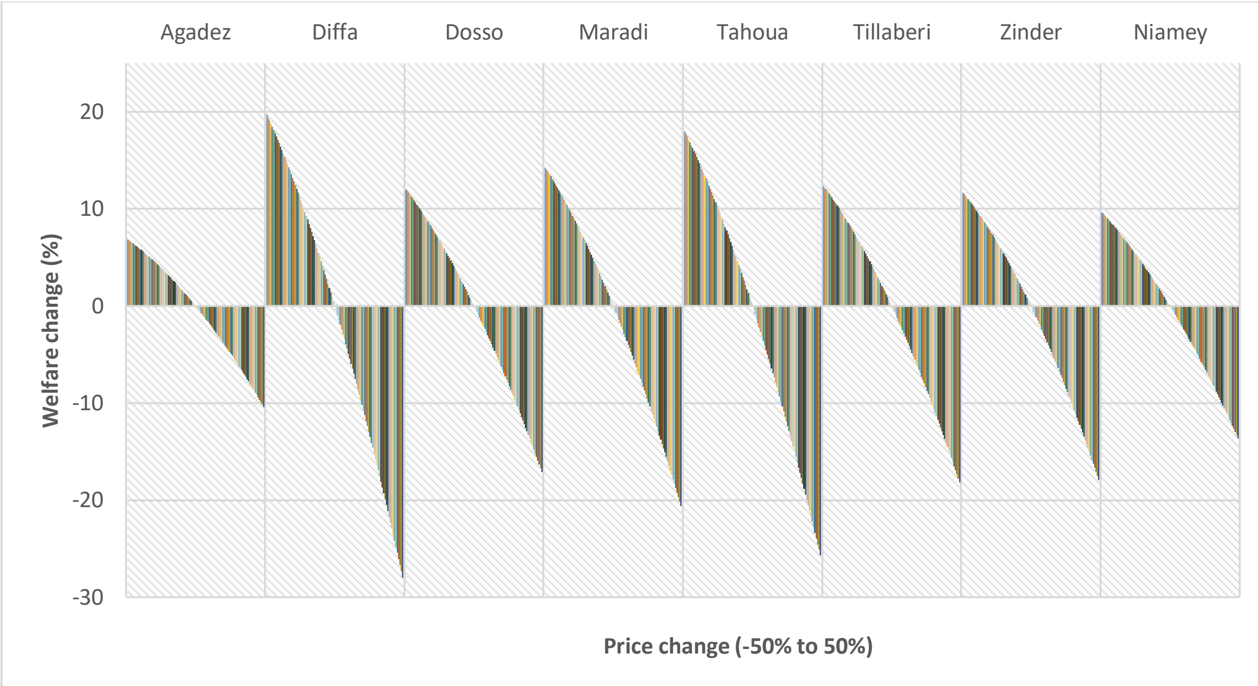

Figure 3-4 Simulation of relative welfare change based on millet consumer price variation

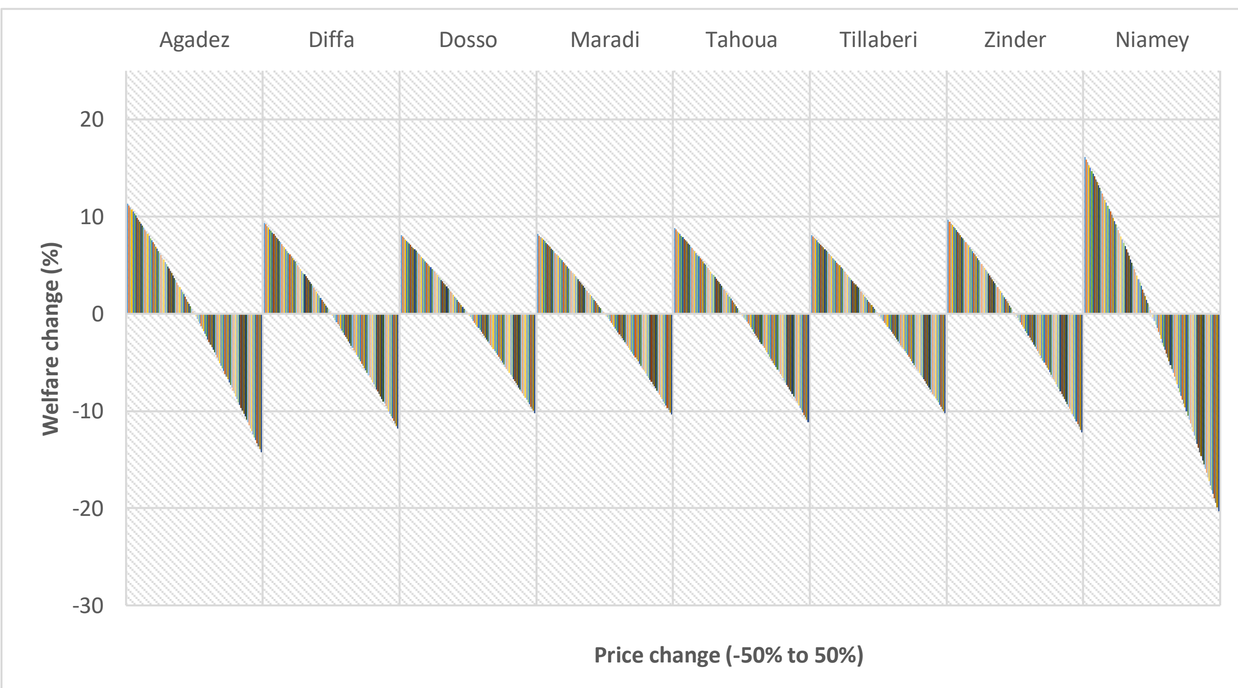

Figure 3-5 Simulation of relative welfare change based on sorghum consumer price variation

3.7 Conclusion

In this paper, we sought to estimate the income and price elasticities for food staples and use the estimated elasticities to conduct a short-term welfare analysis of food price change in Niger. We also aimed to identify the underlying factors for the differences in food budget shares across households. In so doing, we provided greater understanding of the relationship between income, price level, welfare, and the demand for food staples in this West African economy.

We empirically estimated income and price elasticities using the LA-AIDS model, and because we largely utilized unit values in this study, we used the ordinary least squares approach with household demographics to correct for endogeneity induced by quality bias and measurement errors. We supplemented the LA-AIDS model with the QUAIDS and Rotterdam models for a robustness check.

In general, this study revealed that demand functions in urban and rural areas, and those across regions and income groups, are different. The study also revealed that targeted food policies should be formulated based on specific food demand patterns for an effective impact on food security. In addition, we found that socio-economic factors such as household size, household head's age, gender, and education significantly affect food consumption in most cases.

A budget share analysis revealed that millet, the most-consumed cereal, represents 14.70% of a household's food budget at the national level. In urban and rural households, the millet share of the food budget is 9.17% and 18.41%, respectively. In addition, we found rice to have the highest share of an urban household's food budget, while millet has the highest portion of a rural household's food staples budget. While mostly consumed in Niamey, sorghum has the lowest share of the food budget in both urban (6.65%) and rural (7.96%) households.

Our analysis revealed that all these staples are normal goods, but maize, rice, and sorghum are luxury items for the national sample of households. Millet was found to be a necessity in Niger. Based on own-price elasticity estimation, we found consumers to be more responsive to rice and cassava flour price changes. This observation applies to both urban and rural households. Compensated and uncompensated cross-price elasticities imply that sorghum is the closest substitute for millet. We also found that urban households tend to have a more diversified cereal diet in comparison to their rural counterparts. This is consistent with Cheng and Larochelle's (2018) findings.

This investigation revealed that larger households allocate a greater share of their food budget to millet and maize. In addition, rural households allocate the largest share of their food budget to millet, and they demand significantly less cassava flour as compared to their urban counterparts. Furthermore, we found that the more educated the household head is, the higher the budget share allocated to rice and sorghum. Regional heterogeneity in staple consumption was found for Diffa, Maradi, Tahoua, and Zinder and was associated with higher maize and millet budget share in comparison to Agadez.

Using the estimated price elasticities, we assessed the welfare impacts of a millet or sorghum price change. Assuming a zero-marketing margin (consumer and producer prices increase at the same rate), a 20% millet price increase reduces the average household welfare by 5.88%. Yet, it is important to mention that the benefits and costs are not evenly distributed across the population. When the millet price increases by 20%, average rural household welfare reduces by 6.08%, while urban household welfare drops by 4.95%. Overall, poorer rural and urban households lose the most from higher millet prices. This indicates that support programs should target the poorest quintile, especially the poor in the regions hit hardest by higher prices, such as Diffa, Tahoua, and Maradi.

Sorghum price changes produce a smaller welfare effect since sorghum is a luxury and a small share of the household staple food budget. A 20% increase in sorghum price reduces the overall welfare by 4.38%, which represents a 59,670 FCFA loss on the average household income. Urban, non-farming, and higher income households lose the most from such an increase.

Our findings provide policy makers with two key insights. On demand side, defining millet as a necessity is important in addressing hunger and food insecurity. Also, the price elasticities are useful for ex-ante impact simulation in cases of price shocks. Furthermore, findings from the welfare analysis provide instruments and strategies to address food security and economic in Niger. For instance, pro-poor targeting programs might use millet price as transmission channel to get vulnerable households from poverty or food insecurity trap.

This study has two main limitations, which could be addressed in future investigations if production and marketing data are available. First, we assumed separability between production and consumption in the demand analysis. In the case of Niger, the separability assumption seldom holds. The separability assumption is based on the foundation that households make their production and consumption decisions separately, and requires each output and input to have a complete market, with households to not make their decisions at the corner (Singh et al., 1986). This might not be the case in Niger, especially for rural households. Serra (2015) found a positive and strong correlation between producer and consumer prices in Maradi and Filingue. This implies that ignoring the potential connection between consumption and production can potentially distort the elasticities (Cheng & Larochelle, 2017).

Second, we assumed a constant marketing margin between consumption and production markets in Niger, which visibly distorts the welfare analysis. Dawe and Maltsoglou (2009) argued that failure to explicitly consider marketing margins could lead one to conclude that the poor are hurt relatively more than the rich by a price increase when, in fact, the opposite is true, or vice versa. Nevertheless, these authors acknowledged that high quality empirical data on price variation at different levels of the marketing chain and in different regions, while controlling for interest rates is needed for a sophisticated analysis. Because such complete data sets are rare, especially in developing countries, assuming constant, absolute marketing margins is the most consistent approach to ensure a ceteris paribus analysis. Assuming constant marketing margins, this analysis provides insight on the staple food demand and welfare impact of a food price change.

Lastly, future investigation may shed light on the differences observed in price elasticities across income quintiles for staples. Especially, research may uncover how the household own-produced food quantity connects with the price elasticities. Findings from such research might provide policy makers with better insight on demand response for different income brackets.

Chapter 4 - Improved Sorghum Seed Adoption in Small-scaled Farming: A Theoretical Argument for Demand-led Breeding

4.1 Introduction

Often, studies elucidating improved technologies implementation focus on the adoption (demand) rather than creation (supply). Notwithstanding the seminal review by Shawaki et al. (1993) highlighting the important role of demand and supply in the process of technological change, theoretical and empirical studies in Sub-Saharan Africa (SSA) have rarely investigated new technologies in a structural setting where supply and demand are concurrently addressed. The current theoretical argument aims to fill this gap in the literature. In this analytical study, we evaluate the sequences of technology adoption and market demand for improved food products through the lenses of preference matching.

Failing to take both production and consumption traits into account increases producers' uncertainty, leading to low adoption. In fact, Dalton (2004) found that yield, which is the most-valued attribute by breeders is not significant in determining farmer willingness to pay for new rice varieties, hence the necessity to revisit the paradigm of plant profile development. Varieties will have a greater chance of adoption and diffusion if preferences of all agents along the value chain are met. Thus, elicitation and matching of producer, processor, and consumer preferences is required in order to be effective. Such an inclusive approach might help breeders focus their resources and time investments on the most-valued demand side traits.

This study defines a more comprehensive, conceptual approach to the development of varietal profiles by focusing on market-driven preferences. Through market supply and demand for the seeds and food product, we set up a general equilibrium framework. We subsequently determined the strategic relationship in the market for new sorghum breeds through a supply versus demand (dis)equilibrium assessment.

This study highlights the issue of coordination and motivation in breeding and production. The coordination aspect stems from the general value chain organization point of view. The motivation refers to the incentives carried along the value chain as far as a new variety is concerned. Overall, this investigation makes two contributions to the adoption literature. First, we provide a comprehensive review of causes of new varieties adoption. Second, this study poses a general equilibrium model in terms of a single crop value chain. This is implemented in terms of market analysis by identifying supply and demand segment connectedness to derive a market-oriented solution to low technology uptake.

In the next section, we present a literature review of studies having assessed producer and consumer preferences for sorghum, followed by the theoretical framework discussing causes and solutions to low varietal uptake and presenting a general equilibrium model of preferences matching. The last section discusses findings and concludes this investigation.

4.2 Literature Review

Seeds are key determinants to agricultural productivity. Adoption of improved seeds is often considered a crucial step towards structural transformation of agrarian economies and food security. During the last decades, the international community and national agricultural research systems have invested considerable resources in developing new and high-yielding varieties to improve overall agricultural productivity (Camara et al., 2015; Feed the Future, 2018). However, low adoption rates of improved crop varieties are observed especially in Sub-Saharan Africa (SSA). In 2010, improved cultivars of sorghum and millet represented 34% and 23%, respectively, of the total farmed area of these crops in Sub-Saharan Africa (Armah & Klawitter, 2010). The adoption rate for improved sorghum in West Africa is only 4% (Walker et al., 2015).

Traditional agricultural systems in low income countries (LICs) are often confronted with complex and heterogeneous environments. Efforts to explain partial adoption on farms have focused overwhelmingly on risk aversion in the producer's profit maximization framework. According to Armah and Klawitter (2010), the low adoption rate of improved sorghum cultivars is mainly due to inaccessibility and ineffective breeding processes. They argue that improved farmer involvement in the breeding program and better distribution programs could increase the likelihood of adoption (Armah & Klawitter, 2010). Based on these premises, the participatory breeding approach was introduced to better account for farmers' preferences in variety development. However, this approach ignores other agents at the lower end of the value chain. The current study argues that processors and consumers should be involved in the breeding process since they both drive the product demand. Also, the non-separability between production and consumption at rural household level supports the strategical importance of an inclusive breeding program.

Our approach addresses plant profile development as a product market where supply responds to demand. That is, the very inception of the crop breeding program should be demand-led or consumer-oriented. As such, traits developed in the new variety are not the result of the breeder's sole educative guess or any ex-post procedure involving farmers. Instead, trait selection should proceed from a rigorous preferences elicitation along the product value chain.

In this section, we review previous studies focused on the adoption of new crop varieties in developing countries. We specifically focus on studies that used discrete choice methods to examine determinants of varietal adoption by sorghum farmers. Next, we provide a brief review of approaches used in plant profile development. Third and last, we report the few studies aimed at determining consumers' preferences for sorghum varieties.

4.2.1 On Farmer's Preferences for New Crop Varieties

In a more general setting, farmers are profit-maximizing, economic agents. As such, the farmer's propensity to risk affects their choice of the agricultural technology that will produce the expected profit (Sulewski & Kłoczko-Gajewska, 2014). Often, a risk-averse farmer prefers improved cultivars that reduce the risk of production loss and increase their production efficiency. A study by Asrat et al. (2010) found environmental adaptability and yield stability to be the most desired attributes for farmers' choice of crop varieties. In a more specific context of Sub-Saharan Africa, several empirical studies found resistance to insect attack, tolerance to striga, adaptability to marginal land, and climate conditions to be important determinants in farmers' adoption decisions (Mottaleb, 2018; Kassie et al., 2017; Ghimire et al., 2015; Walker & Alwang, 2015; CGIAR, 2014; Trouche et al., 2009).

Notwithstanding their superior performance on marginal production conditions, modern sorghum varieties are poorly adopted in Eastern Ethiopia. Building upon this observation, Cavatassi et al. (2011) investigated the risk-reducing trait attributed to improved varieties. Their results revealed that farmers use improved varieties to mitigate moderate risks in production. They also found that sorghum producers facing the most vulnerability to extreme weather events were less likely to adopt improved varieties. Based on the later finding, the authors argued that improved varieties adoption was not always perceived by farmers as an effective means of coping with drought. For these authors, the uptake of improved varieties would have been enhanced had stress-tolerance traits been included by the breeder.

Although farmers were either early or fully involved in the new cultivars breeding, breeders assumed yield was farmers' main interest. Drawing on the fact that new crop varieties have mostly been promoted in developing countries based upon superior yield vis-à-vis local cultivars, Dalton (2004) investigated upland rice production and consumption characteristics. He used a hedonic price model to determine that five traits explain the willingness to pay for new rice varieties. These characteristics include plant cycle length, plant height, grain color, elongation/swelling, and tenderness. Dalton's findings revealed that yield was not a significant explanatory variable of the willingness to pay for seed. In addition, his findings suggested that post-harvest and production characteristics must be considered in varietal development and promotion. Yet, inclusion of some of these risk-reducing traits may come at the cost of yield and quality characteristics.

Additionally, studies by Mrica et al. (1995), Smale et al. (2018), and Okuthe et al. (2000) found that farmers' perceptions of the varietal yield, tolerance for striga, adaptability to poor soil (production attributes), quality of local porridge (consumption attributes), along with household socio-economic characteristics significantly affect their choice. This implies that beyond varietal traits, socio-economic factors may also affect farmers' adoption decision making. In the following section we elaborate more on the necessity to go beyond particpatory crop breeding.

4.2.2 Demand-led Breeding

Over the last decades, crop breeding moved from an original top-down varietal development (conventional breeding) to a more inclusive process (participatory breeding) model

(Asrat et al., 2010; Ghimire et al., 2015). In this section, we distinguish formal or conventional breeding from participatory breeding. Conventional or formal plant breeding (FPB) is defined as a plant profile development system in which the breeder decides which traits breed, regardless of downstream users' (farmers, processors, and consumers) preferences. Until the mid-1990s, FPB was the most popular system in developing countries where most crop breeding programs were in the public sector and were carried out at government agricultural experiment stations (Impact, 2009). This process has been criticized for ignoring indigenous germplasm, failing to breed for conditions facing poor farmers, and emphasizing selection for broad versus local adaptation (Evenson & Gollin, 2009; Atlin et al., 2001).

Participatory plant breeding (PPB) emerged in response to criticism of FPB. In PPB, the breeding process includes on-farm evaluation and use of local landraces. It also involves breeders, farmers, and extension agents and entails assessments of varietal performance under evolving climatic variability, provides perspective on needs and opportunities, and enhances adoption (Haussmann et al., 2012). The PPB is also named farmer-participatory or farmer-led selection and is widely documented (Nkongolo et al., 2011; Atlin et al., 2001; Rogers, 1983). Atlin et al. (2001) argued that PPB mostly relies on farmer visual evaluation or phenotypic mass selection to select traits adaptable to multiple environments (MET).

However, we argue that breeding programs should be more inclusive than both FPB and PPB. As defined by Kimani et al. (2017), the demand-led plant breeding or consumer-oriented breeding (COB) is a more inclusive plant breeding program. COB improves the uptake of new varieties by mitigating the asymmetry of preferences between supply and demand (Syngeta, 2014). The COB process takes into account the preferences of the end users, while retaining the superior performance valued by upstream users (Walker; & Alwang;, 2015). The demand-led breeding in genetics is the equivalent of "the sharing is winning" model in industrial organization. The latter depicts co-creation based on a complementary relationship among partners, inducing value creation along the value chain; it builds goodwill and establishes trust and respect (Bigliardi & Galati, 2013).

In the table below, we summarize the three breeding approaches based on agent involvement. While FPB involves only the breeders, PPB moves one step ahead and includes farmers in the ex post breeding process. However, COB acts as a more inclusive approach where all agents are involved from the inception to the completion of the breeding program.

Table 4-1Sorghum value chain stakeholder's involvement in breeding approaches

Breeding approach	Stakeholders involvement			
	Breeders	Farmers	Processors	Consumer
Formal breeding (FPB)	Yes	No	No	No
Participatory breeding (PPB)	Yes	Yes	No	No
Consumer-oriented breeding (COB)	Yes	Yes	Yes	Yes

Source: Author

Overall, we argue that modern plant breeding would be enhanced by embracing a more inclusive approach where all stakeholders are involved. Demand-led breeding or client-oriented breeding (COB), which shares several similarities with the industrial vertical integration strategies, provides an answer to low sorghum uptake (Pereira et al., 2018; Ribaut & Ragot, 2019). Although participatory plant breeding (PPB) is an essential component of COB, farmers, and consumers (clients) should be involved at an earlier stage of the breeding program. An investigation by

Witcombe & Yadavendra (2014) in India provided support for COB. These authors found that two rice varieties developed using COB have been more popular than any other previously-released upland variety in the country.

4.2.3 Consumers' Preferences for New Crop Varieties

Several previous studies have assessed consumer preferences for sorghum. Early in 1977, Laswai et al. found that improved varieties (IV) were less appealing to consumers than the local varieties (LV) in Tanzania, although the IV had higher-yielding attributes. Among the key weaknesses highlighted by Laswai et al. (1977) was that IVs were more susceptible to storage pests and had tedious threshing, affecting the quality of grains. Oppen & Rao (1988) developed a market-derived selection index for consumer preferences of sorghum. Their study accounted for two types of sorghum-formulated product attributes. On one hand, they assessed evident characteristics such as moldiness and grain size. On the other hand, they evaluated invisible attributes, such as dry volume, swelling capacity, and the protein content of the grain. Findings suggest both evident and invisible attributes jointly determine consumer preference for sorghum-formulated products.

Kebakile et al. (2003) investigated the consumer preferences for sorghum-based food products. Their survey in Botswana revealed that products such as bread, biscuits, pasta, breakfast flakes, traditional and commercial sorghum beer, extruded sorghum-soy meals, and fermented beverages are often made of sorghum. The authors' estimation of the preferences revealed that consumers value sorghum-formulated products whenever they are nutritious, healthy, affordable, and can maintain traditional flavors. In addition, the study found preferences for sorghum-formulated products to be affected by the age, place of origin, household size, educational level, residential area, and gender of the consumer.

Along the same lines, Mafuru & Norman (2008) investigated the quality attributes of sorghum paste “ugali” made from three improved varieties (IV) and two local varieties (LV). The findings revealed that color and taste were the most important criteria used by consumers to evaluate the quality of the sorghum paste. The white/khaki color and neutral or slightly sweet taste was especially preferred by consumers.

A study by Makindara et al. (2013) focused on consumer preferences and market potential for sorghum-based beer in Tanzania. The authors found price, taste, and household income to influence sorghum-formulated beer consumption. Along similar lines, Kayodé et al. (2007) evaluated the sorghum brewing microenterprises in Benin. Most of the surveyed consumers preferred opaque, sour, and pink-colored sorghum-based beer.

Overall, few studies exist that elicit consumers’ preferences for sorghum-formulated products. Of the studies that do exist, only one focused on consumer preference for traits that can inform breeding programs. This uncovers the weak consideration of the preference of the end-user in the overall sorghum varieties development, reinforcing the assumption of asymmetric information and unmatched preferences along the sorghum value chain.

4.2.4 Partial Conclusion of the Literature Review

This review revealed a void in the literature for a comprehensive preferences elicitation along the sorghum value chain. To the best of our knowledge, no study compared the preferences of both the supply and demand of the improved varieties. Additionally, we found no investigation aimed at eliciting the breeders’ preferences. Also, when preferences on the demand side were studied, the investigation often focused on farmers. While few studies elicited consumer preferences for sorghum, only a few products were targeted. As a result, narrow evidence for consumer-oriented breeding was provided. Furthermore, the studies focused on farmer preferences for sorghum revealed some heterogeneity. The observed heterogeneity is influenced by the geographical, social, cultural, environmental, and economic conditions of the surveyed households. This implies that a successful breeding program must holistically account for all agents' spatial and temporal preferences, echoing the call from the African Plant Breeders Association (APBA, 2019), the Food and Agriculture Organization of United Nations (FAO, 2010), and the scientific community represented by CABI, CIAT, CIMMYT, and the CGIAR (Dwivedi et al., 2019) for more demand-led breeding in Africa.

There is a need to test the hypothesis of asymmetric information and preferences in the sorghum new varieties profile development. Beforehand, we provide a conceptual argument to support an inclusive study that connects consumers' preferences to breeding traits. In the following section, we provide the theoretical arguments that support the consumer-oriented breeding.

4.3 Theoretical Foundations of Crop Breeding and Adoption

In less-developed economies, barriers to technology adoption take different forms, such as transaction cost, culture, and regulations. While emphasizing barriers to technology adoption, in this study, we focus on the asymmetry of information that increases transaction costs along the crop value chain. We theoretically explain the low adoption of newly-improved varieties by asymmetric information faced by the seed suppliers (breeder), the intermediaries (farmers and processors) and the downstream grain consumers. We conduct this analysis using the analytical framework of information flow in agricultural markets. Following Marette et al. (1999), we assume both supply and demand information asymmetry due to difficulties in evaluating preferences on the supply side and product (seed and grain) characteristics on the demand side.

In this study, we mainly focus on market-induced uncertainty in the sorghum producer profit maximization problem to explain the adoption decision. We address crop breeding as a market where supply responds to demand. That is, the very inception of the crop breeding program should be demand-led. As such, traits developed in the new variety are not the result of the breeder's educative guess or any a posteriori procedure. Instead, trait selection proceeds from a rigorous preferences elicitation along the crop's value chain.

In the next sections of this chapter, we present the asymmetric information and bounded rationality frameworks to analytically contextualize the research problem. Next, we introduce the special case of adoption under production and market uncertainties to illustrate how market-oriented uncertainties preclude farm-level adoption. Then, we present the theoretical solution to the market-induced uncertainty in the adoption decision of the farmer. The last section lays out the hypothesis upon which empirical studies can be built.

4.3.1 Market-oriented Causes of Adoption Uncertainties

In this section, we explain how low uptake of newly developed varieties is caused by farmers' increased uncertainty about the improved grain market demand. We use two major economic frameworks to explain the issue. First, we assess the low adoption rate as a market failure induced by asymmetric information. The friction that occurs in the channel of preference transmission between the crop breeder and the grain consumer relates to weak demand-driven crop variety development. Also, "lemon" seed drives out the good quality seeds and results in an overall mistrust of breeding products. Second, we analyze the issue from the perspective of bounded rationality. The heterogeneity (cross-sectional) and or dynamism (time) in the preferences of the farmer, processor, and consumer induces segmentation from the demand side of the market. Lastly, we briefly present how weakly-coordinated intellectual property rights preclude breeder willingness to involve consumers at the early stage of a new variety development.

4.3.1.1 Asymmetric Information

Defining crop breeding as a market characterized by supply and demand, let us assume the supply side of the market involves breeders who generate new crop varieties that are supplied on the seed market. This segment determines all the embodied technological innovation included in the new variety. The breeder is the key economic agent identified at this stage of the value chain. The demand side of the value chain encompasses production, processing, and consumption of grains. The improved sorghum grains obtained from the new crop varieties are the traded product on this market. The demand side agents are therefore farmers, processors, and consumers. On one hand, we define and identify pure consumers as those not involved in sorghum production but who purchase either the grain or its derived products. We identify farmers and processors as both producers and consumers. Because farmers and processors consume part of their production/transformation and sell the surplus, they are more than just intermediaries interested in spatial and/or temporal arbitrage.

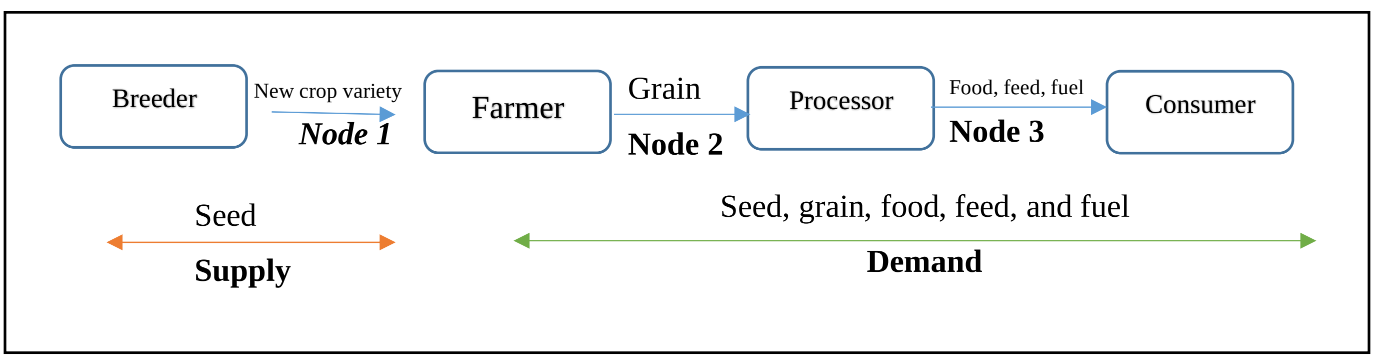

Figure 4-1 Food product value chain: From breeding to consumption

Source: Author

Along the value chain presented in Figure 4-1, we identify three main nodes of strategic interactions where asymmetric information between agents can occur. First, it may happen that the attributes included by the breeder in the new variety do not match the producers' expectations. Node 1 represents the point where asymmetry of information between the breeder and farmer occurs. Second, it may happen that the new variety meets producer preferences but is not valued by the processor, likely because it does not ensure optimal processing output. This is the second node (Node 2), where the asymmetry of information between the breeder and the processor occurs. Last, we identify the third node (Node 3) between the processor and the consumer. Here, the information asymmetry may result from a mismatch between the preferences of the processor and the consumer. The disequilibrium in any of these nodes impedes the crop uptake, as it breaks the flow along the value chain, increasing the farmer's uncertainty of adoption.

Heterogeneous and/or dynamic preferences among breeders, farmers, processors, and consumers induces disequilibrium in any of the nodes of the value chain. For each agent considered in this setting, the heterogeneity is based on either taste or scale. Heterogeneity in taste represents differences in preferences. Heterogeneity in scale represents differences in magnitude of the desired attributes. In either case, sociodemographic characteristics of agents, differences in their attitudes and perceptions, social influences, and past experiences are primary causes of cross-sectional heterogeneity.

4.3.1.2 Bounded Rationality and Latent Segmentation Model

The cross-sectional heterogeneity in preferences is explained based on the demographic characteristics of agents, differences in attitudes and perceptions, social influences, and past experiences. In addition, we assume agents to be rational in their decision-making. This implies that agents maximize their utility, choosing goods and services bundles that yield the highest satisfaction possible. Because individuals might be idiosyncratically different one from another, cross-sectional differences in preferences due to diversity and rationality arise. Posed in the context of crop adoption and preferences for food, feed, and fuel derived from grain, the idea of dynamic or temporally-heterogeneous preferences is quite complex. We therefore use the theory of bounded rationality to explain the overtime change in an individual preference. It is important to highlight that a choice behavior is rational if it is complete and transitive in addition to the desirability and convexity assumptions.

In many economic situations, including cropland allocation at the household level, choice inconsistency tends to have some regularity (Porgo et al., 2018). For some reason, the decision maker's choices may reveal that, at the time t, she strictly preferred variety X to Y, and in a different time $t + 1$, she strictly preferred Y to X. According to Spiegler (2011), these inconsistencies can be characteristics of present bias, temptations, and dynamic implications of reference-point effects.

The present bias is induced by risk aversion and refers to the tendency of people to give stronger weight to current payoffs when considering trade-offs between the current and future moment (Rabin & O'Donoghue, 1999). In the case of choice among crop varieties, a risk-averse farmer may be reluctant to adopt the new variety in the first year of its introduction. These risk-averse farmers are known as late majority or laggards in the new technology adoption process.

The temptation to shift among alternatives is another factor that may explain dynamic preferences. Consider a two-stage decision problem where a farmer chooses the crop to grow in first stage and the variety to grow in the second stage. After a visit to the experimental field, the farmer may decide to grow the newly-introduced variety. However, once the plot is tilled, and based on the signal provided by the demand side of the market, the farmer's marketing uncertainty for the new variety may significantly change. Thus, the farmer may be tempted to stick with the traditional variety.

The dynamic implications of the reference-point effect assumes the cases where there is a change in the expected sunk cost of adopting the new variety between t and $t+1$. As a farmer subscribes for the seeds of the new crop variety at time t, the expected cost of production is estimated at level L, which maximizes the farmer's profit. At time $t+1$, and after the farmer committed to the new variety, additional information on the new variety induces a positive change in L such that the expected profit unexpectedly and significantly declines. In an unconstrained contract case where the farmer is still able to cancel the contract, they might prefer to cancel or reduce the acreage allocated to the new variety. For each market occurring at each of the nodes of Figure 4.1, the supply side should be aware of this potential preference change. For a newly-introduced, improved variety, this dynamism in preferences is often a source of uncertainty.

4.3.1.3 Weak Intellectual Property Environment

Some supply side hurdles can explain the low uptake of new sorghum varieties. Breeders in developing economies are often faced with the complexity of preference elicitation and the weak intellectual property structure. Preference elicitation is complex due to the cross-sectional and/or dynamic intra and across agents' heterogeneity of preferences. First, breeders are rational economic agents and therefore possess their own preferences. Preferences for sorghum traits are not homogenous among breeders. Based on their social and cultural environment, past experiences, geographical location, and the information they are exposed to, each breeder values a specific attribute or trait. Consequently, the final variety released by a breeder includes some level of subjectivity, which, to some extent, affects farmers' and consumers' adoption of the product.

Additionally, preference heterogeneity among producers, processors, and consumers makes the overall preference elicitation complex at the breeder level. As described in the previous section, each stakeholder of the sorghum value chain has their own preference ranking. Developing the same variety for all stakeholders involves some uncertainty in the breeder's decision-making process. Although they are a quasi-public goods producer, the breeder maximizes a profit function, which is defined by the value farmers', processors', and consumers' attachment to the variety. In such a case, poorly designed and enforced intellectual property may be a disincentive for the breeder.

4.3.2. The Model of New Sorghum Variety Adoption Under Uncertainty

In this section, we propose a technology adoption under uncertainty model. We follow Koundouri et al. (2006) and Mukasa (2016), and consider a risk-averse and profit-maximizing farmer using inputs $\boldsymbol{x} = (\boldsymbol{x_1}, \boldsymbol{x_2}, \dots., \boldsymbol{x_j}, \dots \boldsymbol{x_m})$ to grow a newly-introduced variety of sorghum $\boldsymbol{y}$. We assume that the farmer cannot perfectly predict the quantity of sorghum to produce when making the cropland allocation decision. Two major sources of uncertainty for the farmer are production and marketing. On one hand, uncontrolled production conditions (soil, weather, plant diseases) make the quantity to be harvested imperfectly predictable. On the other hand, because the grain to be harvested is new to the consumer, the farmer could not perfectly predict the consumer demand. Unpredictable demand explains the uncertainty for the farmer to perfectly foresee the return on their investment. Consequently, through a backward effect, the farmer cannot perfectly predict their expected quantity $\boldsymbol{y}$ of sorghum to be produced. Therefore, we assume the farmer to incur a production and marketing risk represented in equation (1) by the variable $\boldsymbol{e}$ following a distribution $\boldsymbol{Z}(.)$. We assume distribution $\boldsymbol{Z}(.)$ to be exogenous to the farmer's production decision. Based on the aforementioned framework, let us assume that the sorghum producer uses a continuous, twice differentiable, and concave production function:

$$y = y(e, x) \tag{1}$$

For simplicity in modeling, let's also assume that sorghum grain price p and input prices $w = (w_1, w_2, \dots, w_j, \dots w_m)$ are not affected by the stochastic factor e. We also assume that w_i and p are known by the sorghum producer when their production decisions are made. To account for the subsistence farming in developing economies, we also assume that the sorghum producer consumes a portion c_1 of their production. Consequently, the sorghum farmer faces the following budget constraint:

$$\sum_{j=1}^{m} w_j x_j \leq p * [y(e, x) - c_1] + F \tag{2}$$

where F represents off-farm income (nonagricultural wage, transfer, or remittances). The profit π derived by the farmer from their sorghum production is given by:

$$\pi = p * [y(e, x)] - \sum_{j=1}^{m} w_j x_j \tag{3}$$

Because of the uncertainty associated with the new sorghum variety production and marketing, the farmer cannot perfectly predict π. The producer therefore chooses inputs to maximize the expected utility of their sorghum production profit $EU(\pi)$. We assume the utility function U to be a Von Neumann-Morgensten utility function, mapping the risk preferences of the farmer. We assume a rational sorghum farmer for whom:

$$\frac{\partial U(.)}{\partial \pi} > 0 \quad \text{and} \quad \frac{\partial U^2(.)}{\partial \pi^2} < 0 \tag{4}$$

Assumption (4) implies that the individual is averse to risk in attitude preferences. In this new uncertainty framework, the farmer is faced with the following optimization problem:

$$Maximize \quad \{EU[p * [y(e,x)] - \sum_{j=1}^{m} w_j x_j]\} \tag{5}$$

$x_1, x_2, \dots., x_j, \dots x_m$

Subject to:

$$\sum_{j=1}^{m} w_j x_j \leq p * [y(e,x) - c_1] + F$$

The first-order condition derived from equation (5), with respect to a single input x can be expressed as follows:

$$pE\left[\frac{\partial U(.)}{\partial \pi} * \frac{\partial y(.)}{\partial x}\right] - w * E\left[\frac{\partial U(.)}{\partial \pi}\right] = 0 \tag{6}$$

which implies

$$pE\left[\frac{\partial U(.)}{\partial \pi} * \frac{\partial y(.)}{\partial x}\right] = w * E\left[\frac{\partial U(.)}{\partial \pi}\right] \tag{7}$$

Equation (7) implies, in the case of adoption of the new sorghum variety, that:

$$\frac{w^1}{P} = E\left[\frac{\partial y(.)}{\partial x^1}\right] + \frac{cov[\partial y(.)/\partial x^1; \partial U(.)/\partial \pi]}{E[\partial U(.)/\partial \pi]} \tag{8}$$

And in case of the non-adoption of the new sorghum variety:

$$\frac{w^0}{P} = E\left[\frac{\partial y(.)}{\partial x^0}\right] + \frac{cov[\partial y(.)/\partial x^0; \partial U(.)/\partial \pi]}{E[\partial U(.)/\partial \pi]} \tag{9}$$

Assuming the sorghum farmer was risk-neutral, we would have:

$$\frac{cov[\partial y(.)/\partial x; \partial U(.)/\partial \pi]}{E[\partial U(.)/\partial \pi]} = 0 \tag{10}$$

and equation (7) and (8) would generally reduce to:

$$\frac{w}{P} = E\left[\frac{\partial y(.)}{\partial x}\right] \tag{11}$$

The term $\frac{cov[\partial y(.)/\partial x; \partial U(.)/\partial \pi]}{E[\partial U(.)/\partial \pi]}$ captures the deviation from risk neutrality, as expressed by Koundouri et al. (2006) and Mukasa (2016). A risk-averse farmer with no information on the improved variety would be more sensitive to production and market uncertainty and would be less likely to adopt the newly-introduced variety. However, in a case where the new variety is well known by the farmer for its production efficiency and marketing premium, we would expect a risk-averse farmer, who bears higher profit uncertainty, to have a higher probability of adoption. For such a farmer, this would be an optimal hedging strategy against adverse production and marketing conditions.

Furthermore, let us model the adoption decision process. The sorghum farmer's decision to adopt the improved variety x^1 over the traditional variety x^0 can be modeled using an indicator function in the expected profit framework. We write the indicator function mapping the adoption decision of the farmer as:

$$I^* = g'[EU(\pi^1) - EU(\pi^0)] \qquad (12)$$

Where I^* is a latent and unobserved function representing binary adoption variable I. Superscript 1 stands for adoption and 0 stands for non adoption. The variable I^* takes the value of 1 when $I > 0$ and I^* takes the value of 0 when $I \leq 0$. It follows that the sorghum farmer will adopt the improved variety if its expected utility of profit is higher than the expected utility of profit under non-adoption. Furthermore, assume that both the improved and the traditional varieties sell at the same price p. Also, recall that the farmer imperfectly predicts the profit induced by the adoption due to production and marketing uncertainties, while also assuming that the adoption of the improved sorghum entails sunken costs. All these imply that additional production and marketing information on the new variety might have a positive value as the farmer's decision to adopt relies on the information they possess. With this additional cost (c^1) in the condition of adoption, the sorghum farmer will adopt if and only if:

$$EU(\pi^1) - EU(\pi^0) > c^1 \qquad (13)$$

Or

$$\begin{Bmatrix} p * EU[y(x^1, x_i, e) - y(x_i, e)] - \left\{\sum_{j=1}^{p} w_j x_i - \sum_{j=1}^{m} w_j x_i\right\} \\ - \sum_{j=p+1}^{m} w_j^1 x_j^1 \end{Bmatrix} > c^1 \quad (14)$$

where $c^1 \geq 0$ represents the value of the new information (transaction cost) required by the sorghum farmer to adopt. Variable c also depends on the sunk costs incurred by the adoption, the production and market uncertainties, and other farmer-specific characteristics, such as geographic localization and education. This means that the sorghum farmer will adopt the improved seed if and only if the marketed value of the expected production gains, due to the new variety adoption, exceeds the cost differential of the conventional production inputs used on the farm and the additional cost incurred by the new variety adoption.

$$p * EU[y(x^1, x_i, e) - y(x_i, e)] \geq \left\{\sum_{j=1}^{p} w_j x_i - \sum_{j=1}^{m} w_j x_i\right\} + \sum_{j=p+1}^{m} w_j^1 x_j^1 + c^1 \quad (15)$$

It follows that that the sorghum farmer's willingness to adopt the improved varieties increases as their production and marketing uncertainties decrease (as c^1 gets close to zero). The participatory breeding may help decrease the uncertainty related to production (Ghimire et al., 2015; Nkongolo et al., 2011; Trouche et al., 2009; Atlin et al., 2001) by improving drought, disease, and striga tolerance. However, the uncertainty related to the marketing of the newly-introduced, improved sorghum grain can only decrease if consumers are involved in the breeding procedure. By involving farmers, processors, and consumers and taking their preferences into account, the inclusive breeding program can bring the variable c^1 to zero (perfect information) and therefore increase the likelihood of adoption.

4.3.3 Theoretical Solution to Market-oriented Uncertainties in Adoption

As a solution to address the marketing uncertainties causing low uptake to improved varieties, we suggest the preference matching. Next, we analytically support this solution with a general equilibrium model for preferences mapping, which pinpoints how matched preferences along the value chain can improve adoption. In the context of improved sorghum varieties, both theories effectively promote the ex-ante preferences assessment by the breeder.

4.3.3.1 Matching Theory

We define the relationship between the breeder and heterogeneous demand as the interaction between a finite number of sellers and buyers in a market. Sellers and buyers are all assumed to be rational. Following Camina (2006) and Shapley and Roth (2012), we assume that rational agents engage in unrestricted mutual trade when the outcome is beneficial. Otherwise, some individuals would devise new trades that make them better off. In a market characterized by a set of different sorghum grains, each representing a crop variety owned by the seller, each buyer wants to buy, at most, one type of grain representing one variety. This is a two-sided matching market where agents are either seller or buyer, and there exists bilateral exchange among them.

The dynamics of adoption associated with the threshold model are illustrated in Figure 4-2. We assume an S-shaped adoption cumulative density function and consider an initial case of the asymmetric market information system where the farmer, due to high market-oriented uncertainties, has a threshold[3] (A) associated with a probability of adoption P(A). Assuming that a consumer-oriented breeding program is implemented where breeders, farmers, and consumers all get involved in the varietal development program, the improved variety developed carries

[3] The threshold can be perceived as the level of exposure necessary to induce adoption of the technology. In other words, the threshold is a "hypothetical construct that represents a weighted value of all actor characteristics, previous experiences, and external factors that modulate a decision to adopt an innovation" (Wejnert, 2010)

farmer, processor, and consumer preferences. This reduces the asymmetric preference problem and therefore decreases the farmer’s uncertainty for marketing. As a result, the farmer’s adoption cumulative density function shifts left. For the same probability of adoption P(A), this implies that the farmer has a lower threshold of adoption (B). Similarly, the farmer’s initial threshold of adoption is associated henceforth with a higher probability of adoption P(B).

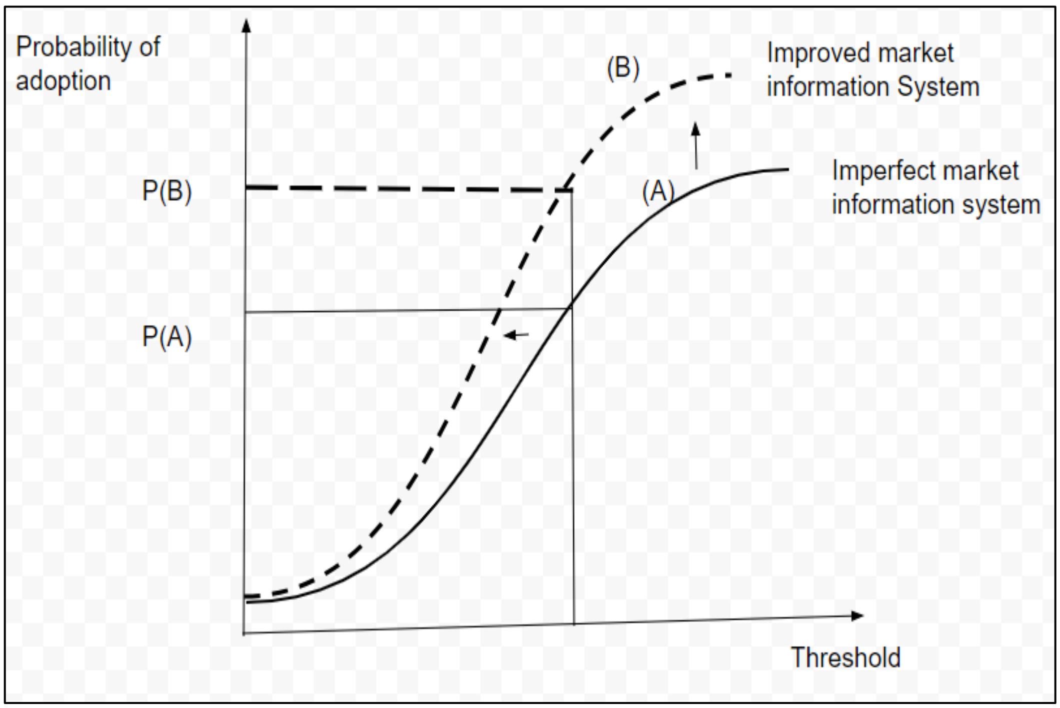

Figure 4-2 Threshold of the Improved variety adoption decision under imperfect market information system (A) and improved market information system (B)

Source: Author

4.3.3.2 A General Equilibrium Model of Dynamic Preferences

In this section, we use the general equilibrium framework to support matching theory as a solution to the asymmetric information problem to adoption. We proceed by explaining the mechanism of preference transmission that occurs along the new sorghum variety value chain. Our model identifies the breeder as the primary supplier of the new product (new variety) and consumers of food products as the primary demanders of the new food product (from the new variety). Along this value chain, farmers (food producers) and processors are perceived as “active” intermediaries. Farmers and processors are “active” in the sense that they both produce and consume the marketed products, which are sorghum-based food or feed products. Therefore, farmers, processors, and consumers maximize both profit and utility in this model.

Based on the sorghum market value chain described in the first section of this chapter, we assume a production-neutral varietal change where only the consumption drives production along the seed-food product value chain. In such a framework, the demand for seed is derived from the demand for food, as it can be seen in Figure 4-3. Any shock in food demand resulting from a change in tastes, preferences and population, or income growth induces a shift in consumer demand. As a result, the quantity of food demanded increases (F1 to F2). This, in consequence, increases the demand for grain (G1 to G2) at the farm gate and seed (S1 to S2) at the breeder gate, implying that any technological changes by the breeder that affects the taste and preference of the consumer might induce a shift in the seed demand by the producer. Thus, a negative effect on taste and preferences contributes to low varietal uptake.

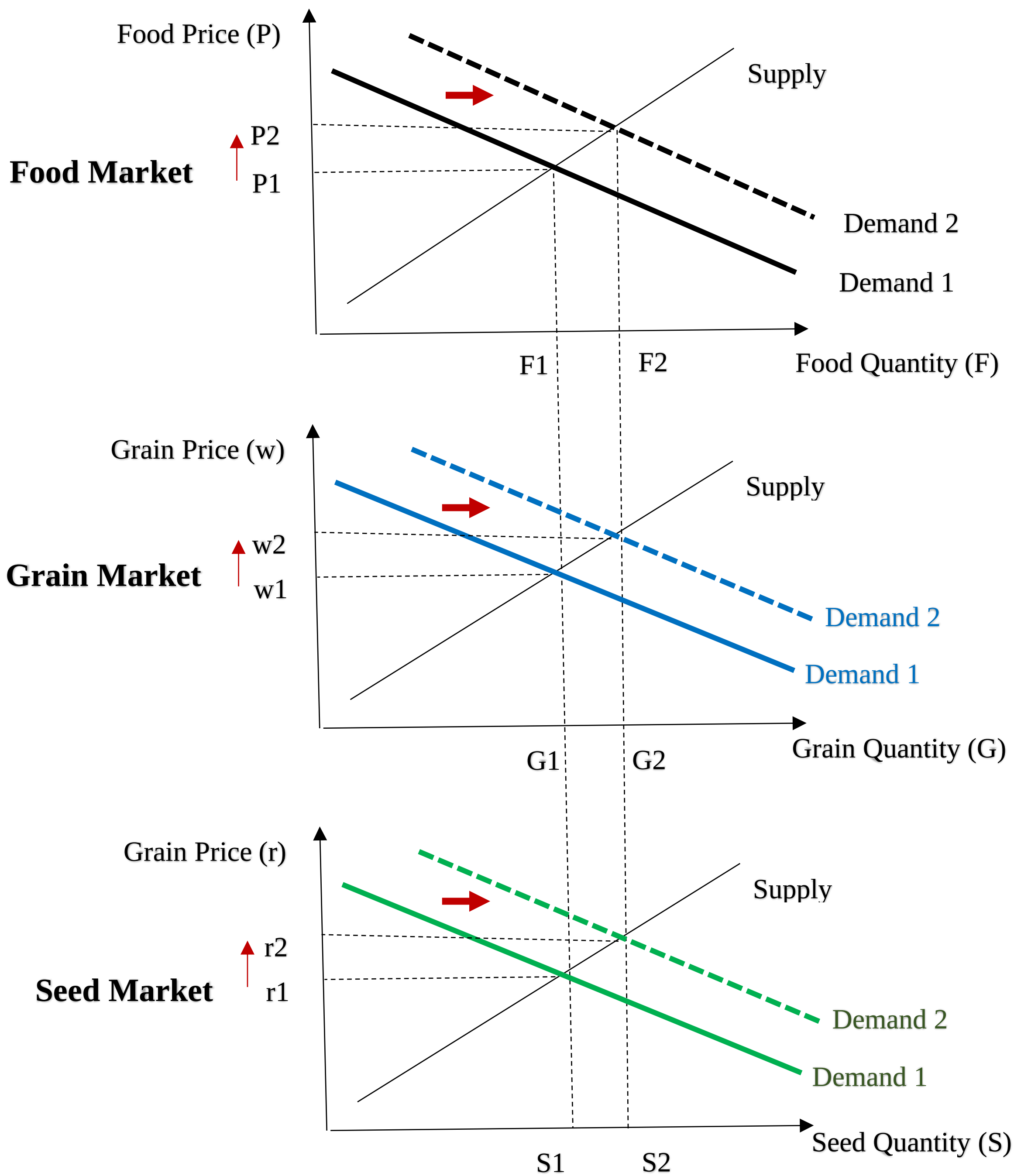

Figure 4-3 Primary and derived demand and supply of seed, grain, and food product markets

Note: A change in preferences shifts food demand from 1 to 2. This induces a positive demand shifts on grain and seed markets. Source: Author

Following Marsh (2003) and Balgatas (2007), we modeled the sorghum value chain in terms of a general and integrated system of equations. The economic model consists of a system of inverse demands and primary supplies specific to the seed, grain, and food products sectors. Figure 4-4 shows a simple case of equilibrium between producer profit maximizing and the consumer utility maximizing problems. A general equilibrium is achieved along the value when interacting stakeholders perfectly access market information for price and preferences.

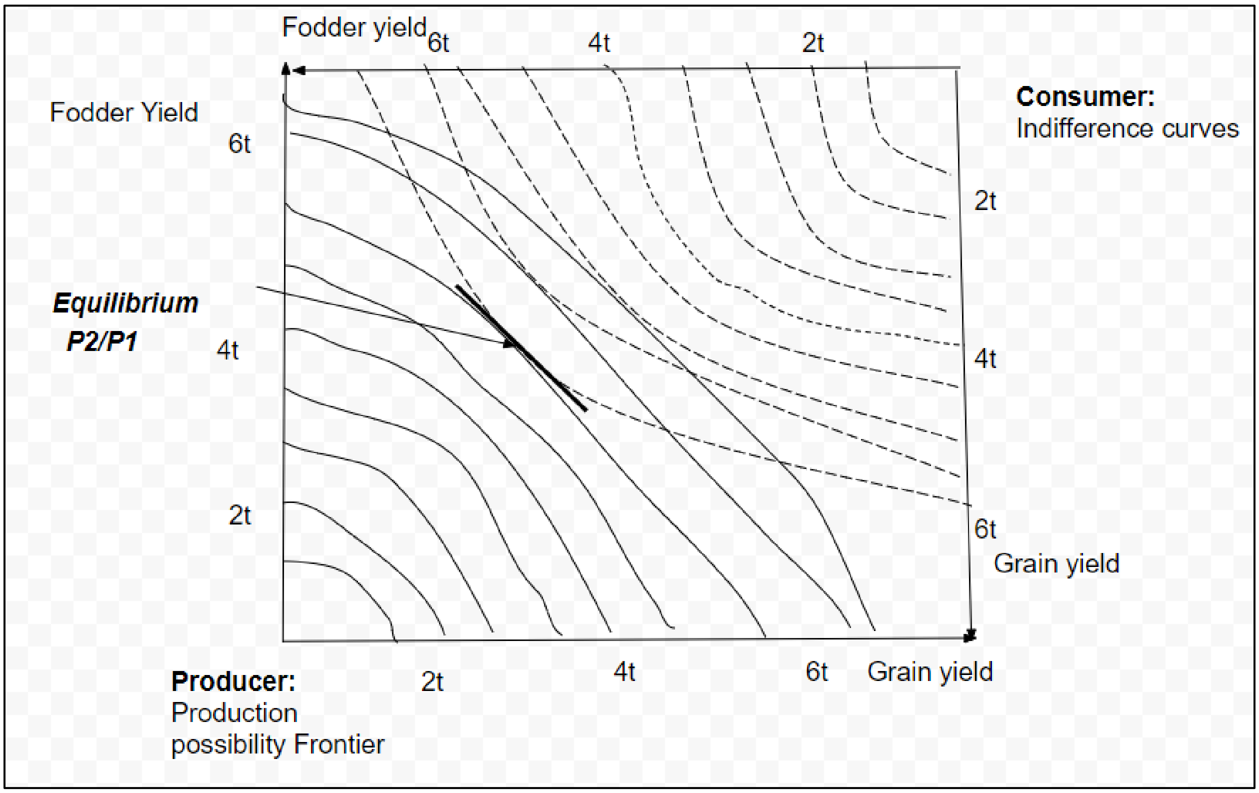

Figure 4-4 Edgeworth box showing equilibrium between producer profit and consumer utility maximization problems

Source: Author

Using the system of equation to model preferences along the new variety adoption channel is appropriate because of potential simultaneity between prices and supplies. This is also important because of correlated errors among the market-level equations (Marsh, 2003). The model treats the demand of the final food product as exogenous. A such, and under competitive conditions, any increases (decreases) in this primary demand are expected to increase (decrease) derived demand of grain on the processing market and seed on the seed market (Tomek & Kaiser, 2014).

Food Market

Equation (1) is the primary or upstream demand equation of this general equilibrium model. The primary demand for sorghum is determined at the retail food level through sorghum-based food. This is a dynamic price equation of the retail sorghum-based food price as a function of consumer disposable income ($\boldsymbol{Y_d}$), per capita consumption ($\boldsymbol{Q_f^d}$) of sorghum, per capita consumption of other cereals**,** such as maize, millet**,** and rice ($\boldsymbol{Q_{sub}}$)**,** and complements ($\boldsymbol{Q_{comp}}$)**,** such as sugar and milk, processing or disembodied ($\boldsymbol{A_p}$)**,** and grain intrinsic or embodied ($\boldsymbol{A_g}$) attributes, cost of advertisement ($\boldsymbol{C_{adv}}$), and the value of food byproducts ($\boldsymbol{P_{fb}}$). Equation (2) specifies the food supply by the processor. The supplied quantity is a function of the price of the supplied food, the price of processing inputs such as labor ($\boldsymbol{P_L}$), capital ($\boldsymbol{P_K}$), interest rate ($\boldsymbol{r}$)**,** and the cost of the food processing technology ($\boldsymbol{T_f}$). When the market clears, suppl***y*****,** and demand quantities (prices) equate.

(1) $P_f^d = \Psi_1\{Y_d, Q_f^d, A_p, A_g, Q_{sub}, Q_{comp}, C_{adv}, P_{fb}, \mu_1\}$ (Inverse demand)

(2) $Q_f^s = \Psi_2\{P_f^s, P_L, P_K, r\ , T_f, \mu_2\}$ (Food product supply)

(3) $Q_f^s = Q_f^d = Q_f\ ;\ P_f^d = P_f^s = P_f$ (Market clearing)

Grain Market

The grain price equation is derived from inverse demand relation. It represents the demand price for sorghum grain by firms who further process them into ready-to-eat food. The price of grain is hypothesized in equation (4) to be a function of the quantity of grain demanded

($\boldsymbol{Q_g^d}$), the retail food price ($\boldsymbol{P_f}$) itself is a function of the intrinsic grain attributes ($\boldsymbol{A_g}$), the quantity demanded of other grains ($\boldsymbol{Q_{other(g)}}$), the average transaction cost on the grain markets ($\boldsymbol{C_{tra}}$), and the grain by-product values ($\boldsymbol{P_{gb}}$). Equation (5) presents grain supply as a function of grain price ($\boldsymbol{P_g^s}$), production input prices ($\boldsymbol{P_L}, \boldsymbol{P_K}$), interest rate ($\boldsymbol{r}$)**,** and the production technology cost ($\boldsymbol{T_g}$).

(4) $P_g^d = \Psi_3\{Q_g^d, P_f(A_g), Q_{other(g)}, C_{tra}, P_{gb}, \mu_3\}$ (Inverse demand)

(5) $Q_g^s = \Psi_4\{P_g^s, P_L, P_K, r, T_g, \mu_4\}$ (Grain supply)

(6) $Q_g^s = Q_g^d = Q_g$; $P_g^d = P_g^s = P_g$ (Market clearing)

Commercial Seed Market

Equation (7) represents the commercial seed demand market. Sorghum grain producer demand for commercial seed ***is used,*** along with fertilizer, labor, and capital. In this model, the price of commercial seed is defined in equation (7) as a function of the quantity of commercial seed demanded by farmers ($\boldsymbol{Q_{cs}^d}$), the retail sorghum grain price ($\boldsymbol{P_g}$)**,** which accounts for intrinsic grain attributes ($\boldsymbol{A_g}$), the quantity demanded of commercial on other cereal seed market***s*** ($\boldsymbol{Q_{other(cs)}}$), and the average transaction cost on the commercial seed markets ($\boldsymbol{C_{tra}}$). Equation (8) defines supply of commercial seed as a function of commercial seed price ($\boldsymbol{P_{cs}^s}$), production input prices ($\boldsymbol{P_L}, \boldsymbol{P_K}$), interest rate ($\boldsymbol{r}$)**,** and the commercial seed production technology cost ($\boldsymbol{T_{cs}}$).

$P_{cs}^d = \Psi_5\{Q_{cs}^d, P_g(A_g), Q_{other(cs)}\ C_{tra}, \mu_5\}$ (Inverse demand)

(7) $Q_{cs}^s = \Psi_6\{P_{cs}^s, P_L, P_K, r, T_{cs}, \mu_6\}$ (Commercial seed supply)

(8) $Q_{cs}^s = Q_{cs}^d = Q_{cs}$; $P_{cs}^d = P_{cs}^s = P_{cs}$ (Market clearing)

Base Seed Market

The base and commercial seeds markets are similar. While commercial seed is produced by certified seed producers for other farmers, base seed is supplied by the breeder to certified seed producers. Equation (10) is the inverse demand for base seed. This is the downstream demand equation in this general equilibrium model. The demand for base seed is a function of the quantity of base seed demanded by certified seed producers ($\boldsymbol{Q_{bs}^{d}}$), the commercial sorghum seed price ($\boldsymbol{P_{cs}}$**)**, which accounts for intrinsic grain attributes ($\boldsymbol{A_g}$), the quantity demanded of base seed on other cereal seed market***s*** ($\boldsymbol{Q_{other(bs)}}$), and the average transaction cost on the base seed markets ($\boldsymbol{C_{tra}}$). Equation (11) defines the supply of base seed as a function of the base seed price ($\boldsymbol{P_{bs}^{s}}$), production input prices ($\boldsymbol{P_L}, \boldsymbol{P_K}$), the time it takes for the breeder to get the base seed (time), the intellectual property right***s*** policy that is in effect within the country or region (I), and the government transfer to breeding research institutes ($\boldsymbol{G_{transfer}}$).

(9) $P_{bs}^{d} = \Psi_7\{Q_{bs}^{d}, P_{cs}(A_g), Q_{other(bs)}\ C_{tra}\ , \mu_7\}$ (Inverse demand)

(10) $Q_{bs}^{s} = \Psi_6\{P_{bs}^{s}, P_L, P_K, time, I, G_{transfer}, \mu_8\}$ (Base seed supply)

(11) $Q_{bs}^{s} = Q_{bs}^{d} = Q_{bs}\ ;\ P_{bs}^{d} = P_{bs}^{s} = P_{bs}$ (Market clearing)

We assume the breeder to be a quasi-public goods producer. The breeder generates new varieties that fall in the public domain and contribute to social welfare improvement. From their breeding research and process, the breeder publishes research papers that lead to professional gain. Also, the new varieties developed by the breeder may provide the host institution with intellectual property rights or patents.

Based on equation (10), the price elasticity of the base seed is:

(12) $\varepsilon_p = \frac{\Delta Q_{bs}^{d}}{\Delta P_{bs}^{d}} \frac{P_{bs}^{d}}{Q_{bs}^{d}}$

Based on the interconnection among equations (1) – (12) through the grain intrinsic attribute A_g, equation (13) implies:

$$(13) \qquad \varepsilon_p = \frac{\Delta Q_{bs}^d}{\Delta P_{bs}^d}\frac{P_{bs}^d}{Q_{bs}^d} = \left[\frac{\Delta Q_{bs}^d}{\Delta P_{cs}^d} * \frac{\Delta Q_{cs}^d}{\Delta P_g^d} * \frac{\Delta Q_g^d}{\Delta P_f^d} * \frac{\Delta Q_f^d}{\Delta P_f^d} * \frac{\Delta P_f^d}{\Delta A_g}\right] * \frac{P_{bs}^d}{Q_{bs}^d}$$

Equation (14) mathematically captures the relationship between all segments of the sorghum value chain. It implies that variable A_g, representing the intrinsic grain attributes, is the link through which the demand for sorghum-based food is transmitted to the breeder gate demand for base seed. Therefore, the higher (lower) the effect of the grain attribute on the food price, the higher (lower) the effect of the change in consumer preferences on the demand for the base seed.

Variables used in the modeling are described in Table 4-2. We assume that the error terms, μ_1 through μ_8, are white noise, although they may be contemporaneously correlated. Overall, the derived demand for base seed of sorghum generally depends upon the primary demand for sorghum-based food. Thus, the specification of equations (1) – (12) captures the effects of change in sorghum-based food demand on the base seed price.

Table 4-2 Definition of variables in sorghum supply and demand

Variables	Description
Q_i^s, Q_i^d, Q_i	Are respective demanded, supplied and equilibrium quantities of food (f), grain (g), commercial seed (cs) and base seed (bs)
P_i^s, P_i^d, P_i	Are respective demand, supply, and equilibrium price of food (f), grain (g), commercial seed (cs) and base seed (bs)
$P_{other(i)}$	Is the price for other food (f), grain (g), commercial seed (cs) and base seed (bs)
P_{comp}	Price of complements
P_L, P_K	Labor (L) and capital (K) price, respectively
r	Interest rate
C_{tra}	Transaction cost
T_i	Is technology cost for food (f), grain (g), commercial seed (cs) and base seed (bs) production
A_p, A_g	Are respective processing (p) and grain attributes (g) contained in either the food product or grain, commercial seed and base seed
μ_i	Error term
I	Intellectual property right or research patent
$G_{transfer}$	Government transfer to new variety development
$time$	Time lag between new variety breeding inception and the procurement of the commercial seed

Source: Author

4.3.4 Hypotheses for Prospective Empirical Investigation

This theoretical review lay the ground for a two-step empirical investigation. In the first step, the adoption study can provide a comprehensive assessment of farm-level adoption drivers. In the second step, the multi-agent preference elicitation might contribute to preference rating by stakeholders across the value chain. With respect to sorghum adoption in West Africa, we hypothesize that traditional varieties still represent a large portion of sorghum acreage. Also, based on the findings of Timu et al. (2014) in Kenya, we expect local traditional varieties to get higher farmers' scores, with respect to drought tolerance. However, farmers are likely to prefer newly-developed, improved varieties when it comes to yield potential, striga resistance, and shortness of the maturity cycle. We therefore expect yield potential, drought and striga resistance, and the maturity cycle to be the major drivers of variety adoption.

Additionally, we expect the multi-agent preference assessment to shed light on preference heterogeneity in the sorghum industry. We expect scientists to give more importance to production traits as they simply focus on farmers' preferences. Because of their dual economic status induced by non-separability of production and consumption, we expect that weights for agronomic, processing, and consumption to be insignificantly different for farmers. Processors and consumers are likely to lean towards flour quality, cooking time, starch, and swelling qualities as well as other consumption-oriented traits. We therefore suggest simulating the proposed general equilibrium model as a first start for empirical investigation.

Overall, our null hypothesis for the general equilibrium model of sorghum preferences is an asymmetric distribution across segments of the value chain. In summation, we formulate the following hypotheses for prospective empirical investigations:

For the Breeder

Hypothesis 1: Royalties payments received by breeders following a new variety introduction positively contribute to consumer-oriented breeding

***Hypothesis 2*:** Production traits are highly valued over processing and consumption attributes

For the Producer

Hypothesis 3: Traditional sorghum varieties are produced and consumed by more farmers than improved varieties

Hypothesis 4**:** Production traits such as yield, drought-resistance, and striga resistance significantly determine farmer choice of sorghum variety

Hypothesis 5: Production traits are ranked higher than consumption attributes by sorghum producers

For the Consumer

Hypothesis 6: Consumption attributes such as grain color, sugar content, and taste are valued more than production traits by consumers

Hypothesis 7: Grain price negatively affects consumer choice of sorghum variety

General Hypothesis (Heterogeneous preferences along the value chain)

Hypothesis 8: Value and rank assigned to production, consumption, processing, and economic attributes by breeders, producers, processors, and consumers are different

Prospective researchers could test the above-mentioned hypotheses using both a revealed and stated preferences analysis. Using household-level data, one could estimate a multinomial logit model of the main sorghum cultivated in the surveyed regions. The statistical significance test can be conducted to identify determinants of traditional and improved varieties adoption. Control variables in such estimation might include the Likert scaled score for agronomic and post-harvest attributes of the cultivated varieties. Also, the researcher might control for household-specific social and cultural determinants by including household demographic and economic variables.

We suggest the use of a stated preference approach to conduct the multi-agent preference assessment. Primary data can be collected using a best-worst scaling approach. The survey questionnaire may include a set of attributes combined in choice sets presented to each survey respondent. To test preference asymmetry along the value chain, the researcher can estimate rank and compare an attribute's value for breeders, farmers, processors, and consumers. For each agent, ranking the averaged value of attributes enables them to determine the importance of agronomic, processing, and consumption attributes in the agent utility function. The second part of the asymmetry analysis may consist of comparing each single attribute value across agents.

4.4 Conclusion

In this chapter, we reviewed the theoretical framework supporting varietal adoption, primarily considering low varietal adoption as a market failure problem. We explained market failure in an improved seed adoption context with asymmetric market information systems and its corollary bounded rationality of agents. Next, we presented a theory of technology adoption under uncertainties and highlighted how demand-driven uncertainties determine adoption at the farm level. We suggested the matching theory as a theoretical solution to address low adoption, and we explained its rationale using the general equilibrium model. Building upon our theoretical argument, we lay down a few hypotheses that can be used to empirically assess market-oriented adoption drivers.

The asymmetry of information causes market failure in the sense that supply and demand have different information and mismatching preferences. In the context of the traditional seeds market, we considered that the breeder may have more knowledge of the developed improved seed than the farmer and the consumer. This asymmetry of information precludes the marketing of the improved seed. Mismatching preferences arise when the breeder, the farmers, and the consumers have taste and scale heterogeneity for crop varieties. As a result, “lemon” seeds crowd the improved seeds out of the market.

Next, we presented the theory of bounded rationality to partly explain dynamic individual preferences. Based on the assumption of rational choice behavior, inconsistencies in the economic agent choice can be the result of present bias, temptations, or dynamic implications of reference-point effects. The preference shift is a consequence of the time change in the case of present bias. However, heterogeneous preferences induced by temptation, along with dynamic implications of the reference-point are due to contingencies of the dynamic decision-making process.

The complexity of preference elicitation and weak intellectual property rights in developing countries are also possible reasons of low adoption on the supplier side. On one hand, sorghum breeders may have heterogeneous preferences based on their social and cultural environment, past experiences, geographical location, and the information they are exposed to. On the other hand, the heterogeneity among producers’, processors’, and consumers’ preferences makes the overall preference elicitation complex and costly for the breeder. The absence of intellectual property protection or research incentives precludes potential willingness to engage in consumer-oriented breeding. Adopting a breeding-incentives accounting for the adoption scale of varieties might be a strategical step to engage breeders in consumer-oriented breeding.

In showing how asymmetric information increases uncertainty and precludes adoption, we presented a theoretical model of the farmer’s adoption decision under uncertainty. From this model, we identified production and marketing factors as a potential source of uncertainty for adoption. The market-induced uncertainty is caused by asymmetric information and bounded rationality and explains the frictions along the value chain. Then, we suggested the matching theory as an approach to improve varietal crop adoption, ensuring that breeding programs are based on contemporaneous mutual interest of both supply and demand. Lastly, we presented the theoretical model of dynamic preferences that may support prospective empirical investigation. The matching theory stands as a partial answer to overcoming asymmetric preferences along the seed value chain. If consumption drives production along the seed-food value chain, matching the preferences of supply and demand improves the promotion of the newly-developed variety. This provides the improved variety with traits to effectively increase the profit for the famer and the processor while raising the utility of the final consumer.

Based on the theoretical argument presented, we made two main hypotheses, with respect to future empirical research. First, we hypothesized agronomic traits to significantly affect farmers' decisions to adopt improved seeds. Second, we expected organoleptic traits to influence the decision to grow traditional sorghum varieties. For the cross-agent preferences comparison, we expected heterogeneity in preference ranking and values.

In summation, it is tempting to conclude with a set of prescriptions or guidelines for restoring adoption. However, our purpose is analytical and more modest. We argue for a more inclusive way of thinking about plant breeding. We argue for crop breeding that mimics manufacturing product development, where the endpoint consumer is the key stakeholder. Targeting consumer preferences from breeding inception helps trigger market-driven adoption. Preference elicitation along the food supply chain is one of key components to include in plant profile development. Embedded within preference assessment are fundamental issues of attribute values and ranking in the framework of the matching theory. Across-agents preference ranking and matching can effectively help account for tradeoffs among seed attributes. Until empirical evidence is presented to strengthen or weaken our argument, it makes little sense to embark on ambitious demand-led breeding to enhance food security and foster agricultural productivity.

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Appendix A -

Appendix of Chapter 1

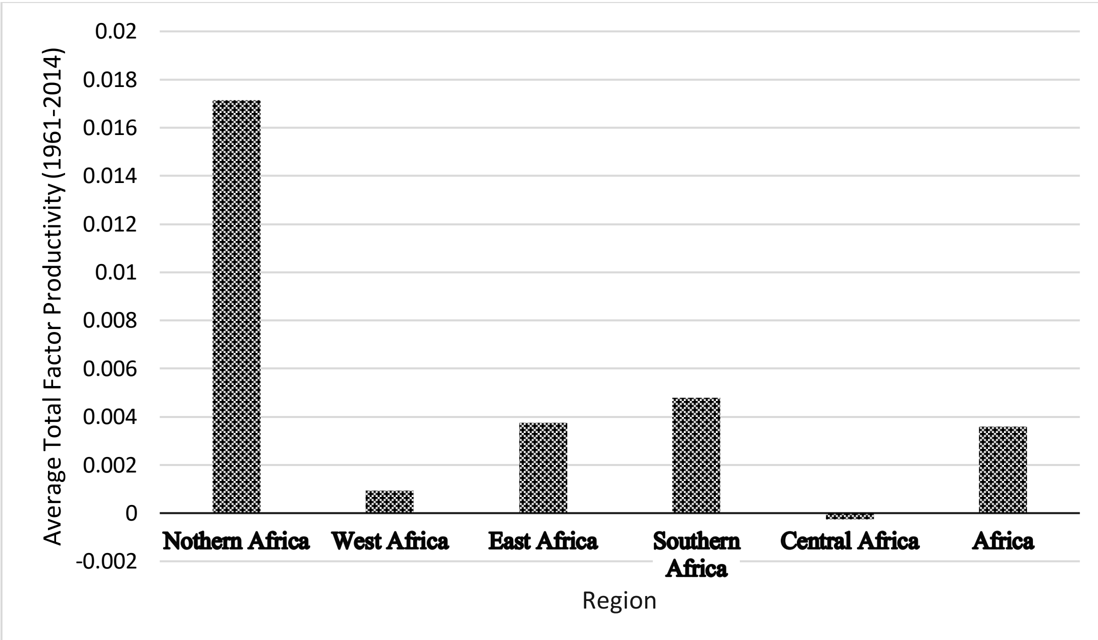

Fig 1-a. Average Total Factor Productivity Growth per Region in Africa (1961-2014)

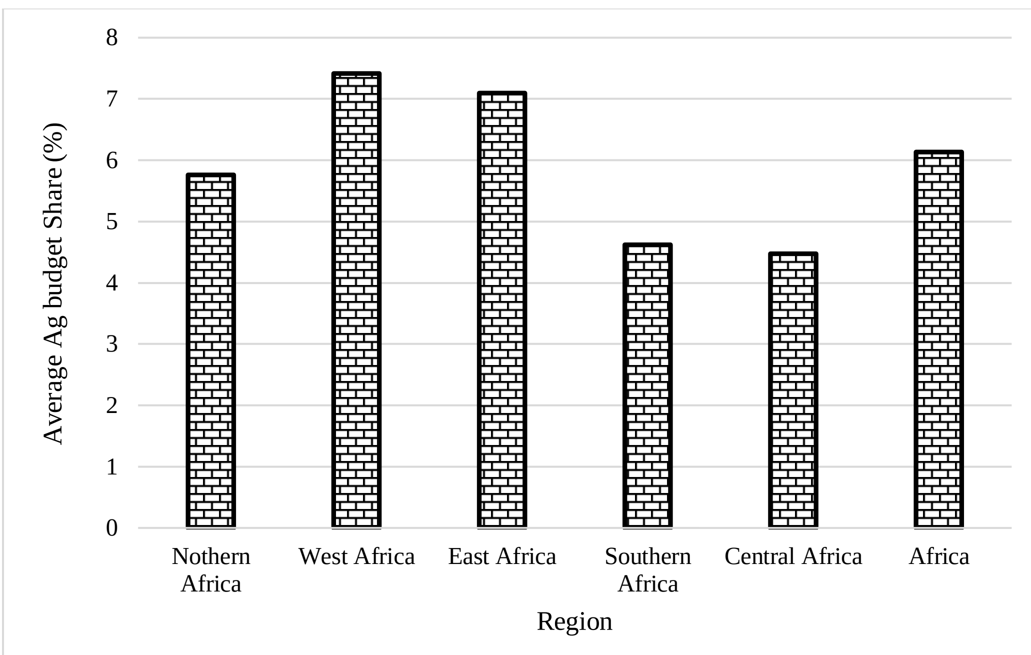

Fig 1-b. Average Agricultural Budget Share per Region in Africa (1961-2014)

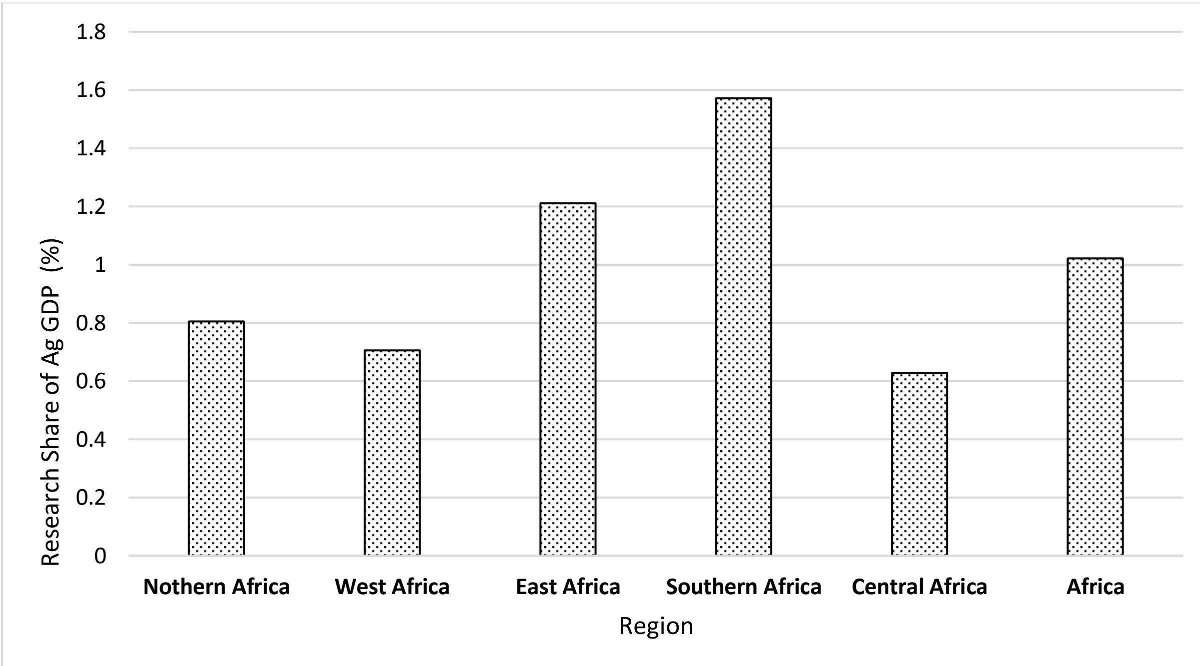

Fig 1-c. Average Research Share of Agricultural GDP per Region in Africa (1980-2016)

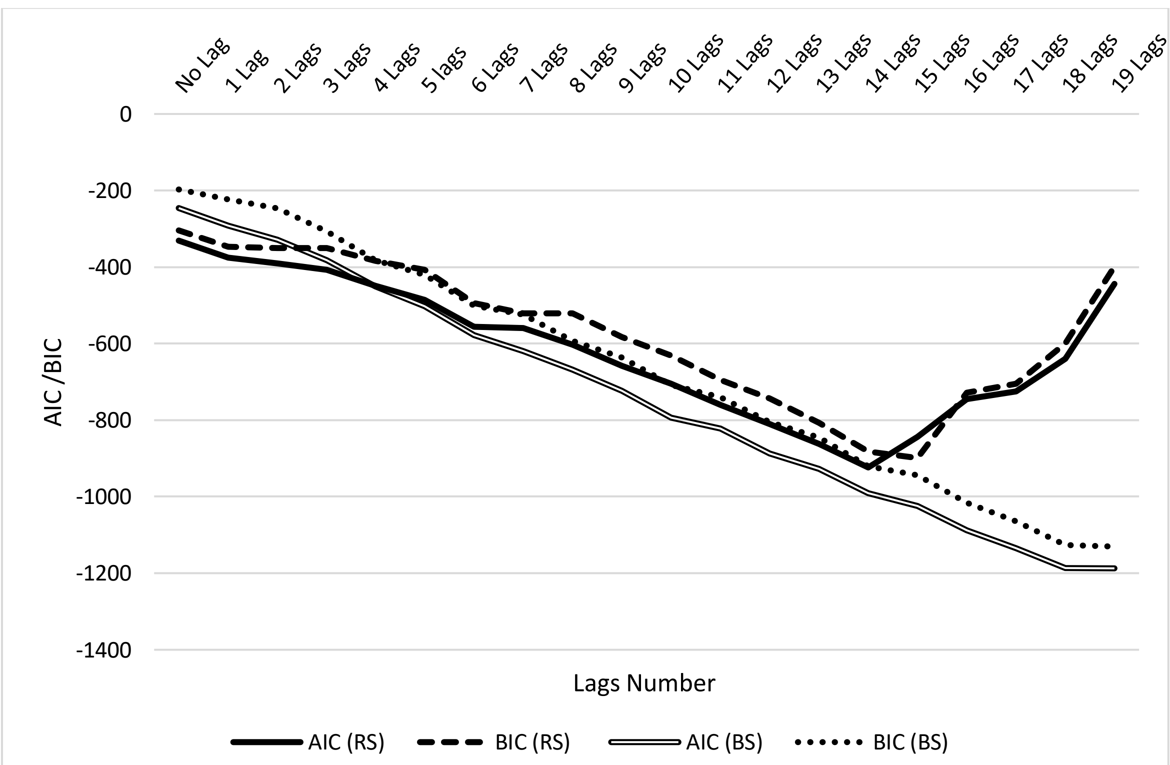

Fig 1-d. AIC and BIC for different number of lags of BS and RS models

Supplemental material on the conceptual Framework

In this section, we present the theoretical framework that explains the mechanism through which public spending affects agricultural productivity. Following Blankenau et al. (2007), Glomm and Ravikumar (1997), and Helms (1985), we consider that the effect of agricultural budget share and tax level on the agricultural productivity index occurs in the framework of the endogenous growth model. We define (i) the three-period-lived agent problem, (ii) the representative firm producing a single agricultural goods problem, (iii) the government problem, and (iv) the production technology. Next, we consider a simple overlapping generational model of agricultural productivity index growth and define three-period-lived homogeneous agents.

The Agent's Problem

We consider identic agent within a generation that is born each period. For simplicity, we normalize the continuum agents to 1. The agent in the first period is considered to be a learner and does not own the own farm. In the second period, we consider the agent as a producer of farm products and an earner of an off-farm income through wage. In the final period, the agent is considered old and unproductive.

The initial old agent is endowed with K_0 units of physical capital used in farm production, and the original earner is endowed with h_0 units of human capital. Learners and earners in each generation receive an endowment of public education, extension training, farm input subsidy, and government transfers given by E_t. The agent combines public inputs E_t and farming human capital of the prior and current generations, h_t, to create period t+1 human productive farming capital according to:

$$h_{t+1} = \varepsilon E_t^{\mu} h_t^{1-\mu} \qquad (1)$$

Where $\mu \epsilon [0, 1]$ and $\varepsilon > 0$ (Glomm & Ravikumar, 1997). The parameter μ determines the relative importance of the agricultural expenditure and human capital of the preceding generation in generating human capital.

The earner in period $t + 1$ inelastically supplies her one unit of labor endowment to her own farm and to the representative firm (off-farm income) and receives after-tax labor income in proportion of her stock of human capital equal to $\omega_{t+1}h_{t+1}(1 - \tau_i)$, where τ_i is the tax rate on income and ω is the farm wage to a unit of farming human capital. This income is allocated for both consumption and savings. Earners save for old age through savings, capital accumulation, and the capital holdings for period t learner at the end of the period $t + 1$ are $K_{t,t+2}$ where the time subscript $t + 2$ implies that the capital is productive in period $t + 2$. The return on a unit of capital purchased in period t is $r_{t+1}(1 - \tau_i)$ units, where r_{t+1} is the period $t + 1$ capital rental rate. For simplicity, we assume that capital depreciates fully, and that labor and capital are taxed at the same rate.

Let's denote $C_{t,t+1}$ and $C_{t,t+2}$ as the consumption of periods t+1 and t+2, respectively, of the agent and τ_c is the tax on the consumption. Assuming logarithmic preferences in $C_{t,t+1}$ and $C_{t,t+2}$ with $\beta \in [0,1]$, we write the representative agent problem as:

$$\max_{C_{t+1}, C_{t+2}, K_{t+2}} \ \ln C_{t+1} + \ln C_{t+2} \qquad (2)$$

Subject to

$$C_{t+1}(1 + \tau_c) + K_{t+2} \leq \omega_{t+1}h_{t+1}(1 - \tau_i)$$

$$C_{t+2}\,(1 + \tau_c) \leq (r_{t+2}(1 - \tau_i))K_{t+2}$$

$$C_{t+j} \geq 0, j = 1,2$$

This implies that in each period, the agent consumes and invests in productive capital for less than or equal to her total net wage or returns on capital. The solution to the agent problem is:

$$K_{t+2} = \tilde{\beta}(\omega_{t+1}h_{t+1}(1-\tau_i) \text{ where } \tilde{\beta} = \frac{\beta}{1+\beta} \quad (3)$$

The Firm Problem

In this agricultural production model, a representative agricultural firm combines human productive capital and the physical capital made of manpower, tractors, and all other agricultural tools to generate a single hypothetical good or output Y_t. We assume a Cobb-Douglass production function where K_t and L_t represent the quantity of physical and human capital, respectively. The physical capital in this model is assumed to be borrowed from the market, where households accumulate their capital stock at a competitive rental rate. The labor is supplied by households and costs a competitive wage rate. In this firm model, we use the framework set up by ERS (1996). We assume that the changes in agricultural outputs (crops and livestock) are induced by two factors: (1) the changes in agricultural intermediate inputs (fertilizer, pesticides, energy, feed, and seed), capital (equipment, real state, and inventories), and labor (L); (2) the change in output is due to the change in productivity growth, which is not accounted for by the change in inputs. The sources of agricultural productivity growth A(.) are agricultural research and development, extension, education, and infrastructure.

We define

$Y_t = A_t K_t^{\alpha} L_t^{1-\alpha}$. Where $\alpha \in [0,1]$ (4)

Where A_t is the agricultural productivity index, $A_t > 0$. A_t is the outcome of our model. In other words, A_t is total factor productivity (TFP) defined as the ratio of agricultural output (food, livestock, poultry) by all inputs involved in the production, represented here by capital and labor. In this model, A_t is not constant, instead it is a function of the time trend (t) and includes several factors in X, such as government spending, weather, tax, and time trend. We therefore write:

$$A_t = A_t(X) \qquad (5)$$

For convenience, we write A_t in this paper, but we really mean the dynamic productivity function $A_t(X)$.

Our main hypothesis in this paper is that government expenditure variation partly determines the TFP. Increasing government expenditure or decreasing tax rates, both at the border (tariff) and on the domestic market (consumption tax) determine expansionary fiscal policy and give a positive signal to domestic production. This positive signal induces production enhancement, which may result in increased TFP. In Africa, the irrigation rate in agriculture was only about 6% of the collective cropland, compared with a world average of about 18% (Svendsen et al., 2009) as of 2009. Because about 95% of farms depend on rainfall, which is highly variable and unpredictable (Abebrese, 2017).

From Equation (4), we derive:

$$A_t = \frac{Y_t}{K_t^{\alpha} L_t^{1-\alpha}} \qquad (6)$$

In a simple macroeconomic model, where we assume A_t to be constant with respect to K_t and L_t, we define $y_t = \frac{Y_t}{L_t} = Ak_t^{\alpha}$ as the per effective labor unit output. Further, assuming competitive market for inputs (K, L) and outputs (Y), the firms take prices as given and hire additional inputs until $r_t = A\alpha k_t^{\alpha-1}$ for capital and $\omega_t = A(1-\alpha)k_t^{\alpha}$ for human capital or labor.

In this dynamic productivity setting, write:

$$r_{t+1} = A_{t+1}\alpha k_{t+1}^{\alpha-1} \qquad (7)$$

$$\omega_{t+1} = A_{t+1}(1-\alpha)k_{t+1}^{\alpha} \qquad (8)$$

The Government

In this model, the government is assumed to spend a share of output Y on agricultural projects. These include agricultural input imports, input subsidies, extension service administrative funds, rural infrastructure aiming to improve market accessibility, and social spending in cases of droughts and floods, among others.

We write agricultural expenditures $E_t\ as$:

$$E_t = \tilde{e}Y_t \qquad (9)$$

Where $\tilde{e}\ \equiv \exp{(e)}$

We assume an additional share of output g by the government on other sectors and a share b of output is funded through deficit spending. All the public expenditures are financed through taxes on labor (τ_i), capital income (τ_i), consumption (τ_c), or through borrowing (b). We assume a balanced government budget such that:

$$\tau_i\omega_t h_t + \tau_i r_t K_t + \tau_c(C_{t-1,t} + C_{t-2,t})\, h_t = (e + g + b)Y_t \qquad (10)$$

Our model considers this government expenditure stream to result in a technological improvement for the overall economy through education, research, health, and infrastructure construction. Specifically, the empirical model we present in the next section aims to estimate the effect of agricultural expenditure share or research share of agricultural GDP on the total factor productivity of the sector.

From Equation (1), we derive the following:

$$E_t^{\mu} = \frac{h_{t+1}}{\varepsilon h_t^{1-\mu}} = \frac{h_{t+1}}{h_t} * \frac{h_t^{\mu}}{\varepsilon}$$

$$E_t^{\mu} = (1+\gamma)\ \frac{h_t^{\mu}}{\varepsilon} \text{ and } E_t = (1+\gamma)^{1/\mu} * \frac{1}{\varepsilon^{1/\mu}} = \tilde{e}A(.)k_t^{\alpha}$$

We thus derive:

$$1 + \gamma = \varepsilon(\tilde{e}A(.)k_t^{\alpha})^{\mu} \qquad (11)$$

One can plug (1), (5), (6), and (11) into (3) to get the steady state production capital equation as follows:

$k = \{\tilde{\beta}[A]^{1-\mu}(1-\alpha)\varepsilon\tilde{e}^{-\mu}(1-\tau_i)\}^{1/(1-\alpha-\alpha\mu)}$ (12)

Equation (12) expresses the steady state relationship among capital (k), total factor productivity (A(.)), agricultural expenditure share (e), and tax (τ_i). One can use the implicit function theorem to derive the impact of agricultural expenditure share (e) on the total factor productivity (A(.)) as follows:

$$\frac{d[A]}{d\tilde{e}} = -\frac{\frac{\partial k}{\partial \tilde{e}}}{\frac{\partial k}{\partial [A(.)]}}$$

Where:

$$\frac{\partial k}{\partial \tilde{e}} = \delta * \frac{-\mu}{1-\alpha-\alpha\mu} * [A(.)]^{1-\mu/1-\alpha-\alpha\mu} * \tilde{e}^{\mu-1+\alpha+\alpha\mu/1-\alpha-\alpha\mu} \qquad (13)$$

And

$$\frac{\partial k}{\partial [A]} = \delta * \frac{1-\mu}{1-\alpha-\alpha\mu} * [A(.)]^{\alpha-\mu+\alpha\mu/1-\alpha-\alpha\mu} * \tilde{e}^{\mu/1-\alpha-\alpha\mu} \qquad (14)$$

With $\delta = \{\tilde{\beta}(1-\alpha)\varepsilon {y_t}^{\mu}(1-\tau_i)\}^{1/(1-\alpha-\alpha\mu)}$

We get:

$$\frac{d[A]}{de} = \frac{\delta * \frac{\mu}{1-\alpha-\alpha\mu} * [A]^{(1-\mu)/(1-\alpha-\alpha\mu)} * \tilde{e}^{(\mu-1+\alpha+\alpha\mu)/(1-\alpha-\alpha\mu)}}{\delta * \frac{1-\mu}{1-\alpha-\alpha\mu} * [A]^{(\alpha-\mu+\alpha\mu)/(1-\alpha-\alpha\mu)} * \tilde{e}^{\mu/(1-\alpha-\alpha\mu)}} \; (15)$$

Equation (15) simplifies to:

$$\frac{d[A]}{d\tilde{e}} = \frac{\mu}{1-\mu} * \frac{A}{\tilde{e}}$$

This implies

$$\frac{d[A]}{A} = \frac{\mu}{1-\mu} * \frac{d\tilde{e}}{\tilde{e}}$$

That is:

$$Log\ A = \left[\frac{\mu}{1-\mu}\right] * log\tilde{e}$$

Let's assume there is an expansionary fiscal policy in the agricultural sector. That is, in a case where a government increases its spending in agricultural budget outlays, (such as subsidies on machines, fertilizers, pesticides, seeds, and other inputs, building rural roads to improve market accessibility, as well as more research and extension funds), we expect the overall agricultural productivity to increase. This causes a positive IS shock due the exogenous changes in the agricultural goods and services, as well as the change in the expectations that such a budget increment has on farming households. This positive IS shock leads to a right shift in IS[4] and an aggregate demand curve (AD). Therefore, an overall increase in output (Y) follows. Without getting into the induced effect of such a change on the money market, we expect the output increase to sustain in the long run and therefore positively impact total factor productivity in the agricultural sector. There are therefore direct and indirect effects of government expenditures on agricultural productivity. The direct effect goes through the economic environment created and entertained by the importance attached to the agricultural sector by the government. All forms of subsidies and food purchased by the government are considered to directly affect productivity. The indirect effect goes two ways. On one hand, infrastructure building enhances market access, which in turn gives a positive signal to productivity. On the other hand, education, professional training, exports, and imports policies, along with minimum wage establishment induces technical improvement in food productivity.

[4] The IS curve shift right by $\frac{1}{1-MPC}\Delta G$ where MPC is the marginal propensity in consumption and ΔG is the increase in the government agricultural spending (Mankiw, 2015).

Appendix B -

Appendix of Chapter 2

The Fractional Regression Model Estimates

In this appendix, we report the fractional regression model estimates for Nigeria and Niger. Because the tables are very large, we present the information by crop. For each crop group or crop, namely cereal, maize, sorghum, millet, and rice, we present three-column groups or cases. In order, the case report results for the pooled model, where all households were pooled regardless of whether they accessed irrigation in the previous seasons. The second case reports estimates for households without access to irrigation, and the third group reports estimates for households having access to irrigation. In each case, we report three different regression models to show how our study improved the traditional Mendelsohn land use model.

Model 1: We presented the traditional Mendelsohn model with spatial and climatic variables

Model 2: We added household characteristics and prices to Model 1

Model 3: We added food consumption, access to market, and income to Model 2 to capture trade impact on land use.

2.A. Nigeria

2.A.1- Cereals

Variables	Pooled sample			Without irrigation			With Irrigation		
	Model 1	Model 2	Model3	Model 1	Model 2	Model3	Model 1	Model 2	Model3
Longitude	0.19***	0.16**	0.13*	0.22***	0.20***	0.16**	-1.89	-1.65*	-2.87***
	(0.07)	(0.08)	(0.08)	(0.07)	(0.07)	(0.07)	(1.64)	(0.90)	(1.03)
Longitude Squarred	0.01*	2.3e-3	2.20e-3	0.01**	5e-4	1.46e-3	0.08	0.10**	0.17***
	(0.001)	(0.001)	(4e-3)	(2e-3)	(3.2e-4)	(2.5e-3)	(0.07)	(0.05)	(0.06)
Latitude	1.65***	1.37***	1.30***	1.67***	1.37***	1.31***	1.00	1.54	0.36
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(1.42)	(1.55)	(1.60)
Latitude Squarred	-0.07***	-0.06***	-0.05***	-0.07***	-0.06***	-0.05***	-0.08	-0.09	-0.04
	(3.2e-3)	(e-3)	(2.1e-3)	(3e-3)	(2.2e-3)	(5.4e-3)	(0.05)	(0.07)	(0.07)
Daily average temperature (Long run average)	0.35	0.21	0.15	0.40	0.32	0.23	-9.44	-22.59	-16.74
	(0.31)	(0.32)	(0.32)	(0.32)	(0.32)	(0.32)	(14.99)	(19.29)	(19.15)
Daily average temperature (Long run average) Squarred	-2.12 e-3	-1.26e-3	-8.6e-4	-1.2e-3	-1.3e-2	-1.40e-3	0.06	0.14	0.10
	(2.3e-3)	(1.5e-3)	(3.2e-4)	(e-3)	(1.4e-2)	(2.3e-3)	(0.09)	(0.12)	(0.12)
Daily average rainfall (Long run average)	0.70	2.50	3.15***	0.35	1.31	4.04**	26.60	75.61**	3.13***
	(1.77)	(2.00)	(1.02)	(1.78)	(1.94)	(0.96)	(24.87)	(36.94)	(0.88)
Daily average rainfall (Long run average) Squarred	-17.57**	-19.98**	-23.34**	-16.02*	-15.62*	-19.14**	-203.77	-509.75**	-1,037.64***
	(8.85)	(9.11)	(9.23)	(8.88)	(8.93)	(9.06)	(177.03)	(235.12)	(314.66)

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

2.A.1. Cereals (continued)

Variables	Pooled sample			Without irrigation			With Irrigation		
	Model 1	Model 2	Model3	Model 1	Model 2	Model3	Model 1	Model 2	Model3
Diversification Index	0.21***	0.19***	0.19***	0.22***	0.20***	0.20***	0.72*	0.87**	1.34***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.38)	(0.41)	(0.42)
Averaged distance to farm	2.6.e-4	2.3.e-4	2.6e-4	3e-3	2e-3	3.2e-3	-0.02	-0.04**	-0.04*
	(2.5e-4)	(1.3e-4)	(1.2e-3)	(1.3e-3)	(3.1e-3)	(2.0e-3)	(0.02)	(0.02)	(0.02)
Averaged household farm slope	-0.05***	-0.04***	-0.04***	-0.05***	-0.04***	-0.04***	-0.13*	-0.10	-0.16**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.07)	(0.07)	(0.07)
Averaged household farm Elevation	1.13 e-3***	1.21 e-3***	1.2e-3***	3.2e-3***	1.4e-3***	1.20e-3***	3.6e-3	3.5e-3	3.47e-3***
	(2.3e-4)	(3.4e-4)	(2.4e-4)	(4.3e-4)	(1.3e-4)	(2.3e-4)	(2.1e-3)	(3.3e-3)	(1.3e-4)
Adult Equivalent		0.01**	0.01		0.01**	0.01		-0.02	0.05
		(0.01)	(0.01)		(0.01)	(0.01)		(0.05)	(0.05)
Household Head Age		-1.43e-3	-1.5e-3		-3.2e-3	-1.22e-3		2.2e-3	0.02
		(e-3)	(3e-3)		(3.1e-3)	(1.1e-3)		(0.01)	(0.01)
Maize Price		0.01***	0.01***		0.01***	0.01***		0.09**	0.01***
		(2e-3)	(0.001)		(3e-3)	(2e-3)		(0.04)	(0.001)
Sorghum Price		0.02***	0.01***		0.02***	0.02***		-0.06	0.01***
		(e-3)	(0.001)		(3.2e-3)	(4.4e-3)		(0.05)	(0.001)
Millet Price		-0.03***	-0.03***		-0.03***	-0.03***		-0.04	-0.03***
		(0.01)	(0.01)		(0.01)	(0.01)		(0.06)	(0.01)
Rice Price		-6.3e-4	-7.3e-4		-0.00*	-2.3e-3*		0.04**	-7.3e-4
		(0.001)	(0.001)		(0.001)	(0.001)		(0.02)	(0.001)

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

2.A.1. Cereals (continued)

Variables	Pooled sample			Without irrigation			With Irrigation		
	Model 1	Model 2	Model3	Model 1	Model 2	Model3	Model 1	Model 2	Model3
Distance to market			1.04e-3*			8e-4			0.02**
			(e-3)			(7e-4)			(0.01)
Per capita Food Expenditure			1.3e-4			3e-5			1.2e-3***
			(0.001)			(e-4)			(2.2e-4)
Per Capita Income			-1.2e-5**			-4e-5***			1.3e-3
			(0.5e-5)			(0.00)			(0.001)
2012.year	1.3e-3	0.10	0.07	2.3e-3	0.11	0.07	-3.2e-3	0.32	0.89
	(0.04)	(0.08)	(0.09)	(0.04)	(0.08)	(0.09)	(0.41)	(0.79)	(0.79)
2015.year	0.01	0.25***	0.22***	0.02	0.25***	0.22***	-0.49	0.45	-0.10
	(0.03)	(0.05)	(0.05)	(0.03)	(0.05)	(0.05)	(0.35)	(0.71)	(0.67)
Using Irrigation	0.61***	0.63***	0.65***	-0.02***					
	(0.15)	(0.15)	(0.15)	(0.00)					
Total farm acreage	-0.02***	-0.03***	-0.03***	-0.03***	-0.03***	-0.03***	-0.19***	-0.15**	-0.15**
	(0.001)	(0.001)	(0.001)	(0.01)	(0.001)	(0.001)	(0.07)	(0.07)	(0.07)
Longitude x Latitude	-0.03***	-0.02***	-0.02***	-25.02**	-0.03***	-0.02***	0.07	0.04	0.06
	(0.01)	(0.01)	(0.01)	(12.60)	(0.01)	(0.01)	(0.07)	(0.05)	(0.05)
Constant	-23.04*	-15.54	-12.89		-19.66	-15.94	390.58	917.30	68.39
	(12.50)	(12.83)	(12.87)	5,378	(12.79)	(12.82)	(620.41)	(799.12)	(792.83)
				6252					
Observations	5,507	5,504	5,504	6364	5,375	5,375	129	129	129
AIC	6371	6363	6345	0.105	6242	6244	141	148.1	152
BIC	6490	6521	6503	2483	6393	6415	189.6	211	226.3
Pseudo R2	0.106	0.108	0.108	0	0.107	0.108	0.121	0.145	0.179
Likelihood-ratio test of rho=0	2537	2815	2859	2524	2770	2810	86.98	129.2	110.8
Prob > chi2	0	0	0	0	0	0	0	0	0

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

2.B. Niger

2.B.1. Cereals

Variables	Pooled sample			Without irrigation			With Irrigation		
	Model 1	Model 2	Model3	Model 1	Model 2	Model3	Model 1	Model 2	Model3
Longitude (degree)	-0.38*	-0.32*	-0.26	-0.23**	-0.24**	-0.20	-26.76	-4.74	7.96***
	(0.20)	(0.19)	(0.23)	(0.12)	(0.12)	(0.13)	(20.67)	(22.63)	(3.07)
Longitude Squarred	0.01*	4.88e-3	4.68e-3	2e-3	3e-3	e-3	-0.02	-0.01	-1.45***
	(0.001)	(3.4e-3)	(4.5e-3)	(1.5e-3)	(2.5e-3)	(e-3)	(0.27)	(0.34)	(0.34)
Latitude (degree)	-1.14	0.56	1.13	0.93	0.93	1.75***	-50.49**	-47.90*	5.10***
	(1.51)	(2.02)	(2.25)	(0.61)	(0.61)	(0.66)	(23.01)	(26.91)	(2.07)
Latitude Squarred	0.03	-0.03	-0.05	-0.04*	-0.04*	-0.07***	1.08**	1.31*	-2.24***
	(0.06)	(0.07)	(0.08)	(0.02)	(0.02)	(0.02)	(0.51)	(0.72)	(0.66)
Daily average temperature (Planting year)	-35.51***	189.23**	219.81**	-28.63***	-103.25	-57.12	-0.70	8.90	37.16***
	(7.62)	(82.23)	(92.43)	(7.17)	(80.36)	(82.79)	(11.62)	(12.96)	(13.56)
Daily average temperature (Long run average)	14.79***	-146.37**	-167.71**	19.02***	77.93	45.76	3.75	-0.00	
	(5.65)	(60.81)	(68.71)	(4.28)	(57.95)	(59.85)	(14.79)	(16.30)	
Daily average rainfall (Planting year)	183.85***	-931.15**	-1,077.80**	138.37***	516.37	0.34	- 1,471.85***	- 1,410.90***	- 114.79***
	(36.67)	(407.31)	(455.83)	(31.93)	(397.54)	(0.49)	(256.26)	(384.36)	(18.89)
Daily average rainfall (Long run average)	42.01***	-315.07**	-362.76**	42.15***	180.90	-0.27	1,604.48	2,440.15	
	(11.93)	(134.48)	(150.62)	(10.44)	(129.00)	(0.35)	(1,849.48)	(2,201.99)	
Daily average temperature (Planting year) Squarred	0.21***	-1.11**	-1.29**	0.17***	0.61	29.24***	-	-	19.07***
	(0.04)	(0.48)	(0.54)	(0.04)	(0.47)	(4.08)			(3.66)
Daily average temperature (Long run average) Squarred	-0.09***	0.86**	0.99**	-0.11***	-0.46	-262.23	-	-	
	(0.03)	(0.36)	(0.40)	(0.03)	(0.34)	(359.40)			
Daily average rainfall (Planting year) Squarred	-1,667.25***	8,044.27**	9,322.99**	-1,230.18***	-4,567.82	108.43	-	-	35.46***
	(341.13)	(3,541.71)	(3,962.86)	(290.69)	(3,460.00)	(92.89)			(20.95)

Note: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.01

B.1. Cereals (continued)

Variables	Pooled sample			Without irrigation			With Irrigation		
	Model 1	Model 2	Model3	Model 1	Model 2	Model3	Model 1	Model 2	Model3
Diversification Index	9.28***	9.32***	10.30***	10.26***	10.27***	10.27***	0.73	-0.28	-0.28
	(0.36)	(0.36)	(0.18)	(0.18)	(0.18)	(0.18)	(1.03)	(1.85)	(1.72)
Soil wetness	-1.26e-3	-1.71e-3	-2.7e-3	-1.3e-3	-2e-3	-2.7e-3	-0.08	-0.06	-0.03
	(0.001)	(0.001)	(0.001)	(3e-3)	(1.5e-3)	(0.001)	(0.05)	(0.07)	(0.07)
Soil nutrient	0.06	0.05	-0.02	-0.01	-0.01	-0.02	1.15	0.37	0.28
	(0.04)	(0.04)	(0.02)	(0.02)	(0.02)	(0.02)	(0.71)	(0.96)	(1.05)
Household Equivalent adults		-2.3e-3	0.01		-4.1e-3	0.01		0.06	0.21
		(1.5e-3)	(0.01)		(3.2e-3)	(0.01)		(0.09)	(0.13)
Household head age		-4.03e-3	-1.4e-3		-7e-3	-1.4e-3		0.01	-1e-3
		(0.00)	(0.00)		(5e-3)	(0.001)		(0.02)	(0.02)
Maize Price		-0.11	-0.24		0.45	0.27		-76.27	-82.10***
		(0.91)	(0.91)		(0.64)	(0.63)		(50.29)	(29.12)
Sorghum Price		-0.53	-0.58		1.33***	1.14***		-6.56	-13.40
		(0.78)	(0.76)		(0.39)	(0.39)		(4.10)	(13.04)
Millet Price		-7.62***	-8.59***		2.00	1.59***		-1.38	7.12*
		(2.87)	(3.13)		(2.86)	-0.05		(6.70)	(4.17)
Rice Price		-0.64	-1.30		-0.36	-1.21**		20.03	27.46**
		(0.84)	(0.83)		(0.57)	(0.57)		(22.99)	(13.07)
Distance to nearest market			4.6e-4			6.6e-3**			-0.07***
			(0.001)			(3.1e-4)			(0.02)
Distance to nearest asphalted road			3.79e-3*			4.2e-3***			-0.07***
			(1.7e-3)			(3.1e-4)			(0.02)

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

B.1. Cereals (continued)

Variables	Pooled sample			Without irrigation			With Irrigation		
	Model 1	Model 2	Model3	Model 1	Model 2	Model3	Model 1	Model 2	Model3
Per Capita Food Expenditure			-1.2e-3			1.3e-3***			3e-3
			(0.00)			(2.2e-5)			(2.7e-3)
Per capita Income			2.3e-4**			-2.3e-3***			4.1e-3**
			(e-5)			(1.2e-4)			(3.1e-3)
Female Head of household (Male = 0)		-0.04	-0.04		-0.07**	-0.06**		0.01	-0.57
		(0.03)	(0.03)		(0.03)	(0.03)		(0.58)	(0.64)
Access to Irrigation	1.34***	0.63	0.63						
	(0.50)	(0.46)	(0.46)						
Total farm acreage	2.14e-3**	2.15e-3**	2.14e-3**	2.3e-3**	2.3e-3**	2.2e-3**	-0.01	-0.05	-0.05
	(0.001)	(e-3)	(e-3)	(1.02e-3)	(e-3)	(e-4)	(0.03)	(0.03)	(0.03)
Longitude x Latitude	0.01	0.02	0.01	0.02**	0.02*	0.01	1.63*	0.33	-1.32
	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.98)	(1.09)	(1.56)
Constant	879.43***	-1,777.61*	-2,163.37**	390.83	1,037.92	454.67	285.95	-49.95	56.71
	(326.02)	(957.10)	(1,052.18)	(256.88)	(965.08)	(386.49)	(0.00)	(0.00)	(50.01)
Observations	4,844	4,844	4,844	4,783	4,783	4,783	61	61	61
AIC	4142	4150	4054	3981	3988	3996	81	92.60	96
BIC	4252	4299	4123	4091	4124	4165	106.4	134.8	144.6
Pseudo R2	0.239	0.240	0.240	0.256	0.256	0.256	0.315	0.369	0.400
Likelihood-ratio test of rho=0	2917	2971	2772	3969	3713	3689	4725	1188	7.470e+08
Prob > chi2	0	0	0	0	0	0	0	0	0

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

Appendix C -

Appendix of Chapter 3

Annex 1. Demand Analysis

Table 3-a. Compensated (Hicksian) own price and cross-price elasticities for staple food items in urban and rural Niger

	Urban (n = 513)					Rural (n = 719)				
Food items	**Maize**	**Millet**	**Rice**	**Sorghum**	**Cassava flour**	**Maize**	**Millet**	**Rice**	**Sorghum**	**Cassava flour**
Maize	-0.0252	-0.120***	0.0956**	-0.143***	0.192***	-0.484***	0.320***	-0.0365*	-0.0535***	0.255***
	(0.0507)	(0.0257)	(0.0417)	(0.0243)	(0.0147)	(0.0118)	(0.0144)	(0.0189)	(0.0152)	(0.0143)
Millet	-0.193***	0.156**	0.207***	-0.265***	0.0952***	0.258***	-0.602***	0.351***	-0.0390***	0.0326***
	(0.0514)	(0.0734)	(0.0224)	(0.0777)	(0.0152)	(0.0119)	(0.00970)	(0.0157)	(0.00932)	(0.00503)
Rice	0.0690***	0.115***	-0.271***	0.0525***	0.0351***	-0.0556**	0.472***	-0.464***	0.0711***	-0.0231**
	(0.0189)	(0.00975)	(0.0244)	(0.0104)	(0.00702)	(0.0248)	(0.0263)	(0.0202)	(0.0128)	(0.0114)
Sorghum	-0.289***	-0.507***	0.133***	0.780***	-0.118***	-0.143***	-0.186***	0.124***	0.197**	0.00757
	(0.0566)	(0.120)	(0.0346)	(0.181)	(0.0296)	(0.0309)	(0.0381)	(0.0136)	(0.0794)	(0.00662)
Cassava flour	0.796***	0.328***	0.103**	-0.320***	-0.908***	1.203***	0.0452	-0.190***	-0.0221	-1.036***
	(0.0813)	(0.0503)	(0.0423)	(0.0700)	(0.0105)	(0.116)	(0.0309)	(0.0560)	(0.0179)	(0.0163)

Note: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 3-b. Uncompensated (Marshallian) own price and cross-price elasticities for staple food items in urban rural Niger

	Urban (513)					Rural (n=719)				
Food items	**Maize**	**Millet**	**Rice**	**Sorghum**	**Cassava flour**	**Maize**	**Millet**	**Rice**	**Sorghum**	**Cassava flour**
Maize	-0.357***	-0.464***	-0.447***	-0.321***	0.0869***	-0.736***	0.00935	-0.281***	-0.195***	0.183***
	(0.0605)	(0.0445)	(0.0394)	(0.0322)	(0.00829)	(0.0193)	(0.00712)	(0.0188)	(0.0128)	(0.0124)
Millet	-0.423***	-0.0392	-0.128***	-0.368***	0.0334**	0.00420***	-0.911***	0.0993***	-0.180***	-0.0392***
	(0.0576)	(0.0816)	(0.0161)	(0.0773)	(0.0142)	(0.00152)	(0.00363)	(0.00392)	(0.00747)	(0.00172)
Rice	-0.129***	-0.0603***	-0.586***	-0.0444***	-0.0248***	-0.342***	0.122***	-0.726***	-0.0808***	-0.100***
	(0.0141)	(0.00778)	(0.0354)	(0.00603)	(0.00278)	(0.0360)	(0.0110)	(0.0262)	(0.00953)	(0.0103)
Sorghum	-0.457***	-0.693***	-0.185***	0.675***	-0.183***	-0.343***	-0.434***	-0.0765***	0.0798	-0.0492***
	(0.0677)	(0.108)	(0.0436)	(0.187)	(0.0266)	(0.0298)	(0.0371)	(0.00942)	(0.0852)	(0.00440)
Cassava flour	0.627***	0.208***	-0.116***	-0.366***	-0.963***	0.999***	-0.212***	-0.388***	-0.135***	-1.098***
	(0.0908)	(0.0409)	(0.0304)	(0.0684)	(0.00962)	(0.117)	(0.0298)	(0.0506)	(0.0172)	(0.0127)

Note: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Annex 2 Welfare Analysis

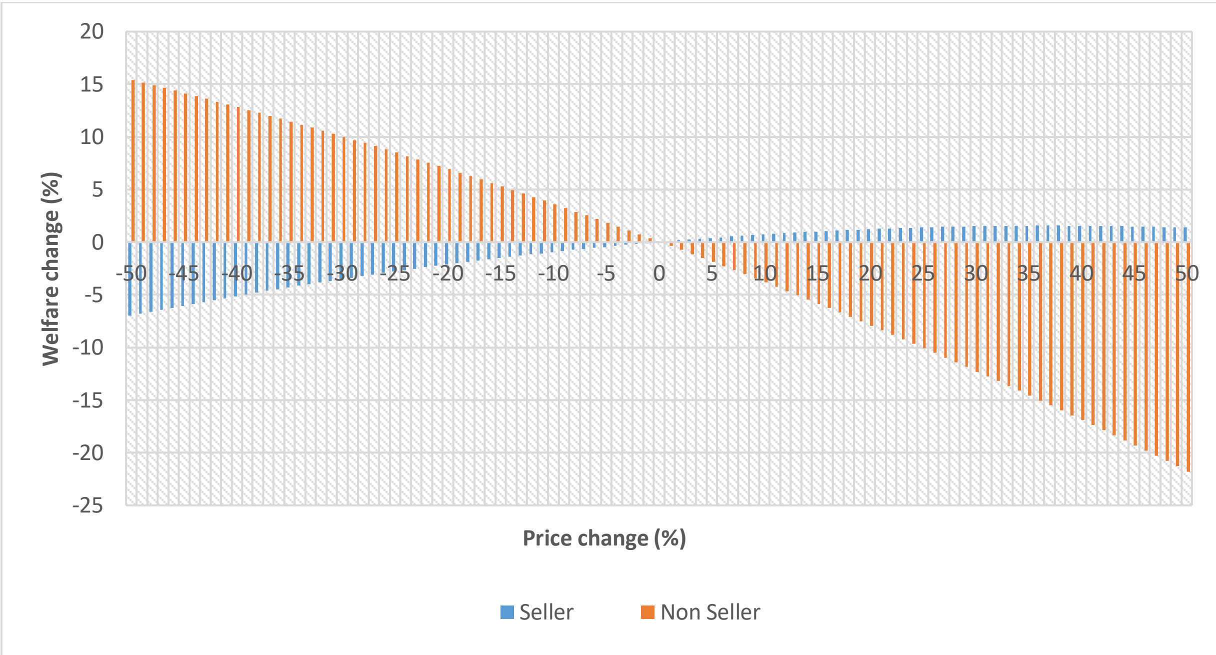

Fig 3.a. Simulation of relative welfare change for net sellers and non-sellers based on millet consumer price variation

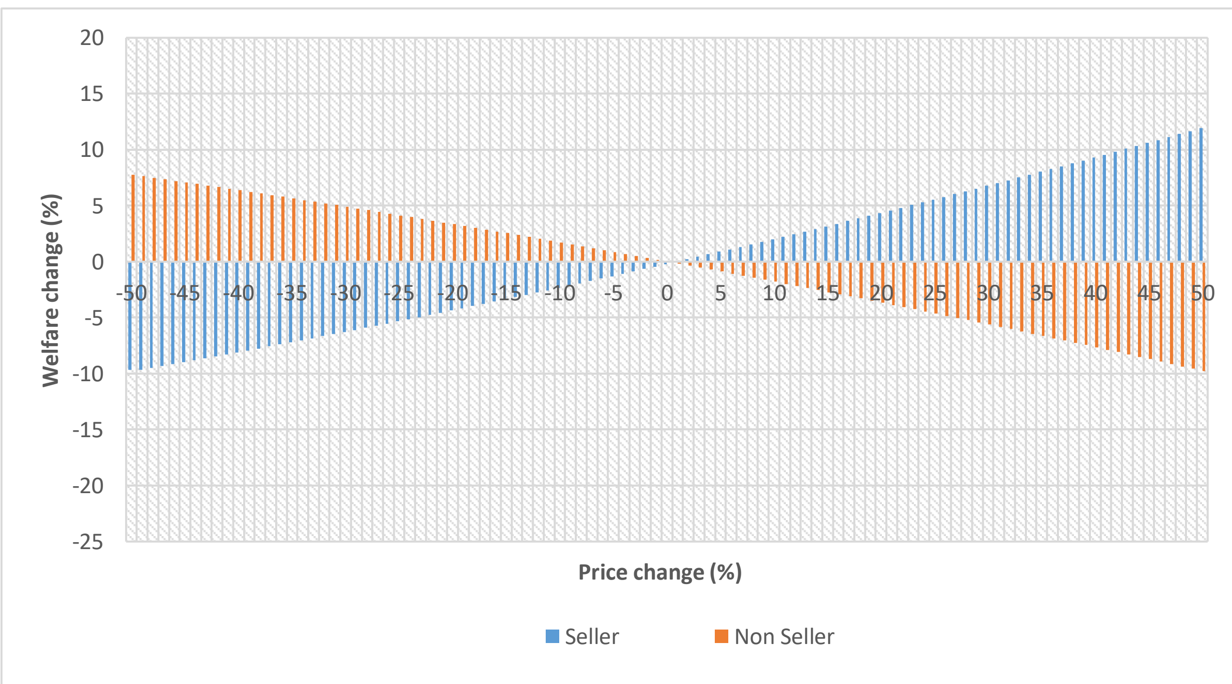

Fig 3.b. Simulation of relative welfare change for net sellers and non-sellers based on Sorghum consumer price variation