Allocation of farm output and farmer-agribusiness linkages:

Cyclical decisions and welfare effects

by

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B.Sc., Makerere University, 2010
M.Sc., Makerere University, 2017

AN ABSTRACT OF A DISSERTATION

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Department of Agricultural Economics
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Abstract

Agricultural commercialization has been a major development policy in Uganda as in most of Sub-Saharan Africa. The quest is to use agriculture as an engine of development to ensure high income, food security, and industrialization. While effort has been placed in implementing programs targeted towards commercialization, levels of subsistence farming are still high. This dissertation contributes three essays aimed at understanding: (1) output allocation on smallholder farms and determinants of allocation choice, (2) production and income thresholds that may foster increased market participation by smallholder farmers, and (3) the economic benefits created by Ag-Public Private Partnerships (Ag-PPP) to small holder farmers.

The first essay (chapter 2) models the farm output allocation process, among Ugandan farmers, to show how farmers distribute production, and documents factors that influence the choice of an allocation strategy. It thus evaluates both participation and the level of allocations. The study analyzes the ex-post decision when output is known with certainty and argues that households maximize utility at this stage; ex-ante decisions become inconsequential at this point. The study finds that levels of self-provisioning are high, approximately 66% of produced output, while commercialization stands at 27%. Furthermore, findings show that crop diversification increases the share of output allocated to home consumption and reduces that for marketing and storage. Non/off-farm income eases the burden of producing for the market – farmers with higher off-farm incomes tended to produce and allocate more for home use. Also, farmers with high output tended to allocate more to the market. We found that household food sufficiency reduced the share allocated to the market and was associated with higher shares allocated to storage. Adopting a policy prescribed enterprise increased shares given to the market and storage and decreased the share for home use. The significance and size of effects on choice of allocation strategy varied by farm size and shock exposure.

The second essay (Chapter 3) analyzes the conditions that are necessary to motivate farmers to supply larger output levels to the market. The study investigates this problem by assessing if there exist

production and nonfarm income thresholds at which farms can release more output for the market while staying food sufficient. Exploiting temporal and spatial variations in Household Food Sufficiency (HFS) and output allocation in Uganda, findings show income and production thresholds much higher than earned annual average non-farm incomes and farm production. These thresholds lead to varied effects of marketing on HFS. Both farm and nonfarm income are positively associated with HFS, and thus market participation, but the farm income effect is dominant. This suggests that implementing farm-based interventions may provide superior results than nonfarm interventions in securing food security and indirectly market participation in developing countries. Findings further show that the effects of policy outcomes may be incongruous with farmer needs and production circumstances if detailed and in-depth procedures are not considered in policy formulation, implementation, and analysis.

In the third essay (Chapter 4), the study estimates the effects of an Ag-PPP that sought to create a sustainable Business-to-Business linkage by offering multiple transfers and guarantees to farmers. Here, the economic benefits to farmers, created by the PPP to common bean producers in Uganda is evaluated. Ag-PPPs play critical role in agrarian societies where agriculture is the predominant sector in creating employment, generating GDP, and securing food supply. Findings show that by leveraging the potential to create synergies among actors, the PPP created positive outcomes for farmers and stimulated increased production from targeted interventions. The study documents evidence of a significant increase in sales and sales revenue due to increases in bean production. For example, PPP farmers were likely to report 209 Kg/hectare higher yield compared to non-PPP farmers. Also, PPP farmers were more likely to report positive quantities of production to allocated to the market. Public private partnerships have checks and balances which ensure that benefits are allocated fairly among actors. Thus, the occurrence of scenarios that could marginalize and impoverish the weakest actors, often farmers, is tremendously curtailed.

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In the third essay (Chapter 4), the study estimates the effects of an Ag-PPP that sought to create a sustainable Business-to-Business linkage by offering multiple transfers and guarantees to farmers. Here, the economic benefits to farmers, created by the PPP to common bean producers in Uganda is evaluated. Ag-PPPs play critical role in agrarian societies where agriculture is the predominant sector in creating employment, generating GDP, and securing food supply. Findings show that by leveraging the potential to create synergies among actors, the PPP created positive outcomes for farmers and stimulated increased production from targeted interventions. The study documents evidence of a significant increase in sales and sales revenue due to increases in bean production. For example, PPP farmers were likely to report 209 Kg/hectare higher yield compared to non-PPP farmers. Also, PPP farmers were more likely to report positive quantities of production to allocated to the market. Public private partnerships have checks and balances which ensure that benefits are allocated fairly among actors. Thus, the occurrence of scenarios that could marginalize and impoverish the weakest actors, often farmers, is tremendously curtailed.

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Dedication

In dedication to my parents, brothers, and sisters.

Chapter 1 - Introduction

The quest to transform agriculture into a capitalized and commercialized engine of growth has preoccupied many governments in developing countries. As such, the overarching policy goal is increasing farmer income while ensuring food security. This opportunity exists because smallholder farmers in developing countries produce 70% of the world's food, yet most of them live in vulnerable communities characterized by poverty and food insecurity (FAO, 2015). Farming in low-income nations is often for subsistence, and in some cases is below subsistence, not enough to guarantee stable household welfare (Fedoroff, 2015; Lipton, 2013). Because subsistence production is viewed as inefficient by some policy experts, it is believed that its reduction is a natural process to be accelerated by policy (Lipton, 2013).

For Uganda, the focus of this analysis, the government, since 1997, has suggested and implemented a battery of policies and programs (PEAP, PMA, NDP I, II, III, DSIP, NAP, NAES)[1] all aimed at transforming subsistence farmers into enterprise farmers and smallholder farmers into commercial farmers (MAAIF, 2011, 2016; MAAIF & MFPED, 2000; NPA, 2010, 2015, 2020). According to the World Bank, (2018), closing the potential-performance divide in Ugandan agriculture will require commercialization, value-addition, and trade. From a policy perspective, the important question is to know the conditions necessary to stimulate production for markets given limited production, competing uses of farm production, and incongruence between farm production circumstances and policy. One of the major threats to commercialization policies is the competing uses of farm production and how small-scale farms distribute it.

Agricultural commercialization occurs when agricultural enterprises rely increasingly on the market for the sale of farm produce and acquisition of production inputs (Poulton, 2017). This is encouraged

[1] NDP -National Development Plan I, II & III, DSIP- Agriculture Sector Development Strategy And Investment Plan, NAES-National Agricultural Extension Strategy, PEAP-Poverty Eradiation Action Plan, NAP – National Agricultural Policy, PMA- Plan for Modernization Agriculture.

by an increase in the demand for food, inputs and raw materials for agro-industries and workers by the non-agricultural sector during the transformation process. While agricultural commercialization is an endogenous process that depends on other sectors, it relies heavily on the decisions made on the farm by farmers, as well as in markets by input suppliers, traders and processors (Poulton, 2017). This study focuses on the farm sector. Approaches that have been used to increase market participation or commercialization among farmers include increasing farm productivity and efficiency; providing financing for technology adoption; opening up market opportunities; improving infrastructure, including roads, market institutions and support services (Poulton, 2017). Others include providing support to farmers in enterprise choice (Courtois et al., 2011; Njuki et al., 2007), and providing production subsidies for targeted crops (Hemming et al., 2018; Sibande et al., 2017). These strategies have had mixed effects. For instance, Sibande et al. (2017) and Hemming et al. (2018) noted that fertilizer subsidies increased maize production and thus market participation in Malawi, but had no evidence of enhancing poverty reduction.

By encouraging market participation and trade by commercializing agriculture, policymakers believe that smallholder farms can serve as a source of raw materials to industries and food to urban consumers and rural producers who cannot meet their food requirements through own production. Conventional wisdom posits that small-scale farmers should be better off by being able to produce and market their crops. This leads to higher incomes, improved consumption, and nutritional outcomes (Christiaensen & Demery, 2018) since feedback mechanisms between production and markets are essential in supporting income generation and buffering consumption in case of production shortfalls. While this is true, efficient interaction between food and market production outcomes on the farm is needed if farmers are to reap economic benefits and opportunities from policy interventions.

Farm output has multiple uses: (1) immediate sale for cash, (2) immediate consumption, (3) storage (for food and or sale), (4) gifts, (5) payment of labor and land, and (6) seed. Allocation choices among small scale farmers are often entrenched and biased toward retention of output, rather than market sales. Therefore, many farmers keep most or all their farm production, which could be inconsistent with profitmaximization (the upshot of commercialization). This preference pattern suggests a desire for consumption smoothing and generation of income only from ‘surplus production.’ Despite the presence of theoretical frameworks explaining the consumption and asset smoothing motive (Carter & Lybbert, 2012), empirical evidence to explain output allocation choices and their dynamics is lacking. For commercialization prospects to succeed on small-scale farms, production must be large enough to meet household food and market needs. Given farm and farmer characteristics in the developing world, there seems to be an incongruity between the policy goals of fostering growth and improving welfare through commercialization, and farmer’s production circumstances.

This study assessed farm households’ decisions on how to allocate production and documents factors that affects the choice of allocation strategy. The study then isolates the impact of the household’s decision to market part of production on food security; measured as Household Food Sufficiency (HFS) and on its resilience to shocks. To further inform policy, threshold levels of production and non-farm income that may encourage market participation are identified and quantified. Because many social protection programs, development projects, and policies that aim to improve the household’s welfare modify intra-household commitment and decision behavior, the study assessed the welfare effects of such interventions.

The farmers' decision environment is dominated by three competing states: (1) to ensure that the household meets immediate household food and cash needs through sale/consumption; (2) to earn income from higher prices through deferred sales facilitated by storage, and (3) to ensure that they remain food secure by retaining output to meet future consumption needs. These decisions are cyclic and must be fulfilled on a day-to-day basis, and at the end of each production season. If production is limited, allocations that favor food availability may be optimal to support the household’s nutritional and food needs. Otherwise, storage and sales are important in managing transient hunger, consumption smoothing, supplementing household income and as an asset (Asesefa Kisi et al., 2018; Dil Farzana et al., 2017; Janzen & Carter, 2019; Le Cotty et al., 2019). If the household commits to storage based on present information, it can maximize, ex-ante, future profits or avoid the costs of purchasing expensive food. Antoniou & Fiocco (2019) noted that expecting higher prices, buyers and producers are inclined to store.

When food markets are absent or weak, farmers choose to be self-sufficient (de Janvry et al., 1991) before they chose to produce for the market. However, in this analysis, we contend that food markets in many third world villages are present and are becoming integrated with regional markets. Trade is increasing the demand for food crops. For example, net cereal demand and imports by the developing world are expected to grow until 2050 (FAO, 2009). Also, staples in developing countries are fast transitioning into industrial and or cash crops, thus playing a dual role. For example, in Uganda, farmers market between 30-50% of produce from maize, beans, soybeans, rice, groundnuts, sesame, banana, and Irish potatoes (UBOS, 2010). There has been growing demand for agricultural produce both for processing and direct consumption yet, raising supply to meet these requirements is still a challenge (EPRC, 2018; Fowler & Rauschendorfer, 2019).

In chapter two, the farm output allocation process is modelled to show how farmers chose to distribute production (the ex-post decision when output is known with certainty) and factors that influence the choice of an allocation strategy are documented. It thus evaluates both participation and the level of allocations. With knowledge on the allocation strategies, chapter three exploits temporal and spatial variations in Household Food Sufficiency (HFS) and output allocation to markets to analyze the effect of market participation and assess the conditions that are necessary to motivate farmers to supply more to the market. The study investigates production and nonfarm income thresholds that hasten the release of farm output to the market while ensuring that the farm household stays food sufficient. An emerging trend in implementing agricultural commercialization policies is Ag Public Private Partnerships (Ag-PPPs) (Hermans et al., 2019). In Chapter 4, the study presents estimates of the economic benefits to farmers, from an Ag-PPP that sought to create a sustainable Business-to-Business linkage by offering multiple transfers and guarantees to farmers .

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Chapter 2 - Determinants of farm output allocation in smallholder farms

2.1. Introduction

A successful green revolution in Asia put small holder farms at the top of development agendas (FAO, 2015). Development interventions emphasize the smallholder farmer as a panacea to development, poverty reduction, and trade (Lipton, 2013) through agricultural commercialization. This is achievable if farmer self-sufficiency motives are balanced with trade requirements, output use, and employment choices. Smallholders have an enormous potential to supply and support food markets in developing countries, yet only 17 to 27% (Carletto et al., 2017) of what they produce goes to the market. Unlike in the developed world, farm output in developing countries is an important endowment that has multiple uses: (1) sale for cash, (2) home consumption, (3) buffering shortages in lean periods, (4) gifts, (5) payment of labor or debts, and (6) seed. Once the production season ends (i.e., the output is known with certainty) a smallholder farmer's problem is how to ration that output to maximize utility. Allocation choices are often entrenched and biased toward retention of output, rather than market sales (Barrett, 2008; FAO, 2015; Kraybill et al., 2012; Sharashkin, 2008; Sibhatu & Qaim, 2017). This bias may curtail the role that small farms can play in supplying raw materials, generating foreign exchange, and bridging national food supply gaps. These allocation choices make policy proposals seem incongruous to farmer production circumstances, as will be explained in this study.

Smallholders must make output allocation choices while trying to fit into opportunities offered by commercialization and transformation of food supply chains which threaten to make them nonviable economic units (FAO, 2015). Limited empirical work has been undertaken to assess the factors that determine how farmers distribute/use their farm production and what would entail an optimal allocation. This study models the farm output allocation process to show how farmers allocate production and document factors that influence the choice of an allocation strategy. By doing so, the study evaluates both participation and level of allocations.

Studies that have tried to explain farm output allocation have either done so using one component at a time (univariate models for output use). For example, studies have examined quantification of marketed surplus and determinants of market participation (Barrett, 2008; Gafaro & Pellegrina, 2018; Key et al., 2000; Kyaw et al., 2018; Mdoda & Obi, 2019). Others have used specific crops or categories with simulations to model supply responses or market participation (Barrett, 2008; Musah et al., 2014; Fafchamps, 1992; Siziba et al., 2011). These approaches analyze the parameters of output disappearance separately, and thus do not fully capture the fact that increasing the proportion of one option decreases proportions of the others (zero sum; there is an automatic negative correlation) that occurs when farmers make allocations.

By assuming and analyzing one disappearance option at a time, it is inferred that the allocation problem that the farmer faces is sequential and allocation choices are independent. This may introduce bias if the allocation decision process is simultaneous or a joint framework process. Other implicit assumptions and limitations in prior studies are; first, farmers have enough volume to consume and provide surpluses to market, and secondly, the farm household's decision is modeled at a pre-production period, and it is assumed that output is optimally produced, profits are maximized and that farmers maximize their utility ex-ante.

This essay addresses the single farm output allocation component analysis and the sequential assumption by using a different empirical strategy that factors into the automatic correlation between allocation options. This guarantees that tradeoffs between allocation choices that farmers make are captured. The study analyzes the ex-post decision when output is known with certainty and argues that the household maximizes utility at this stage; ex-ante decisions become inconsequential at this point. The farmer's problem is analyzed using a much broader dataset that is nationally representative of Ugandan farmers and spans ten production seasons (five years). The study was able to investigate cross sectional and time series variation in farm output use by focusing on a farming household and considering a full portfolio of food crops produced on the farm.

The study uses fractional multinomial logit analysis to evaluate the joint conditional means of shares as they are explained by the farm, farmer, and institutional characteristics. There are three main findings, as follows. First, the levels of self-provisioning are high, approximately 66% of produced output, while commercialization stands at 27%. These allocations vary by farm size, but not exposure to a distressing event. Second, the choice of an allocation strategy and levels of allocation are influenced by an interplay of factors. The study finds that crop diversification increases the share of output allocated to home consumption and reduces that for marketing and storage. Consistent with the farm size hypothesis, the value of production and cropped area increase shares of output allocated to the market. Non/off-farm income eases the burden of producing for the market – farmers with higher off-farm incomes tended to produce and allocate more for home use. Furthermore, the study finds that household food sufficiency is positively associated with allocations to storage, and not marketing. Third, while our empirical estimates are robust across different scenarios (pooled farms, farm size, and shock exposure), the significance and size of effects vary within farms. This study uses these estimates to infer and derive implications of output allocation strategies, how they may vary given policy change, and potential policy interventions.

In the following section of this chapter, background information on the farm household's output allocation behavior is supplied. In section three, the study develops the theoretical framework to explain the farmers rationing and allocation problem given farm characteristics while section four presents the empirical model. In section five, the data, study setting, farm output allocation mix and descriptive statistics are presented. Section six presents and discusses the results, while section seven concludes and offers policy implications.

2.2. Allocation of farm output in smallholder farms

Allocation objectives of produced output for a farming household in the developing world can include: (1) to ensure that the household meets immediate household needs through sale/consumption; (2) to earn income from higher prices through deferred sales facilitated by storage, (3) to ensure that the farm family remains food secure by retaining output to meet future consumption needs, and (4) to support social obligations (e.g. gifts offered) and farm production (e.g. the in-kind payment of labor and land). The zero sum and automatic correlation between the output shares following allocation suggests that the allocation process is, in part, a simultaneous one and choices are interdependent. However, when output is offered as gifts, from a portion of home kept production, this can be a spontaneous decision that may not be planned for.

If production is limited, allocations that favor food availability have been found optimal to support the household's nutritional and food needs, management of transient hunger, consumption smoothing, supplementing household income and as an asset (Asesefa Kisi et al., 2018; Dil Farzana et al., 2017; Janzen & Carter, 2019; Le Cotty et al., 2019). Smallholders sell a limited proportion of output in the market and sales only make a miniature contribution to smallholders' income. For example in Kenya, Ethiopia, Bangladesh, Nepal, and Vietnam, over 60% of production is kept for home use (FAO, 2015). Sibhatu & Qaim (2017) showed that over 60% of cereals, 70% of tubers, 40% of legumes, and 80% of milk in Ethiopia are used for subsistence purposes.

However, even with many small farms being subsistent, they contribute significantly to the food economy. According to FAO (2015), smallholders contribute 63% of food in Kenya, 69% in Tanzania, 70% in Nepal, and 85% in Bolivia and Nicaragua. Also, when farmers sell, they contribute to the supply of raw materials to industries and generation of foreign exchange from exports. Excess production opens marketing opportunities, thus enabling households to sell to supplement farm income. Participation in markets is influenced by several factors. Key et al., (2000) examined the supply response in the presence of transaction costs. They proved that the existence of idiosyncratic transaction costs may promote self-sufficiency instead of market participation. They argue that lowering transaction costs both increases market participation and production for the market. Also, farmers exit or limit their participation in markets when transaction risks after entry are high or benefits from market participation cannot be sustained (Andersson et al., 2015; Ola & Menapace, 2020). FAO (2015) noted that smallholders often have limited supply and farmers are geographically dispersed which makes it hard for traders to reach them. Furthermore, limited managerial and logistical skills to be able to sell through sophisticated channels, high start-up costs required to enter the market, missing food markets, and limited capital endowments also affect allocations to the market (FAO, 2015).

Households may commit to storage based on present information, which allows them to maximize, ex-ante, future profits or avoid the costs of purchasing expensive food. Antoniou & Fiocco, 2019 noted that expecting higher prices, buyers and producers are inclined to store. The household's decision to store depends on the availability of inventory credit, the stability of product markets, the market price, household consumption needs, availability of storage facilities, and household immediate cash needs (Le Cotty et al., 2019). Urgent need for cash to support household needs often forces farmers to sell produce at once after harvest at a low price (Le Cotty et al., 2019).

The other important use of farm production in developing countries is fulfilling social obligations or make in-kind payments. In such situations, the farmer gives part of production to the next of kin, friends, or neighbors or uses it to pay for labor, land, and other obligations. This may influence other allocation decisions. For example, Di Falco & Bulte (2011) and Jakiela & Ozier (2015) noted that to evade their 'sharing obligations,' households tend to reduce savings in liquid assets or endowments to hide incomes. Farm production is also used as an in-kind wage to pay for services offered on the farm in developing countries (Kurosaki, 2008; Takane, 2008).

2.3. The Model

The conceptual analysis presented below starts with a simple separable utility maximization problem (Gorman, 1959). The household's output quantity and rationing problem is then incorporated into a utility maximization problem. For convenience, home consumption (C^O) and savings (S) are our choice variables in output disappearance. In what follows, i is used to index the farmer, c to index crop, and t to index time and $t+\tau$ is some future time when disposition of stored output occurs. The household's production, fixed at the end of each production season, $\bar{Y}$ is $\bar{Y} = C^O + M + \theta S$. Where; $C^O = \sum p_{cit} c_{cit}^o$, $S = \sum p_{cit+\tau} k_{cit}$ and earnings $M = \sum p_{cit} m_{cit}$. The term k_{cit} is the quantity kept for future consumption or sale, c_{cit}^o is the quantity allocated for home use (food, gifts, seed, and paying for land, debt and labor) while m_{cit} is the quantity allocated for marketing. The variable M is the value of the marketed surplus. The variable p_{cit} is the selling price for a given crop commodity at a point in time. This price is net of transaction costs such as transport costs, market search costs, storage costs, and market taxes among others that are incurred in selling the crop in the market. The study assumes that consumption can be valued using the price of the marketed part of the output, that is, if the farmer had not consumed it, they would have sold output at that price. The parameter θ is a discount factor that accounts for probable future benefits from storage. Let θ denote a stochastic indicator function that ranges between zero and one such that the marginal benefit from storage is greatest at a higher θ (θ =1) and lowest when θ=0. This marginal benefit from storage increases with the selling price, $p_{cit,t+\tau}$. For simplicity in the analysis, no explicit functional form is assumed for θ.

Retention for home consumption (C^O) yields Food and Nutrition Security benefits (FSB) and cushions households, especially deficient producers, from food shortages. Marketed surplus (M) yields Farm Income Benefits (FIB) which the farmer can use to meet other household needs and diversify calorie sources and types. Storage (S) yields two types of benefits: Lean season Sales Income Benefits (LSIB) which are benefits from potential future higher prices if farmers sell stored output and Lean Season Food

Security Benefits (LFSB) if farmers consume stored output in the lean seasons and or avoid the cost of buying expensive food. Thus, LSIB and LFSB yield total storage benefits (SB). Storage is consumed at some future period $t + \tau$. *Ceteris paribus* benefits from each allocation choice increase at a diminishing rate as more is allocated to a given choice option. The benefits reflect the conditions in which the farm works and farming household lives. Also, the study assumes that benefits from the choice of an allocation strategy reflect existing institutional arrangements, complete markets and regulations in commodity trade and use. To minimize notation, we drop some subscripts in subsequent equations.

This discussion can be presented mathematically[2] as:

$$FSB = B_1(C^O, p_t),\ \ FIB = B_2(M, p_t),\ \ \text{LSIB} + \text{LFSB} =\ SB = B_3(\theta S, p_{t+\tau});$$

$$\frac{\partial B_j}{\partial P} > 0\ for\ j = 1{,}2{,}3; P \sim p_{t,t+\tau};$$

$$\frac{\partial B_1}{\partial C^O} > 0,\ \ \frac{\partial B_2}{\partial M} > 0,\ \theta\,\frac{\partial B_3}{\partial S} > 0$$

The term $\frac{\partial B_i}{\partial P}$ is unambiguously positive for FSB because of the psychological nature of the decision to allocate production to food. Allocations to food are often entrenched (Barrett, 2008; Kraybill et al., 2012; Sibhatu & Qaim, 2017) suggesting a limited price effect.

Because the household cannot produce all the food and food types it desires, the household chooses how much consumption to acquire from the market (c_{it}^m) such that $C^m = \sum p_{cit}^m c_{cit}^m$ which yields food security benefits (FSB^m). Where:

$$FSB^m = B_4(C^m, p_t{}^m) \text{ such that; } \frac{\partial B_4}{\partial P^m} < 0 \text{ and } \frac{\partial B_4}{\partial C^m} > 0$$

Food purchases are financed using income (I) which is cash earned from off/non-farm work ($W = wh$, where w is the wage rate and h is hours worked), cash transfers (T) from various sources, earning from

[2] To minimize notation, we drop some subscripts in subsequent equations.

crop sales ($M = \sum p_{cit} m_{cit}$), and livestock sales ($L = \sum p_{Lit} m_{Lit}$). Thus, the household's total income is: $I = W + T + M + L$. For simplicity, let Z be the sum of T and L (non-labor income), taken as given allowing the household to only choose the number of hours (h) to work to earn non/off-farm income. The household also spends part of its income on private and non-food items (X). With full disposal of income, then $I = C^m + X$. Thus, the full income constraint of the farmer becomes: $wh + Z + M - C^m - X = 0$. The study hypothesizes that a farm household's choice and utility are affected by the characteristics (π) of the farm head, the farm, and institution factors.

The study considers an allocation to be optimal if and when benefits from the different allocations are maximized given market, farm, farmer, and institutional characteristics (π) and production levels. Thus, the household's problem is to maximize:

$$Max\ U = U(FSB, SB, FSB^m, h; \theta, \pi) + V(X;\ \theta, \pi)$$

Subject to:

$$\bar{Y} = C^O + M + \theta S \text{ or } M = \bar{Y} - C^O - \theta S \quad [2.1]$$

$$w.h + Z + M - C^m - X = 0 \quad [2.2]$$

$$C^O, S, M, C^m, h \geq 0$$

Assuming a separable utility function, the partial Lagrange for the household's problem is:

$$\varphi = U(FSB, SB, FSB^m, h; \theta, \pi) + \lambda(w.h + Z + \bar{Y} - C^o - \theta S - C^m \text{- X}) \quad [2.3]$$

If $FSB,$ and SB are concave functions of output ($\bar{Y}$), then the necessary and sufficient conditions for an interior solution are shown in Eq 2.4 to 2.8. We assume that the second-order conditions of (Eq 2.3) are satisfied.

$$\frac{\partial \varphi}{\partial C^o} = 0 \rightarrow \frac{\partial FSB}{\partial C^o} + \theta \frac{\partial SB}{\partial C^o} - \lambda = 0, \quad [2.4] \qquad \frac{\partial \varphi}{\partial s} = 0 \rightarrow \frac{\partial SB}{\partial S} - \lambda = 0, \quad [2.5]$$

$$\frac{\partial \varphi}{\partial C^m} = 0 \rightarrow \frac{\partial FSB^P}{\partial C^m} - \lambda = 0 \quad [2.6]$$

$$\frac{\partial \varphi}{\partial h} = 0 \rightarrow U_h + \lambda w = 0 \quad [2.7]$$

$$\frac{\partial \varphi}{\partial \lambda} = 0 \rightarrow U_\lambda + w.h + Z + \bar{Y} - C^o - \theta S - C^m - X = 0 \quad [2.8]$$

Consider the case when θ =0. Eq. 2.4 can be written as: $\frac{\partial FSB}{\partial C^o} = \lambda$, this implies that the marginal product of consuming own production is equal to the shadow price of own production which under perfect and competitive markets equals the market price of purchasing a given crop commodity for consumption. In this case, we hypothesize that households are likely to consume stored food products as opposed to selling it. They thus obtain only lean season benefits. Next, consider the case where θ>0. Here, the household on top of Food Security Benefits also enjoys storage benefits (from sales of produce or avoiding buying expensive food). The effect is also ambiguous because the consumption market price of the stored food commodity varies with time $(t+\tau)$ and may be higher which makes the households consume stored food since it would cost them more to obtain it from the market.

The solution to equations 2.4-2.7 yields optimal quantities of $C^{o*}, S^*$and h^* and optimal demand for C^{p*}. That is: $C^{o*} = C^{o*}(w, p_t, \tau, \pi)$, $h^* = h^*(w, p_t^m, \tau, \pi)$, $S^* = S^*(w, \theta p_{t+\tau}, \tau, \pi)$, $C^{m*} = C^{m*}(w, p_t^m, Z, \tau, \pi, \theta) = C^{p*}(w, p_t^m, I, \tau, \pi, \theta)$

2.4. Estimation strategy

Because the allocation process is zero sum (once a farmer apportions more to one choice, less is left for other choices), the study adopted the fractional multinomial logit model, hereafter defined as FMLOGIT model, to implement our conceptual framework and to examine factors that determine allocation choice. The fractional multinomial logit model proposed by Papke & Wooldridge (1996) assumes that the correlation between proportions is automatic, which allows fractional responses with a continuous scale between 0 and 1. This provides a consistent estimator even when responses take on boundary values. The goal here is to analyze how farm, farmer, and institutional factors affect the allocation of farm output to different uses. The FMLOGIT model is suitable for this study because farm output and a choice of its disappearance are known with certainty and we can calculate exact proportions allocated to each use option.

The FMLOGIT model thus allows the examination of: (1) how the association between shares in allocation is net of automatic correlation, and (2) how the different allocation shares relate to explanatory variables. The model assumes that proportions in FMLOGIT depend on the explanatory variables X. Thus, allowing us to model the conditional means in multivariate fractional dependent data of the shares jointly. The econometric fractional multinomial logit model that the study estimates takes the form:

$$E(OS_{ik}|X) = G(X\beta)$$

$$= G\left(\beta_0 + \sum_{i=1}^{n} Farmer\ attributes_i + \sum_{i}^{n} Farm\ attributes_i\right.$$

$$\left. + \sum_{i}^{n}\ Institutional\ variables_i\right), k = 1, \ldots, 3 \qquad [2.9]$$

where, $G(.)$ is the logistic function and X is a vector of explanatory variables. The term OS_{ik} is the $output\ disappearence\ share$ for farm i. Consider farm i with fixed farm output, $\bar{Y}$, and y_{ik} stochastic allocations to each choice option k, where k choices include own consumption (C^O), marketed surplus (M), and storage (S). Then, $Output\ disappearence\ share\ (OS_{ik}) = \frac{y_{ik}}{\bar{Y}}$. Following Mullahy (2015), the assumption is that the normalized farm output shares (OS_{ik}) satisfy $OS \in (0,1)$ and the $E(OS_{iK}|X) = \xi_K(X;\alpha)$, where the generic parameters $\alpha = [\alpha_1 .. \alpha_3]$ is shared across the three conditional mean parameters $\xi_K(X;\alpha)$ to enforce the adding up restriction $\sum_1^3 E(OS_k|X) = 1$. By allowing random parameters to be correlated across equations, we have unrestricted substitution patterns across share alternatives.

Henceforth, the dependent variable is the proportion of total farm output from food crops allotted to the market, storage, food and to gifts. In the study’s final model, allocations to food and gifts are summed and are analyzed as one category. This allows the study to evaluate shares of total output allocated instead of probabilities of allocations. Furthermore, it allows the evaluation of both the choice of a given output use possibility and the extent of use, which depicts the relative valuation farmers place on produced farm output.

The right-hand side variables are those hypothesized to affect farm output allocation. To examine the impact of farm characteristics, the value of livestock is used as a proxy for farm liquidity, having non/off-farm stable income as a proxy for earnings volatility and the Households Food Sufficiency score (HFSs) as an indicator of food self-sufficiency. The HFSs was calculated as the difference between the overall amount of food available in caloric terms (sum of annual own Food Production (FP), Food Acquisitions (FA) and Food from Gifts (FGI)) less Food Sales (FS), Food Losses (FL), Food Given Out (FGO) and annual Household Adult Equivalent Requirements (HAER). That is: HFSs = {FP + FA+ FGI} – {FS + FL+FGO} – { HAER }. To calculate the HAER, we used the information on household members (sex and age) from the household roster and assume a moderate level of individual activity. Using minimum dietary information from (USDHHS & USDA, 2015), we then calculate annual adult equivalent caloric requirements for each household member for the period they stayed in the household and then sum each member's requirement to obtain the household's requirement. The possibility of seasonality in production and consumption is accounted for by the fact that data was collected across different month of the year (see Figure 2-7 in supplementary Appendix A).

For risk/shock exposure, a dummy of having experienced a distressing event each year was used while the crop diversification index is a risk management strategy. The study used the total value of production and acreage cropped as a proxy for farm size. To evaluate institutional/market and policy factors; the study used distance to the market as a proxy to explain market access and for policy connectedness, the study used qualitative (0,1) variables for participation in National Agricultural Advisory Services (NAADS). NAADS is a statutory semi-autonomous body in Uganda mandated to manage the distribution of agricultural inputs and supply of extension and advisory services to farmers (MAAIF, 2015). It is an important policy proxy because the government of Uganda implemented it nationally and a core policy to commercialize production, boost incomes, and food security. The study used a dummy (1= benefited/adopted) for being a beneficiary of the policy training program and being an adopter of a policy recommended enterprise/received a policy subsidy. The study included farm owner characteristics such as the age of the farm head, sex of the farm head, and household size to control for farmer characteristics. Also, individual fixed effects were added to the model to control for unobserved individual-specific characteristics and a dummy for locality to capture differences between urban-based and rural farms. The observations were clustered at the household level to control for potential correlation overtime for the same household. Clustering helps in ensuring that standard errors are estimated robustly.

First, the model (Equation 2.9) was estimated for the entire sample and then further estimated for three distinct categorizations: (1) a model that examines whether the choice of allocation mix differs between small, medium, and large farms, (2) whether risk exposure or shock leads to differing allocation strategies, and (3) a model of the rural and urban sample. The third estimation was a further robustness check since we observed a nontrivial urban sample (13% of sampled households). To assess whether farm size affects the allocation mix, the sample was subdivided into subsamples of small farms (<5 acres), medium (5< acres <12.5), and large farms (>12.5 acres). This division is a modification of farm size classification by Agricultural Area Utilized (AAU) (FAO, 2018). In the modification, farms in class 1,2 and 3 (0 – 2 hectares) form small farms, farms in class 4 (equal to or greater than 2 ha and less than 5 hectares) form medium size farms while farms in class 5-12 (equal to or greater than 5 hectares) form large farms. This further split is arbitrary because the study thought to have an adequate sample in each categorization. For exposure to risk or a distressing event, the sample was divided into farms that experienced any shock or distress event in the past 12 months and those that did not. Risk events/shocks include weather shocks such as drought, irregular rain, floods and landslides; social shocks like loss of employment, death or serious illness/accident of a key household member, production shocks like unusually high level of crop pests and disease, livestock diseases, high price of agricultural inputs and low prices of agricultural output. Others include thefts and conflict/insecurity episodes. All the explanatory variables in the subsample models stayed the same as those in the full model.

2.5. Data and setting

A fractional multinomial logit model was implemented on an overall sample of 10,843 observations with 3,833 households from Uganda. This sample includes only agricultural households, all of which had production for each year. The reason being a household had to have some level of production and disposition of production to allow the computation of shares. A total of 206 observations were dropped because they did not meet this criterion. An additional 162 observations were excluded because of missing values for some targeted variables. Because of sample rotation, the data is an unbalanced panel and spans ten production and disposition periods. The sample is constructed from five waves (2009/2010 to 2015/2016) of the Uganda National Panel Surveys (UNPS)/Living Standard Measurement Surveys - Integrated Surveys in Agriculture (LSMS -ISA) collected by the Uganda Bureau of Statistics (UBOS) with support from the World Bank (UBOS, 2011, 2014a, 2014b, 2016, 2019a).

This study used data from both the agriculture and household questionnaire, which supplied ten sequential production and disappearance periods (storage, consumption, and marketing). The ten production seasons were aggregated into five years (two seasons per year) allowing identification of parameters of interest. The sample includes, inter alia, data on household output disappearance, household asset ownership (land and livestock), off/non-farm income sources and values, characteristics of the farm household, characteristics of the agricultural holding, and foods consumed including their sources, quantities, and value. These farms have full production and disposition data which allowed the study to construct farm output allocation shares.

To obtain the output shares used in the analysis, the study used both value of production and consumption[3] and calories in crops produced to aggregate over farm production and consumption. Conversion factors from Harvest-Plus Uganda (Hotz et al., 2012) and the United States Department of Agriculture (USDA, 2019) were used to convert the kilograms of farm output produced into caloric equivalents. In this study, only aggregation and computations based on calories are reported. This is because calories are time-invariant allowing the study to isolate true allocation effects. The study computed the share for each disappearance option as the value/calories allocated to each option (home use, market, and storage) divided by the total value/calories produced. All the monetary measures used in the study are adjusted to constant 2009 Uganda shillings (UGX) equivalents using the gross national expenditure deflator (World Bank, 2020).

2.5.1. Farm output allocation mix

The relevant section of the LSMS-ISA surveys for this research is the quantification of farm production and its disposition. Specifically, the study used the information on how much was produced, how much of production was; sold, given out as gifts and reimbursement for labor and land; consumed by the household; used to make processed food products for sale and animal feeds; used for seed; placed in storage; and lost. For this study, the proportion for home use includes farm output given out as gifts and reimbursement for labor and land, consumed, used as seed and animal feeds. Farm output marketed includes production that the farmer sold or used to make processed food products for sale while the proportion stored was all output that was still in storage by the time of the survey.

Typically, the retention of farm output is entrenched (FAO, 2015; Sharashkin, 2008; Sibhatu & Qaim, 2017). This phenomenon is also seen in our analysis where up to 66.6% of farm output is kept for

[3] To calculate the value of production, the study used the prices reported for each crop to aggregate over crops. For values of consumption, the prices of food purchased, and quantities purchased were used. The proportions obtained using both methods of aggregation were not statistically different.

home use with 8% of the farmers producing exclusively for food (Table 2-1). This is the case despite the fact that the government of Uganda's policy desired to cut the proportion of production that is retained on the farm from 80% to 30% by 2016 (Kraybill et al., 2012). The variation in allocations to food is higher between farmers than within the farm over time. This suggests a food self-sufficiency motive on the part of the farming household. A farm household is driven by the desire to have more output available for home use and this decision is consistent over time Figure 2-1. Marketed output ranged between 24% and 29% and averaged 27% of production, between 2009 and 2016, which is within the range of averages reported for other SSA countries by (Carletto et al., 2017). Allocations to the market varied more between farmers than within the farms over time. This finding suggests that similar farms have the same allocation behavior. Also, at least 75.4% of farms reported selling at least part of their output (Table 2-1).

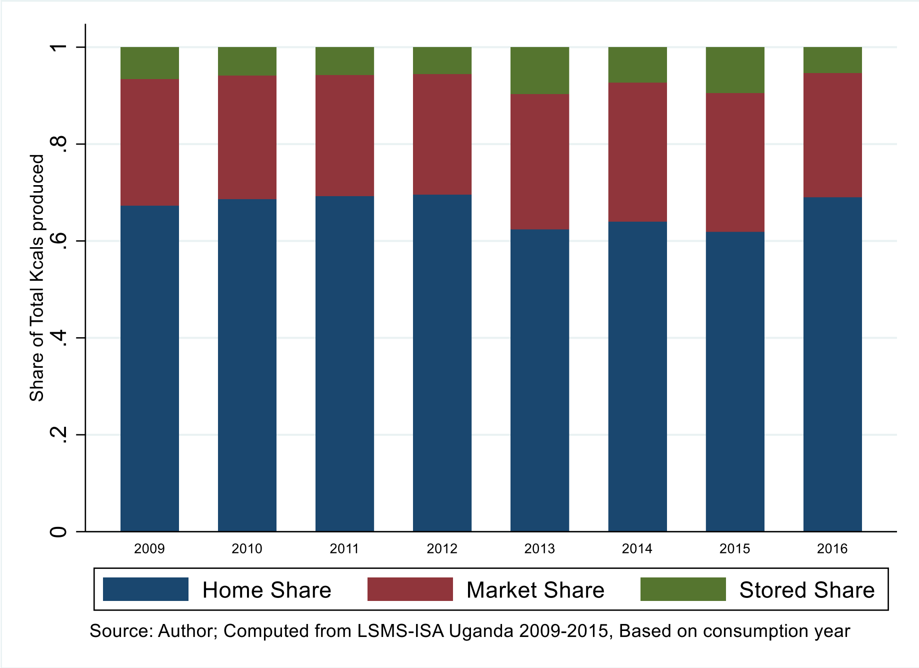
Table 2-1: Farm output uses and participation rates

Dependent variable	**Sample statistics**			**Participation rates**		
	Mean	**SD [be, wi]**	**p50**	$\mathbf{OS_{ik} = 0}$	$\mathbf{OS_{ik} = 1}$	$\mathbf{0 < OS_{ik} < 1}$
Home Share	0.666	0.268 [0.235, 0.160]	0.617	0.005	0.084	0.911
Market share	0.265	0.254 [0.225, 0.152]	0.208	0.244	0.002	0.754
Stored share	0.069	0.147 [0.130, 0.094]	0.000	0.575	0.001	0.424

Source: Author rendering of LSMS-ISA data. N= 10843. SD is the overall variation over time and individuals, while "be" denotes between deviation (between individuals) and "wi" is within deviation (variation within individuals' overtime). $OS_{ik} = 0$ means the farmer never produced for a given disappearance option, $OS_{ik} = 1$ means the farmer produced exclusively for a given option and $0 < OS_{ik} < 1$ means the farmer produced for a mix of disappearance options. For the proportion kept at home, about 6.4% is gifted to others, used to reimburse labor or land.

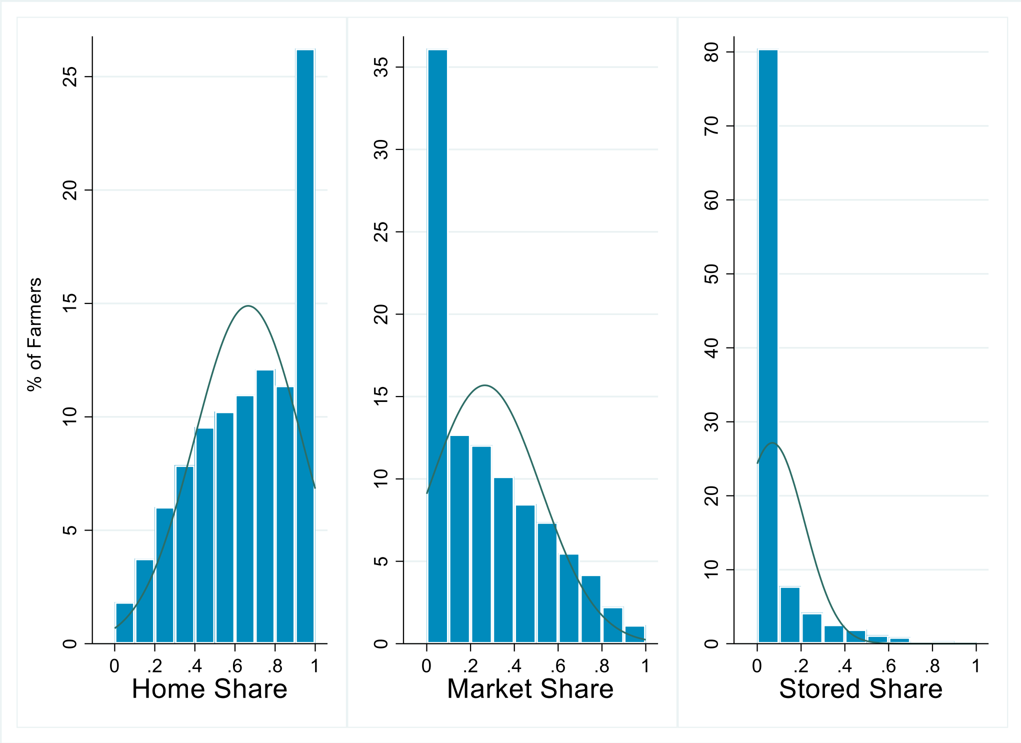
Figure 2-2 shows the distribution of proportions allocated to different disappearance options across farms. The figure shows that the distribution of allocations is positively skewed towards output retention while its negatively skewed towards marketing. The pattern observed in Figure 2-2 will support the threshold analysis framework (presented in chapter 3) as it shows a clear preference for subsistence as a major output use option. This also supports the study's conceptual framework presented earlier. The proportions allocated to each disappearance option formed the dependent variable for the study.

Figure 2-1: Shares of farm output allocated to disappearance options by year



In Figure 2-1, proportions are calculated based on total calories produced. N=10,843. The nature of allocation choice has been consistent through time. When the calculations are based on value of production instead of calories, the different shares do not significantly change i.e. averaged over time the proportions are: sale: 26.55, food: 60.21, stored: 6.88 and gifts: 6.36.

Figure 2-2: Distribution of shares allocated to disappearance options by farmers



2.5.2. Explanatory variables and descriptive analysis

The descriptive statistics and definition of the variables are shown in Table 2-2. Value of production was measured as the total annual shilling value of all farm production (crops and sold livestock). The mean value of production was UGX 6.8 million which is about seven times higher than the median farm's production. This suggests significant heterogeneity in farm incomes, with few high-end earners and many low-end earners. Transport costs capture the total amount spent on transport to deliver farm produce to the market if the farmers took part in marketing. About 87.2% of the farms in the study reported not incurring transport costs because they either never marketed produced output or sold at farm gate. On average farmers reported spending 4,700 UGX on transport costs. Market distance (KM) is the distance from the household's residence to nearest market that sells Ag produce.

Livestock wealth was measured as the total shilling value of livestock on the farm in a given year. Here, livestock included all animals (cattle and pack animals, small animals, and poultry) kept on the farm. Non-farm income includes all incomes earned off the farm including property and investment income, current transfers and other benefits, and non-agricultural household enterprise earnings. Non/off-farm income was accessed by 86% of the farmers, with average annual earnings of UGX 4.8 million (more than 5 times the median off/non-farm income of farmers). This implies that there is a disparity in off/nonfarm income earnings with many low income and few high income earners.

The Herfindahl Index (HI) of diversification was used to estimate the extent of crop diversification among the sampled farmers. The index was calculated as the sum of square of the proportion of acreage under each crop to the total cropped area, that is: HI = $\sum_{i=1}^{N} Pi^2$ where Pi is the proportion of the area allocated to the ith crop to total cropped area. The index takes the value of one for a specialized farm and a value of zero for a highly diversified farm. The farms in the sample had a moderately diversified crop portfolio (HI=0.404). The Household food sufficiency score was measured as the difference between the total of produced and purchased calories less calories given out, sold, lost and household adult equivalent requirements (as discussed in detail earlier). The score showed that households in the sample were food sufficient with an average HFS score of 0.76 million calories. However, about 47.5% of the households in the sample could not meet their caloric requirements (are below daily adult dietary equivalent requirements).

Table 2-2: Surveys of farming household, full sample: Descriptive statistics

Covariates	Mean	SD [be, wi]	p50 (Median)
Production value (M UGX)	6.795	39.890 [22.120,32.439]	0.897
Transport costs (T UGX)	4.705	90.195 [50.124,63.298]	0.000
Market distance (KM)	28.489	20.176 [20.322,2.230]	27.475
Livestock wealth (M UGX)	0.368	3.800 [2.357,2.898]	0.000
Non-farm income (M UGX)	4.827	49.877 [33.909,37.238]	0.932
Number of household members	6.683	3.413 [3.227,1.308]	6.000
Crop diversification (Herfindahl Index)	0.404	0.188 [0.165,0.121]	0.356
Age (complete years) of farm head	47.085	15.342 [15.282,3.933]	45.000
Household food sufficiency score (M Calories)	0.779	4.664 [3.435,3.478]	0.135
Cropped area (acres)	7.195	14.498 [8.676,11.474]	4.250
Farms (<5 acres)	0.552	-	-
Farms (5<acres>12.5)	0.364	-	-
Farms (>12.5 acres)	0.085	-	-
1 (Sex of farm Head: Male)	0.703	-	-
1 (Policy Training beneficiary: Yes)	0.136	-	-
1 (Policy enterprise beneficiary: Yes)	0.120	-	-
1 (Suffered shock in last 12 month: Yes)	0.427	-	-
1 (Location: Urban)	0.130	-	-

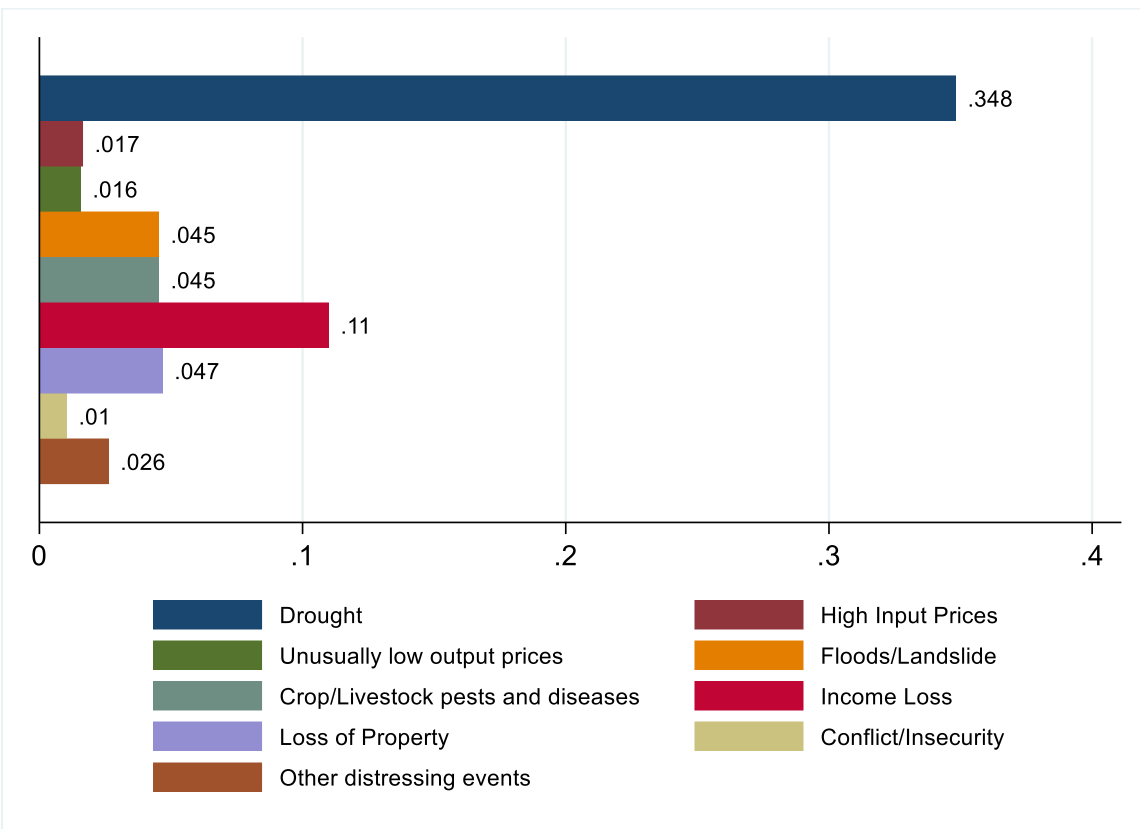
Notes: N=10,843. SD is the overall deviation over time and individuals, while “be” denotes between deviation (between individuals) and “wi” is within deviation (variation within individuals’ over time)

All monetary units are in UGX and are adjusted to constant 2009 Uganda shillings (UGX) using the gross national expenditure deflator.

Source: Author rendering of LSMS-ISA data.

For the policy variables, about 14% of the sample reported having taken part in capacity building programs organized by the government of Uganda while up to 12% used enterprises promoted and subsidized by the government. The study used this national geographic coverage to assess the effect of the policies on farm output allocation. The farms were mostly rural (87%), and 43% reported having experienced a distressing event within 12 months before the study. The sufficiently large share of household that experienced a distressing event allowed evaluation of its potential impact on choice of output disappearance. Figure 2-3 shows the types of distressing events experienced by sampled households. A majority (34.8%) reported drought or irregular rains as the main distressing event encountered while up to 11% of the sample reported loss of income source as a key event. Stresses in the ‘other category’ are not explicitly defined in the raw data. All these events had implications on household food security and thus allocation of farm production as will be discussed later. The average total cropped area in a year was 7.2 acres with more than half (55.2%) of the farms in the sample cultivating an average of less than 5 acres.

Figure 2-3: Types of distressing events experienced by farmers

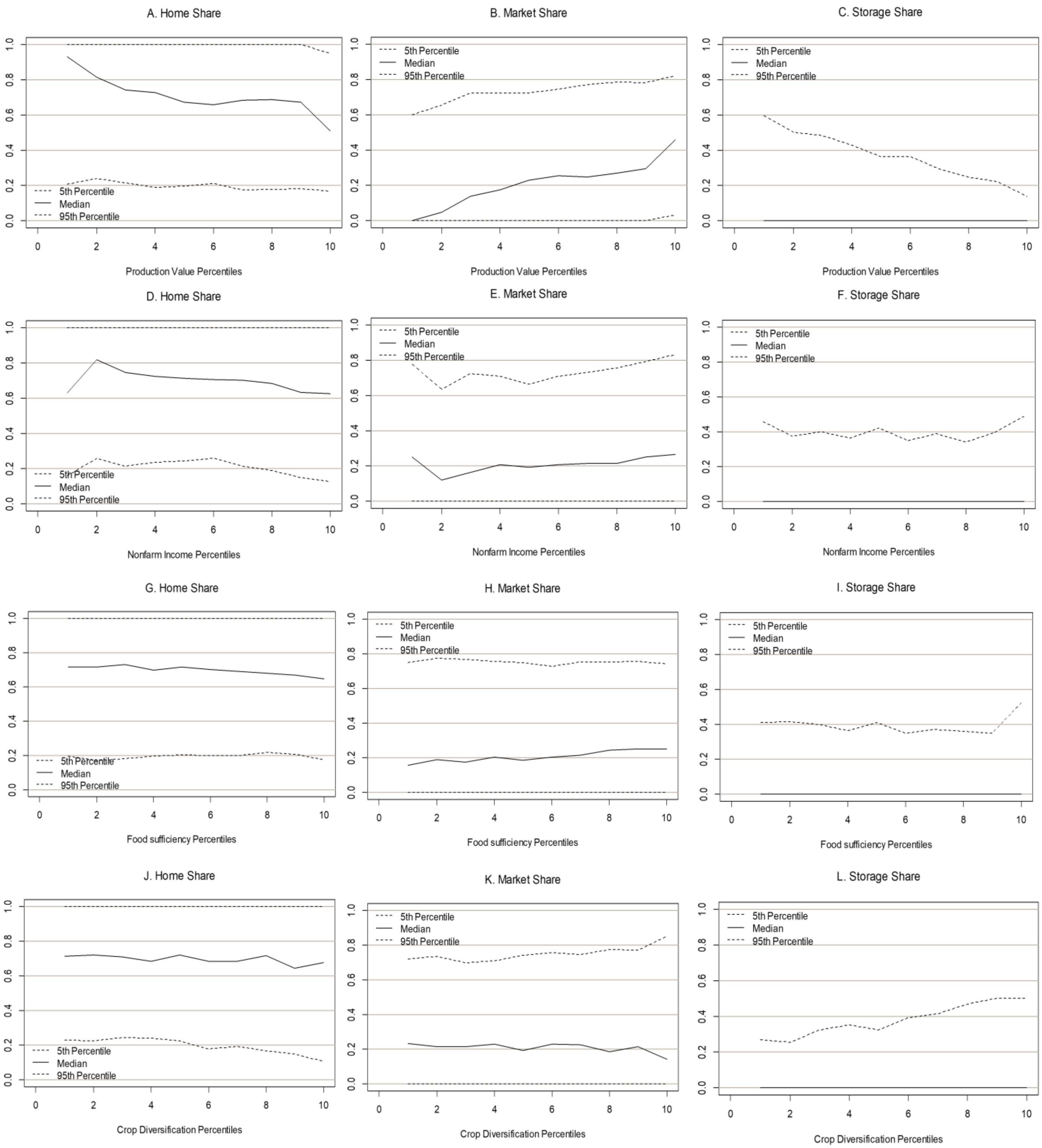


In Figure 2-3, income loss includes loss of employment, illness of major and other income earners leading to low incomes, death of the major or other income earners. Loss of property includes theft of farm and non-farm assets and loss of items to fire.

Figure 2-4 shows variation of output allocation across select variables. To construct Figure 2-4, each household was placed in one of ten percentiles of value of production, nonfarm income, household food sufficiency score and the crop diversification index. This was done to ensure equal distribution of households in each bin. For each bin, the size of 5th, 50th (median) and 95th percentile of the three allocation shares for output was calculated. The dotted lines stand for 5th and 95th percentiles while the solid line represents the median. Figure 2-4 conveys a message of the variation of allocations as the size of the variables changes. Panels A and B of Figure 2-4 show that as the value of production increases, allocations to home use become less pronounced while allocations to markets become important. Allocations to storage are scarce and become less important as the value of production increases. Similarly, for nonfarm income (Panels D, E and F), allocations to home use tend to decline with nonfarm income while they increase for the marketed share, especially at higher percentiles. Dispersion in allocations increases with increasing income as shown by the fanning out of the 5th and 95th percentiles. Allocations to storage are stable with nonfarm income.

Shares given to home use, the market and storage tend to be stable across food sufficiency scores depicting limited variation (Panels G, H, and I). This phenomenon partly reinforces the argument that food sufficiency takes precedence and allocations to food are entrenched. Also, there is no clear evidence of fanning in or out of the 5th and 95th percentiles. For crop diversification, allocations to home use decline with increased crop specialization (high crop diversification index) while those to markets increase (Panel K). The share to storage is limited but the 95th percentiles suggested an increase at higher levels of crop production specialization.

Figure 2-4: Allocation of farm output variation across: Production, Nonfarm income, Food sufficiency and Crop diversification



2.6. Estimation results

The results of the fractional multinomial logit model analysis for the full sample are reported in section 2.6.1, the results of the analysis by farm size and exposure to a distressing event are shown in sections 2.6.2 and 2.6.3, respectively. The results of the analysis by locality (rural verses urban), as a robustness check are reported in Table 2-6, Appendix A. Direct model estimates do not give much meaning, so marginal effects evaluated at means of explanatory variables are reported. Coefficient estimates of the same models are reported as supplementary materials in Appendix A. For the FMLOGIT model, marginal effects must sum to zero over equations because covariates are associated with reallocation across output disappearance options. The R^2 as a goodness of fit measure is not reported because it is not appropriate for fractional multinomial logit models given that it has multiple dependent variables (Buis, 2017). Based on goodness of fit measures, the models with log transformed household food sufficiency, value of production, non-farm income, livestock value, and acres cropped are preferred. The estimated AIC and BIC for the log transformed model were 16,127.89 and 16,345.58 compared to non-log transformed model of 16,675.36 and 16,893.21, respectively. Also, models with log transformed variables had more significant variables. The interpretation and discussion of results is thus based on estimates of the model with log transformed variables.

2.6.1. Full sample analysis

The results of the full sample estimates for farm output allocation mix are shown in Table 2-3. Where they are different, these results are contrasted with those of the analysis when the sample is split between rural and urban households as reported Table 2-6, Appendix A. The coefficient on the crop diversification index is the largest, and is negatively associated with the share of output kept for home use and positively to shares allotted to the market and storage. Because a lower index value (a value of zero) indicates a diversified farm and one implies full specialization, the results imply that farmers tend to diversify for food security purposes and farmers are more likely to keep their products for home use than for storage and market. Smallholder subsistence farmers have been found to diversify as they try to spread risks associated with crop failure, price spikes, and to diversify diets (Makate et al., 2016; Rahman, 2009).

Table 2-3: Fractional multinomial logit estimation of farm output disappearance mix: Full sample average marginal effects results

	Market share	Home share[1]	Storage share
Crop diversification index	0.122***	-0.154***	0.032***
	(0.015)	(0.016)	(0.008)
Log Household food sufficiency	-0.091***	0.028	0.063***
	(0.034)	(0.035)	(0.008)
Log total production	0.054***	-0.038***	-0.016***
	(0.002)	(0.003)	(0.001)
Log total non-farm income	-0.001***	0.002***	-0.001***
	(0.000)	(0.000)	(0.000)
Log livestock value	0.001***	-0.002***	0.001***
	(0.000)	(0.000)	(0.000)
1 (Training beneficiary: Yes)	0.005	-0.003	-0.001
	(0.008)	(0.009)	(0.005)
1 (Enterprise beneficiary: Yes)	0.028***	-0.047***	0.019***
	(0.008)	(0.009)	(0.005)
Log acres cropped	0.001***	-0.001***	0.000**
	(0.000)	(0.000)	(0.000)
Log market distance	-0.001	0.007**	-0.006***
	(0.003)	(0.003)	(0.001)
1 (Sex head: Male)	0.049***	-0.048***	-0.002
	(0.007)	(0.007)	(0.004)
Age head	-0.002***	0.002***	0.000
	(0.000)	(0.000)	(0.000)
Household size	-0.010***	0.009***	0.002***
	(0.001)	(0.001)	(0.001)
1 (Experienced distress event: Yes)	0.001	-0.009*	0.008***
	(0.005)	(0.005)	(0.003)
1 (Locality: Urban)	-0.009	0.026**	-0.016***
	(0.009)	(0.011)	(0.006)

Notes: N=10,469. Robust standard errors generated by the delta method are in parentheses. The dependent variables are shares of farm output allocated to the market, home use, and storage. */**/*** show 10%/5%/1% significance levels.

Source: Author estimation using LSMS-ISA data.

[1]Includes food, gifts, payment for wages and land.

The Household Food Sufficiency (HFS) variable, which was measured as the household's ability to meet its dietary requirements, negatively affects the share of output allocated to the market and positively the share allocated to storage. The marginal effects indicate that a unit point increase in HFS reduces the market share by 9.1 percentage points and increases the stored shared by 6.3 percentage points. When disaggregated by locality, HFS positively and significantly affects allocations to home use. Specifically, a unit change in HFS raises the share of output allocated to home use by 5.9 percentage points (Table 2-6 Appendix A). This suggests households that value food self-sufficiency and thus need to preserve food for lean seasons, are more likely to keep a part of farm output than to contribute output to the market. Some studies, for example, Ntakyo & Van Den Berg (2019) have shown that increased production for the market does not necessarily lead to improved calorie consumption, thus farmers at times produce for subsistence reasons. The authors recommend a mixed policy approach that focuses both on market-oriented production, production for own consumption, and nutrition sensitization.

The results provide evidence consistent with the farm size hypothesis. Specifically, large farms are likely to offer more to the market than small farms. This study shows that the value of crops produced, and area cropped positively affect the share of farm output allocated to the market, while the value of crops produced negatively affects proportions allocated to home use and storage. Whereas the effect of value of production remains the same when the sample is divided into rural and urban households, the effect of area cropped remains significant for only rural households. Increasing area cropped by 1 acre is associated with 0.1 percentage point increase and decrease of the share of output marketed and output allocated to home use, respectively (Table 2-6, Appendix A and Table 2-3) This result implies that small farms are more likely to keep output than offer it to the market and the effect is important for only rural households. In general, these results are consistent with the evidence provided by (Fafchamps, 1992; Kyaw et al., 2018).

The coefficient on non-farm income is negative for the share offered to the market and storage and is positive for the share kept for home use. Specifically, for a unit increase in income, the share that farmers allocate to the market and storage is reduced (by 0.1%) while that allocated for home use increases (by

0.2%). This suggests that as farmers get opportunities for off-farm employment and thus more income, they tend to produce little to satisfy their food requirements. Such farmers' production is not driven by the market motive. Similar effects on market participation were observed by Kan et al. (2006). This effect is however only important for rural and not urban households (Table 2-6, Appendix A). It is possible that for urban households, consumption is better smoothed through purchases from the market using off-farm income and thus the observed effect. Also, according to Rahman & Mishra (2020), having non-farm income opportunities improves the dietary diversity of rural households since it has a positive effect on their food expenditures. Therefore, non-farm income is a good complement to farm production allowing farmers to source food from off-farm sources.

Using the value of livestock as a proxy for farm liquidity, the study finds that being liquid induces farmers to sell and store more and keep less for food. Farmers in developing countries, especially in Sub Saharan Africa, use livestock as a source of income and as a coping strategy to help alleviate food shortages in lean or failed seasons (Lai, 2007; Mahmood et al., 2014). With the knowledge that they can liquidate assets, farmers may be tempted to market more of their produced food. Also, farmers who experienced a distressing event are likely to allocate farm output to storage. This suggests an avoidance of negative effects that a distressing event may bring.

Participation in commercialization orientated policy enterprises significantly affected the output allocation mix. The effect was the same in the rural/urban sample as in the pooled sample. Relative to non-participants, farms that took part in enterprises promoted (subsidized) by the policy are on average likely to allocate 2.8% more output to the market, 4.7% less on food, and 1.9% more on storage. Because enterprises promoted by the policy were more geared towards commercial crops and emphasized market orientated production, this result is justifiable. Barrett (2008) noted that at a micro-scale, insufficient private access to productive assets, financing, and improved production technologies limits smallholder farmer production and thus surplus for the market, noting that breaking such barriers eases market participation by smallholder farmers in the third world.

Because transaction costs incurred are endogenous to the marketing decision (Key et al., 2000), the study used the distance to the nearest agricultural market as a proxy in the estimated model. Key et al. (2000) noted the importance transaction costs in agricultural market participation. Here, we find that distance to the market is positively associated with the share of production given to home use and negatively to the share allocated to storage. Thus, if markets are far from production hamlets, farmers are likely to allocate production to home uses than to the market. While our a priori expectation, as noted by Barrett (2008) and Key et al. (2000), was a significant negative effect of the transaction cost proxy, we find a negative but insignificant effect that was only important for the pooled and rural sample. As a robustness check, the same model was estimated using median transport cost incurred in the village. The results of this estimation are shown in Table 2-7, Appendix A. The estimates of the auxiliary regression showed that transport costs are positively associated with the shares of farm output allocated to markets and storage and negatively to shares for home use. The observed pattern here could be because up to 87.2% of the farmers in the sample reported zero transport costs because they either sell at farm gate or do not participate in output markets as sellers.

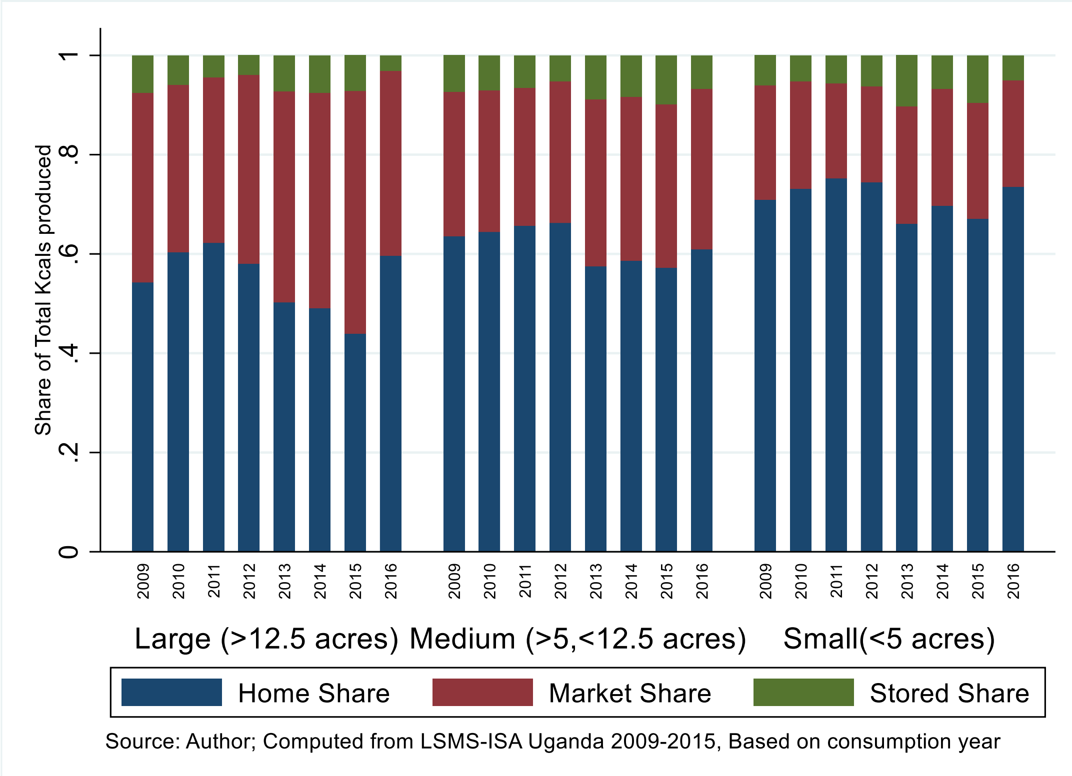
For the effect of farm holder demographics on allocations; the age of the farm head negatively affects allocations to the market and positively allocations to home use. Within available disappearance possibilities, young farmers are thus more likely to give more output to the market. On the other hand, the observed positive and negative relationship between male farm heads and allocations to the market and food respectively imply that male farmers are more likely to offer output to the market. Household size negatively and positively affects the shares of output allocated to the market and home use respectively. Results show that large households tend to have their production driven by food for household consumption than for marketing. This is consistent with the findings by Kyaw et al. (2018) and Siziba et al. (2011) who showed that household size negatively affects market participation, possibly because large households fail to produce marketable surpluses beyond their consumption needs. It is also possible that the costs of having to buy food is high for large households.

2.6.2. Farm size effect on the choice of output disappearance

Following full sample estimates, the study further examined whether factors determining the output allocation mix change by farm size. Here, total area cultivated per year is used as the proxy for farm size. Figure 2-5 shows the distribution of allocation mixes across farm sizes. The results of the fractional multinomial logit model estimates are reported in Table 2-4. Note that area cropped is included as a regressor to explain variations within farm subcategories. The study finds that the direction (effect) on the output allocation mix is the same as that of regressors used in the full model for the following variables: the value of production, age, and sex of the farm head, and being a training beneficiary. Significance and not the direction of effect varies for choosing to adopt a policy promoted enterprise, cropped area, nonfarm income, livestock wealth, crop diversification, distance to the nearest market, household food sufficiency, having experienced a distressing event, and size of the household.

Specifically, crop diversification had significant effects on small and medium farms, negatively influencing shares of output allotted to the market and storage and positively affecting shares allotted to home use. Small and medium farms in the sample were on average more diversified with indices of 0.34 and 0.35, respectively as compared to larger farms with an index of 0.45. Therefore, on average, large farms are more specialized. Household food sufficiency positively influenced shares allocated to storage for all farm categories, positively influenced allocations to home use for small and large farms, and negatively affected shares of output allocated to the market for small and large farms. Nonfarm income affects the allocation mix for small and medium farms. It negatively influenced allocations to the market and positively to home use. This implies that if a small or medium farmer has a nonfarm income source, they are less likely to grow and allocate production to the market instead producing for home use. Large farms had significantly higher non-farm incomes compared to small and medium farms. They earned thrice and twice as much as small and medium size farms, respectively.

Figure 2-5: Shares of farm output allocated to disappearance options disaggregated by farm size



Notes: In Figure 2-5, the proportions are calculated based on total calories produced. The proportions allocated to different uses show that on average, the proportion allocated to the market increases with cropped area. Farmers with more acres allotted higher proportions to the market compared to those with fewer cropped acres. In the home use category, 6.5%, 6.1% and 6.8% of large, medium, and small farm output was given out as gifts, respectively. N for large farms =1,303, N for medium farms=3,506 and N for small farms = 6,027.

Additionally, the policy variable (Enterprise beneficiary) becomes insignificant for small farms, stays important for medium farms, and marginally significant for large farms. Within medium-sized farms and large farms, choosing to adopt a policy-induced enterprise positively and significantly influenced allocations to the market and storage and negatively to home consumption. This has important policy implications when it comes to policy targeting. Here, the policy seems to have worked/benefited medium and large farms compared to small farms, yet small farms account for the large proportion of farming in Uganda. For cropped area, significant effects were only observed for small and medium farms. As shown in Table 2-4, small and medium farms with more cropped areas are more likely to allocate farm output to the market and less to home uses.

Distance to the market significantly affected allocations of medium sized farms and allocations to storage for farms classified as small. While large farms sold in further markets (on average 31.3 kilometers) compared to small and medium farms that sold to markets 27.4 and 29.2 kilometers away, respectively, large farms marketed significantly more output which lowered the per unit transaction cost of marketing. Specifically, large farms on average marketed five times (15.7 Million UGX) more output than medium sized farms (3.3 million UGX) and about sixteen times more output by value compared to small farms (0.97 million UGX). Also, farms classified as large sold more (38%) by share of production on average compared to medium (30.3%) and small (21.8%) farms. Large farms therefore could be characterized by economies of scale (lower transaction costs per unit of output sold or more transported per kilometer), while the effect on small farms could be masked by the fact that they do not participate much in output markets.

Other than shares allocated to the market for medium and large farms, and shares allocated to home use for large farms, the effect of livestock wealth is the same as in the full sample estimate for all farm sizes. Exposure to a distressing event affected only small farms. The proportion kept for home use is reduced by the distressing event while that allocated to storage is increased. This suggests that a distressing event that negatively affects food production affects immediate food availability of small-scale farmers which triggers them to store more in anticipation of another possible distress event or as they try to cope through the distressing event.

Consistent with the analysis from the full sample, this disaggregate analysis reveals that while the direction of a range of factors is the same, their significance and size varies within and between farms. This is key in program design and policy generation.

Table 2-4: Determinants of output disappearance mix: Average marginal effects analysis by farm size.

	Small Farms (n=5807)			**Medium Farms (n=3399)**			**Large Farms (n=1263)**		
	Market share	Home share[1]	Storage share	Market share	Home share[1]	Storage share	Market share	Home share[1]	Storage share
Crop diversification index	0.154***	-0.205***	0.051***	0.198***	-0.284***	0.086***	0.074*	-0.103**	0.028
	(0.018)	(0.019)	(0.011)	(0.029)	(0.032)	(0.017)	(0.044)	(0.048)	(0.025)
Log Household food sufficiency	-0.145***	0.101***	0.045***	-0.062*	-0.022	0.083***	-0.156***	0.079***	0.077***
	(0.019)	(0.021)	(0.012)	(0.034)	(0.034)	(0.012)	(0.025)	(0.027)	(0.013)
Log total production	0.043***	-0.026***	-0.018***	0.051***	-0.030***	-0.021***	0.070***	-0.046***	-0.024***
	(0.002)	(0.002)	(0.001)	(0.003)	(0.003)	(0.002)	(0.005)	(0.005)	(0.003)
Log total non-farm income	-0.001*	0.001**	-0.000	-0.002***	0.002***	-0.001	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)
Log livestock value	0.001**	-0.002***	0.001***	0.001	-0.001***	0.001***	0.000	-0.001*	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)
1 (Training beneficiary: Yes)	0.012	-0.017	0.005	-0.003	0.010	-0.008	-0.005	0.015	-0.010
	(0.012)	(0.013)	(0.008)	(0.012)	(0.013)	(0.008)	(0.020)	(0.021)	(0.012)
1 (Enterprise beneficiary: Yes)	0.008	-0.015	0.007	0.029**	-0.055***	0.027***	0.049**	-0.071***	0.022**
	(0.012)	(0.014)	(0.008)	(0.012)	(0.013)	(0.008)	(0.020)	(0.021)	(0.011)
Log acres cropped	0.019***	-0.031***	0.013***	0.008***	-0.009***	0.002	0.000	0.000	-0.000
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.000)	(0.000)	(0.000)
Log market distance	0.001	0.006*	-0.007***	-0.007*	0.016***	-0.008***	-0.008	0.011	-0.003
	(0.003)	(0.003)	(0.002)	(0.004)	(0.004)	(0.002)	(0.008)	(0.008)	(0.004)
1 (Sex head: Male)	0.028***	-0.021**	-0.007	0.067***	-0.066***	-0.001	0.052***	-0.064***	0.013
	(0.008)	(0.009)	(0.005)	(0.010)	(0.011)	(0.007)	(0.019)	(0.020)	(0.010)
Age head	-0.002***	0.002***	0.000	-0.003***	0.003***	-0.000	-0.002***	0.002***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)
Household size	-0.016***	0.016***	0.000	-0.011***	0.010***	0.002**	-0.010***	0.009***	0.001
	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)
1 (Experienced distress event: Yes)	0.002	-0.015**	0.013***	0.005	-0.008	0.003	-0.017	0.020	-0.002
	(0.006)	(0.007)	(0.004)	(0.008)	(0.008)	(0.005)	(0.012)	(0.013)	(0.007)
1 (Locality: Urban)	-0.006	0.019	-0.013**	0.027*	-0.011	-0.016*	0.010	-0.016	0.006
	(0.011)	(0.012)	(0.007)	(0.014)	(0.016)	(0.009)	(0.026)	(0.027)	(0.013)

Notes: Robust standard errors generated by the delta method are in parentheses. The dependent variables are shares of farm output allocated to the market, home use, and storage. */**/*** show 10%/5%/1% significance levels

Source: Author rendering of LSMS-ISA data.

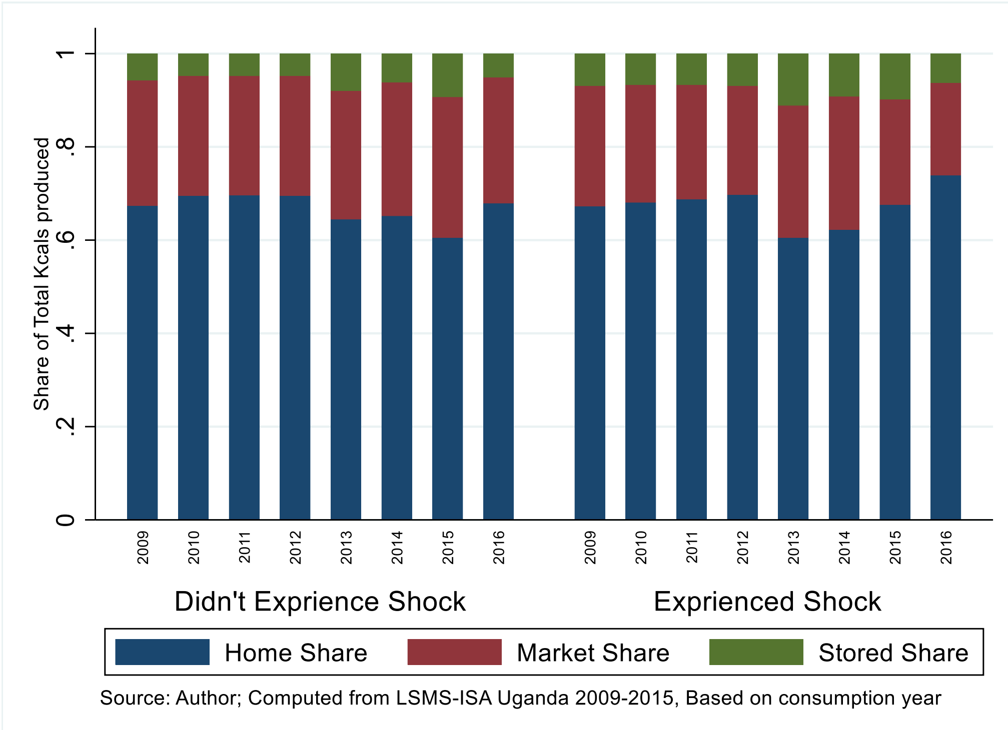
[1] Includes food, gifts, payment for wages and land..

2.6.3. Risk/distress exposure analysis

The analysis in this section attempts to answer the question of whether shares of output allocated to different uses varies or changes if a farm/farmer was exposed to a distressing event that affects farm production, markets, or household resources. Analyzing by exposure to a distress event is important because (1) farmers are likely to have different allocation patterns if they experience a shock and (2) stability is important for consistent decisions. The sample was split into those farmers the reported experiencing a distressing event in the year and those that did not and the fractional multinomial logit model as in Equation 2.9 was estimated for each category. The study found that 42.7% of the farmers reported to have experienced a distressing event in the year of the study.

Figure 2-6 shows the distribution of allocations for farmers that experienced (did not experience) a distressing event while Table 2-5 supplies average marginal effects for choice of output disappearance by distressing event exposure for the estimated models. The study finds that transport costs, being a beneficiary of a policy enterprise, the value of output produced, cropped area, nonfarm income, crop diversification, age and sex of the farm head, and household size significantly determine the shares of output allotted to different disappearance options in a similar fashion as that observed in the model with the full sample. This result implies that the effects of key variables may not be affected by exposure to distress factors with farmers behaving the same way. However, having received training organized by the government positively and significantly affected allocations to storage for farmers exposed to a distressing event and negatively for those not exposed. This implies that farmers are likely to become conscious and store if they receive information that encourages them to use storage as a coping or mitigation strategy.

Figure 2-6: Shares of farm output allocated to disappearance options disaggregated by exposure to distressing events



The proportions are based on total calories produced. The proportions allocated to different uses (dependent variables) shows no clear difference in average allocations because of exposure to a distressing event. N for distressed households=4,517 and N for none distressed Households=5,952.

Participation in enterprises promoted by the government negatively affected allocations to home use for distressed and non-distressed households and positively affected allocations to markets and storage for farmers that never experienced a distressing event. Also, for exposed farmers, household food sufficiency is positively associated with shares allocated to storage and the effect of HFS becomes insignificant on the marketed share and the share allocated to food. The effect of HFS becomes significant for allocations to home consumption for farmers that never experienced a distressing event.

Table 2-5: Output disappearance mix: Average marginal effects analysis by exposure to a distressing event

	Experienced a distressing event (n=4,517)			**Never experienced a distressing event (n=5,952)**		
	Market share	Home share[1]	Storage share	Market share	Home share[1]	Storage share
Crop diversification index	0.084***	-0.117***	0.033**	0.142***	-0.174***	0.032***
	(0.023)	(0.025)	(0.014)	(0.019)	(0.021)	(0.009)
Log Household food sufficiency	-0.059	-0.006	0.065***	-0.122***	0.059***	0.063***
	(0.050)	(0.051)	(0.012)	(0.015)	(0.017)	(0.009)
Log total production	0.048***	-0.028***	-0.020***	0.058***	-0.045***	-0.014***
	(0.003)	(0.004)	(0.002)	(0.002)	(0.002)	(0.001)
Log total non-farm income	-0.002***	0.003***	-0.001***	-0.001**	0.001**	0.000
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Log livestock value	0.001*	-0.002***	0.001***	0.001***	-0.002***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
1 (Training beneficiary: Yes)	-0.005	-0.013	0.018**	0.014	0.005	-0.019***
	(0.012)	(0.013)	(0.008)	(0.010)	(0.012)	(0.007)
1 (Enterprise beneficiary: Yes)	0.021*	-0.033**	0.012	0.034***	-0.058***	0.024***
	(0.012)	(0.014)	(0.008)	(0.010)	(0.011)	(0.006)
Log acres cropped	0.001***	-0.001***	0.000**	0.002***	-0.002***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Log market distance	-0.003	0.011**	-0.007***	0.001	-0.004	-0.005***
	(0.004)	(0.004)	(0.002)	(0.003)	(0.003)	(0.002)
1 (Sex head: Male)	0.056***	-0.043***	-0.012**	0.044***	-0.051***	0.007
	(0.009)	(0.010)	(0.006)	(0.008)	(0.009)	(0.005)
Age head	-0.002***	0.002***	0.000*	-0.002***	0.002***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Household size	-0.008***	0.006***	0.002**	-0.012***	0.011***	0.002***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
1 (Locality: Urban)	-0.013	0.035**	-0.022**	-0.005	0.019	-0.014**
	(0.014)	(0.016)	(0.009)	(0.011)	(0.012)	(0.006)

Notes: Robust standard errors generated by the delta method are in parentheses. The dependent variables are shares of farm output allocated to the market, home use, and storage. */**/*** show 10%/5%/1% significance levels.

Source: Author rendering of LSMS-ISA data.

[1] Includes food, gifts, payment for wages and land.

2.7. Conclusions and policy implications

Recognizing the dual role that farm output plays in servicing the needs of smallholder farmers in the developing world, the study examined factors that affect how farmers distribute farm production, using Uganda as a case study. Specifically, factors that affect how farmers allocate realized output to the market, home use, and storage are evaluated. To show empirical patterns of interest, the study connects the theoretical framework with farm output allocation choices made on the farm. Because the allocations sum to one, such that increasing one allocation decreases the others, the analysis deviates from the approach of modeling allocation decisions separately or singly and uses a joint modeling framework at allows conditional means to be modeled jointly. This was implemented using the fractional multinomial logit setting (Papke & Wooldridge, 1996). The analysis is implemented for all farms (assuming uniformity in decisions), for a subsample of farms by size (assuming farm size may alter allocations mixes), by distress categorization (assuming behavior changes given distressing events), and by locality (rural only verse urban only farm households).

First, we found that self-provisioning was high (66.6% of produced output), while marketed output was only 27%. In terms of market participation, our empirical model finds that farm production, cropped area, livestock wealth, participating in interventions promoted by government policy, and farms being managed by male heads have a positive relationship with shares allocated to the market. On the other hand, crop diversification, non-farm income, household food sufficiency, household size, and farms managed by older heads were negatively associated with the shares given to the market. The study finds that allocations to home use were positively associated with high off-farm income, older heads, and large household size while more production, liquidity, and cropped area were associated with less allocations to home use. Farms with more diversified crop portfolio assigned more produced output to home use. Finally, allocations to storage were positively influenced by policy prescribed enterprises, area cropped, livestock wealth, transport costs, and household food sufficiency. The results suggest that less diversified farms, farms with more production, and high non-farm incomes were less likely to keep output for storage.

Further analysis by reclassifying farms by farm size and exposure to distress events did not change the conclusions from the full sample analysis. However, this disaggregate analysis reveals that while the direction of a range of factors is the same, their significance and size varies within farms. We find that being rural has important effects on allocations of some households. For example, being rural positively affects allocations to home use and significantly influences the effects of non-farm incomes and cropped area on allocations.

Even if smallholders in Uganda only allocate a portion of their production to the market, put together, they play an important role in supplying food and servicing industries. Taken as a whole, achieving desired allocations will require interventions specifically tailored to the farm's production abilities, production circumstances, and farm characteristics. From this analysis, the study proposes the following potential policy instruments in ensuring the best allocations: (1) support policies that allow production at the intensive margin. These are production-enhancing policies that increase production per unit area, and (2) support policies to create off/non-farm income opportunities. These lessen the stress on the produced output in meeting household needs and allows households to diversify on calorie sources.

First, consider promoting intensified production. Increased production leads to more allocations to the market while allowing farmers to have sufficient volumes for home use. Because most farms are small, intensification of production may allow then to achieve more output per unit and thus desired allocations. While there has been limited adoption of improved technologies in developing counties, we see here that farmers positively responded to market production if supplied with market-oriented technologies. As such, promoting at a wider scale, targeted market-oriented interventions could be the first step in fostering adoption and production for markets. Our findings suggest that medium and large-scale farms are more likely to use such interventions and supply more to the market.

Next, consider creating off/non-farm income opportunities. Non-farm income constrained farmers preferred allocating to markets than to home use. We found that the distribution of farm output is such that those with high nonfarm incomes produce less, mostly to service their own consumption needs while those with less income will produce more to meet their food and income needs. If off/non-farm income opportunities are created, farmers will be able to lessen demands on farm income, thus allowing more allocations to the market while at the same time allowing them to source food from the market to meet production shortfalls. Our findings reveal that non/off-farm incomes are more important for rural compared to urban households.

While we analyze how allocations vary and document factors that influence the choices of allocation strategies in different contexts, future research could: (1) assess the partners of substitution within and between allocations and how these are explained by farm context, (2) evaluate the effect of each distressing event category on allocation choice and household food sufficiency, and (3) evaluate the effect of price transmission across time and space on production and farm output allocation decisions.

Appendix A: Supplementary materials for chapter 2

A.1 Additional Figures

Figure 2-7: Distribution of households by month of data collection

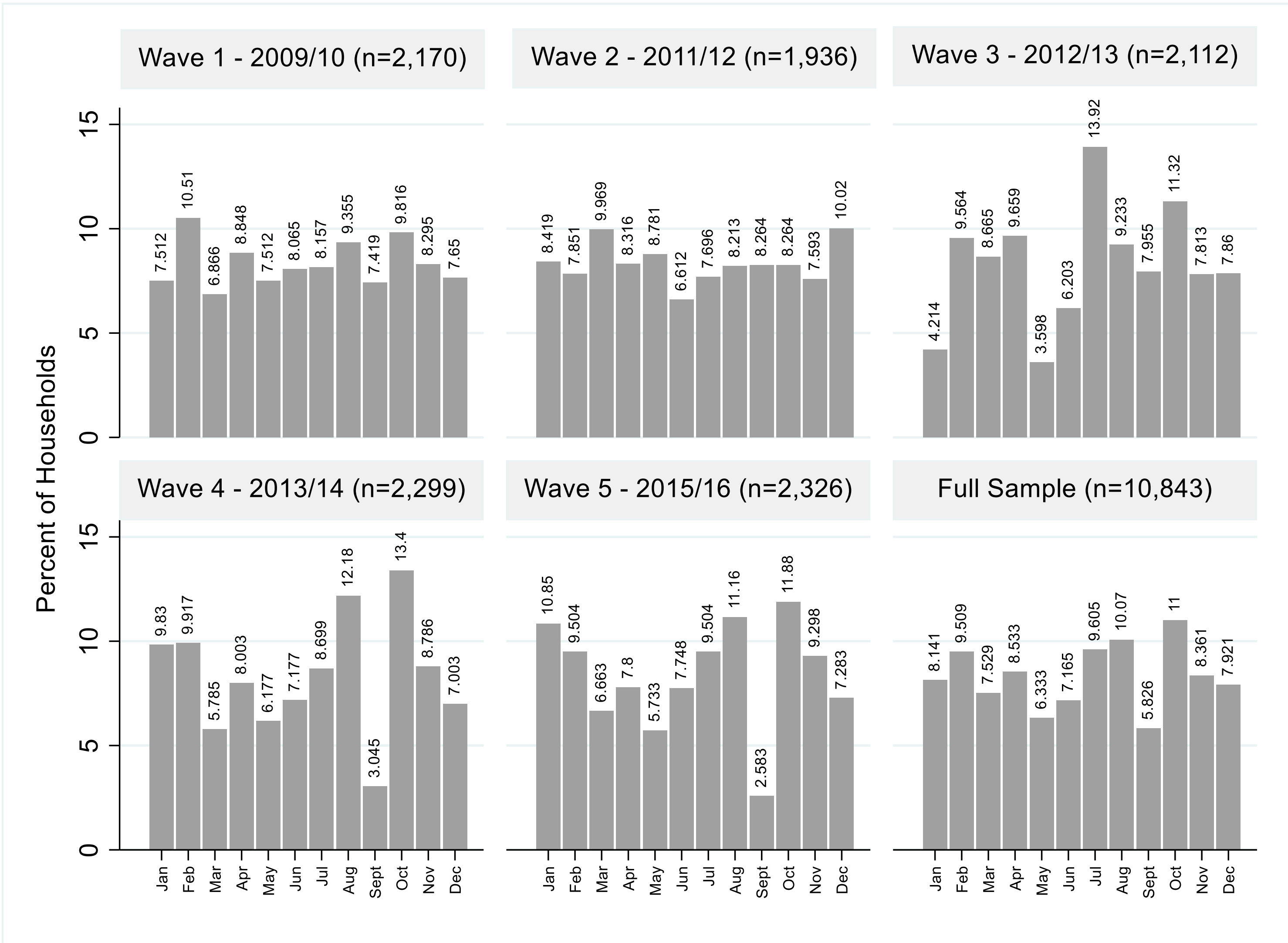
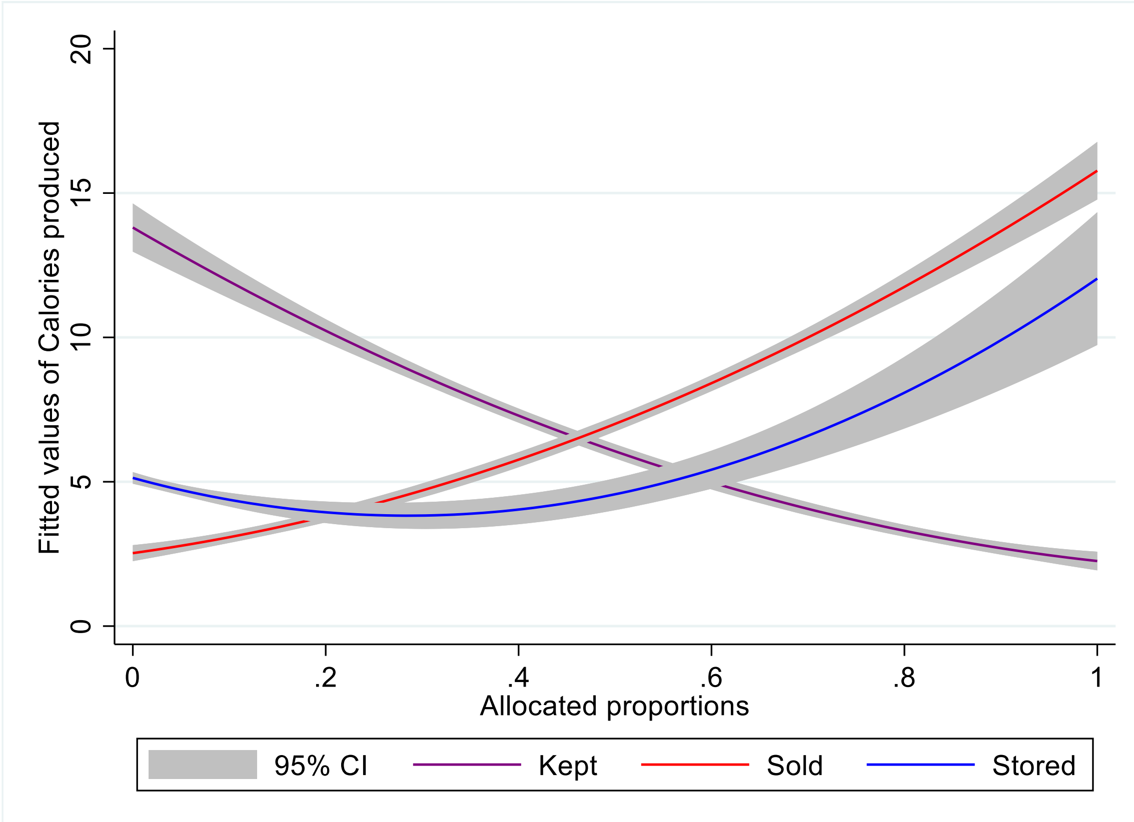


Figure 2-8: The association between calories produced and allocations



In Figure 2-8, the prediction for calories produced from a regression of total available calories (y axis variable) on each of the proportions kept, sold, or stored and their squares (x axis variable) was computed. The plots depict the resulting line plots along with confidence interval. Sales and storage increase with production while what farmers keep decreases with increase in production.

A.2 Additional tables

Table 2-6: Fractional multinomial logit estimation of farm output disappearance mix: Average marginal effects result by Locality

	Rural sample (n=9114)			Urban Sample (n=1355)		
	Market share	**Home share[1]**	**Storage share**	**Market share**	**Home share[1]**	**Storage share**
Crop diversification index	0.109***	-0.145***	0.035***	0.175***	-0.194***	0.019
	(0.016)	(0.018)	(0.009)	(0.038)	(0.041)	(0.021)
Log Household food sufficiency	-0.123***	0.059***	0.064***	-0.035***	-0.030*	0.065***
	(0.012)	(0.014)	(0.008)	(0.010)	(0.017)	(0.019)
Log total production	0.056***	-0.040***	-0.017***	0.048***	-0.035***	-0.013***
	(0.002)	(0.002)	(0.001)	(0.004)	(0.005)	(0.002)
Log total non-farm income	-0.001***	0.002***	-0.001***	-0.002	0.000	0.001
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Log livestock value	0.001***	-0.002***	0.001***	0.002**	-0.002***	0.001
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)
Training beneficiary: Yes	0.008	-0.007	-0.001	-0.014	0.023	-0.009
	(0.008)	(0.009)	(0.006)	(0.023)	(0.026)	(0.013)
Enterprise beneficiary: Yes	0.026***	-0.042***	0.016***	0.047**	-0.086***	0.039***
	(0.008)	(0.009)	(0.005)	(0.022)	(0.026)	(0.013)
Log acres cropped	0.001***	-0.001***	0.000**	0.002	-0.002	0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.002)	(0.000)
Log market distance	-0.001	0.008***	-0.007***	-0.001	0.004	-0.003
	(0.003)	(0.003)	(0.002)	(0.005)	(0.006)	(0.003)
Sex head: Male	0.050***	-0.047***	-0.003	0.043**	-0.047**	0.004
	(0.007)	(0.008)	(0.004)	(0.020)	(0.022)	(0.011)
Age head	-0.002***	0.002***	0.000	-0.002***	0.002***	0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)
Household size	-0.011***	0.009***	0.002***	-0.009***	0.009***	0.000
	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.001)
Experienced distress event: Yes	0.001	-0.010*	0.009***	0.000	-0.004	0.004
	(0.005)	(0.005)	(0.003)	(0.014)	(0.016)	(0.008)

Note: Robust standard errors are in parentheses. The dependent variables are shares of farm output allocated to the market, home use, and storage. */**/*** show 10%/5%/1% significance levels.

Source: Author rendering of LSMS-ISA data.

[1] Includes food, gifts, payment for wages and land.

Table 2-7: Fractional multinomial logit estimation of farm output disappearance mix: Auxiliary full sample average marginal effects results for estimates using median transport costs.

	Market share	Home share[1]	Storage share
Crop diversification index	0.121***	-0.151***	0.028***
	(0.015)	(0.016)	(0.008)
Household food sufficiency	-0.094***	0.029	0.065***
	(0.033)	(0.034)	(0.007)
Log total production	0.055***	-0.038***	-0.017***
	(0.002)	(0.002)	(0.001)
Log total non-farm income	-0.001***	0.002***	-0.001***
	(0.000)	(0.000)	(0.000)
Log livestock value	0.001***	-0.002***	0.001***
	(0.000)	(0.000)	(0.000)
1 (Training beneficiary: Yes)	0.006	-0.004	-0.001
	(0.008)	(0.009)	(0.005)
1 (Enterprise beneficiary: Yes)	0.025***	-0.044***	0.019***
	(0.008)	(0.009)	(0.000)
Log acres cropped	0.001***	-0.001***	0.000**
	(0.000)	(0.000)	(0.000)
Log median transport costs	0.001***	-0.002***	0.001***
	(0.000)	(0.000)	(0.000)
1 (Sex head: Male)	0.047***	-0.046***	-0.001
	(0.007)	(0.007)	(0.004)
Age head	-0.002***	0.002***	0.000
	(0.000)	(0.000)	(0.000)
Household size	-0.010***	0.009***	0.002***
	(0.001)	(0.001)	(0.001)
1 (Experienced distress event: Yes)	-0.001	-0.005	0.007**
	(0.005)	(0.005)	(0.003)
1 (Locality: Urban)	0.005	0.017	-0.011**
	(0.009)	(0.010)	(0.005)
N	10,836		
Log Likelihood	-8321.57		
AIC	16703.13		
BIC	16921.85		

Notes: Robust standard errors generated by the delta method are in parentheses. The dependent variables are shares of farm output allocated to the market, home use, and storage. Source: */**/*** show 10%/5%/1% significance levels.

Author estimation using LSMS-ISA data.

[1]Includes food, gifts, payment for wages and land.

Table 2-8: Output disappearance mix: Coefficient estimates for the full sample

	Market share	**Home share**[1]	**Storage share**
Crop diversification index	0.031	-0.700***	1.669***
	(0.140)	(0.130)	(0.257)
Log Household food sufficiency	-1.326***	-0.902***	3.229***
	(0.188)	(0.125)	(0.254)
Log total production	0.471***	0.189***	0.340***
	(0.018)	(0.016)	(0.031)
Log total non-farm income	0.003	0.011***	0.986***
	(0.003)	(0.003)	(0.006)
Log livestock value	-0.010***	-0.017***	1.028***
	(0.003)	(0.003)	(0.005)
1 (Training beneficiary: Yes)	0.042	0.017	0.941***
	(0.087)	(0.083)	(0.164)
1 (Enterprise beneficiary: Yes)	-0.167**	-0.352***	1.519***
	(0.084)	(0.081)	(0.159)
Log acres cropped	0.001	-0.005***	1.003***
	(0.001)	(0.002)	(0.002)
Log market distance	0.086***	0.100***	0.814***
	(0.024)	(0.023)	(0.045)
1 (Sex head: Male)	0.231***	-0.044	0.813***
	(0.066)	(0.063)	(0.123)
Age head	-0.010***	0.001	1.009***
	(0.002)	(0.002)	(0.004)
Household size	-0.070***	-0.014	1.085***
	(0.010)	(0.009)	(0.017)
1 (Experienced distress event: Yes)	-0.123**	-0.138***	1.261***
	(0.049)	(0.046)	(0.091)
1 (Locality: Urban)	0.211**	0.285***	0.504***
	(0.094)	(0.092)	(0.178)
N	10,469		
Log Likelihood	-8033.95		
AIC	16127.89		
BIC	16345.58		

Notes: Robust standard errors generated by the delta method are in parentheses. The dependent variables are shares of farm output allocated to the market, home use, and storage. */**/*** show 10%/5%/1% significance levels.

Source: Author rendering of LSMS-ISA data.

[1] Includes food, gifts, payment for wages and land.

Table 2-9: Determinants of output disappearance mix: Coefficient estimates by farm size

	Small Farms			Medium Farms			Large Farms		
	Market share	Home share[1]	Storage share	Market share	Home share[1]	Storage share	Market share	Home share[1]	Storage share
Crop diversification index	-0.007	-1.049***	2.056***	-0.472*	-1.641***	3.114***	-0.284	-0.679	1.963**
	(0.192)	(0.172)	(0.348)	(0.261)	(0.251)	(0.489)	(0.491)	(0.491)	(0.959)
Log Household food sufficiency	-1.380***	-0.523***	2.903***	-1.374***	-1.186***	3.561***	-1.894***	-1.283***	4.176***
	(0.220)	(0.200)	(0.404)	(0.216)	(0.180)	(0.357)	(0.236)	(0.237)	(0.457)
Log total production	0.471***	0.222***	0.307***	0.472***	0.240***	0.288***	0.657***	0.367***	-0.024
	(0.022)	(0.020)	(0.040)	(0.030)	(0.029)	(0.056)	(0.052)	(0.051)	(0.100)
Log total non-farm income	0.002	0.008*	0.990***	0.002	0.010**	0.988***	0.010	0.009	0.981***
	(0.005)	(0.004)	(0.009)	(0.005)	(0.005)	(0.010)	(0.010)	(0.010)	(0.019)
Log livestock value	-0.008*	-0.014***	1.021***	-0.009**	-0.014***	1.023***	-0.014*	-0.018**	1.031***
	(0.004)	(0.004)	(0.007)	(0.004)	(0.004)	(0.008)	(0.008)	(0.007)	(0.015)
1 (Training beneficiary: Yes)	-0.020	-0.101	1.122***	0.098	0.123	0.779***	0.171	0.210	0.619
	(0.136)	(0.127)	(0.253)	(0.129)	(0.122)	(0.242)	(0.234)	(0.232)	(0.457)
1 (Enterprise beneficiary: Yes)	-0.070	-0.127	1.197***	-0.262**	-0.455***	1.716***	-0.251	-0.516***	1.768***
	(0.136)	(0.127)	(0.252)	(0.120)	(0.116)	(0.228)	(0.214)	(0.212)	(0.416)
Log acres cropped	-0.101***	-0.236***	1.337***	0.004	-0.039**	1.034***	0.002	0.002	0.996***
	(0.030)	(0.027)	(0.054)	(0.020)	(0.019)	(0.038)	(0.003)	(0.003)	(0.005)
Log market distance	0.107***	0.111***	0.782***	0.087**	0.139***	0.773***	0.038	0.081	0.881***
	(0.029)	(0.026)	(0.052)	(0.039)	(0.037)	(0.073)	(0.073)	(0.073)	(0.142)
Sex head: Male	0.251***	0.082	0.667***	0.264**	-0.084	0.820***	-0.071	-0.334*	1.405***
	(0.081)	(0.074)	(0.148)	(0.104)	(0.101)	(0.198)	(0.195)	(0.187)	(0.372)
Age head	-0.013***	-0.001	1.014***	-0.008**	0.006*	1.002***	-0.004	0.007	0.997***
	(0.002)	(0.002)	(0.004)	(0.003)	(0.003)	(0.006)	(0.005)	(0.005)	(0.010)
Household size	-0.089***	0.013	1.076***	-0.064***	-0.007	1.071***	-0.052***	-0.007	1.060***
	(0.015)	(0.013)	(0.027)	(0.014)	(0.012)	(0.025)	(0.019)	(0.018)	(0.036)
1 (Experienced distress event: Yes)	-0.180***	-0.212***	1.392***	-0.016	-0.047	1.063***	-0.010	0.075	0.935***
	(0.069)	(0.064)	(0.128)	(0.079)	(0.075)	(0.149)	(0.130)	(0.130)	(0.254)

Locality: Urban	0.172	0.229**	0.599***	0.322**	0.206	0.472*	-0.086	-0.142	1.228**
	(0.116)	(0.108)	(0.214)	(0.150)	(0.146)	(0.286)	(0.256)	(0.253)	(0.495)
N	5,807			3,399			1,263		
Log likelihood	-4181.68			-2752.15			-1018.64		
AIC	8423.36			5564.31			2097.27		
BIC	8623.37			5748.24			2251.51		

Notes: Robust standard errors generated by the delta method are in parentheses. The dependent variables are shares of farm output allocated to the market, home use, and storage. */**/*** show 10%/5%/1% significance level.

Source: Author rendering of LSMS-ISA data.

[1] Includes food, gifts, payment for wages and land.

Table 2-10: Output disappearance mix: Coefficient estimates by exposure to a distressing event

	Experienced a distressing event			**Never experienced a distressing event**		
	Market share	Home share[1]	Storage share	Market share	Home share[1]	Storage share
Crop diversification index	-0.091	-0.616***	1.707***	0.074	-0.765***	1.691***
	(0.219)	(0.201)	(0.401)	(0.175)	(0.165)	(0.323)
Log Household food sufficiency	-1.131***	-0.884***	3.014***	-1.519***	-0.928***	3.447***
	(0.272)	(0.182)	(0.365)	(0.168)	(0.158)	(0.316)*
Log total production	0.473***	0.228***	0.299***	0.461***	0.155***	0.385***
	(0.027)	(0.023)	(0.046)	(0.022)	(0.021)	(0.041)
Log total non-farm income	0.012**	0.023***	0.965***	-0.006	0.000	1.006***
	(0.005)	(0.005)	(0.009)	(0.005)	(0.004)	(0.009)
Log livestock value	-0.015***	-0.021***	1.036***	-0.006*	-0.014***	1.020***
	(0.004)	(0.004)	(0.007)	(0.004)	(0.004)	(0.007)
1 (Training beneficiary: Yes)	-0.270**	-0.267**	1.537***	0.361***	0.311***	0.327
	(0.122)	(0.116)	(0.228)	(0.122)	(0.116)	(0.231)
1 (Enterprise beneficiary: Yes)	-0.074	-0.211*	1.286***	-0.246**	-0.472***	1.718***
	(0.119)	(0.115)	(0.224)	(0.113)	(0.109)	(0.215)
Log acres cropped	0.000	-0.004**	1.004***	0.004**	-0.006**	1.002***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)
Log market distance	0.087**	0.116***	0.797***	0.083***	0.087***	0.829***
	(0.036)	(0.034)	(0.067)	(0.028)	(0.027)	(0.052)
1 (Sex head: Male)	0.404***	0.103	0.492***	0.067	-0.189**	1.122***
	(0.088)	(0.083)	(0.164)	(0.083)	(0.078)	(0.155)
Age head	-0.014***	-0.001	1.015***	-0.008***	0.003	1.005***
	(0.003)	(0.002)	(0.005)	(0.002)	(0.002)	(0.005)
Household size	-0.059***	-0.015	1.074***	-0.081***	-0.014	1.095***
	(0.013)	(0.012)	(0.023)	(0.012)	(0.011)	(0.022)
1 (Locality: Urban)	0.240*	0.347**	0.413	0.207*	0.254**	0.539**
	(0.144)	(0.136)	(0.270)	(0.110)	(0.108)	(0.209)
N	4,517			5,952		
Log likelihood	-3504.71			-4515.19		
AIC	7065.42			9086.38		
BIC	7245.06			9273.74		

Notes: Robust standard errors generated by the delta method are in parentheses. The dependent variables are shares of farm output allocated to the market, home use, and storage. */**/*** show 10%/5%/1% significance levels.

Source: Author rendering of LSMS-ISA data.

[1] Includes food, gifts, payment for wages and land.

Table 2-11:Output disappearance mix: Auxiliary model coefficient estimates for the full sample

	Market share	Home share[1]	Storage share
Crop diversification index	0.088	-0.638***	1.550***
	(0.139)	(0.129)	(0.254)
Log Household food sufficiency	-1.354***	-0.921***	3.276***
	(0.184)	(0.123)	(0.250)
Log total production	0.477***	0.193***	0.329***
	(0.018)	(0.016)	(0.031)
Log total non-farm income	0.004	0.011***	0.985***
	(0.003)	(0.003)	(0.006)
Log livestock value	-0.010***	-0.016***	1.026***
	(0.003)	(0.003)	(0.005)
1 (Training beneficiary: Yes)	0.043	0.014	0.943***
	(0.086)	(0.082)	(0.162)
1 (Enterprise beneficiary: Yes}	-0.178**	-0.348***	1.525***
	(0.082)	(0.079)	(0.156)
Log acres cropped	0.001	-0.005***	1.003***
	(0.001)	(0.002)	(0.002)
Log median transport cost	-0.009**	-0.017***	1.027***
	(0.004)	(0.004)	(0.008)
1 {Sex head: Male)	0.216***	-0.044	0.828***
	(0.065)	(0.062)	(0.121)
Age head	-0.011***	0.001	1.009***
	(0.002)	(0.002)	(0.004)
Household size	-0.068***	-0.011	1.079***
	(0.010)	(0.008)	(0.017)
1 (Experienced distress event: Yes)	-0.108***	-0.110**	1.218***
	(0.048)	(0.046)	(0.090)
1 (Locality: Urban)	0.145	0.192**	0.664***
	(0.089)	(0.087)	(0.169)
N	10,836		
Log likelihood	-8321.57		
AIC	16703.13		
BIC	16921.85		

Notes: Robust standard errors generated by the delta method are in parentheses. The dependent variables are shares of farm output allocated to the market, home use, and storage. */**/*** show 10%/5%/1% significance levels.

Source: Author rendering of LSMS-ISA data.

[1] Includes food, gifts, payment for wages and land.

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Chapter 3 - Food sufficiency and market participation: Production and income thresholds for market participation by smallholder farmers.

3.1. Introduction

Policy makers in Sub Saharan Africa (SSA) are hopeful that smallholder farmers will be a panacea for economic development, food security, and poverty reduction through the commercialization of production (Lipton, 2013; World Bank, 2018). While smallholders have enormous potential to supply and support food markets and agro-industrialization in the developing world, they typically sell less than 27% of their production to the market (Carletto et al., 2017). As a result, the decisions of the farmers in allocating output to own consumption is often entrenched. Nonetheless, smallholder farmers are among the most affected by poverty, undernutrition and low dietary quality (Muthini et al., 2020). As commercialization prospects gain traction, one important question is: under what conditions can policy transform smallholder farmers into commercial, market oriented, or enterprising farmers without being in conflict with household needs?

The decisions made on the farm result in the level of farm household welfare, including what and when to produce, how much food the household consumes, leisure to expend, wealth, and income. These directly affect agricultural commercialization. For a farmer in the developing world, where agriculture is the predominant source of livelihood, allocation choices of farm output (for food, marketing, gifts, and storage, among others) play a vital role in determining household welfare. In agrarian societies, household food sufficiency is the most important aspect of a household's welfare. For example, subsistence production accounted for: 58% of caloric consumption in rural Ethiopia (Sibhatu & Qaim, 2017), 66% of farming in Russia (Sharashkin, 2008), and 80% of grains and 70% of vegetables in China (Gale et al., 2005), among others.

In Uganda, the focus of this paper, based on Living Standard Measurement Surveys – Integrated Surveys on Agriculture (LSMS-ISA) data, farms kept an average of 66% of farm output (in caloric terms) between 2010 and 2016. This is against the backdrop of policy makers in 2003 desiring to cut retained output from 80% to 30% by 2016 (Kraybill et al., 2012). The aim was to foster agro-industrialization by releasing more farm output to the market and to feed the growing urban population. This was deemed important because capacity utilization of agro-industries, which accounts for 60% of industrialization and 54% of export earnings in Uganda, has remained low due to shortages in the supply of raw materials (EPRC, 2018; Fowler & Rauschendorfer, 2019). Capacity utilization ranges from 20% to 40% for industries processing coffee, sunflower, soybeans, rice, maize, beef, fish and cassava, and 66% for the dairy industry (EPRC, 2018; Fowler & Rauschendorfer, 2019). This excess input demand by industries leaves major gaps to be filled.

This essay analyzes the conditions necessary to motivate farmers to supply more agricultural output to the market. The study hypothesizes that, *ceteris paribus*, farmers will allocate more to the market if they have achieved food self-sufficiency. The paper models the farmer market participation problem as a rationing problem for realized annual farm output. The study identifies production and nonfarm income thresholds at which farms can release more output to the market while remaining food sufficient. Food sufficiency is used as an important indicator for market participation and household welfare because: (1) it has a strong influence on farm production and output allocation, (2) household food expenditures account for a large share of household budgetary outlays (FAO, 2015), (3) farm output has multiple uses, and (4) self-provisioning is high and production is often sub-subsistence (Lipton, 2013).

Previous literature has documented factors that determine market participation, which include, transport and transaction costs (Key et al., 2000), crop portfolio choice, farmer preferences, and attitude towards risk (Fafchamps, 1992). Others in the literature have enumerated factors, such as farmer characteristics such as age, sex, education (Kyaw et al., 2018); farm characteristics including total production, price of produce, livestock wealth (Fafchamps, 1992; Kyaw et al., 2018; Ntakyo & Van Den

Berg, 2019), and institutional factors such as limited access to market information and extension services, access to roads and farmer group membership (Gyau et al., 2016; Kyaw et al., 2018). This empirical evidence provides insights into the determinants of market participation, but offers no information on thresholds that would motivate farmers, including food crop producers, to supply more to the market. While the determinants of market participation presented in the literature may be functions of income and production thresholds, previous research has not quantified these thresholds.

This study addresses this research gap using a panel of nationally representative household data of Ugandan households. First, the study quantifies “Household Food Sufficiency (HFS)” and then uses threshold estimation techniques to identify and quantify threshold levels that may allow households to remain food secure and participate in markets. Furthermore, the study segments and characterizes households to inform policy targeting and program interventions. This will help align policy/intervention outcomes with farmers’ production circumstances.

Exploiting temporal and spatial variations in HFS and output allocation in Uganda, the study identifies and quantifies income and production thresholds at magnitudes much higher than earned annual average non-farm incomes and farm production. These thresholds lead to varied effects of marketing on household food sufficiency (HFS). While both farm and nonfarm income are positively associated with HFS (improve HFS), increasing the possibility of market participation, the farm income effect is dominant. This suggests that implementing farm-based interventions is likely to provide better results than nonfarm interventions in securing food security and indirectly market participation in developing countries. Farmers with more food and higher cash incomes are likely to market more. Therefore, holding other things equal, higher levels of food sufficiency should increase market participation by raising incomes. Evaluation of a commercialization policy shows that policy transfers in terms of capacity building, but not enterprise prescriptions, significantly improve household food sufficiency. This suggests that the farmer’s choice of enterprises could be close to optimal given farm conditions.

This study supplies insights for improved policy targeting and farmer decision making related to commercialization of production. The results contribute to a body of sophisticated literature that seeks to develop frameworks for farmer targeting and selection by development agencies when implementing programs to foster commercialization, improve farmer incomes, and enhance food security. Importantly, the study shows that the effects of policy outcomes may be incongruous with farmer needs and production circumstances if detailed and in-depth procedures are not considered in policy formulation and analysis. While this analysis is focused on Uganda, farm and farmer characteristics in Sub Saharan Africa (SSA) are similar. These findings thus offer broader lessons for policy in the developing world.

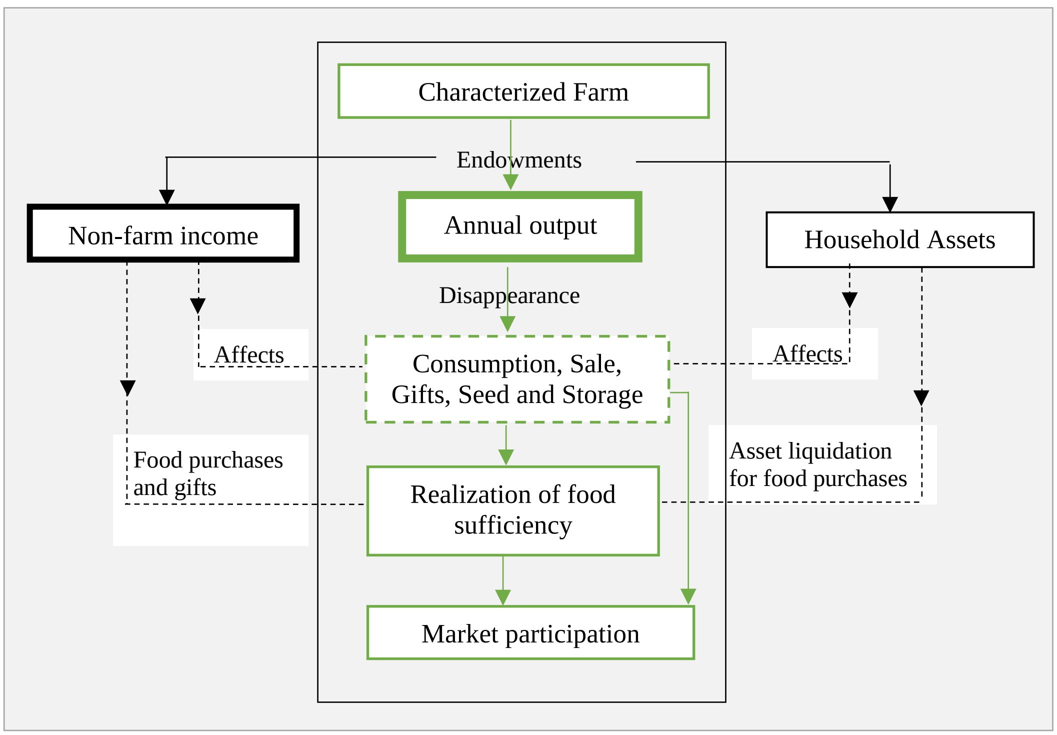
The rest of the essay is organized as follows. In section two, a depiction of the household's farm output allocation problem is presented. Section three describes the data used and key descriptive statistics. The estimation and empirical model are presented in section four. Section five discusses the results, section six offers program and policy implications, while section seven concludes the essay.

3.2. Depiction of the household's farm output allocation problem

Figure 3-1 illustrates a simplified household output allocation and decision problem. The study models this problem as a rationing problem for realized annual farm output. The farm household, given off/non-farm opportunities to earn income and liquidate assets, can maximize utility, assumed to be the realization of household food sufficiency subject to its incomes, production (allocated for home use and markets), and assets (physical and livestock). Here, household food sufficiency is defined as the household's ability to meet its food (dietary) needs from all available food sources. Food can be obtained through the subsistence pathway or market pathway (Muthini et al., 2020) or as gifts, a common practice in SSA societies. The assumption is that once the farm household can meet household food requirements, from different pathways, it should be able to participate in the market holding other factors constant.

The center panel of Figure 3-1 traces out the typical path to food self-sufficiency (subsistence pathway) and output market participation by households in the developing world. Because production is at a subsistence level, yet policy seeks to increase the quantity of farm output that is marketed, the study investigates (a) the effect of market participation on HFS, and (b) levels of farm production and (c) levels non-farm income that would allow households to release more output to the market. To the extent that the effect of policy is evaluated, the study investigates the association between policy interventions and food sufficiency. Farm production and non-farm income are used to investigate thresholds because they are important sources of livelihood for rural households in developing countries (Nagler & Naudé, 2017; World Bank., 2017).

Figure 3-1: Illustration of the households Allocation and rationing problem



Source: Authors' construction based on experience working with farming households in Uganda.

The study constructed a measure of household welfare as the "Household Food Sufficiency Score (HFSs)." This measure captures the caloric or dietary adequacy of household production, market purchases, gift sources and output disappearance vis a vis its requirements. The HFSs is calculated as the difference between the overall amount of food available (sum of annual own Food Production (FP), Food Acquisitions

(FA), and Food from Incoming Gifts (FIG)) less Food Sale (FS), Food Losses (FL), Food Gifted Out (FGO) and annual Household Adult Equivalent Requirements (HAER), as in Eq. 3.1 and defined in what follows below. Because storage is unallocated, yet 78% of households reported storing produce for food, the study assumes that storage is available for food. Otherwise, HFSs would be calculated net of storage.

$$\text{HFSs} = \{\text{FP} + \text{FA} + \text{FIG}\} - \{\text{FS} + \text{FL} + \text{FGO}\} - \{\text{HAER}\} \tag{3.1}$$

This approach accounts for all food sources and uses, feedback loops between production, markets, and social aspects of the household. This approach is superior to direct dietary score measures[4] because it integrates production, market, and social aspects. The approach also assesses food availability and access at a farm and local level. Furthermore, it does not lump food groups together, but accounts for individual food item calories and individual household member caloric requirements. Implicitly, the household's food sufficiency score we construct is a household's food calorific balance sheet allowing identification of surpluses and deficits. For FP, FA, FGI, FS, FL, and FGO, the quantities contributed by each source in terms of kilograms are calculated, and then the kilograms[5] are converted into caloric equivalents using conversion factors from Harvest-Plus Uganda (Hotz et al., 2012) and United States Department of Agriculture (USDA, 2019).

Annual *Food Production (FP)* is the sum of all Calories produced by a household in a year from all food crops. Annual *Food Acquisitions (FA)* is the sum of all Calories purchased by the household from the market and consumed at home while *Food from Incoming Gifts (FIG)* is the total of Calories that the household received from food gifts/handouts each year.[6] Food utilization terms are; *Food Sold (FS)* which is the sum of Calories sold out of production, *Food Lost (FL)* the sum of Calories lost out of production

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[4] Other food security and dietary measures often used include: Food Consumption Score (FCS), Household Consumption and Expenditure Survey (HCESs), Household Food Insecurity and Access Scale (HFIAS), Household Hunger scale (HHS), and Household Dietary Diversity Scale (HDDS)

[5] Milling recovery ratios are not factored into calculations for corn, millet, rice, and sorghum. Data were unavailable to allow these adjustments.

[6] Items such as oils and fats, sweets, and sugar are not included in caloric calculations, because data for actual volumes of each consumed by the farmers was not readily available.

and *Food Given Out as Gifts (FGO)* is the sum of Calories given out for social causes out of production. Production and consumption years were matched to create the production-consumption year to avoid overlaps in production and consumption and to ensure accountability for food produced and consumed. To calculate the *Household's Adult Equivalent Requirement (HAER)*, we used the information on household members (sex and age) from the household roster and assume a moderate level of individual activity. Using minimum dietary information from(USDHHS & USDA, 2015), we then calculate per capita annual caloric requirements for each household member[7] for the period they stayed in the household and then sum each member's requirement to obtain the household's requirement. Variations in the month of data collection accounts for the possibility of seasonality in production and consumption (Figure 3-7, Appendix B)

Mixed food security situations based on the household's decisions to allocate farm output are observable. Some households remain self-sufficient in food production (HFSs > 0) producing enough to meet their own food needs, meet social obligations, and selling surpluses. Others are not self-sufficient (HFSs < 0) and must adopt different coping strategies. Previous literature has documented common coping strategies to include selling assets, migration, income source diversification, crop diversification, storage of production, reducing food intake, and consuming bulk less nutritious foods (Asesefa Kisi et al., 2018; Dil Farzana et al., 2017; Janzen & Carter, 2019). When markets and consumption exhibit seasonality, cyclic decisions, and market failures, some of these strategies might fail. The household's susceptibility depends on how far the household is below the breakeven mark of the food sufficiency score. Also, the food sufficiency score varies depending on a household's allocation of production across uses (Figure 3-8 and Figure 3-9, Appendix B). Given the household's problem, the study evaluates the following two hypotheses:

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[7] Dietary requirements are calculated assuming a moderate activity level. It's also possible to calculate the same assuming an active or sedentary life. Though our calculation is based on data from a 7-day recall period, then extrapolated to cover a year, variations in weeks and month of data collection reduced the potential effect of seasonality in consumption.

1. There exist threshold levels, of farm and non-farm income at which farmers can release more output to the market while staying food sufficient.

2. Market participation, farm income and non-farm income affect the household's food sufficiency differently.

Here, farm and non-farm income thresholds are the 'value(s)' that appropriately split the sample into subsamples (regimes) such that the household stays food sufficient, by our definition of HFS, given different proportions of production allocated to the market. For example, "how big should farm/non-farm income be" for the household to securely market and stay self-sustaining in meeting its food requirements, defined as household food sufficiency. The sample is split into groups depending on whether the initial incomes are above or below these thresholds.

The study assumes that households behave rationally. That is: households know exactly and understand the decisions they are making, as well as produce and sell crops that matter for them. Also, it assumes that the household and its members are eating as much as they can afford given their period circumstances, lifestyles, and health of its members. Also, we assume that institutions exist to regulate production and market forces.

3.3. Data and descriptive analysis

3.3.1. Data and choice of variables

To investigate production and non-farm income thresholds and the relationship between allocation choices (share allocated to markets) and household food sufficiency, data from the World Bank Living Standard Measurement Surveys – Integrated Surveys Agriculture (LSMS-ISA) of 2009/2010 to 2015/2016 for Uganda was used (UBOS, 2011, 2014a, 2014b, 2016, 2019). Both the agricultural and household questionnaires were used to construct a balanced panel consisting of 680 households (3,400 in total) of agricultural households (all of which had production for each year). While the data set was much richer (had more households), balancing the panel meant losing some households. The study followed this path because it rigorously wanted to track households over time and the preferred model required a balanced panel.

Using the households total production and consumption data from Living Standard Measurement Surveys, information on calories of crops grown and consumed from Harvest-Plus Uganda (Hotz et al., 2012) and the United States Department of Agriculture (USDA, 2019), variables on total household caloric requirements, total calories consumed and produced were constructed. Weights of produced farm output were standardized using conversion factors obtained from the International Food Policy Research Institute (IFPRI)-Uganda and we used them to calculate food sufficiency scores (in calories) using Eq. 3.1.

The LSMS-ISA data used in the study to establish relations of interest included; crop production and foods consumed (value[8] and calories), household characteristics (head age, head gender, household labor endowment, incomes, and wealth), farm characteristics (size and crop diversification), locality, market proximity, and policy influence, measured by participation in National Agriculture Advisory Services (NAADS), (see Table 3-5, Appendix B for the definition of variables used). Using calories to aggregate over farm production and consumption was helpful in this case because calories are time-invariant allowing the study to isolate reported allocation effects. All monetary measures were adjusted to constant 2009 Uganda shillings (UGX) using the gross national expenditure deflator (World Bank, 2020).

The policy variable that is important to highlight is participation in NAADS enterprises and its capacity-building programs. The NAADS is a statutory semi-autonomous body under the Ministry of Agriculture, Animal Industry and Fisheries (MAAIF) that is mandated to manage the distribution of agricultural inputs and provide extension and advisory services to farmers for sustainable household food security and incomes in Uganda. This is an important policy variable given that it was implemented

[8] To find the price of commodities for households that never participated in markets (to allow us to get UGX value), we matched the price of the nearest neighbors at Enumeration area level, Village, parish, subcounty or district level, took the average and used it as the commodity price.

nationally and was a core policy that sought to commercialize production, boost incomes, and food security. This variable captures the effects of this commercialization policy.

3.3.2. Descriptive statistics and analysis

Table 3-1 displays the summary statistics of the variables used in the study. Division of the sample was used to create subgroups which were used to compare differences in means. For food sufficient farmers, the sample was divided into food sufficient (with HFSs ≥0) and deficient (HFSs <0) groups. While market-oriented producers split the sample into those that marketed 50% or more of their food production and those that marketed less than 50% of production. For food sufficiency-oriented producers (subsistence oriented), the sample was divided into those that kept 50% or more of the food produced and those who did not. About 71.2% of the farmers kept 50% or more of their farm production as food, 20.6% marketed 50% or more of the food produced, and only 12.1% produced exclusively for food.

As shown in Table 3-1, food sufficient and market-orientated farmers produced more food crops by value compared to their counterparts. Also, self-sufficiency-orientated farmers produced less food (by value) than non-subsistence-oriented farmers. There are no differences in the value of cash crops produced. Farmers categorized as food sufficient have significantly higher non-farm incomes than food deficient farmers. In terms of total cropped annual area, being food sufficient or market-orientated are associated with cultivating 1.5 and 1.3 more hectares, respectively, compared to 1.4 fewer hectares for self-sufficiency-oriented farmers. Also, farmers oriented towards food self-sufficiency are likely to be more diversified. Farmers oriented towards self-sufficiency are likely to have significantly lower assets and food expenditures. About 15% and 16% of the household in the sample reported taking part in the government's program (NAADS) enterprises and their capacity building programs, respectively. Food sufficient and market orientated farmers were more likely to have received help from policy interventions. Furthermore, food sufficient households are likely to have fewer members (both total and those offering agricultural labor) in the household.

Table 3-1: Descriptive statistics of variables (2009-2015).

Variable	Mean (std. dev) Full Sample	Mean (std. dev) Rural Sample	Food sufficient Households	Market oriented Households	Subsistence oriented Households
	(1)	(2)	(3)	(4)	(5)
Non-farm income (M UGX)	4.72	3.64	3.96	0.91	-0.78
	(25.74)	(23.17)	(0.000)	(0.405)	(0.421)
Food production (M UGX)	7.50	7.62	9.58	12.40	-8.67
	(30.6)	(32.23)	(0.000)	(0.000)	(0.000)
Cash crop production (M UGX)	1.97	2.33	2.69	0.92	-0.07
	(55.14)	(60.37)	(0.179)	(0.695)	(0.972)
Monthly food expenditure (M UGX)	0.04	0.04	0.01	0.00	-0.00
	(0.03)	(0.03)	(0.000)	(0.001)	(0.001)
Livestock wealth (M UGX)	0.67	0.59	0.31	0.21	-0.10
	(3.98)	(3.49)	(0.037)	(0.210)	(0.510)
Value of assets (M UGX)	11.01	8.44	8.52	4.85	-4.36
	(42.04)	(23.72)	(0.000)	(0.009)	(0.009)
Distance to a market center (km)	32.93	33.79	-0.52	0.20	0.61
	(18.89)	(17.61)	(0.450)	(0.806)	(0.388)
Distance to population center (km)	24.45	26.46	1.62	3.97	-3.08
	(16.11)	(15.60)	(0.006)	(0.000)	(0.000)
Farm Labor (Members ≥10 years)	5.13	5.08	-0.45	-0.07	0.17
	(2.68)	(2.66)	(0.000)	(0.535)	(0.108)
Household size (number)	7.22	7.23	-0.86	-0.13	0.20
	(3.34)	(3.37)	(0.000)	(0.378)	(0.111)
Cropped area (hectares)	3.33	3.45	1.54	1.34	-1.37
	(7.07)	(7.59)	(0.000)	(0.000)	(0.000)
Proportion of food crops marketed	0.28	0.28	0.16	0.48	-0.38
	(0.25)	(0.24)	(0.000)	(0.000)	(0.000)
Crop diversification Index	0.39	0.38	-0.06	0.01	-0.02
	(0.17)	(0.17)	(0.000)	(0.117)	(0.006)
1(Urban)	0.10	-	-0.00	0.01	0.00
			(0.715)	(0.663)	(0.946)
1(Took part in NAADS enterprise)	0.15	0.15	0.03	0.10	-0.08
			(0.012)	(0.000)	(0.000)
1(Received NAADS capacity building)	0.09	0.16	0.09	0.09	-0.07
			(0.000)	(0.000)	(0.000)
N	**3,400**	**2,820**	**3,400**	**3,400**	**3,400**

Source: Authors' calculation from LSMS-ISA data. Column 1 and 2 show pooled and rural sample means respectively, columns 3 to 5 show the comparison of differences in means between food sufficient and deficient households, market-orientated farmers (sold ≥50% of food products), and self-sufficiency-orientated farmers (kept ≥50% of food produced). Numbers in parentheses for columns 3-5 are p-values.

Table 3-2 shows the levels of different components (in caloric terms) used to compute the food sources and disappearance contributions, household requirements and the household food sufficiency score. On average, households can meet their dietary requirements with minimal surpluses available for other uses. Even with more output kept for food, self-sufficiency-orientated (subsistence) farmers are likely to be food deficient and produced fewer calories than they needed. They were also more likely to buy food from the market. This implies that they are not sufficient in food production. In total, about 66.1% of the calories produced on the farm were kept and used either as food, seed, or gifts, depicting elevated levels of self-provisioning.

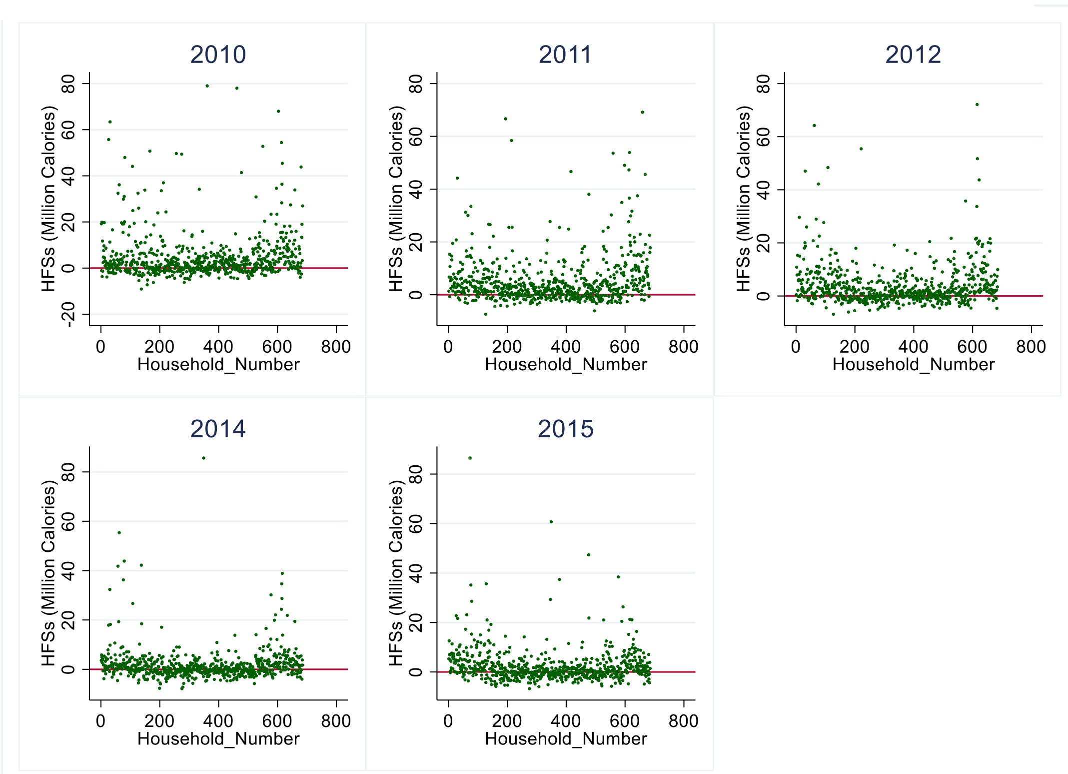
Table 3-2: Household Food Sufficiency score (HFSs) components (million Kcals)

HFSs Component	**Mean (std) - Full Sample**	**Mean (std) – Rural Sample**	**Food sufficient Households**	**Market oriented Households**	**Subsistence oriented Households**
	(1)	(2)	(3)	(4)	(5)
Food production (FP)	5.93	5.86	6.08	7.14	-6.09
	(8.46)	(8.41)	(0.000)	(0.000)	(0.000)
Kept for food	2.75	2.71	2.23	0.24	0.10
	(3.53)	(3.31)	(0.000)	(0.111)	(0.443)
Food acquisitions (FA)	1.59	1.47	0.83	-0.04	0.15
	(1.90)	(1.81)	(0.000)	(0.597)	(0.043)
Food from Gifts (FGI)	0.21	0.21	0.14	-0.03	0.02
	(0.66)	(0.68)	(0.000)	(0.274)	(0.384)
Food Sales (FS)	2.44	2.41	3.11	6.93	-5.31
	(5.40)	(5.34)	(0.000)	(0.000)	(0.000)
Food Losses (FL)	0.06	0.07	0.07	0.10	-0.11
	(1.24)	(1.35)	(0.100)	(0.060)	(0.021)
Food given Out (FGO)	0.30	0.28	0.31	0.06	-0.03
	(0.81)	(0.76)	(0.000)	(0.075)	(0.384)
Household dietary requirement	4.02	4.03	-0.99	-0.02	0.09
(HFR)	(1.98)	(2.00)	(0.000)	(0.788)	(0.238)
Household food sufficiency score	0.89	0.76	4.54	0.01	-0.57
(HFSs)	(4.92)	(4.82)	(0.000)	(0.955)	(0.002)
N	**3400**	**2820**	**3400**	**3400**	**3400**

Source: Authors' calculation from LSMS-ISA data. Columns 3 to 5 show the comparison of differences in means between food sufficient and deficient households, market-orientated farmers (sold ≥50% of food products), and self-sufficiency-orientated farmers (kept ≥50% of food produced). Numbers in parentheses for columns 3-5 are p-values.

The distribution of household food sufficiency scores across households by year is illustrated in Figure 3-2. The red line of Figure 3-2 splits households into food sufficient and deficient households. The food sufficiency score, when household consumption is the sole source of output disappearance, shows that 66.8% of the households are food sufficient, and scores vary by year. When all output disappearance options are accounted for, including postharvest losses, only 51.9% of the households can meet their dietary requirements. According to UBOS (2010), only 56.7% of the households in Uganda were unable to meet their usual food requirements due to limited production, crop losses, limited capital, and inadequate land for cultivation.

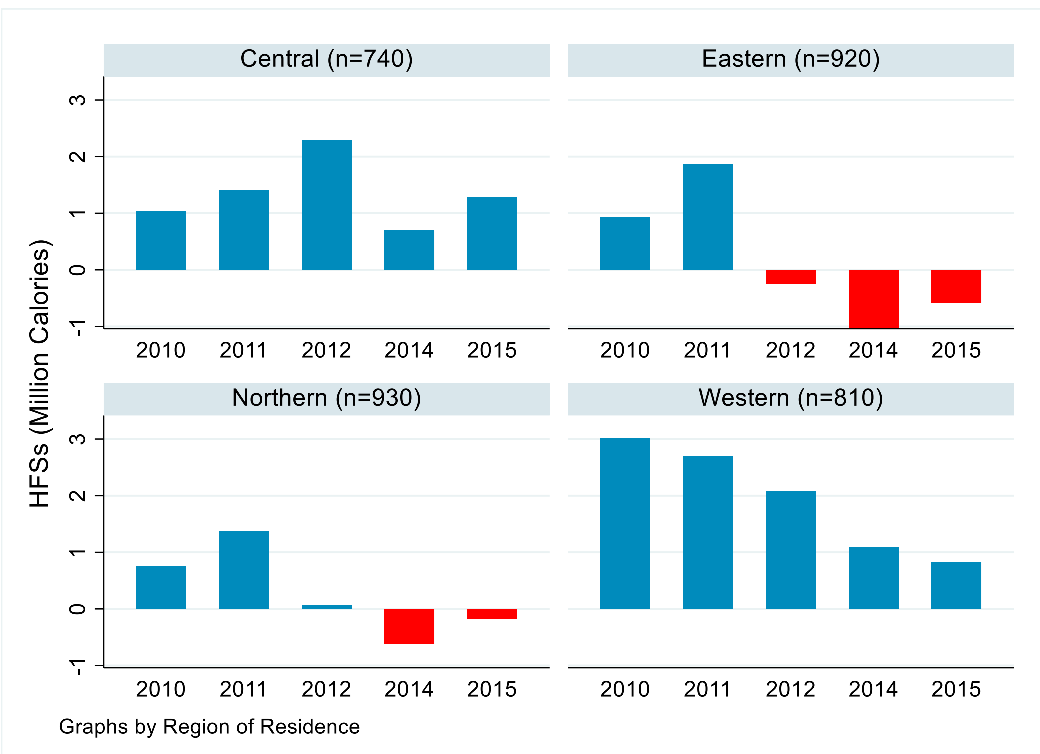
Figure 3-2: Distribution of Household Food sufficiency scores (HFSs) accounting only for household food requirements



Source: Authors' rendering of LSMS-ISA data (N=3,400)

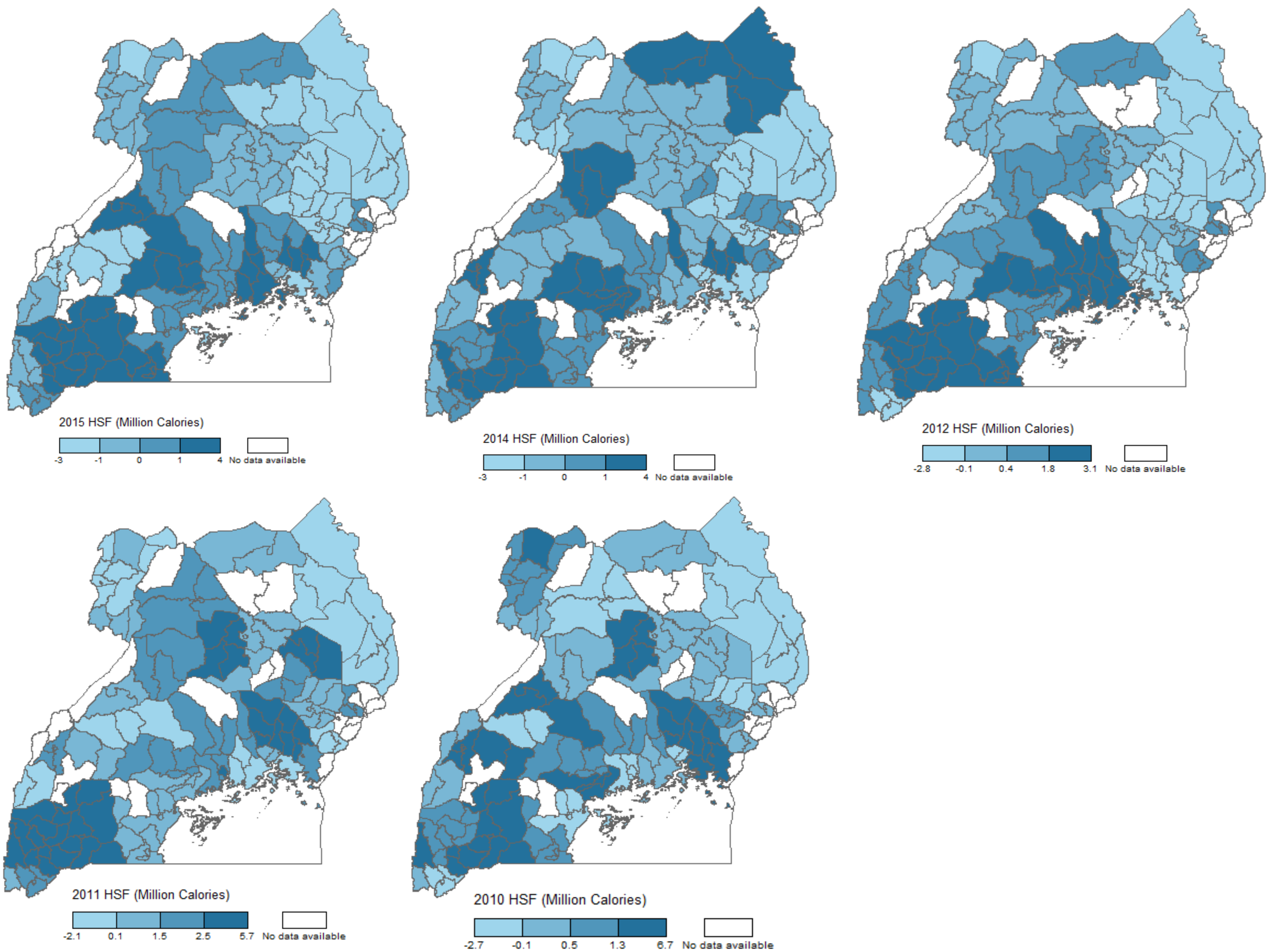
As shown in Figure 3-3 and Figure 3-4, food sufficiency varies by region with households in Northern and Eastern Uganda having the lowest annual average scores. Also, the proportion of farm output sold varies by region/district as shown in Figure 3-5. Comparing Figure 3-4, Figure 3-5 and Figure 3-6, regions with households that sell more output have higher food sufficiency. The possible reasons for the disparities in household food sufficiency include: much of Northern Uganda receives monomodal rainfall (one long rainy season followed by one long dry season) each year. This implies that households have to store food longer, yet food markets in the region are not highly developed. For Eastern Uganda, part of the region receives monomodal rainfall, but the region is also exposed to frequent extreme weather events which include a combination of too much rain causing floods in some years and prolonged droughts in other years. Both regions are predominantly rural, with less developed food and commodity markets. Central and Western Uganda have highly developed markets and bimodal rainfall. The regions also have more affluent households, which increases opportunities for purchasing food from the market. Generally, the number of households that can meet their dietary requirements has been declining as shown in Figure 3-8 and Figure 3-9 (Appendix B). Generalized to SSA, these finding depict the importance of ecological variations, weather, incomes and markets in determining food security and participation in food markets.

Figure 3-3: Regional distribution of Household Food Sufficiency scores by year



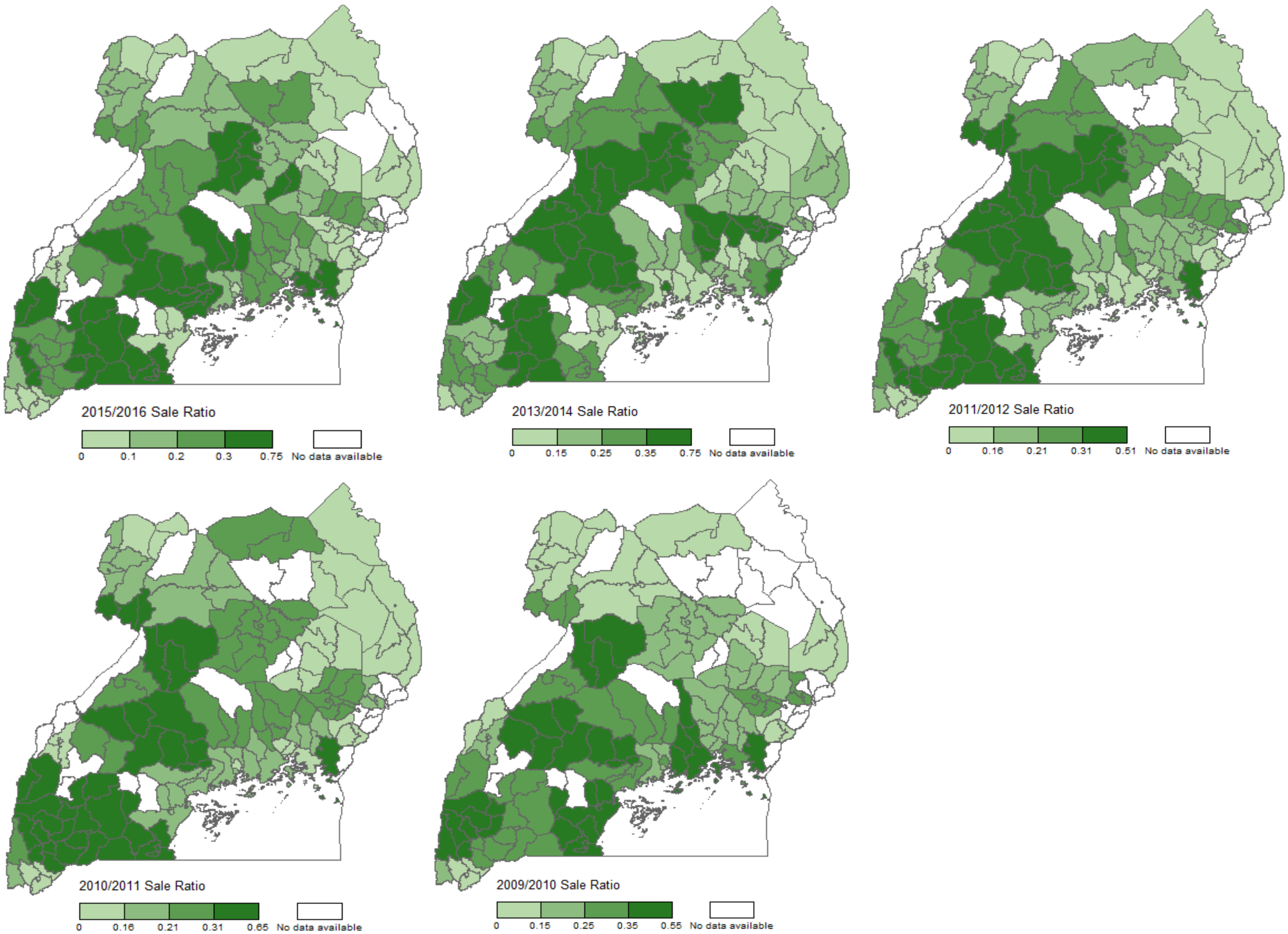
Source: Authors' rendering of LSMS-ISA data

Figure 3-4: Household Food/Dietary Sufficiency by district (2010 – 2015)



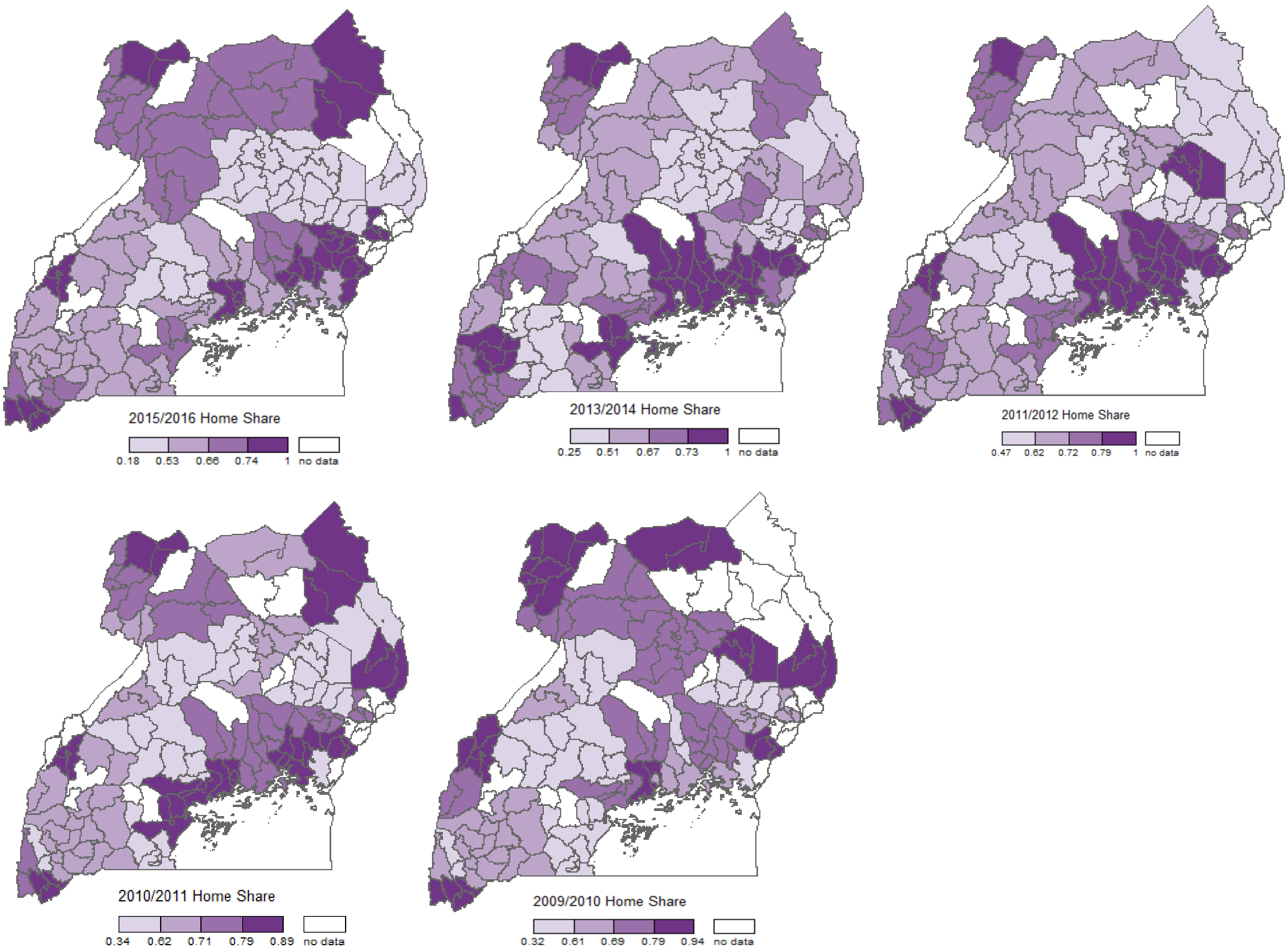
Notes: White areas also include water bodies. Sources: Authors' rendering of LSMS-ISA data sets.

Figure 3-5: Proportion of food crop output sold by District (2009-2016)



Notes: White areas also include water bodies. Sources: Authors' rendering of LSMS-ISA data sets.

Figure 3-6: Proportion of food crop output kept for Home use by District (2009-2016)



Notes: White areas also include water bodies. Sources: Authors' rendering of LSMS-ISA data sets.

3.4. Estimation and the empirical model

To identify and quantify thresholds, a panel threshold model of farm food production and non-farm income was estimated with a balanced panel of households for the period 2009 to 2015. Hansen (2000) noted that samples may have distinct characteristics and behave in ways that make structural relationships in economic and behavioral models different. Recognizing differences in the intensity of effects and thus choosing a correct specification has important implications in policy targeting and design. Estimating a model that accounts for regimes allows for the identification of different effects of variables of interest on outcomes, due to variation in farm/farmer characteristics.

In this study, the possibility of the existence of a nonlinear relationship and a threshold for farm output and non-farm income[9] at which a household remains food sufficient after allocating a portion of farm output to the market is investigated. Below this threshold, the household is more food insecure. Following Hansen (2000) & Wang (2015), the study's empirical strategy considers a household (i) with an observed food sufficiency status at time t of $HFSs_{it}$ (the dependent variable) and making allocation decisions of farm output (particularly how much to market). A threshold model which takes the form in Eq. 3.2 is posited to model observed effects for our balanced panel.

$$\ln HFSs_{it} = b + \boldsymbol{X}_{it}(q_{it}, \gamma_k)\beta_j + u_i + \varepsilon_{it} \tag{3.2}$$

where

$$\boldsymbol{X}_{it}(q_{it}, \gamma_k) = \begin{cases} X_{it} I(q_{it} \leq \gamma_k) \\ X_{it} I(\gamma_k < q_{it} < \gamma_k) \\ X_{it} I(q_{it} > \gamma_k) \end{cases}$$

Where there are i = 1…n households, t indexes year, and *j* is the number of regimes found. The variable $q_{it} = q(x_{it})$ is the threshold variable and is used to split the sample into subgroups. It is an

[9] Income includes wages/salaries, income from entrepreneurial activities, remittances, gifts, and all other earnings by household members.

element of the vector x_{it} of exogenous variables with a continuous and or discrete distribution. Since the model can only accommodate one threshold variable at a time, a choice must be made between threshold variables. According to Hansen (2000), this can be done by employing the heteroskedasticity-consistent Lagrange multiplier (LM) test. Here, since the study is interested in both (1) nonfarm income and (2) value of production thresholds, both threshold variables were used separately by estimating two models.

The term[10] γ_k is the threshold parameter that divides the equation into multiple regimes with coefficients β_1 and β_2 if the hypothesis for a single threshold is not rejected, and β_j if multiple thresholds are found. The parameter u_i captures individual fixed effects. The terms $\boldsymbol{X}_{it}$ are controls and capture household and farm characteristics that affect food sufficiency. In the study's specification, the variable $\boldsymbol{X}_{it}$ contains characteristics of the household (age of the head, market proximity, locality, off-farm income, and gender), and characteristics of the agricultural holding (livestock wealth, assets, size of the labor force, total area cropped, crop diversification index, and scale of production) and institutional characteristics (participation in government programs). The term ε_{it} is the disturbance assumed to be independently and identically distributed.

In addition to the model that includes threshold effects, the study also reports the results of the base model (assuming no thresholds) as in Eq. 3.3. This model is equivalent to estimating a fixed or random-effects model without the hypothesized threshold variable (q_{it}). In this case, all the regressors are placed in the same category; Z_{it}. This model is included to compare differences in effects on HFS by market proportions created by regimes and thresholds.

$$\ln HFSs_{it} = b + \beta Z_{it} + u_i + \varepsilon_{it} \tag{3.3}$$

[10] The "xthreg" Stata command used in this estimation requires that the number of thresholds must be a positive integer and less than 3.

Our full sample had a nontrivial urban sample (10% of households). We thus also estimated a separate model of rural households as a robustness check. We could not estimate a similar model for the urban-only sample because there were few observations, thus limited variability, to achieve model convergence.

3.5. Results and discussion

3.5.1. Model choice and threshold tests

Table 3-3 presents results from diagnostic tests in model choice and threshold values. The threshold effect test is sequential. First, the hypothesis of no thresholds (linear model) verses single-threshold model for both non-farm income and value of food produced is evaluated. This is equivalent to testing whether coefficients are the same in each regime. Under the null hypothesis, the threshold is not identified (Wang, 2015). The estimates show that the no thresholds/linear model can be rejected at a 5% level of significance for both non-farm income and value of production thresholds (Table 3-3). This confirms the existence of at least one threshold.

Table 3-3: Threshold effect tests

Threshold Variable	**Threshold tests**		**Threshold value**
	F-stat	p-value	Threshold [CI]
	(1)	(2)	(3)
Non-Farm income			
No Threshold ($\boldsymbol{\beta_1 = \beta_2}$)	5.79	0.016	Na
Single threshold	7.22	0.219	15.6496 [15.6291, 15.6796]
Value of food produced			
No Threshold ($\boldsymbol{\beta_1 = \beta_2}$)	21.08	0.000	Na
Single threshold	25.64	0.017	11.4573 [11.3911, 11.4956]
Double threshold	6.98	0.292	14.4408 [14.4266, 14.4477]

Notes: N=3400. Exponentiate the threshold value to get the shilling value e.g., exp (15.6496) = 6,259,431.974 UGX. Average exchange rate over study period is 1USD = 2,928.25 UGX.

Number of bootstraps used is 1000, grid searches used were 400 and the trimming percent was 5%.

Asymptotic critical values for confidence interval construction are reported in Hansen, (2000).

For the non-farm income threshold, a single threshold model was accepted and evaluated. For the value of food production, the single threshold model was rejected in favor of a double threshold. See Hansen (2000) and Wang (2015) on hypothesis tests and model choice criteria. The threshold effect test when only rural households are used is shown in Appendix B.

3.5.2. Income and production thresholds

The estimates of the income and production thresholds and their confidence intervals for the full sample are shown in Table 3-3, Column 3. More information about threshold estimates can be learned by constructing confidence intervals as shown in Figure 3-10 and Figure 3-11 in the supplementary Appendix B. The threshold estimate is the point at which the Likelihood Ratio function (LR γ) equals zero. These threshold estimates depict the behavior of households based on their characteristics and the decisions they make. The Least Squares Estimate (LSE) of γ (threshold) for non-farm income is UGX 6.3 million, which is approximately 33% more than the average income of households in the sample and exceeds the incomes of the first through to the third quartile of the sample. The lower and upper non-farm income bounds are UGX 6.2 million and 6.4 million, respectively. Non-farm income is highly variable in the sample. About 88.2% of households fall below the income threshold and earn an average annual income of 1.3 million UGX. This result implies that by raising non-farm incomes from its average (4.7 million), to the threshold value, 15.7% of the households would meet the income threshold and increase market participation. When the study considers only the rural sample, we also find a single threshold for non-farm income of 4.17 million UGX with a lower and upper bound of 4.10 and 4.32 million UGX, respectively (Table 3-6, Appendix B). With an average rural non-farm income of 3.64 million UGX, this threshold is 12.7% % higher. This result reveals a wide gap that needs to be filled if non-farm income is to boost agricultural market participation among smallholder farmers. This is important because rural non-farm activities, that form part of complex income strategies of the poor, are growing in importance and account for between 35 to 50% of rural income in the third world (Nagler & Naudé, 2017; World Bank, 2017)

For value of food produced, Figure 3-10 and Figure 3-11 Panel B, show that there seems to be a second threshold for both the full and rural-only sample, and further investigation as shown in Figure 3-10 and Figure 3-11, Panel C Confirms it. The value of food produced estimates show that the LSE of the threshold is 1.9 million UGX. This is higher than the value of food produced on about 50% of the farms. About 7.7% of the farmers can be classified as being in regime one with an average value of food produced of 0.05 million UGX, while 53.1% and 39.2% can be placed in regimes two and three with an average value of food produced of 0.66 and 20.3 million UGX respectively. Farm incomes are highly variable between farms, a sign that a "one size fits all" policy would be suboptimal if applied to motivate market participation. For example, to achieve the threshold food production value, farmers earning 0.632 Million UGX (2^{nd} Quartile) need to double their value of production (an increase of 195.7%) to stay food secure and edge towards selling more to the market.

When the farm income model is estimated for only the rural sample, three thresholds corresponding to four regimes, were found (Table 3-6-Appendix B). Here, regime one constitutes 60.3% while regime two, three and four constitute 46.24%, 37.06% and 10.67% of the sample, respectively. As noted by Burnham & Anderson (2004), it is important to avoid overfitting the model and to ensure parsimony. The study thus used R-square, AIC and BIC to compare the two and three threshold model for the rural sample. The three-threshold model had an R-square, AIC and BIC of 0.213, -601.17 and -500.12 compared to 0.208, -596.12 and -501.01 for the two-threshold model. Since an extra threshold does not add much to model fit, we report results of the two-threshold model in Table 3-7 of appendix B. Under the two-threshold-rural model, the threshold farm production income is 1.2 million UGX with lower and upper limits of 1.09 and 1.22 million UGX, respectively. While these threshold estimates seem lower that the average value of production, production is highly skewed with few large farms driving these averages. Consequently, several low value producers fall below these thresholds.

3.5.3. Household food sufficiency, market participation, and farm characteristics

The coefficients of primary interest are those on the proportion of produced food that is marketed. Estimating a model that accounts for regimes shows the different effects of marketed allocations of farm output on household food sufficiency. The effect varies depending on the income or value of food a farm produces (Table 3-4). From a policy perspective, recognizing differences in the intensity of effects and thus choosing a correct specification has important implications in policy targeting. Without accounting for regimes, the blanket effect of the proportion of food marketed would have been ($\widehat{\boldsymbol{\beta}}_{\mathbf{1}} = -0.315$) for the full sample and ($\widehat{\boldsymbol{\beta}}_{\mathbf{1}} = -0.245$) if only the rural sample is considered. However, when regimes are possible, for the non-farm income model, the proportion sold has a negative and significant effect ($\widehat{\boldsymbol{\beta}}_{\mathbf{2}} = -0.339$) on HFS for only the farmers earning less than the threshold income and is negative but not significant for farmers above the threshold. Considering the value of food crops produced on the farm, the study finds significant negative effects for all the three regimes but with variable effect intensities on HFS. For farmers at the lowest level below the threshold, the proportion marketed had the highest negative and significant effect on household food sufficiency ($\hat{\beta}_1$= - 0.962). The effect was lowest ($\hat{\beta}_3$= -0.166) for farms above the threshold even though they sold an average of 35.2% of food produced (Table 3-4).

Considering only rural households (Table 3-7, Appendix B), for non-farm income, the study found effects of the marketed proportion slightly less the those of the full-sample model with the proportion marketed having a negative and significant effect of ($\hat{\beta}_1$= -0.259) and ($\hat{\beta}_2$= -0.161) for those below and above the income threshold, respectively. For the value of farm production, the effects of the marketed proportion on HFS were only significant for regime two ($\hat{\beta}_2$= -0.319) and regime three ($\hat{\beta}_3$= -0.200). The effect was only positive but not significant for the farmers below the threshold (regime 1) who sold an average of 10.4% by value of their farm produce.

Table 3-4: Fixed effects panel threshold model estimates

Variable	Base Model (linear model)	Non-farm income Threshold Model	Farm production Threshold Model
	(1)	(2)	(3)
Regime-dependent regressors			
Proportion of produced food marketed			
$\hat{\beta}_1$	-0.315***	-0.339***	-0.962***
	(0.049)	(0.050)	(0.145)
$\hat{\beta}_2$	-	-0.140	-0.315***
		(0.088)	(0.056)
$\hat{\beta}_3$	-	-	-0.166**
			(0.066)
Regime-independent regressors			
Labor endowment (Members ≥ 10 years)	-0.030***	-0.030***	-0.030***
	(0.006)	(0.006)	(0.006)
Log market distance	-0.028	-0.025	-0.021
	(0.116)	(0.116)	(0.115)
Total cropped area (hectares)	0.004***	0.004***	0.004***
	(0.001)	(0.001)	(0.001)
Log livestock wealth	0.001	0.000	0.000
	(0.001)	(0.001)	(0.001)
Log non-farm income	0.003	0.002	0.003
	(0.002)	(0.002)	(0.002)
Log value of farm production	0.078***	0.076***	0.067***
	(0.007)	(0.007)	(0.007)
1 (Participated in NAADS enterprise: Yes)	-0.067**	-0.069**	-0.069**
	(0.033)	(0.033)	(0.033)
1 (Received NAADS capacity building: Yes)	0.098***	0.100***	0.099***
	(0.032)	(0.032)	(0.032)
Log asset value	0.016**	0.015**	0.015**
	(0.007)	(0.007)	(0.007)
Crop diversification Index	-0.092	-0.091	-0.080
	(0.064)	(0.064)	(0.064)
N	3,400	3400	3400
Log likelihood (Model)	-1852.917	-1803.206	-1835.253
AIC	3735.834	3638.206	3706.516
BIC	3827.807	3736.31	3816.884
R^2	0.106	0.125	0.118

Dependent variable: Log household food sufficiency score. Standard errors are in parentheses. */**/*** show 10%/5%/1% significance levels. Other controls: Gender and age of the household head, and household locality (urban/rural). All these controls were not significant at a 5% level.

Source: Author rendering of LSMS-ISA data.

While the a priori expectation was that some levels of marketing would have a positive association with HFS, the negative relationships found here imply that some households could be: (1) giving up food sufficiency for reasons such as alleviating liquidity constraints so that they can purchase non-food items, services or other calories, (2) trying to meet personal preferences, trading the calories they produce for less calorie foods and to diversify their calorie sources, (3) having limited access to food from markets, or (4) having liquidity and output limitations to acquire enough calories.

Contrary to the notion that farmers mostly market surplus production, we find that even with deficit production, some farms (accounting for 33% of the sample) still marketed an average of 25% of their farm produce. With liquidity constrains, farmers make such sales to support the purchase of nonfarm goods and services. Generally, observed nonfarm income and food produced cannot meet household dietary needs of some households given other household/farm expenses.

Considering other factors that may influence HFS, higher production has a positive correlation with household food sufficiency. As shown in Table 3-4, a 1% increase in the value of farm production is associated with an increase of between 0.07% to 0.08% in household food sufficiency. The magnitude is slightly less (0.05%) if we consider only rural households (Table 3-7, Appendix B).Thus, any avenue that improves farm production could improve household food sufficiency. This analysis suggests that even if markets existed, it is less likely that the farms that are more prone to food deficiency, would supply adequately to these markets. This is because small farms have a high elasticity of food production (Fafchamps, 1992). On the other hand, large farms, including those producing food crops, are likely to offer more for marketing as output increases. In addition, nonfarm income was positively associated, only for the rural sample (Table 3-7, Appendix B), with HFS. This correlates with previous research findings that have shown the growing importance of non-farm income to households in rural communities (Nagler & Naudé, 2017; World Bank, 2017).

Furthermore, increasing cropped area, but not labor endowment improves the household's food sufficiency score. A household's labor endowment would be expected to increase its food sufficiency because of potentially higher production ability. However, the results show otherwise. This effect can be presumed probable because: (1) active labor means more caloric requirements which may not be sufficiently covered by reached output, (2) a bigger household requires more calories, (3) not all persons classified as being in the household's labor force provide full labor for agricultural production, (for example all members above 10 years old are classified as part of the labor force in the survey), and (4) a multiplicity of factors explain the production of farm output and may not be adequately accounted for. Nevertheless, findings show that increasing the total area cropped is significantly associated with an increase in household food sufficiency. Often, a higher cropped area translates into more output but not productivity (OECD & FAO, 2016) which implies more calories available for the households. Crop diversification results show that, for the rural sample, households that are more diversified are associated with higher levels of HFS. These results are in line with other studies that have shown that households usually diversify production to spread risks and for food security reasons.

Policy transfers in terms of capacity building but not enterprise prescriptions significantly improved household food sufficiency. The association between household food sufficiency and policy interventions that thought to increase market orientation among farmers was assessed by adding two policy variables as regressors. The study reveals that taking part in enterprises prescribed by the policy had a negative association with our food sufficiency measure and thus household welfare. This suggests that given farm conditions and experiences, the farmer's choice of enterprises could be close to optimal. Also, the negative value may be reflecting self-selection such that participants are less food self-sufficient than nonparticipants. Conversely, participation in capacity-building programs offered by the same policy had a positive association. Previous studies have shown that extension/capacity-building services to farmers are critical in enhancing productivity, revenues and thus food security (Danso-Abbeam et al., 2018; Davis et al., 2012; Nakano et al., 2018; Todo & Takahashi, 2013)

3.6. Discussion, program, and policy implications

In developing countries, food self-provisioning is high and offers a direct path to food sufficiency and rural household welfare. Rural households take part in nonfarm markets to supplement their incomes, a proportion of which is spend on food. Therefore, the precursor to market participation could be Household Food Sufficiency. The study investigated the effect of market participation and the conditions that could encourage farmers to participate in markets. The model reveals that farmers with higher food and cash incomes are likely to market more. Thus, holding other things equal, higher levels of food sufficiency should increase market participation by raising incomes. Also, the findings suggest that farmers who are self-sufficiency orientated produce less than they need and are more food deficient. However, some food deficient farmers took part in markets selling an average of 25% of their farm produce. Presumably, both food and cash crop incomes are important in securing food sufficiency and thus farm output supplied to the market. These findings have several policy implications about market participation by guaranteeing farmer food sufficiency.

Improving both cash and food crop productivity could give farmers confidence in their food security and could improve transfers to the market. Technological change which has the potential of raising resource productivity even for farms with scares resources will likely play a vital role in securing food supply and production for markets. If policy is to realize the quest for increased market participation, agricultural research should consider region-specific crops, for both food and cash, in developing innovations aimed at improving productivity. Bias towards cash crops by agricultural research could be counterproductive and may be incongruous to increasing output released for the market.

Even if we assume that farmers are rational and their choice of enterprises is close to optimal given farm conditions, supporting them to enhance production, for example through targeted extension services could go a long way in improving food sufficiency and thus market participation. Such extension approaches could include setting up nucleus farms to roll out extension programs and channeling services through farmer cooperatives. As noted by Fafchamps (1992), crop choice matters for a household's food security and market integration. Given that farmers in the same region tend to grow similar crops, they face higher risks if crops fail, and this should be considered in promoting innovations and in developing commodity markets.

Given that farmers use non-farm enterprises largely for survival (Christiaensen & Demery, 2018), expanding opportunities for non/off-farm employment may fail to fully achieve food sufficiency and thus market participation requirements. However, combining productivity-enhancing technologies with strong commodity markets (with stable prices) and better infrastructure could create wider opportunities for market participation, employment, and income sources. Also, since farm income plays a critical role in securing food security (HFS), policy interventions geared towards directly boosting farm income are likely to lead to better outcomes in facilitating agricultural market development in developing countries.

Since this is a reduced form estimation, these estimates reflect correlations and not causation. They, however, supply a good guide in developing frameworks for promoting commercialization policy. Specifically, results point to a need for careful assessment of households, by type, farm profile and locality when implementing intervention seeking to take smallholder farmers to the market.

3.7. Conclusions

Once farm output is known with certainty, what stays uncertain is household welfare outcomes due to allocation decisions made on-farm output by the household. In this paper, it is assumed that the household maximizes utility that is derived from it being food self-sufficient and or self-sustaining following market participation. Previous literature has documented the causes of limited market participation in third world countries using the farm household framework, but few have linked it to direct household welfare and or extended it to document requirements for accelerated market participation. This study extended this literature to analyze threshold levels that may trigger wider participation in markets, while guaranteeing household food sufficiency. Here, the study first illustrates the farm household's output allocation problem, quantifies its welfare (measured as household food sufficiency), and then uses a simple panel threshold model to show and quantify thresholds. Furthermore, it investigates factors that affect household food sufficiency. The intuition behind the thresholds is that: if food sufficiency constrains the volume sold in the market, improving food sufficiency should encourage market participation allowing farms to supply more to the market.

The study finds thresholds in magnitudes much higher than earned annual average non-farm income and farm production. Consequently, a point estimate is not found at which the proportion of output marketed contributed positively to household food sufficiency. Though the effect varied by income and level of food production, a combination of these factors suggests a wide gap in the realization of household food sufficiency a situation that reinforces self-provisioning at the expense of market participation. The negative association between proportions marketed and household food sufficiency also suggests that some farmers could be giving up food sufficiency for other reasons including; alleviating liquidity constraints to buy non-food items, services, or other calories, and are trading more calorie-dense foods for less calorie foods among others.

The paper proceeds to illustrate that household food sufficiency increases with farm income (both from food and cash crops). This suggests that farmers value farm output and are inclined to convert it into food as opposed to relying on off-farm income to buy required calories. This is particularly important for deficit producers as farm size, which is positively correlated with output, affects household food sufficiency and market participation. Moreover, for the rural-only-sample, non-farm income also positively contributes to household food sufficiency which collaborates, that fact that in rural areas of the developing world where non-farm income opportunities are thin, supplemental incomes from nonfarm source are critical as a stable foundation of food security.

In this essay, the panel threshold model was estimated using the fixed effects framework. A useful extension that may warrant further research is to treat gamma (threshold parameter) as a random parameter so that the threshold is made individual specific. With this approach, the distribution of the threshold can be modeled across the sample and predictions made for points at which marketed proportions can positively influence HFS.

Appendix B - Supplementary materials for chapter 3

B.1 Additional tables

Table 3-5: Definition of variables used in regression estimates in chapter three

Variable	Definition
Household Food Sufficiency score (HFSs)	Difference between the overall amount of food available (Calories) less food utilized (calories) and annual household adult equivalent requirements (Calories)
Proportion of produced food marketed	Share of produce marketed out of total food production
Value of farm production	Total annual shilling value of all farm production (crops and sold livestock)
Non-farm income	All incomes earned off the farm including property and investment income, current transfers and other benefits, and non-agricultural household enterprise earnings
Labor endowment	Household members aged ten years and older that worked on the family farm
Livestock wealth	Total shilling value of livestock (cattle and pack animals, small animals, and poultry) on the farm each year
Asset value	An estimate of the shilling value of household, farm, and non-farm enterprise assets (Excluding livestock)
Cropped area (hectares)	Total of all area allocated to crop production in a year
Participated in NAADS enterprise	Binary variable: 1= yes, 0 otherwise
Received NAADS capacity building	Binary variable: 1=yes, 0 otherwise
Market distance	Distance (KM) from the household's residence to nearest market that sells Ag produce.
Crop diversification Index	Herfindahl Index: sum of square of the proportion of acreage under each crop to the total cropped area. HI = $\sum_{i=1}^{N} Pi^2$
Locality	Binary variable: 1=urban, 0 otherwise

Table 3-6:Threshold effect tests: Rural sample (n=2820)

Threshold Variable	Threshold tests		Threshold value
	F-stat	p-value	Threshold [CI]
	(1)	(2)	(3)
Non-Farm income			
No Threshold ($\boldsymbol{\beta_1} = \boldsymbol{\beta_2}$)	5.71	0.023	Na
Single threshold	6.49	0.297	15.2439 [15.2272, 15.2582]
Value of food produced			
No Threshold ($\boldsymbol{\beta_1} = \boldsymbol{\beta_2}$)	11.44	0.001	Na
Single threshold	14.58	0.030	11.2920 [11.2656, 11.3151]
Double threshold	13.15	0.048	14.0017 [13.8972, 14.0141]
Triple Threshold Model	7.05	0.615	16.5035 [16.4842, 16.5151]

Notes: Exponentiate the threshold value to get the shilling value e.g., exp (15.2439) = 4,171,974.571 UGX and exp (14.0017) = 1,204,650.45 UGX. Average exchange rate over study period is 1USD = 2,928.25 UGX.

Number of bootstraps used is 1000, grid searches used was 400 and the trimming percent was 5%.

Asymptotic critical values for confidence interval construction are reported in Hansen, (2000).

Table 3-7: Fixed effects panel threshold model estimates: Rural sample

Variable	Base Model (linear model)	Non-farm income Threshold Model	Farm production Threshold Model
	(1)	(2)	(3)
Regime-dependent regressors			
Proportion of produced food marketed			
$\hat{\boldsymbol{\beta}}_1$	-0.245***	-0.259***	0.034
	(0.028)	(0.029)	(0.093)
$\hat{\boldsymbol{\beta}}_2$	-	-0.161***	-0.319***
		(0.047)	(0.033)
$\hat{\boldsymbol{\beta}}_3$	-	-	-0.200***
			(0.035)
Regime-independent regressors			
Labor endowment (Members ≥ 10 years)	-0.024***	-0.024***	-0.024***
	(0.004)	(0.004)	(0.004)
Log market distance	0.016	0.017	0.012
	(0.069)	(0.069)	(0.068)
Total cropped area (hectares)	0.003***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)
Log livestock wealth	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)
Log non-farm income	0.004***	0.003***	0.004***
	(0.001)	(0.001)	(0.001)
Log value of farm production	0.054***	0.054***	0.053***
	(0.004)	(0.004)	(0.004)
1 (Participated in NAADS enterprise: Yes)	-0.075***	-0.075***	-0.071***
	(0.019)	(0.019)	(0.019)
1 (Received NAADS capacity building: Yes)	0.086***	0.086***	0.084***
	(0.018)	(0.018)	(0.018)
Log asset value	0.017***	0.017***	0.017***
	(0.004)	(0.004)	(0.004)
Crop diversification Index	-0.113***	-0.111***	-0.113***
	(0.038)	(0.038)	(0.038)
N	2,820	2,820	2,820
Log likelihood	300.339	303.585	314.061
AIC	-572.678	-577.171	-596.123
BIC	-489.455	-488.003	-501.011
R^2	0.201	0.205	0.208

dependent variable: Log household food sufficiency score. Standard errors are in parentheses. */**/*** show 10%/5%/1% significance levels. Other controls: Gender and age of the household head. All these controls were not significant at a 5% level.

Source: Author rendering of LSMS-ISA data.

B.2 Additional figures

Figure 3-7: Distribution of households by month of data collection

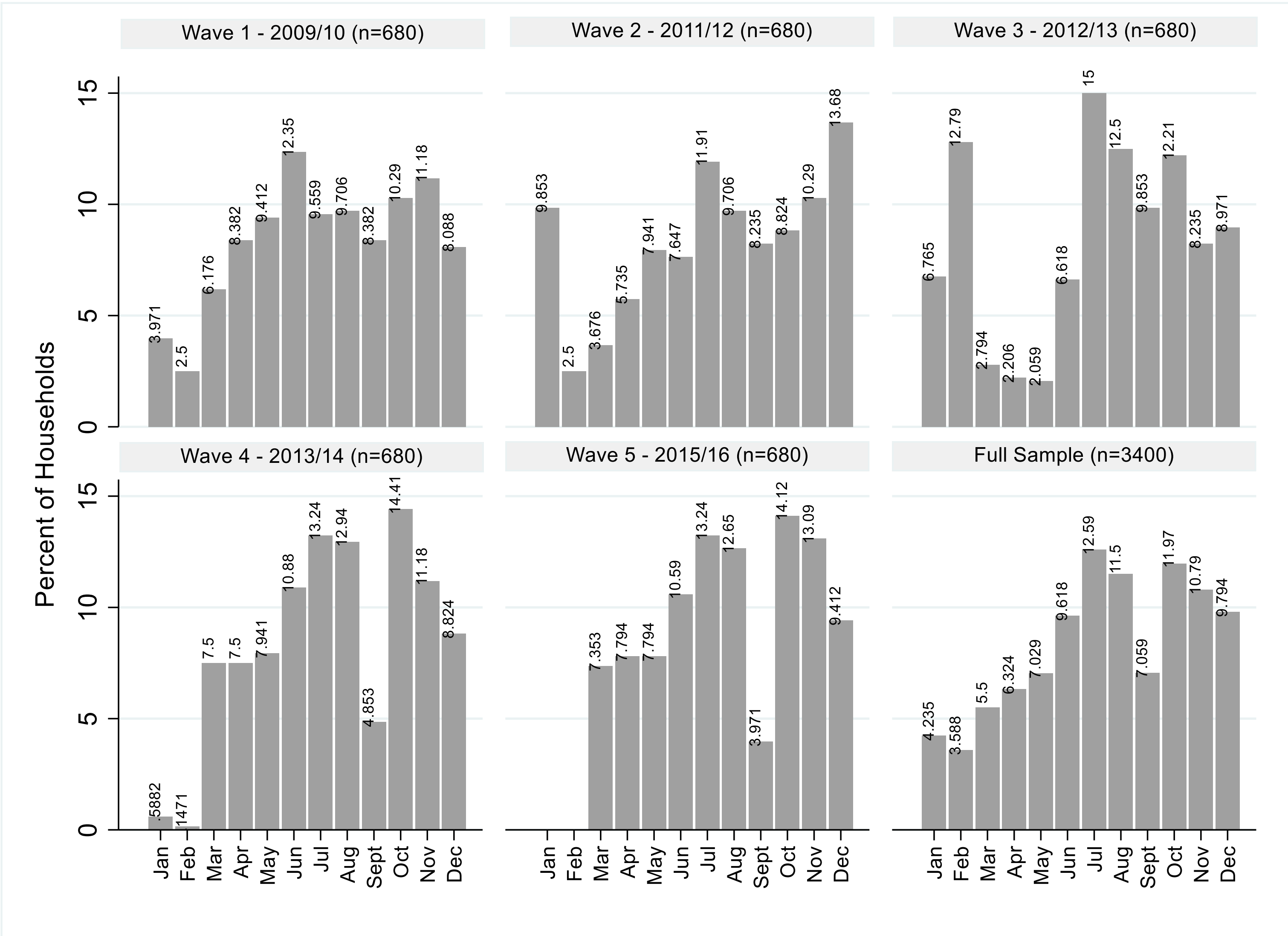
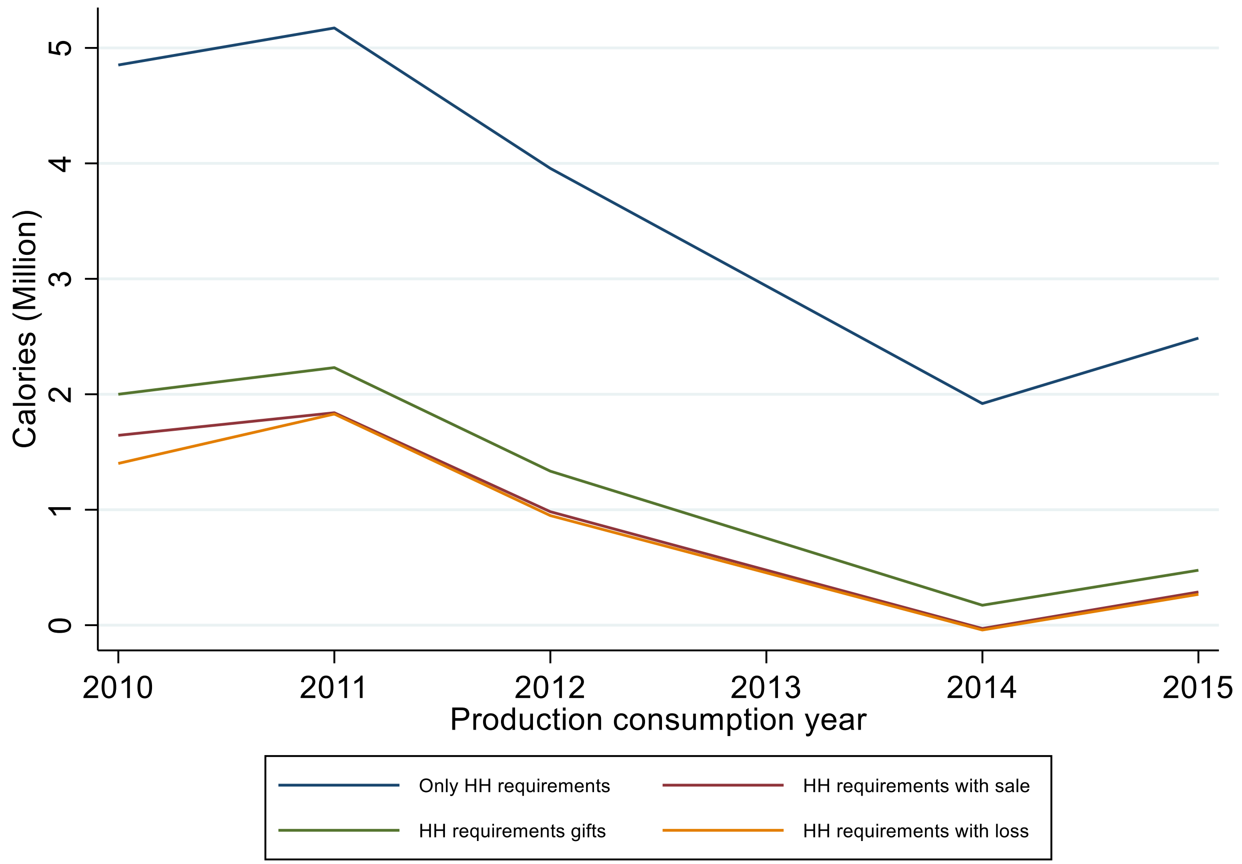


Figure 3-8: Changes in Household Food Sufficiency Scores over time



In Figure 3-8, the Household Food Sufficiency Score (HFSs) varies depending on how the household (HH) allocates realized farm output.

Source: Author rendering of LSMS-ISA data.

Figure 3-9: Changes in Household Food sufficiency including upper and lower bounds

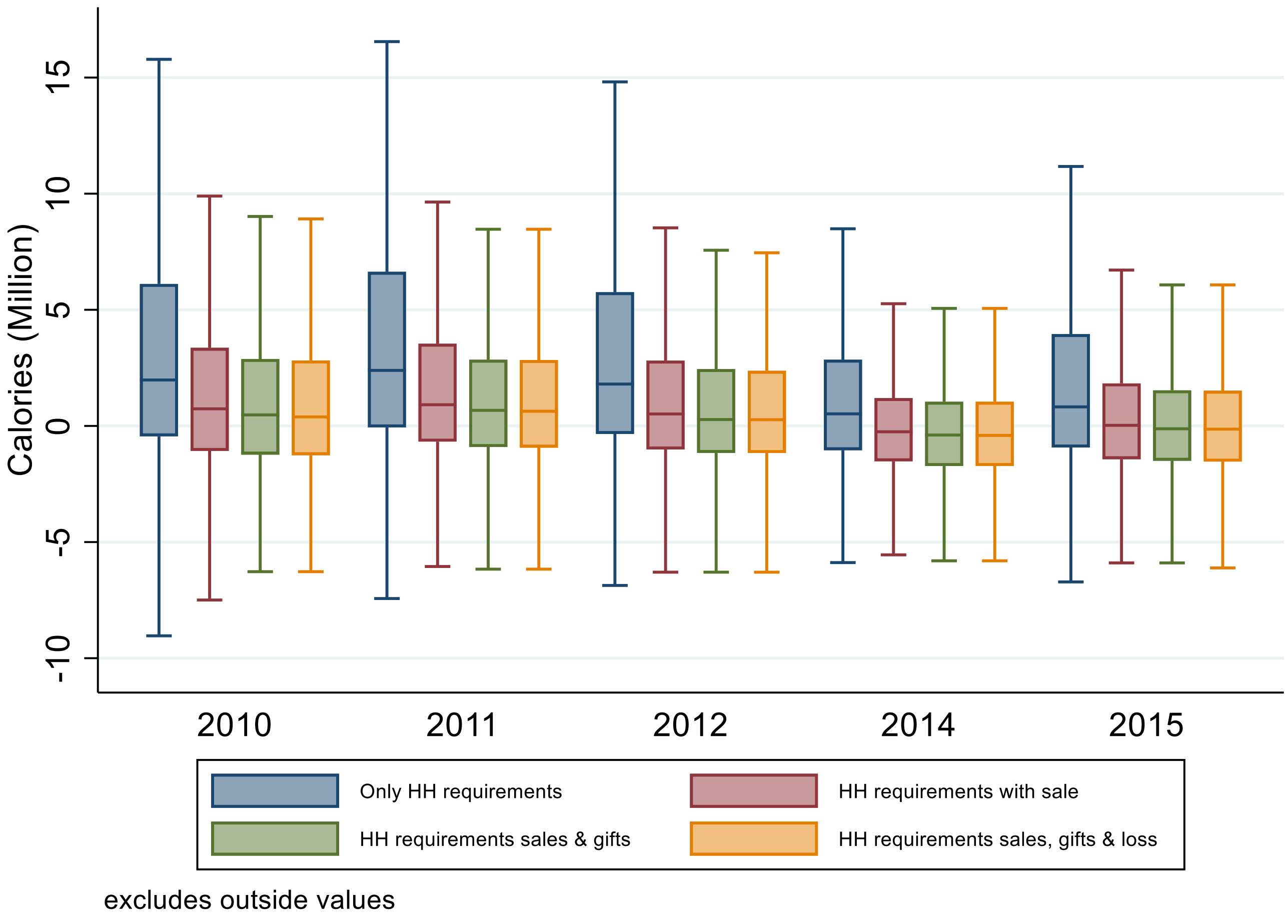


Figure 3-10: Confidence interval construction for thresholds (Full sample)

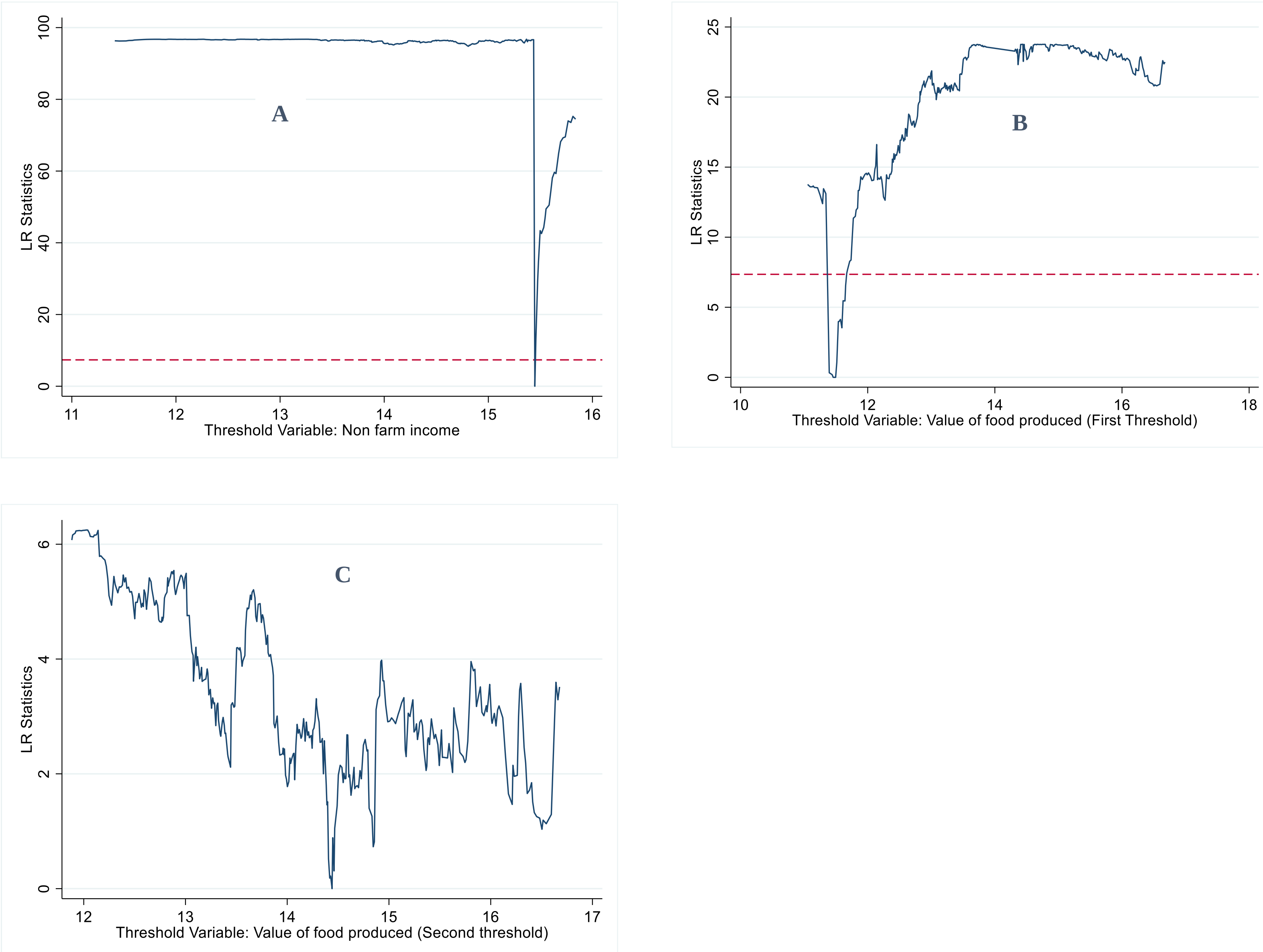
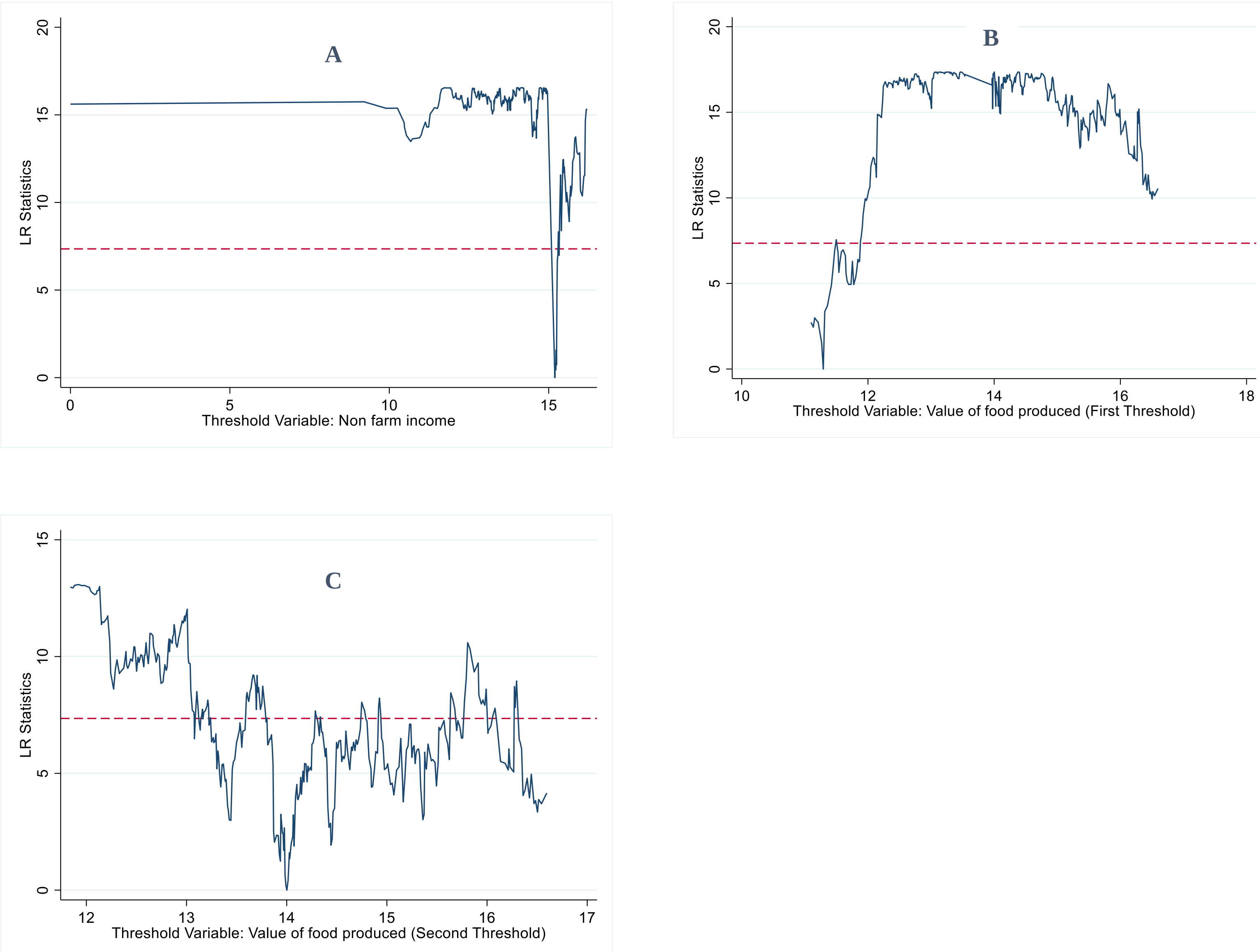


Figure 3-11: Confidence interval construction for thresholds (rural sample)



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Chapter 4 - The economic benefits to small holder farms created by Ag public private partnerships: evidence from bean growers in Uganda

4.1. Introduction

Ag-Public Private Partnerships (Ag-PPPs) are relatively new and emerging as a systematic institutional innovation policy instrument in the developing world (Hermans et al., 2019). According to the FAO (2016), an Ag-PPP (or a PPP) for agribusiness development is a formalized partnership between public institutions and private partners designed to meet sustainable agricultural development objectives. In this partnership, the public benefits are clearly defined, investment contributions and risks are shared, and active roles exist for all partners at various stages throughout the PPP project lifecycle. Common in infrastructure, health, and education, PPPs help bring together actors and allow them to offer services in what they do best and manage risk appropriately (FAO, 2016; Menezes et al., 2018; Weirowski & Hall, 2008). This is important when the public sector is resource and expertise constrained. The use of PPPs has the potential to transform agriculture from subsistence to commercial oriented, and deliver multiple benefits to poor households (FAO, 2016). Ag-PPPs have a critical role to play in agrarian societies where the agricultural sector plays a predominant role in creating employment, generating GDP, and securing food supply (FAO, 2015, 2016).

Scaling up agricultural innovations for commercialization, income, and food security purposes has been pursued through farmer agribusiness linkages (Aragie et al., 2016; Carletto et al., 2017). Different approaches used include, inter alia, direct financing of farmers/farmer groups, using innovation platforms, warranties and credit systems, public-private partnerships, and working through intermediaries (Basu & Wong, 2015; Le Cotty et al., 2019; Norell et al., 2015; Ochieng et al., 2019). Promoting farmer linkage with agribusiness firms has the potential of increasing agricultural production, farmer income, and assets

(Norell et al., 2015; Ochieng et al., 2019). From a development perspective, these interventions are taken as a catalyst and a precondition for better livelihoods.

While such farmer agribusiness linkages have enormous potential, they come with risks given that agribusiness firms also face production risks that could be transferable to farmers. The PPPs, on the other hand, can spread the risks involved with such linkages, build synergies, and tap expertise (FAO, 2016). Once risk is spread, productivity is raised and market costs are decreased, the markets become more integrated, supply grows, and the rationale for food self-sufficiency gives way to portfolio diversification including market integration (Fafchamps, 1992), which is the long-run goal of such interventions. Ag-PPPs recognize the value of integrating research into the multi-stakeholder platform to address multiple challenges that would otherwise stand in the way of success. Ag-PPPs have been used extensively (FAO, 2016; Hermans et al., 2019) but there is limited information, based on empirical analysis, on their impacts to agricultural development and on smallholder farmers.

In this paper we estimate the impacts of an Ag-PPP, hereafter termed the CultiAf-Ag-PPP, which sought to create a sustainable Business-to-Business linkage by offering multiple transfers and guarantees to farmers. Specifically, we investigate the impact of the PPP on the per unit area productivity, marketed volumes and revenues of common bean producers in Uganda. Common beans are widely grown, consumed and are transitioning into an important cash crop in Uganda (MAAIF, 2010). The crop is also quickly gaining significance due to its potential for value addition, and a crop for nutrition-sensitive value chains. Farmers in rural hamlets had the opportunity to tap into and benefit from both up and downstream services offered by the partnership.

By using a partnership approach, we believe that the occurrence of scenarios that could marginalize and impoverish farmers is tremendously curtailed. Often, the greatest benefits of investments in agribusiness would accrue to the agribusiness companies and not to the smallholder farmer (Amanor, 2009). Also, the private sector has a more vested interest in a dynamic and prosperous agricultural sector as it seeks to maximize profits and source cheap products (Amanor, 2009). If not well planned, rigorous investments in farmer - agribusiness linkages could transfer production and marketing risk to farmers (UNISDR, 2013). In an Ag-PPP, there are checks and balances, and consensus is built around partner interests towards a common goal. As such, the PPP diminishes possibilities of farmer exploitation.

The objectives of this study were: (1) to evaluate the impact of an Ag-PPP and its interventions on bean farmer welfare, and (2) to investigate how farmers are likely to respond given production incentives and guarantees. This essay offers evidence of economic benefits to farmers when given production guarantees and support in Uganda and can be generalized to sub-Saharan Africa. The findings inform how to introduce new linkages to a rural society with small scale farmers.

The results show that by leveraging the potential to create synergies among actors, the Ag-PPP created positive outcomes for farmers, and stimulated increased production from targeted interventions. For example, estimates show that with improved high yielding varieties, training in good agronomic practices, and guaranteed markets, farmers in the Ag-PPP were likely to report 209 Kg/Hectare higher yield compared to non-PPP farmers. The results show evidence of a significant increase in sales and sales revenue among men and women farmers due to increases in bean production.

In the following section, we supply background information on the Ag-PPP including its operationalization, interventions, and partners. We give a description of the data, study area, sampling strategy, and balance check in section three. Section four presents the empirical strategy and estimation methods. Section five describes and discusses the results, and section six supplies critical control points in managing an Ag-PPP while section seven offers program, policy implications, and conclusions.

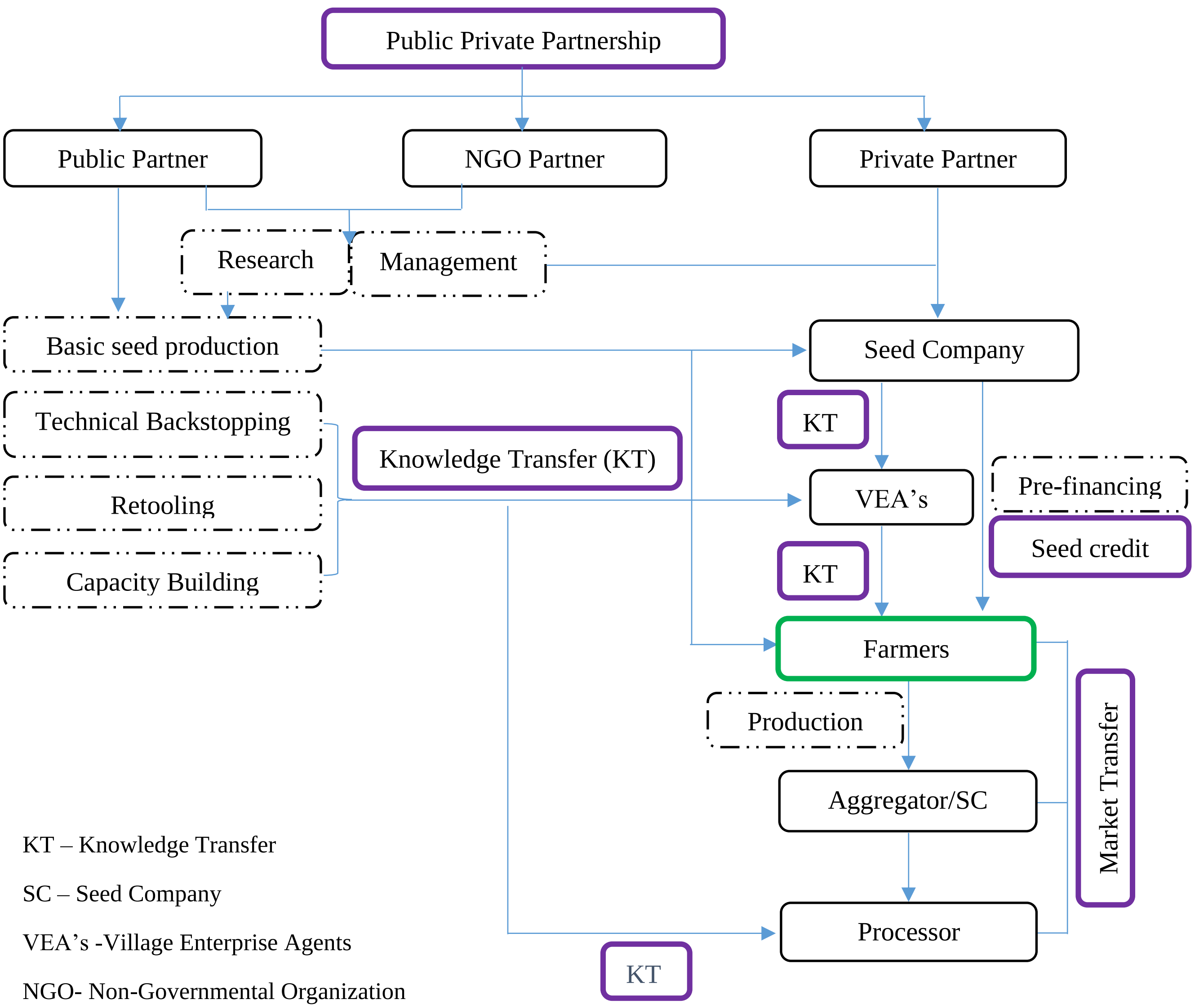
4.2. CultiAf-Ag-PPP intervention synopsis

Partners and their roles

The CultiAF-Ag-PPP, implemented as a project, was initiated in 2015 to test models for increasing the production and supply of nutrient-rich bean varieties suitable for processing into pre-cooked beans in

Uganda and Kenya. The project aimed at integrating research within an innovation system including all stakeholders of the bean value chain, with the processors as the final consumers of grain and farmers as the primary actors at the first node of the chain. Stakeholders in the bean value chain included: processors, a seed company, an aggregator, farmers and researchers. The PPP offered multiple transfers and guarantees to farmers and other actors involved. Figure 4-1depicts the structure of the PPP, players involved, and their roles.

Figure 4-1: The structure of the CultiAf-Ag-PPP, type of partners involved, roles and nature of transfers



KT – Knowledge Transfer

SC – Seed Company

VEA's -Village Enterprise Agents

NGO- Non-Governmental Organization

Note: The components evaluated by the study are highlighted in bold solid boxes.

Uganda's National Agricultural Research Organization (NARO) served as a public partner, managed the partnership at the national level, and led national research. NARO supplied basic/foundation bean seed, for the production of certified and quality declared seed, to the Community Enterprises Development Organization (CEDO) (a seed company). NARO also conducted face to face training of farmers and Village Enterprise Agents (VEAs) in good agronomic practices including: fertilizer use, pest and disease management, field management, and post-harvest handling. Training in gender issues of crop production and marketing was also offered. District local governments (public partner) supported the implementation of activities by offering training venues. The Center for International Tropical Agriculture (CIAT) and the Pan Africa Bean Research Alliance (PABRA) managed and coordinated partnership research at regional and the international levels.

Lasting Solutions Limited (a private partner) supported the processing of beans which guaranteed a market to farmers. Through research the product processor received technical support in product development. Certified and quality declared bean seed supply, community monitoring, farmer training, and aggregation services were offered by the Community Enterprises Development organization as a private sector actor. Thus, the CultiAf-Ag-PPP was a business model, a design to create a sustainable and self-managing intervention. This model enabled specialization and leverage of expertise and capabilities to achieve greater impacts.

PPP Interventions

From the foregoing discussion, notable features of the CultiAf-Ag-PPP to farmers included: Ag-PPP membership, Market Transfers, Seed Credit Transfers, and Knowledge Transfers (KT) (Figure 4-1). By being part of the PPP, farmers had numerous opportunities provided to them. They were given opportunities to attend PPP meetings and interact with various partners, benefit from monitoring, learning and evaluation visits and recommendations, and participate in demonstrations, among other benefits. These nonpecuniary benefits have been found to impact farmer behavior, farm activities and performance (Howley, 2015). Farmers also benefited from other direct PPP transfers. For *market transfers*, the PPP offered a competitive market to farmers for their produce. The partnership did this to remove marketing bottlenecks and incentivize production. The PPP offered farmers higher prices relative to prevailing market prices, prefinancing to farmers who desired it and supported product aggregation. This was necessary because the bean market is lucrative, and the marketing window is short, yet processing required large bean volumes. The farmer groups aggregated their produce at one collection point and ensured that members stuck to quality requirements. Payment for produce was made through the farmer group which then paid its members. For farmers who received seed credit, the cost of seed was deducted before paying for produce.

For the *Seed Credit Transfer,* farmers were offered seed credit of improved bean varieties which they selected from a menu of high nutrient-rich varieties. The processor prescreened and selected twelve varieties for promotion. These were high in iron and zinc, which also ensured that farmers were exposed to nutritious beans for home consumption. Each kilogram of seed cost UGX 4000 (about USD 1.12) and the farmer group served as the guarantor (via social capital) for the seed credit received by its members. In total, approximately 982.5 tons of bean seeds were supplied to 13,503 farmers in four seasons of the first phase of the PPP (2015 to 2017). The farmers mostly produced and marketed beans under the Seed Credit Model (SCM). Furthermore, farmers under the PPP arrangement received training in various Good Agronomic Practices (GAP)[11] in common bean production, collective marketing, post-harvest handling, records and financial management, and safe handling of chemical inputs. This *Knowledge Transfer* benefited 13,772 farmers, of which 59.5% were women. Select model farmers received additional training as Village Enterprise Agents (VEAs) and Trainers of Trainers (TOTs). These farmers received training in leadership and gender in bean production and marketing, post-harvest handling, variety maintenance, east African community grain standards, and innovation platform involvement and management. The VEAs supported day to day extension activities among project farmers and functioned as local contacts in villages.

[11] GAP included: pest and disease management, soil fertility management, weed management, variety choice and maintenance, and plant spacing.

They also played a role of aggregating produce on behalf of the buyer. Other farmer training avenues that the PPP used included agricultural events like farmer field days and shows.

PPP Impact pathways and outcomes

The goal of the public-private partnership model was to improve the welfare of smallholder bean farmers, to be achieved by improving farmers production and market incentives. However, farmer changes in production and market incentives would be realized through a change in the behavior of farmers who become members of the partnership. To do this, the CultiAf-Ag-PPP model introduced three innovations: technical innovations (seed credit, and knowledge), practice innovations and product innovation (new variety seed) to trigger the expected changes in producer behavior. The Ag-PPP transfers came with specific outcomes to farmers: productivity, market, and home sustenance (Table 4-1).

Table 4-1: Summary of Ag-PPP Impact pathways and outcomes

Intervention	Output	Outcomes	Impact (Higher level outcomes) measure
Knowledge Transfer	Access to knowledge	Adoption of some production and management techniques.	Changes in per unit area productivity and higher production
Seed credit	Access to seed of improved varieties	Adoption of improved varieties and use of quality seeds.	Changes in per unit area productivity and higher production
Produce market	Access to a competitive bean market	Improved access to competitive markets	Changes in per unit area sales and revenues. Change in share of beans allocated to the market and for home use

Without access to competitive markets, productivity gains from these innovations would mean little. The Ag-PPP therefore facilitated farmer linkages to the market. While the Ag-PPP introduced different packages, and all farmers in the selected groups had an opportunity to take part in the PPP and choose from the various packages, farmers were free to select into the intervention(s) that they were interested in. As such, there was variation among participating farmers with regards to the package of intervention(s) received. This allowed for the separate analysis of the impact of receipt of each intervention on targeted outcomes.

Selection of farmers for the CultiAf-Ag-PPP

The CultiAf-Ag-PPP selected farmer groups, but not farmers, that directly benefited from program interventions. First, ten districts in the bean corridor (Rakai, Masaka, Lwengo, Lyatonde, Bukomansibi, Sembabule, Kalungu, Mubende, Kiboga and Mityana) were selected because they are major bean growing districts in Uganda. Then, with the guidance of district production and extension staff, two sub counties per district were selected to participate in the project, based on their levels of and suitability for bean production. For the selected subcounties, production staff guided the choice of farmer groups from a list of available groups within the subcounty. These were selected with the choice criteria being that the group: (1) should be registered at subcounty, district, or national level, (2) had a formal management structure, (3) should have a constitution or governing laws/regulations, and (4) had at least some members actively involved in bean production.

Following this criterion, a total of 490 mixed producer farmer groups with 19,220 (9615 men and 9605 female) farmers were selected. A section of these groups were profiled (see Nakazi et al., 2017a) to ascertain the status of groups. These groups had been in existence for an average of 10 years, and had an average of 37 members (16 men and 21 women). Approximately 95.4% of the farmer groups were registered with most (79.7%) registered at district level, and 11.9% at subcounty level. All of the farmers growing common bean in these groups had opportunities to access any of the interventions offered by the project. Here, we assume that farmers are private sector actors.

4.3. Data and study area

4.3.1. Sampling strategy

The study focusses on farmers because they benefited from both upstream and downstream services offered by the partnership. The analysis presented in this chapter is based on data from four rounds of surveys collected by and in partnership with the National Crops Resources Research Institute (NaCRRI)-NARO. The surveys aimed to elicit information from both participating and non-participating farmers. To arrive at the sample of participating farmers for the study: (1) four intervention districts were randomly selected (two from greater Masaka and two from greater Mubende), (2) then from the selected districts, two participating subcounties, and a pool of farmer groups, at least two farmer groups were randomly selected per subcounty, (3) to select farmers, information on the selected farmer group, including the number of farmers and villages of residence was used. Farmer group leaders and VEAs developed the lists of farmers in each group. Using the list of farmers in selected farmer groups and a random starting point, a method (K+1) was used to select farmers to be interviewed. This was such that every kth member on the list was interviewed, to ensure randomization in the choice of the sample by farmer group, village, and district.

To get the counterfactual, non-participating farmers were randomly selected from participating districts, but non-partnership sub-counties. Here, the study used separation by geographical location to motivate identification which implicitly invoked the Stable Unit Treatment Value Assumption (SUTVA). However, the study met a problem with this assignment, since some farmers in intervention groups were spread across different sub-counties. It was possible to find a farmer living in a nonparticipating sub-county but belonging to a participating farmers group with a majority of members in the participating sub-county. Also, some non-participating farmers did not belong to farmer groups. While we found that about 4% of the farmers benefited from spillovers (see the identification and estimation section for details of managing spillovers), we presume that this overlap did not affect the direction of effects in the results of this study and thus they should stay internally valid. This is presumed because farmers were disaggregated based on whether they benefited from partnership interventions directly, reducing the possibility of benefiting from spillover effects. We also estimate a model that accounts for spillovers. The sampling procedure adopted at the baseline determined sampling of farmers in all subsequent survey rounds since the study tracked the same farmers.

Following this procedure, a total of 599 bean-growing households were interviewed by NARO in the first/baseline round in 2016 (2015 production data) in Lyatonde, Rakai, Kiboga and Mubende, 443 households in the second round (2016 production), and 397 in the third round (2018 production) and 239 in the fourth round (2019 production) in the same districts. Data for the study was collected by a team of trained enumerators using Computer Assisted Personal Interviewing (CAPI) techniques. The study followed the same farmers through all stages of the study. However, there were high attrition rates for the last survey because it was conducted by telephone[12] interviews yet some phone numbers provided by farmers were not available, some farmers refused to respond or had no phones.

4.3.2. Balance check and baseline statistics

For the key outcomes tracked, the productivity outcome was associated with access to quality improved seed (on credit and cash) and specialized agronomic and crop management training. The study measured this outcome as kilograms of beans produced per hectare. The market outcome had three sub-outcomes, (1) change in volume (Kilograms) available for sale per hectare, (2) change in total revenues from bean sales per hectare, and (3) the share of total bean production provided to the market. This was associated with more production due to better varieties, productivity, and availability of competitive market for produce.

The study used the first-round sample to check whether outcome variables of the treated groups balanced with the control group (Table 4-2). Columns 2 to 5 show the summary statistics (mean and

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[12] Telephone interviews were selected as a substitute for face-to-face interviews because of lock down restrictions due to COVID-19 that limited movement, and thus access to farmers.

standard deviation) of the baseline sample for the treated and control groups. An average farmer's productivity was 868 and 899 Kg/ha for the treated and control groups, respectively. This was much lower than what is reported in literature. Estimates based on FAO (2020), show that the average yield of dry beans (includes all Phaseolus *spp*) in Uganda between 2007 and 2018 was 1.398 tons/ha, while estimates from UBOS (2019) between 2014 and 2018 show productivity in the range of 1.2 to 1.6 tons/ha. This is compared to the potential yield of 1.8-2.5 tons/ha of newly released/improved bush common bean varieties in Uganda (TASAI, 2016). The average area cropped was 0.6 hectares for the treated group compared to 0.5 hectares for the control group (Table 4-2). About 65% and 45% of the sampled treated and control farmers, respectively, reported growing improved bean varieties, more than one in four farmers applied pesticides to their beans, and between 20 and 34% used fertilizers (Table 4-20, Appendix C). Also, between 20 and 35% of the sampled farmers were already growing some of the varieties that were promoted under the PPP. The use of modern inputs, such as fertilizers and pesticides, remains critically low in Uganda. According to Binswanger-Mkhize & Savastano (2017), input use in Uganda stood at 18% for improved seed, 3% for inorganic fertilizers, 12% for organic fertilizers, and 11% for agro-chemicals. Compared to other countries; Ethiopia, Malawi, Nigeria, Niger, and Tanzania, the use rates of modern inputs is low in Uganda (Binswanger-Mkhize & Savastano, 2017). Compared to national averages, the farmers sampled for this study and included in the PPP used relatively more modern inputs.

The study used a generic bivariate regression (Eq. 4.1) with errors clustered at the village level to compare means of treatment groups at the baseline (Pretreatment period), where α is the intercept, ε is a summary random variable that represents all other causes of Y.

$$Y_i = \alpha + \delta D + \varepsilon_i \tag{4.1}$$

The variables Y include the outcome variables of the PPP, farmer, and farm characteristics shown in Column 1 of Table 4-2. Here, D represents a bivariate variable assigned to PPP or having received seed credit, training, or market services in the year before the PPP.[13] The coefficient estimate δ is the naïve estimator of the effect of D on Y (Morgan & Winship, 2014). That is; the difference between the sample means of observed outcome Y for farmers in the PPP/received intervention and the control group at the baseline. Coefficient estimates test the hypothesis that the coefficient estimated is zero. These comparative tests do not claim causality and assume that (1) the study sample is large enough to run comparisons, (2) sampling error components of the regression error have zero conditional means, and (3) there is no measurement error in predictors which eliminates attenuation bias in estimated coefficients.

In this study, we used two impact estimation techniques. The Difference in Difference (DID) approach and the Regression Adjustment (RA) approach, as will be explained in the identification and estimation section. One key identifying assumption for the Difference in Difference approach is that trends in the outcome variables would have been the same in both groups in the absence of PPP interventions. In the absence of interventions, outcomes are determined by the sum of time-invariant farmer effects and effects common to farmers. Thus, any differences in the two groups in the post-intervention period, when other exogeneous covariates are controlled for, can be assumed to be associated with the PPP. This parallel trend assumption is important in identifying any changes in observed trends. The study could not verify the parallel trends assumption since we did not have data of the two groups pretreatment. However, the study checked the other key identifying assumption that outcomes of the two groups should be similar pretreatment. The study compared farmers assigned to the PPP/benefited from some transfers and those that did not at the pre-treatment/baseline period. If the similarity assumption holds, then there would be no significance differences in means of outcomes pre-treatment.

[13] Essentially, one would assume zero receipts for interventions at the baseline, but a few farmers reported to have received interventions similar to some of PPP transfers.

Table 4-2: Balance check and Baseline summary statistics

Variables	Baseline Treated group (n=266)		Baseline Control group (n=333)		PPP-farmers (n=599)		Seed credit Transfer (n=599)		Market Transfer (n=599)		Knowledge Transfer (n=599)	
	Mean	**SD**	**Mean**	**SD**	**Coef.**	**p-val.**	**Coef.**	**p-val.**	**Coef.**	**p-val.**	**Coef.**	**p-val.**
(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**
Panel A: Outcome variables												
Productivity (Kg/hectare)	868.15	574.67	899.48	740.44	-31.326	0.651	-21.152	0.746	-98.215	0.092	-6.679	0.925
Amount sold per hectare	669.20	541.04	671.93	644.61	-2.729	0.965	22.127	0.724	-114.877	0.036	28.750	0.665
Bean revenue (M UGX/ hectare)	0.93	0.86	0.97	0.99	-0.040	0.100	0.110	0.293	-0.203	0.012	0.105	0.333
Share of production marketed	0.72	0.22	0.68	0.24	0.046	0.061	0.055	0.032	-0.060	0.070	0.047	0.063
Panel B: Farming/Household characteristics												
Beans put to other uses (kg/Ha)	96.13	113.68	92.26	115.48	3.868	0.706	19.816	0.179	59.308	0.010	23.111	0.134
Area planted (hectare)	0.64	1.18	0.48	0.38	0.160	0.043	0.182	0.010	0.348	0.211	0.171	0.016
Value of bean production (M UGX)	0.71	1.01	0.64	0.87	0.068	0.420	0.297	0.013	0.114	0.457	0.296	0.022
Price (T UGX/Kg)	1.44	0.43	1.47	0.36	-0.039	0.416	0.131	0.005	-0.057	0.520	0.109	0.022
Household size (No. Members)	6.12	2.50	0.52	0.50	0.183	0.334	0.271	0.280	-0.107	0.722	0.241	0.352
Education level (1=Post primary)	0.27	-	0.24	0.42	0.034	0352	0.032	0.434	-0.010	0.871	-0.017	0.701
Belongs to farmer group (1=Yes)	0.92	-	0.28	-	0.642	0.000	0.442	0.000	0.342	0.000	0.473	0.000
Sex head (1=male)	0.65	-	0.52	-	0.132	0.006	0.088	0.158	0.158	0.015	0.108	0.081
Crop ownership (1=Female)	0.44	-	0.54	-	-0.104	0.019	-0.122	0.056	-0.101	0.099	-0.144	0.023

Notes: Columns 2 and 5 show the baseline statistics of the sample (n=599). Columns 4 and 5 show the results of OLS regression comparing households selected for the project and those in the control group. Columns 6 to 13 are OLS estimates comparing groups of farmers that benefited from different transfers/interventions compared to the control. The regressions included constants that are not reported here. All standard errors are clustered at the village level.

Monetary values are reported in Uganda shillings (1USD = 3583.99 UGX) averaged over 2015-2018 (BOU, 2020) .

Table 4-2, panel A shows the balance check of pre-treatment outcomes. Columns 6 and 7 show the results of OLS regression (Eq. 4.1), comparing households selected for the PPP and those in the control group. The analysis shows that households assigned to the PPP and control groups are similar in all outcome variables at the baseline. Columns 8 to 13 are OLS estimates comparing groups of farmers that benefited from different transfers offered by the PPP compared to the control. As shown in Column 8 and 9, the households which had received seed credit were similar in all intervention outcomes except marketed shares of bean production. For the market transfer (Column 10 and 11), control and treated households were similar in two outcomes except amount sold and revenues from bean sales. For the knowledge transfer intervention, the control and treated households were similar in all major outcomes. (Table 4-2, Column 12 and 13).

The balance check shows that the farmers under the distinct groups were comparable at the beginning of the PPP. The difference between the two groups was not significantly different for most of the tracked outcome variables at the time of group assignment.

Although only trends and observed partners in targeted outcomes are important for identification in DID, we report some summary statistics of covariates used in the DID model. Considering potential covariates (panel B of Table 4-2), for PPP membership (Table 4-2, Column 6 and 7), except for area cultivated, belonging to farmer groups and sex of the crop owner, the sample in the treated and control group were similar in all other aspects. For the transfers, comparing seed credit recipients in the control and treated group pre-treatment shows that farmers were similar in exogenous covariates such as household size, education level, sex of head and crop ownership (Table 4-2, Column 8 and 9). For the market transfer intervention, the control and treated group were only different in farmer group membership and sex of the head (Table 4-2, Column 12 and 13). Finally, households were only different in farmer group membership and crop ownership for the knowledge transfer intervention.

4.4. Identification and Estimation

4.4.1. Difference-in-Difference estimation of the impact of the Ag public private partnership

To assess the outcome variables of interest, the study used the Difference-in-Difference (DID) approach to obtain the impact of the CultiAf-Ag-partnership on individual farmers. Furthermore, regression adjustment was used as a robustness check for household assignment into the PPP and DID results. The study's empirical strategy exploits the variation in farmer yields, revenues, and output allocation to assess the impact of the PPP and its transfers. So far, we have shown that outcome levels among the farmers in the treated and control group are fairly similar pretreatment. The other important assumption for identification in DID estimates is the Stable Unit Treatment Value Assumption (SUTVA). Here, the study used separation by geographical location to motivate identification which implicitly invoked SUTVA. That is; there are no interaction effects, and the treatment is exhaustive (no hidden versions of the treatment that may affect the outcome) (Lafférs & Mellace, 2020).

We evaluated the sample to check whether SUTVA was achieved. This was done using questions that were asked that linked farmers to the Ag-PPP interventions. This data was collected to ascertain if some non-PPP farmers benefited from spillover effects. The study found that 73 (4.3%) out of 1,675 observations or 9.10% out of 802 non-PPP farmers, reported to have received some Ag-PPP treatments. This was equivalent to 42 farming households spread across study rounds. These were not mutually exclusive between interventions. Compared to the control group sample, 5.6% received knowledge transfer through one of the many avenues used by the Ag-PPP to offer training to farmers. Also, 2% reported to have benefited from the seed credit transfer while 3% benefited from market opportunities indirectly.

Several approaches have been proposed to deal with the possibility of neighborhood effects of treated on non-treated groups: (1) estimation of externalities and researcher defined distance cut-offs, that is, spatial spillovers holding time constant (Clarke, 2017), (2) considering temporal spillovers while holding geographical dispersion constant (Abramitzky et al., 2018), and (3) identification of treatment response with social interactions (Brock & Durlauf, 2007; Manski, 2013). Some studies have noted that assuming that SUTVA is satisfied by part of the study sample, either at individual or other aggregation levels, produces consistent estimates (Clarke, 2017; Huber & Steinmayr, 2019).

While our spillover sample seems small (per intervention), we estimate a DID model that accounts for possible spillover effects. Two robustness checks were estimated: (1) a model with the full sample (ignoring spillovers), and (2) a model with all spillovers excluded. Specifically, we modify the 'close' to treatment method proposed by Clarke (2017) by adding the effect of being a spillover beneficiary, and the initial fixed effect of being in the spillover group. Clarke (2017) noted that by accounting for 'close to treatment' neighborhood interactions and if SUTVA holds for part of the sample, parameter estimates produced by such estimates are consistent. The study also invokes the assumption of partial-fulfilment of SUTVA (Clarke, 2017; Huber & Steinmayr, 2019). To implement the Difference-in-Difference specification for Ag PPP membership, we only include a dummy for being a spillover beneficiary since we know, for certain, PPP membership. The study thus estimated variants of the model in Eq. 4.2 for various outcomes.

$$\mathrm{Y}_{i,\mathrm{t}} = \alpha_0 + \alpha_1 Time_t + \alpha_2 PPP_i + \boldsymbol{\beta} Time_t . PPP_i + \delta\, R(i,t) + X'\,\gamma + \varepsilon_{i,t} \tag{4.2}$$

where $\mathrm{Y}_{i,\mathrm{t}}$ stands for four outcome variables: (1) bean productivity (Kg/hectare), (2) volume of bean marketed (Kg/hectare), (3) revenues earned from bean sales (UGX/hectare), and (4) share of bean production marketed, for household i at time t. The parameter α_1 captures round/time fixed effects (in DID the time trend in the control group), PPP_i is a dummy that denotes whether a household participated in the partnership (1=participated) with α_2 being its parameter. Essentially, α_2 captures the difference between the partnership and non-partnership groups pre-intervention. The added variable $R(i,t)$ is defined as a binary variable which takes a value of 1 if the individual benefited from indirect spillover effects of the PPP and 0 otherwise. Since treatment occurs only in period 1, $R(i,0)$ = 0 for all i. Also, certainty of PPP_i, excludes individuals with spillover benefits.

To avoid treating the partnership as a blanket intervention, given its unique attribute of creating synergies, the study added variants of whether a household benefited from the various transfers (seed credit, knowledge, and market) offered by the PPP. Here, the study estimated a model with both the effect of being a spillover-beneficiary (ϑ) and an initial fixed effect of being in a spillover group (δ). Thus, versions of the model in Eq. 4.3. were estimated using two approaches: (1) estimating the equations as a system, given a possibility of positively correlated/non-independent errors in the three equations and (2) for each intervention separately. Furthermore, (1) a model with the full sample (ignoring spillovers), and (2) a model with all spillovers excluded were estimated as robustness checks.

$$\mathrm{Y}_{mi,\mathrm{t}} = \alpha_0 + \alpha_1 Time_{mt} + \alpha_2 PPPintervention_{mi} + \boldsymbol{\beta} Time_{mt}.PPPintervention_{mi} + \delta\, R(i,t) + \vartheta R(i,t).PPPintervention + X'\,\gamma + \varepsilon_{mi,t}, \qquad \mathrm{m} = 1, \dots, \mathrm{M} \tag{4.3}$$

Where m is the equation number used to represent different regression equations. Here, there were three equations, one for each package (seed credit, market transfer and knowledge transfer). These were estimated for each of the four outcome variables. Notice that Eq 4.3 also includes the ‘spillover-group’ analog δ which is the initial fixed effect and ϑ which captures the effect of being in the ‘spillover group’ following receipt of indirect Ag-PPP intervention treatments.

In Eq. 4.2 and Eq. 4.3, the coefficient β is the DID parameter of interest. The parameter coefficient β can be interpreted as the difference in changes over time. The variable X is a vector of exogenous control variables (not directly affected by the treatment and its transfers), including: (1) the household head’s education and (2) gender, (3) farmer group membership, (4) household size, and (5) crop ownership. Because regression errors are likely to be correlated for individuals (Cameron & Trivedi, 2007) within the same region and similar individuals pre and post-intervention, the study clustered all standard errors at the village level and added district fixed effects. Furthermore, auxiliary models were estimated without district fixed but with clustering at village level.

Additionally, the study added the gender dimension to the analysis by disaggregating households based on the gender of the crop owner. For this approach, separate regressions using Eq. 4.2 and Eq. 4.3. for male and female bean crop ownership were estimated. This is important because beans have traditionally been regarded as a women's crop and women dominate their production and marketing (Nakazi et al., 2017b; Njuki et al., 2011). Therefore, the program aimed to include both genders in all aspects of bean production and marketing to ensure that women farmers were not marginalized and that gains from PPP interventions were equitably distributed across gender categories.

4.4.2. Regression adjustment estimation of the impact of the Ag public private partnership

To validate and check the robustness of the DID results, the study estimated the effects of the partnership using the Regression Adjustment (RA) approach. Particularly, the Inverse Probability Weighted Regression Adjustment (IPWRA) estimator was used. This is important because, our sample is not truly randomized. First, farmers may have had different contexts, and some may have self-selected into the farmer groups that were chosen by the project before treatment assignment (confounding due to selection bias). Secondly, farmers may have been different in some characteristics and thus reacted differently to external shocks, the PPP, and its interventions. As such, this robustness check is important to estimate unbiased treatment effects when there is a possibility of confounding. Another important feature with IPWRA is that it is doubly robust; even if one model (outcome or treatment) is mis-specified, the estimator is consistent. The IPWRA estimator models both the treatment and outcome to account for nonrandom treatment assignment (StataCorp, 2013). IPWRA uses inverse probability weights to estimate correct regression coefficients and then perform regression adjustment analysis. Thus, sample estimating functions for IPWRA include sample estimating functions from both regression adjustment and inverse probability weighting.

Following Cattaneo (2010) and StataCorp (2013), define $z \in \{0,1\}$ as the treatment status for either being part of the Ag-PPP or receiving one of its transfers such that y_z is the potential outcome for an individual in a given treatment group, and y_{iz} is the realization of y_z for a given household. The outcome model used in the study takes the form:

$$E(y|X, z,) = \mu(X, z, \beta_z) \tag{4.4}$$

Where $\mu(X, z, \beta_z)$ is the conditional mean of the outcome variable at a given z and β_z are the parameters of the conditional mean model over all treatment levels. The estimated outcome model used in this study was assumed to be linear ($X\beta_z$).

The conditional probability of the treatment for a household receiving treatment z conditional on covariates (h) defines the propensity score; $\exp(h) = p(z = 1|h)$. The study assumed a logistic function in modeling the treatment because it is the most popular choice for estimating propensity scores (Williamson & Forbes, 2014). With the parametrization γ for the logistic regression and a binary treatment indicator z, then the logistic functional form for the conditional probability model $p(h, z, \gamma)$ is:

$$\log\left\{\frac{exp(h)}{1-exp(h)}\right\} = h^T\gamma \tag{4.5}$$

Such that the fitted propensity scores for each individual i belonging to either of the treatment groups defined by z is:

$$\hat{e}_i = \hat{e}(h_i) = \frac{\exp(h_i{}^T\hat{\gamma})}{1+\exp(h_i{}^T\hat{\gamma})} \tag{4.6}$$

The Inverse Probability Weights (IPW) are then recovered from the propensity scores to adjust for possible cofounding in regression adjustment analysis. Households that benefited from the Ag-PPP or any of its transfers, are assigned weights calculated as: $d_i(z) = 1/\hat{e}_i$, while households in the control group are assigned weights of $d_i(z) = 1/(1 - \hat{e}_i)$. In cases where outcomes are continuous, the inverse probability weight of receiving a treatment is used to weight adjusted mean treatment group differences that are obtained from a linear regression model on the treatment only (Raad et al., 2020).

Three estimates are of importance in this study's treatment effects analysis. These are: The Potential Outcome Mean (POM), the Average Treatment Effect (ATE) and Average Treatment Effect on the Treated (ATET). In Stata (the software that the study used for this analysis), the POM and ATE estimators use normalized inverse-probability weights, thus, $\bar{d}_i(z) = N_z d_i(z)/\sum_i^N d_i(z)$ while the ATET estimator uses normalized treatment-adjusted inverse-probability weights StataCorp (2013). The unnormalized treatment-adjusted inverse-probability weights are computed as $f_i(z) = p(h_i, \tilde{z}, \hat{\gamma})/p(h_i, z_i, \hat{\gamma})$ and the normalized weights as: $\bar{f}_i$(z) =N$f_i/\sum_i^N f_i$. Where Nt is the number of observations in treatment level z. Denote $\alpha' = (\alpha_0, \alpha_1, \dots, \alpha_q)$, $\tau' = (\tau_0, \tau_1, \dots, \tau_q)$ and $\delta' = (\delta_0, \delta_1, \dots, \delta_q)$ the effect parameters for the POM, ATE and ATET, respectively, such that when weights are applied to regression adjustment estimation functions, sample estimating functions of the form in Eq. 4.7 for POM, Eq. 4.8 for ATE, and Eq. 4.9 for ATET are obtained. These are estimatable to obtain effects of interest.

$$S_i^{IPWRA}(X_i, \hat{\alpha}, \hat{\beta})' = \bar{d}_i(z)[\mu(X_i, z, \hat{\beta}_z) - \hat{\alpha}_z] \tag{4.7}$$

$$S_i^{IPWRA}(X_i, \hat{\tau}_z, \hat{\beta})' = \bar{d}_i(z)[\mu(X_i, z, \hat{\beta}_z) - \mu(X_i, 0, \hat{\beta}_z) - \hat{\tau}_z] \tag{4.8}$$

$$S_i^{IPWRA}(h_i, \hat{\delta}_z, \widehat{\beta}, \hat{\gamma})' = \bar{f}_i(z)\frac{Nz_i(\tilde{z})}{N\tilde{z}}\{\mu(X_i, z, \hat{\beta}_z) - \mu(X_i, 0, \hat{\beta}_z) - \hat{\delta}_z\} \tag{4.9}$$

Each of the equations in 4.7, 4.8 and 4.9 was estimated for different treatments taken on by z defined as (1) being an Ag-PPP member equal to 1 and 0 otherwise, and (2) for each of the three transfers such that z was defined as 1 if a farmer benefited from any of the transfers and 0 otherwise. In making these estimations, we assumed that the following assumptions about the process of generating data and the estimation process holds: (1) conditional independence guarantees that once the study controls for all observable variables, the potential outcomes are independent of treatment assignment, (2) the overlap assumption or each individual has a positive probability of receiving each treatment level, and (3) the independent and identically distributed (i.i.d.) sampling assumption ensures each individual's treatment and outcome status is uncorrelated with the treatment and outcome for all the other individuals in the population (StataCorp, 2013).

4.5. Results

The study's empirical strategy compares changes in outcome variables between PPP and non-PPP farmers that were differentially affected by the CultiAf-Ag-PPP. Results of the main Difference in Difference (DID) models and Inverse Probability Weighted Regression Adjustment (IPWRA) model are presented in what follows. Critical control points in managing and sustaining an Ag-PPP at the farm level are presented in section 4.6. These are followed by the discussion of the program and policy implications is in section 4.7. The results of various DID robustness checks are included in the supplementary appendix of this chapter.

Farmers who were assigned to the PPP had an opportunity to access multiple interventions. However, it was likely that a farmer did not receive all of the services/packages since they had the choice of participating in only the services that they believed to be most relevant. Here, the study extends the analysis to specific transfers (seed credit, knowledge, and markets) offered by the PPP. Because the choice to participate in these transfers and also the errors between the equations may be correlated, we estimated models as a system following diagnostic tests (see Table 4-10, Appendix C). The uptake of PPP transfers among PPP farmers was 70% for knowledge transfer, 71% for seed credit transfer, and 55% for market transfer. The impact of each of the transfers is discussed alongside the impact of the overall CultiAf- Ag-PPP intervention.

4.5.1. Difference in Difference estimates of the impact of the public-private partnership

4.5.1.1. Impact of the public-private partnership on farmers' productivity

Table 4-3, Column 1 reports DID results for participation in the CultiAf public-private partnership. The DID coefficient accounting for regional differences, by adding district fixed effects and clusters at the village level, reveals that farmers in the PPP on average reported higher yields (209 Kg/hectare), compared to those not in the partnership. Even without accounting for district fixed effects, the effects remain significant, with PPP farmers likely to report 197 Kg per hectare higher (Table 4-11, Column 1, Appendix

C). The results are robust to any specification, and show that PPP farmers are more likely to report higher bean yields, thus, a productivity-enhancing effect of the PPP. The effects are similar even when the spillover sample is excluded (Table 4-19, Column 1, Appendix C)

Columns 2 to 4 of Table 4-3, report estimates of transfers provided to farmers in the PPP. We evaluated the possibility of error independence across equations and found significant positive correlations in the three equations (Table 4-10 Appendix C). This provided the reason for estimation of the equations of the different interventions as a system. Estimation of the equations as a system is also preferred, given that it produces lower standard errors. As a robustness check we also estimated and report results when equations are estimated separately, with and without district fixed effects and clustering at village level. Another robustness check was estimating the equations without accounting for spillover households and other that excludes spillover households (Table 4-19, Columns 2 to 4, Appendix C).

Table 4-3: Impact of public-private partnership and transfers on bean productivity: DID estimates using systems approach

	Dep. Variable: Bean farmer productivity (Kg/Ha)			
	PPP Membership	**Seed credit Transfer**	**Market Transfer**	**Knowledge Transfer**
	1	2	3	4
Intervention X time	209.054***	68.872***	198.357***	134.166***
	(71.356)	(2.551)	(2.672)	(3.604)
Intervention	3.358	-8.713***	-113.370***	-22.217***
	(73.705)	(2.113)	(2.358)	(3.216)
TIME (1= post-treatment)	-284.714***	-235.032***	-228.850***	-268.123***
	(45.719)	(2.451)	(1.918)	(2.117)
District dummies	Yes	Yes	Yes	Yes
Other covariates	Yes	Yes	Yes	Yes
N	1,554	1,554	1,554	1,554

Standard errors are in parentheses. * p<0.1; ** p<0.05; *** p<0.01. The model is controlled for household head sex, education of head, household size, and farmer group membership. Results in column 2 to 4 are based on seemingly unrelated regression estimates in a panel setting.

The study finds that each of the transfers positively contributed to increased farmer productivity. The market transfer (Table 4-3, Column 3) had the highest effect on bean productivity, alone, increasing productivity by 198 Kg/hectare for farmers who benefited from the intervention. This suggests that farmers respond favorably to project interventions that are presented to them with competitive market opportunities. The effect is higher with (270 Kg/hectare) and without (221 Kg/hectare) district fixed effects when the equations are estimated separately (Table 4-11 and Table 4-12, Column 3, in Appendix C). The robustness check of the effect of different methods of addressing the SUTVA show that when spillovers are not accounted for, there is attenuation bias in the effect of the market transfer (Table 4-19, Panel A, Column 3, Appendix C). On the other hand, excluding the spillover sample leads to a higher estimate (229 Kg/Hectare) of the effect the market transfer on its recipients (Table 4-19, Panel B, Column 3, Appendix C).

Through the partnership, farmers received seed of improved nutrient rich bean varieties for production. As shown in Table 4-3 Column 2, farmers who benefited from seed credit were likely to report 69 Kg/hectare higher compared to farmers that never received seed credit. The effect was much higher, positive, and significant for single equation estimation as shown in Appendix C, Table 4-11 and Table 4-12 Column 2. Similar to the effect of the market transfer, we find attenuation of the seed credit estimate when spillovers are not accounted for, and an upward bias when the spillover sample is excluded (Table 4-19, Column 2, Appendix C).

PPP farmers were given unconditional access to information, training, and knowledge services. We find that farmers who received ‘the knowledge transfer,’ on average reported 134 Kg/hectare more than farmers that never received training (Table 4-3, Column 4). With and without accounting for district fixed effects, the yield advantage is positive but not significantly different from that of farmers that never benefited from training (Table 4-11 and Table 4-12 Column 4, Appendix C). We find a much higher (194 Kg/hectare) effect of the knowledge transfer when we exclude spillover households. The effect of the knowledge transfer is slightly lower when SUTVA is naturally evoked (Table 4-19 Column 4, Appendix C).

4.5.1.2. The impact of public-private partnership transfers on farmers' market outcomes

The market outcome had three specific outcomes: (1) the volume of beans marketed per hectare, (2) the share of bean output marketed out of production, and (3) the revenue from bean sales. The study estimated Eq. 4.1. as a system for the three transfers, and also estimated equations separately for each of these market sub-outcomes as a robustness check. For the single equation estimates, the standard errors for each estimate were clustered at the village level, and with and without accounting for unobserved local heterogeneity by adding district fixed effects. First, the study finds that farmers in the partnership are likely to report selling 199 Kg/hectare higher than those not in the partnership (Table 4-4, Column 1). Not accounting for locality effects results in a reduction of the sales advantage by 22% (Table 4-13, Column 1, Appendix C). The effect of the Ag-PPP on marketed volumes is lower when spillovers are not accounted for and when they are excluded (Table 4-19 Column 1, Appendix C).

Table 4-4: Impact of public-private partnership and transfers on bean sales per hectare: DID estimates using systems approach

	Dep. Variable: Bean output (Kg) sold per hectare			
	PPP Membership	**Seed credit Transfer**	**Market Transfer**	**Knowledge Transfer**
	1	2	3	4
Intervention X time	198.967***	102.041***	177.452***	54.954***
	(63.523)	(3.007)	(2.240)	(2.184)
Intervention	29.787	-16.230***	-109.286***	-11.561**
	(67.979)	(2.646)	(1.973)	(1.824)
TIME (1= post-treatment)	-242.221***	-242.792***	-210.768***	-214.054***
	(39.738)	(1.801)	(1.626)	(1.1.824)
District dummies	Yes	Yes	Yes	Yes
Other covariates	Yes	Yes	Yes	Yes
N	1,560	1,554	1,554	1,554

Standard errors are in parentheses. * p<0.1; ** p<0.05; *** p<0.01. The model is controlled for household head sex, education of head, household size, and farmer group membership. Results in column 2 to 4 are based on seemingly unrelated regression estimates in a panel setting.

First, the study found that by guaranteeing a competitive market (market transfer) for all produce, farmers are likely to report selling 177 kg more per hectare compared to their counterparts without a guaranteed market (Table 4-4, Column 3). When the marketed-volume equation is estimated separately, and without district fixed effects, the marketed-volume advantage is 231 Kg/hectare (Table 4-13, Column 3, Appendix C) while the same is 269 Kg/hectare when district fixed effects are added to account for heterogeneity due to location. When spillover households are not considered, there is an attenuation in the effect of volume of sales marketed. Conversely, the effect is much higher (238 Kg/hectare) when the spillover sample is excluded during estimation (Table 4-19, Column 3).

Farmers who benefited from seed credit as a package are likely to report selling 102 Kg/hectare higher compared to those who never benefited from the seed credit package (Table 4-4, Column 2). However, while the effects stay positive, they were not significant if the seed credit equation is estimated separately, with or without district fixed effects. We find a much higher (191 Kg/hectare) effect of the seed credit transfer when we exclude spillover households (Table 4-19 Column 2, Appendix C). Furthermore, benefiting from the knowledge transfer was associated with 55 Kg/hectare higher sales than non-participation. The effect is positive but not significant if the knowledge model is estimated singly with or without district fixed effects (Table 4-13 and Table 4-14 Column 4, Appendix C). The study found an attenuation of the knowledge transfer estimate when spillovers are not accounted for, and an upward bias when the spillover sample is excluded (Table 4-19, Column 4, Appendix C).

Secondly, the analysis of the share of production allocated to the market (Table 4-5, Column 3) showed that farmers in the Ag-PPP reported selling 16% more than non-Ag PPP farmers if they had access to competitive bean markets. Additionally, Ag PPP farmers were likely to report selling 11% and 10% more than their counterparts if they benefited from seed credit and knowledge transfers, respectively. When the equations for the different transfers are estimated separately, we find that only the market transfer had a significant impact on share of bean output sold (Table 4-13 and Table 4-14, Column 3, Appendix C). With different ways of dealing with spillovers, the effect of the market transfer on the share of marketed output is higher (20%) when spillover households are excluded from the analysis and is lower for access to seed credit and knowledge transfers (Table 4-19, Appendix C).

Table 4-5: Impact of public-private partnership and transfers on share of bean output sold: DID estimates using systems approach

	Dep. Variable: Share of bean output sold			
	PPP Membership	**Seed credit Transfer**	**Market Transfer**	**Knowledge Transfer**
	1	2	3	4
Intervention X time	0.050*	0.112***	0.159***	0.101***
	(0.030)	(0.002)	(0.003)	(0.004)
Intervention	0.053**	-0.012***	-0.052***	-0.010***
	(0.026)	(0.002)	(0.002)	(0.004)
TIME (1= post-treatment)	-0.074***	-0.111***	-0.106***	-0.109***
	(0.022)	(0.001)	(0.001)	(0.002)
District fixed effects	Yes	Yes	Yes	Yes
Other covariates	Yes	Yes	Yes	Yes
N	1,562	1,562	1,562	1,562

Standard errors are in parentheses. * p<0.1; ** p<0.05; *** p<0.01. The model is controlled for household head sex, education of head, household size, and farmer group membership. Results in column 2 to 4 are based on seemingly unrelated regression estimates in a panel setting.

Finally, because the PPP did not discriminate by seed source (use of own saved project variety seed or renewed purchased seed) when buying farmers' produce, farmers in the PPP were likely to earn 336,000 UGX/hectare (Table 4-6, Column 1) more than those not in the PPP. Also, farmers who received help from the market transfer were likely to report earning 353,000 UGX per hectare more than those who never benefited from the market transfer (Table 4-6, Column 3). All other transfers also had a positive impact on farmer revenues, albeit lower than that of the market transfer. For example, the average revenue gain for farmers that benefited from knowledge transfer was 132,000 UGX per hectare. The revenue gains were even higher for being part of the Ag-PPP and having received help from the market transfer, when the models are estimated separately with and without district fixed effects (Table 4-17 and Table 4-18, Appendix C). The estimated effect is positive, but lower when the model is estimated without taking into account spillovers. When spillover households are excluded from the sample, the revenue advantage for being part of the PPP are much higher (Table 4-19, Appendix C).

Table 4-6: Impact of public-private partnership and transfers on bean revenue per hectare: DID estimates using systems approach

	Dep. Variable: Bean revenue (M UGX) per hectare			
	PPP Membership	**Seed credit Transfer**	**Market Transfer**	**Knowledge Transfer**
	1	2	3	4
Intervention X time	0.336***	0.207***	0.353***	0.132***
	(0.106)	(0.009)	(0.007)	(0.007)
Intervention	0.053	0.030***	-0.149***	-0.003
	(0.114)	(0.008)	(0.006)	(0.006)
TIME (1= post-treatment)	-0.109*	-0.200***	-0.042***	-0.080
	(0.065)	(0.005)	(0.009)	(0.006)
District dummies	Yes	Yes	Yes	Yes
Other covariates	Yes	Yes	Yes	Yes
N	1,538	1,538	1,538	1,538

Standard errors are in parentheses. * p<0.1; ** p<0.05; *** p<0.01. The model is controlled for household head sex, education of head, household size, and farmer group membership. Results in column 2 to 4 are based on seemingly unrelated regression estimates in a panel setting.

Overall, the study has demonstrated that the Ag-PPP and its specific transfers had positive effects on farmer productivity, marketed output, and revenues of bean farms. Importantly, offering an assured market leads to higher gains compared to other interventions. In such rural settings, access to markets and market services is always an important bottleneck that farmers face (Key et al., 2000; Nichterlein, 2011). By guaranteeing a competitive market at a price higher than the prevailing market price, farmers are likely to respond with increased production. Cascading effects are therefore likely since each of the outcomes reinforces another. For example, higher productivity leads to more output available for sale and as more is sold, farmers earn higher revenues per hectare cultivated.

Findings in this study provides evidence that corroborates previous studies that have shown that innovative delivery of extension and market services to farmers is important for enhancing productivity and revenues (Danso-Abbeam et al., 2018; Davis et al., 2012; Nakano et al., 2018; Todo & Takahashi, 2013). Also, improved market access has been shown to increase farm productivity, by facilitating specialization, crop choice, and intensification in different parts of the world (Gafaro & Pellegrinaa, 2018; Kamara, 2004; Oppen et al., 1997)

4.5.1.3. Crop owner gender disaggregated analysis of the impact of the public-private partnership and its transfers

The PPP promoted different interventions while mainstreaming gender in all PPP activities to foster equitable men and women participation in bean production and marketing. The aim was to ensure that benefits from bean production are enjoyed equitably by men and women. Also, the PPP sought to avoid male capture since beans are predominantly cultivated by women (Nakazi et al., 2017b). The results from the estimation of the regressions in Eq. 4.2 and Eq. 4.3, for women and men that owned the bean crop to assess the impact of the PPP and its transfers, are shown in Table 4-7. Males obtained more beans (257Kg/hectare) if they were part of the PPP compared to their male counter parts that owned the bean crop but were not in the PPP. Women, on the other hand, obtained 117Kg/hectare if they were part of PPP compared to women not in the PPP. Women reported higher productivity because of receiving seed credit compared to men. Also, because of the knowledge transfer, women reported larger volumes marketed per hectare. The Ag-PPP significantly improved the share of beans allocated to the market for women and the effect was not significant and minor for men. However, men reported higher shares marketed if they benefited from the seed credit and market transfer. The revenue outcomes for men were much higher for all interventions and Ag-PPP membership.

Table 4-7: Gender differentiated impact of the PPP and transfers

	PPP Membership	Seed credit Transfer	Market Transfer	Knowledge Transfer	PPP Membership	Seed credit Transfer	Market Transfer	Knowledge Transfer
	Female owned crop				**Male owned crop**			
	1	2	3	4	5	6	7	8
Farm productivity (Kg/Hectare)								
Intervention X time	116.687	372.524***	161.784***	220.175***	256.766***	121.049***	230.327***	200.734***
	(114.716)	(17.953)	(20.361)	(19.986)	(93.681)	(10.040)	(6.109)	(5.195)
Intervention	69.984	-195.996***	-113.115***	-119.798	-47.446	-79.399***	-170.775***	-158.744***
	(94.242)	(15.743)	(19.776)	(17.930)	(96.829)	(9.196)	(5.558)	(4.794)
TIME 1(post-treatment)	-309.988 ***	-378.672***	-419.418 ***	-384.925***	-273.836***	-208.009***	-171.916***	-242.978***
	(67.516))	(10.228)	(7.088)	(10.859)	(76.371)	(5.188)	(2.686)	(2.822)
N	669	669	669	669	883	883	883	883
Volume marketed per Hectare								
Intervention X time	119.220	248.324***	243.273***	218.849***	185.756**	252.695***	265.461***	137.680***
	(100.237)	(9.502)	(16.731)	(21.970)	(85.932)	(4.809)	(5.577)	(10.327)
Intervention	70.713	-97.162***	-204.858***	-85.108***	-0.159	-103.211***	-137.045***	-26.047***
	(86.213)	(8.290)	(16.278)	(19.713)	((89.438)	(4.427)	(5.066)	(9.455)
TIME 1(post-treatment)	-264.356***	-339.773***	-383.128***	-344.908***	-228.401***	-236.331***	-151.538***	-185.217***
	((59.749)	(5.531)	(5.623)	(11.947)	((67.805)	(2.589)	(2.410)	(5.241)
N	672	669	669	669	886	883	883	883
Share of output marketed								
Intervention X time	0.098**	0.021***	0.008	-0.015	0.000	0.115***	0.140***	0.082***
	(0.045)	(0.003)	(0.008)	(0.010)	(0.037)	(0.004)	(0.003)	(0.003)
Intervention	0.030	0. 040***	-0.030***	0. 009	0.075**	-0.030***	-0.059***	-0.020***
	(0.033)	(0.003)	(0.007)	(0.008)	((0.033)	(0.004)	(0.002)	(0.003)
TIME 1(post-treatment)	-0.112***	-0. 092***	-0. 128***	-0. 138***	-0.026	-0.041***	-0.034***	-0.035***
	(0.033)	(0.002)	(0.003)	(0.007)	(0.028)	(0.002)	(0.002)	(0.003)
N	670	670	670	670	884	884	884	884

Revenue per Hectare (M UGX)								
Intervention X time	0.266	0.234***	0.190***	0.199***	0.329*	0.791***	0.511***	0.760***
	(0.186)	(0.223)	(0.047)	(0.020)	(0.167)	(0.052)	(0.061)	(0.050)
Intervention	0.111	-0.021	-0.147***	-0.025	0.027	0. 490***	0.296***	-0.482***
	(0.137)	(0.020)	(0.044)	(0.018)	(0.174)	(0. 051)	(0.056)	(0.049)
TIME 1(post-treatment)	-0.109	0.332***	-0.363***	-0.339***	-0.068	-0. 317***	0.034***	-0.309***
	(0.139)	(0.090)	(0.091)	(0.091)	(0.127)	(0.038)	(0.068)	(0.068)
N	661	661	661	661	869	869	869	869

Standard errors are in parentheses. * p<0.1; ** p<0.05; *** p<0.01. The model is controlled for household head sex, education of head, household size, and farmer group membership. All models were estimated with district dummies.

Results in column 2,3, 4 ,6,7 and 8 are based on seemingly unrelated regression estimates in a panel setting.

4.5.2. Regression Adjustment treatment effect estimates of the impact of the public-private partnership and its transfers

The study used the Inverse Probability Weighting Regression Adjustment (IPWRA) approach to model the outcomes of interest to account for the possibility of non-randomness and confounding in treatment assignment. The results of the analysis are shown in Table 4-8 for the full sample and Table 4-9 for gender-disaggregated analysis. Treatment effect density plots for variable/covariate balance are shown in Figure 4-2, Appendix C. Only plots for Ag-PPP membership are shown. The estimates corroborate the DID estimates. Except for changes in productivity and volumes marketed per hectare, the Average Treatment Effect (ATE) shows that participation in the partnership and its transfers is likely to lead to better targeted outcomes than not participating (Table 4-8). Furthermore, the Average Treatment Effect on the Treated (ATET) shows that farmers that reported taking part in the partnership are likely to report better outcomes. For example, the average PPP farmer had a yield advantage of 169 Kg/hectare and a revenue advantage of 273,000 UGX/hectare relative to a non-PPP farmer (Table 4-8, Column 1). The estimates from the regression adjustment approach are however lower than DID estimates for the impact on the productivity, volumes sold per hectare, and revenues earned. Results for IPWRA were higher for share of production allocated to the market as compared to DID estimates.

For the different transfers, the RA analysis shows that farmers who received seed credit were likely to post better productivity, volumes marketed, marketed share of production, and revenue. For example, the estimate (ATET) for seed credit (Table 4-8, Columns 2) is significant, indicating that by taking up seed credit, farmers obtain 163 Kg/hectare higher than if they did not. Also, seed credit recipients market more beans (128 Kg) produced per hectare and earn higher revenues (300,000 UGX /hectare). Comparing with DID estimates (Tables 4-3, 4-4, 4-5 and 4-6, Column 2), the estimated advantage was higher for seed credit in the RA analysis framework. Furthermore, ATET estimates for the market transfer show that farmers were likely to report higher outcomes compared to non-participants. However, RA estimates were lower than DID estimates.

Table 4-8: Partnership and Transfer Impacts: Regression Adjustment estimates

		PPP Membership	Seed credit Transfer	Market Transfer	Knowledge Transfer
		1	**2**	**3**	**4**
Productivity (Kg/ Hectare)					
ATE	PPP intervention	167.324***	122.121***	29.002	97.752**
		(39.997)	(42.821)	(40.976)	(46.399)
POM	0(PPP intervention)	710.605***	736.059***	764.745***	748.639***
		(23.510)	(18.903)	(17.396)	(18.782)
ATET	PPP intervention	169.218***	163.014***	124.399***	132.211***
		(36.142)	(33.178)	(36.160)	(33.016)
POM	0(PPP intervention)	677.421***	677.987***	710.027***	694.371***
		(29.494)	(23.354)	(22.607)	(23.070)
N		1,554	1,554	1,554	1,554
Volume marketed (Kg/ Hectare)					
ATE	PPP intervention	170.165***	134.410***	36.391	114.244***
		(35.152)	(37.336)	(36.378)	(44.008)
POM	0(PPP intervention)	514.073***	541.078***	564.634***	546.969***
		(20.503)	(17.224)	(15.569)	(16.837)
ATET	PPP intervention	153.099***	128.286***	106.951***	124.196***
		(31.619)	(30.625)	(31.779)	(29.592)
POM	0(PPP intervention)	489.317***	509.050***	521.337***	502.143***
		(25.688)	(22.152)	(20.064)	(20.847)
N		1,554	1,554	1,554	1,554
Share of output marketed					
ATE	PPP intervention	0.086***	0.078***	0.056***	0.073***
		(0.016)	(0.017)	(0.019)	(0.019)
POM	0(PPP intervention)	0.643***	0.654***	0.663***	0.654***
		(0.012)	(0.010)	(0.008)	(0.011)
ATET	PPP intervention	0.075***	0.0772**	0.069***	0.071***
		(0.019)	(0.018)	(0.017)	(0.018)
POM	0(PPP intervention)	0.638***	0.643***	0.651***	0.642***
		(0.017)	(0.016)	(0.013)	(0.016)
N		1,562	1,562	1,562	1,562
Revenue (M UGX/Hectare)					
ATE	PPP intervention	0.301***	0.283***	0.134*	0.239***
		(0.067)	(0.074)	(0.074)	(0.075)
POM	0(PPP intervention)	0.904***	0.929***	0.959***	0.940***
		(0.040)	(0.036)	(0.030)	(0.036)

ATET	PPP intervention	0.273***	0.300***	0.331***	0.253***
		(0.062)	(0.064)	(0.068)	(0.065)
POM	0(PPP intervention)	0.869***	0.899***	0.891***	0.931***
		(0.049)	(0.045)	(0.037)	(0.047)
N		1,538	1,538	1,538	1,538

Notes: POM is the Potential Outcome Mean (the mean when the intervention is 0; that is never benefited from the intervention). All of the regressions are controlled for head education, household size, farmer group membership and round fixed effects. * p<0.1; ** p<0.05; *** p<0.01.

In the IPWRA, the outcome model is assumed to be linear while the treatment model, logistic.

We find that the knowledge transfer impact has stronger effects for volumes sold per hectare and share of output marketed if estimates are based on the RA relative to the DID approach. For example, Ag-PPP farmers who received the knowledge transfer sell 124 Kg/hectare higher than those that never benefited from the knowledge transfer. Also, they report earning 253,000 UGX per hectare higher. Above all, both Difference in Difference and regression adjustment results show that being part of the Ag-PPP and having benefited from its specific transfers had positive outcomes on bean farmers.

Based on the sex of the crop owner, regression adjustment (ATET) estimates show that by taking part in the Ag-PPP and receiving its transfers, both males and females who reported owning the bean crop report higher productivity, volumes marketed, shares marketed, and revenues compared to their male and female counterparts that did not benefit from any of the interventions (Table 4-9). For example, a female crop owner that was part of the Ag-PPP reported a productivity of 144 Kg/hectare compared to a female crop owner that was not part of the Ag-PPP. Similarly, male crop owners that were part of the Ag-PPP reported producing 186 Kg/hectare compared to their counterparts that were not part of the PPP.

Male farmer productivity and volumes marketed were higher than that of female farmers for Ag-PPP membership, access to seed credit and receipt of knowledge transfer. The effect of market transfer was similar for both men and women. For changes in the share of output allocated to the market, Ag-PPP membership and access to seed credit led to higher changes in the outcome for women than for men. Finally, for changes in revenues, male farmers reported higher outcome values than women farmers for all interventions.

Table 4-9: Partnership and Transfer Impacts by Gender: Regression Adjustment estimates (by crop owner)

		PPP Membership	Seed credit Transfer	Market Transfer	Knowledge Transfer	PPP Membership	Seed credit Transfer	Market Transfer	Knowledge Transfer
		Female owned crop				**Male owned crop**			
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Productivity (Kg/ Hectare)									
ATE	PPP intervention	153.473**	94.204	26.569	136.301	177.928***	131.040***	21.937	60.088
		(61.373)	(80.208)	(56.082)	(84.150)	(54.170)	(50.479)	(56.564)	(53.322)
POM	0(PPP intervention)	665.024***	699.835***	703.407***	699.841***	745.163***	766.623***	812.985***	790.242***
		(28.282)	(24.699)	(23.596)	(24.113)	(37.207)	(28.244)	(24.842)	(28.364)
ATET	PPP intervention	144.197***	109.268**	120.877**	109.192**	185.711***	186.578***	119.951**	136.581***
		(48.284)	(48.599)	(53.869)	(48.555)	(53.674)	(45.551)	(48.377)	(45.416)
POM	0(PPP intervention)	624.059***	626.304***	622.983***	630.452***	709.430***	713.199***	770.626***	736.683***
		(35.997)	(30.825)	(32.081)	(29.640)	(46.187)	(34.444)	(31.680)	(34.358)
N		669	669	669	669	885	885	885	885
Volume marketed (Kg/ Hectare)									
ATE	PPP intervention	158.021***	112.113*	27.776	147.172*	157.239***	136.696***	34.796	81.555*
		(58.247)	(65.036)	(47.251)	(83.098)	(47.235)	(46.175)	(50.918)	(48.610)
POM	0(PPP intervention)	474.506***	504.090***	508.903***	502.076***	556.986***	573.654***	609.032***	586.249***
		(24.678)	(22.279)	(20.937)	(21.366)	(32.852)	(25.792)	(22.296)	(25.472)
ATET	PPP intervention	126.506***	85.846*	102.734**	105.278**	145.491***	141.732***	101.532**	123.294***
		(42.128)	(44.225)	(46.024)	(42.239)	(47.782)	(42.462)	(43.048)	(40.936)
POM	0(PPP intervention)	449.015***	464.490***	445.275***	446.946***	538.317***	544.105***	576.529***	542.842***
		(31.360)	(29.636)	(27.786)	(25.716)	(41.199)	(32.615)	(28.258)	(31.0512)
N		669	669	669	669	885	885	885	885
Share of output marketed									
ATE	PPP intervention	0.088***	0.084***	0.081***	0.079***	0. .075***	0.071***	0.041	0.068***
		(0.023)	(0.024)	(0.020)	(0.024)	(0.021)	(0.022)	(0.025)	(0.025)
POM	0(PPP intervention)	0.634***	0.644***	0.651***	0.646***	0. 658***	0.665***	0.674***	0.663***
		(0.017)	(0.014)	(0.012)	(0.014)	(0.018)	(0.014)	(0.011)	(0.015)

ATET	PPP intervention	0.073***	0.072***	0.068***	0.068**	0. 059***	0.061**	0.063***	0.065***
		(0.027)	(0.026)	(0.026)	(0.027)	(0.026)	(0.024)	(0.023)	(0.025)
POM	0(PPP intervention)	0.632***	0.635***	0.641***	0.638***	0. 658***	0.659***	0.663***	0.653***
		(0.024)	(0.022)	(0.020)	(0.022)	(0.024)	(0.021)	(0.017)	(0.022)
N		671	671	671	671	891	891	891	891
Revenue (UGX/Hectare)									
ATE	PPP intervention	0.295***	0.200*	0.185	0.229**	0.293***	0. 313***	0. 096	0. 218**
		(0.111)	(0.117)	(0.128)	(0.116)	(0. 088)	(0. 094)	(0. 088)	(0.097)
POM	0(PPP intervention)	0.807***	0.849***	0.834***	0.845***	0. 983***	0. .998***	1.057***	1.025***
		(0.049)	(0.050)	(0.043)	(0.050)	(0. 061)	(0. 050)	(0. 041)	(0. 052)
ATET	PPP intervention	0.206**	0.181**	0.301***	0.178*	0. 304***	0. 354***	0. 335***	0. 268***
		(0.083)	(0.093)	(0.096)	(0.097)	(0. 094)	(0. 087)	(0. 094)	(0. 089)
POM	0(PPP intervention)	0.766***	0.815***	0.757***	0.828***	0. 944***	0. 960***	0. 987***	1.013***
		(0.063)	(0.063)	(0.054)	(0.067)	(0. 079)	(0. 063)	(0. 052)	(0. 066)
N		664	664	664	664	874	874	874	874

Notes: POM is the Potential Outcome Mean which in this case is the mean when the intervention is 0 (never received help from the intervention). All of the regressions are controlled for head education, household size, farmer group membership and round fixed effects. * $p<0.1$; ** $p<0.05$; *** $p<0.01$.

In the IPWRA, the outcome model is assumed to be linear while the treatment model, logistic.

Because splitting the sample reduces the size of observations in the regression, these results should be interpreted with caution. If data availability allows, it would also be interesting to show the same analysis with farmers disaggregated by the sex of the household head than crop/plot owner. This is important because intrahousehold dynamics in bean crop production, marketing and use of proceeds may vary between households and thus affect the effects of the interventions.

4.6. Critical control points in managing and sustaining Ag- public-private partnerships at the farm level

Following the implementation of CultiAf-Ag-PPP, the stakeholders/partners involved were asked to draw on their experiences as to what would be critical control points in successfully managing an Ag-PPP at farmer level. This section gives a summary of key issues noted. First, four levels of assessing critical control points identified were initiation/conceptualizing of the PPP, rolling out PPP operations, local level management of the PPP and stakeholder linkages and relationships during delivery of intended interventions. These are intended to proactively identify issues and apply actions to avoid potential negative effects so as to create win-win scenarios at farm level.

In starting/ conceptualizing the PPP, these are the critical aspects to consider:

1) Ensuring that all of the stakeholders who are expected to be part of the PPP take part in setting the modalities of operation. At this stage, its key to know who will be involved in the PPP, what roles they will play, and the level the PPP will operate at for example at individual farmer level, farmer group level, cooperative level among others.

2) The conceptualization stage is the point where stakeholder expectations need to be identified and managed and avenues to ensure sustainable operationalization of the PPP put in place.

3) At this stage, selected PPP partners need to put in place a roll out plan. This plan should include among others: the key interventions that the PPP will put in place, the stakeholder that will roll out

the interventions and their roles. Also, a detailed plan of how the interventions will be rolled out, monitored and evaluated needs to be formulated.

Next is the operationalization of the PPP. Once the ground rules and responsibilities have been set, the key aspects to watch out for in the Ag-PPP could include:

1) Meeting with downstream beneficiaries of the PPP, in this case the farmers selected to be part of the PPP. They should be informed about what the PPP is about and their views of how operations should be put in place collected. If possible, it is of great benefit to reach the very last farmer or beneficiary of the PPP.

2) Creating direct linkages between partners. Clear contracts/memorandums of understanding detailing how processes will be run need to be put in place. For example, clear documentation is needed for product supply, including volumes and the quality of the product required, supply schedules, product aggregation, payment means and timing, and penalties for defaults, among others. Farmers say, "they hate being cheated or having a feeling of being cheated" and agribusiness firms "want the best of the product that they are sourcing." It is critical that all the partners involved in the business-to-business linkage understand each other and have clear guidelines for operations set out. At the stage of operationalizing the PPP, no partner should impose their will on the other. Instead, all operations need to be guided by mutual consent and compromise.

3) The principle of "detect and correct" should guide the operationalization of the PPP. Detection of issues/events that may affect PPP operations should occur in a recurrent process with corrective actions implemented immediately.

At the stage of local management of the PPP, the key persons identified at initiation stage are fundamental to ensure smooth management.

1) This is the point where local leadership including district/province leaders, field extension agents, village enterprise agents, farmers and group leaders, and community leaders play a vital role in overseeing day to day PPP operations.

2) In managing the Ag-PPP, its hard to detach PPP operations from what happens in the community and its norms. As such, upstream PPP management needs to be in concert with local issues and how they could affect operations. Regardless of the intervention, gender issues, and community norms need to be followed for successful linkages. For example, in delivering trainings/meetings, all processes leading up to the event need to be informed and consider gender and community norms issues. How the event is advertised, how the venue is chosen, the timing of the event, who should attend, how facilitation is conducted, how evaluations are conducted etc. all need to be done with a gender and community norm lens.

3) Local leadership needs to have their abilities built in various aspects about the PPP and its operations. Mistakes and PPP mismanagement at the local level could derail PPP operations and affect gains made at other levels.

Stakeholder linkages and relationships during delivery of intended interventions. What happens among upstream actors and managers of the PPP may have significant impacts on farmers and efficiency of PPP operations. Here, clear relationships among PPP managers need to be developed, roles in implementing interventions streamlined, and boundaries for operationalization set. When different stakeholders are delivering services, they should be in tandem to avoid conflicts and creating confusion among the farmers. Also, high-level management of the PPP should have in place checks and balances to manage potential deviation from plans, avoid farmer exploitation and de-risk PPP interventions.

4.7. Discussion, program, and policy implications

While this analysis is based on only one important crop in Uganda’s farming system, the study’s estimates provide some evidence for the importance and economic benefits to farmers of using PPPs to promote innovations that increase production, productivity, market participation, and income. The study did not intend to highlight the importance of beans in the farming system. Rather, it intended to supply evidence of the potential roles and wider impact for which Ag-PPPs can be leveraged in delivering gains for development interventions in developing countries.

This essay analyzed the economic benefits created by an Ag-PPP with multiple transfers among farming households in a rural setting. Why does this study and the results matter? Ag-PPPs are being touted as a panacea for improving productivity and driving pro-poor growth in the agriculture and food sectors. This has spurred funding of programs with cross-cutting approaches aimed at achieving wider impacts. These findings show that by leveraging on its potential to create synergies, the CultiAf-Ag-PPP created positive outcomes for farming communities, and stimulated increased production from targeted interventions. Each component of the PPP contributed positively to production and market outcomes. As such, the study shows how a PPP can lead to positive impacts when well designed and managed and thus positively fits in the theory of change.

The positive benefits implied are robust to different specifications. Findings imply that a PPP can be a good platform for fostering production, increasing incomes, and strengthening a local value chain. The PPP increased reported productivity, the volume of production marketed, revenues and share of bean allocated to the market. Documentation of international experiences and case studies on the performance of different PPPs, mostly focusing on descriptive and qualitative analysis, is provided by (FAO, 2016; Menezes et al., 2018; Weirowski & Hall, 2008).

When modified for other contexts i.e., crops and localities, the nature of this Ag-PPP program can inform food and development policy elsewhere. Standalone interventions have been widely implemented in low-income countries with varying levels of success. Adopting and adapting such programs to fit the PPP framework could have wider impacts. While the CultiAf-Ag-PPP attempted to incorporate sustainability, in essence serving as a catalyst for better opportunities for the main players, our concern is whether the knowledge gained will push actors especially farmers to explore, grow and sustain impacts at scale. Tracking the PPP beyond the program phase to evaluate sustainability issues would thus be important. For future research, the impact of such an Ag-PPP could be investigated after a passage of time. This could help measure program efficacy, its impacts and welfare changes among farmers as time of exposure changes. It would also be critical to investigate dynamics in participation intensities between men and women farmers over time.

Appendix C – Supplementary materials for Chapter 4

C1: Additional tables

Table 4-10: Correlation analysis for residual independence in transfer equations estimated as seemingly unrelated regressions

Treatment	Seed credit	Market transfer	Knowledge transfer	X^2 (p-value)
Outcome: Productivity (Kg/Ha)				
Seed credit	1.000			
Market transfer	0.9918	1.000		3206.384 (0.000)
Knowledge transfer	0.9967	0.9945	1.000	
Outcome: Bean output (Kg) sold per hectare				
Seed credit	1.0000			
Market transfer	0.9917	1.000		3204.770 (0.000)
Knowledge transfer	0.9969	0.9936	1.000	
Outcome: Share of bean output sold				
Seed credit	1.0000			
Market transfer	0.9915	1.000		3217.315 (0.000)
Knowledge transfer	0.9971	0.9912	1.000	
Outcome: Bean revenue (M UGX) per hectare				
Seed credit	1.000			
Market transfer	0.9890	1.000		3151.968 (0.000)
Knowledge transfer	0.9956	0.9909	1.000	

Table 4-11: Impact of public-private partnership and transfers on bean productivity: DID estimates with without district fixed effects

	Dep. Variable: Bean farmer productivity (Kg/Ha)			
	PPP Membership	**Seed credit Transfer**	**Market Transfer**	**Knowledge Transfer**
	1	2	3	4
Intervention X time	196.979***	175.836**	220.774***	149.029*
	(70.988)	(74.132)	(91.393)	(76.025)
Intervention	20.785	-0.947	-80.474**	2.522
	(76.596)	(62.131)	(59.682)	(66.219)
TIME (1= post-treatment)	-260.249***	-229.692***	-199.234***	-214.914***
	(44.731)	(37.994)	(36.388)	(36.576)
Constant	861.541***	859.320***	848.387***	851.713***
	(73.663)	(72.750)	(70.070)	(72.669)
District fixed effects	No	No	No	No
Other covariates	Yes	Yes	Yes	Yes
N	1,554	1,554	1,554	1,554

Robust standard errors clustered at the village level are in parentheses. * p<0.1; ** p<0.05; *** p<0.01. The model is controlled for household head sex, education of head, household size, and farmer group membership.

Table 4-12: Impact of Public-private partnership and transfers on farmer productivity: DID estimates with district fixed effects.

	Dep. Variable: Bean farmer productivity (Kg/Ha)			
	PPP Membership	**Seed credit Transfer**	**Market Transfer**	**Knowledge Transfer**
	1	2	3	4
Intervention X time	209.054***	171.511**	270.475***	148.074*
	(71.356)	(77.880)	(85.029)	(79.267)
Intervention	3.358	13.866	-143.866**	15.324
	(73.705)	(64.128)	(55.307)	(67.546)
TIME (1= post-treatment)	-284.714***	-252.323***	-223.539***	-238.929***
	(45.719)	(38.221)	(36.7880)	(37.685)
Constant	870.935***	864.116***	858.861***	857.458***
	(71.127)	(70.386)	(68.261)	(70.491)
District fixed effects	Yes	Yes	Yes	Yes
Other covariates	Yes	Yes	Yes	Yes
N	1,554	1,554	1,554	1,554

Robust standard errors clustered at the village level are reported in parentheses. We used high dimensional fixed effects linear regression absorbing district effects (Statistics robust to heteroskedasticity). * p<0.1; ** p<0.05; *** p<0.01. The model is controlled for household head sex, education of head, household size, and farmer group membership.

Table 4-13: Impact of public-private partnership and transfers on output sold per hectare: DID estimates without district fixed effects

	Dep. Variable: Bean output (Kg) sold per hectare			
	PPP Membership	**Seed credit Transfer**	**Market Transfer**	**Knowledge Transfer**
	1	2	3	4
Intervention X time	155.710**	113.020*	231.852***	101.234
	(63.354)	(67.693)	(79.307)	(67.215)
Intervention	44.244	40.559	-103.415*	36.810
	(70.110)	(61.821)	(55.207)	(64.897)
TIME (1= post-treatment)	-221.756***	-192.263***	-180.555***	-183.524***
	(39.491)	(33.695)	(33.461)	(32.709)
Constant	653.123***	650.076***	650.308***	645.983***
	(63.322)	(62.370)	(61.063)	(62.096)
District fixed effects	No	No	No	No
Other covariates	Yes	Yes	Yes	Yes
N	1,554	1,554	1,554	1,554

Robust standard errors clustered at the village level are in parentheses. * p<0.1; ** p<0.05; *** p<0.01. The model is controlled for household head sex, education of head, household size, and farmer group membership.

Table 4-14: Impact of public-private partnership and transfers on output sold per hectare: DID estimates with district fixed effects

	Dep. Variable: Bean output (Kg) sold per hectare			
	PPP Membership	**Seed credit Transfer**	**Market Transfer**	**Knowledge Transfer**
	1	2	3	4
Intervention X time	198.967***	110.673	268.482***	101.609
	(63.523)	(71.855)	(73.034)	(71.106)
Intervention	29.787	53.616	-150.220***	47.823
	(67.979)	(63.932)	(50.797)	(66.468)
TIME (1= post-treatment)	-242.221***	-211.178***	-199.767***	-203.303***
	(39.738)	(33.160)	(33.195)	(33.117)
Constant	653.453***	647.439***	651.554***	643.767***
	(59.666)	(58.458)	(57.503)	(58.393)
District fixed effects	Yes	Yes	Yes	Yes
Other covariates	Yes	Yes	Yes	Yes
N	1,560	1,560	1,560	1,560

Robust standard errors clustered at the village level are reported in parentheses. We used high dimensional fixed effects linear regression absorbing district effects (Statistics robust to heteroskedasticity). * p<0.1; ** p<0.05; *** p<0.01. The model is controlled for household head sex, education of head, household size, and farmer group membership.

Table 4-15: Impact of public-private partnership and transfers on share of bean output sold: DID estimates without district fixed effects

	Dep. Variable: Share of bean output sold			
	PPP Membership	**Seed credit Transfer**	**Market Transfer**	**Knowledge Transfer**
	1	2	3	4
Intervention X time	0.050	0.025	0.158***	0.036
	(0.030)	(0.030)	(0.036)	(0.028)
Intervention	0.056**	0.058**	-0.068*	0.047*
	(0.026)	(0.027)	(0.035)	(0.028)
TIME (1= post-treatment)	-0.071***	-0.063***	-0.073***	-0.065***
	(0.022)	(0.018)	(0.019)	(0.019)
Constant	0.669***	0.672***	0.682***	0.673***
	(0.031)	(0.030)	(0.029)	(0.030)
District fixed effects	No	No	No	No
N	1,562	1,562	1,562	1,562

Robust standard errors clustered at the village level are in parentheses. * p<0.1; ** p<0.05; *** p<0.01. The model is controlled for household head sex, education of head, household size, and farmer group membership.

Table 4-16: Impact of public-private partnership and transfers on share of output sold: DID estimates with district fixed effects

	Dep. Variable: Share of bean output sold			
	PPP Membership	**Seed credit Transfer**	**Market Transfer**	**Knowledge Transfer**
	1	2	3	4
Intervention X time	0.050*	0.019	0.169***	0.031
	(0.030)	(0.030)	(0.038)	(0.029)
Intervention	0.053**	0.063**	-0.084**	0.052*
	(0.026)	(0.027)	(0.037)	(0.028)
TIME (1= post-treatment)	-0.074***	-0.067***	-0.078***	-0.068***
	(0.022)	(0.019)	(0.019)	(0.019)
Constant	0.676***	0.679***	0.690***	0.681***
	(0.030)	(0.028)	(0.028)	(0.028)
District fixed effects	Yes	Yes	Yes	Yes
Other covariates	Yes	Yes	Yes	Yes
N	1,562	1,562	1,562	1,562

Robust standard errors clustered at the village level are reported in parentheses. We used high dimensional fixed effects linear regression absorbing district effects (Statistics robust to heteroskedasticity). * p<0.1; ** p<0.05; *** p<0.01. The model is controlled for household head sex, education of head, household size, and farmer group membership.

Table 4-17: Impact of public-private partnership and transfers on bean revenue per hectare: DID estimates without district fixed effects

	Dep. Variable: Bean revenue (M UGX) per hectare			
	PPP Membership	**Seed credit Transfer**	**Market Transfer**	**Knowledge Transfer**
	1	2	3	4
Intervention X time	0.328***	0.189	0.524***	0.190
	(0.105)	(0.127)	(0.137)	(0.123)
Intervention	0.060	0.167	-0.175	0.149
	(0.116)	(0.103)	(0.072)	(0.104)
TIME (1= post-treatment)	-0.087	-0.024	-0.025	-0.015
	(0.061)	(0.058)	(0.054)	(0.055)
Constant	0.936***	0.922***	0.938***	0.918***
	(0.138)	(0.141)	(0.139)	(0.142)
District fixed effects	No	No	No	No
N	1,538	1,538	1,538	1,538

Robust standard errors clustered at the village level are in parentheses. * p<0.1; ** p<0.05; *** p<0.01. The model is controlled for household head sex, education of head, household size, and farmer group membership.

Table 4-18: Impact of public-private partnership and transfers on bean revenue per hectare: DID estimates with district fixed effects

	Dep. Variable: Bean revenue (M UGX) per hectare			
	PPP Membership	**Seed credit Transfer**	**Market Transfer**	**Knowledge Transfer**
	1	2	3	4
Intervention X time	0.336***	0.194	0.566***	0.197
	(0.106)	(0.137)	(0.122)	(0.131)
Intervention	0.053	0.183*	-0.234***	0.160
	(0.114)	(0.109)	(0.070)	(0.110)
TIME (1= post-treatment)	-0.109*	-0.053	-0.048	-0.044
	(0.065)	(0.058)	(0.057)	(0.056)
Constant	0.913***	0.899***	0.916***	0.894***
	(0.121)	(0.124)	(0.119)	(0.124)
District fixed effects	Yes	Yes	Yes	Yes
Other covariates	Yes	Yes	Yes	Yes
N	1,538	1,538	1,538	1,538

Robust standard errors clustered at the village level are reported in parentheses. We used high dimensional fixed effects linear regression absorbing district effects (Statistics robust to heteroskedasticity). * p<0.1; ** p<0.05; *** p<0.01. The model is controlled for household head sex, education of head, household size, and farmer group membership.

Table 4-19: Robustness check estimates for varying SUTVA assumptions

Difference in difference estimates	PPP Membership	Seed credit Transfer	Market Transfer	Knowledge Transfer
	1	**2**	**3**	**4**
Panel A: With SUTVA automatically assumed[1]				
Productivity (Kg/ Hectare)	209.338***	53.950***	184.926***	127.863***
	(75.817)	(2.298)	(2.435)	(3.363)
	1554	1554	1554	1554
Volume marketed (Kg/ Hectare)	166.688***	64.018***	130.085***	31.056***
	(68.157)	(2.269)	(1.301)	(1.158)
	1554	1554	1554	1554
Share of output marketed	0.039	0.096***	0.156***	0.084***
	(0.030)	(0.002)	(0.002)	(0.004)
	1562	1562	1562	1562
Revenue (MUGX/Hectare)	0.339***	0.124***	0.273***	0.069***
	(0.110)	(0.007)	(0.005)	(0.004)
	1538	1538	1538	1538
Panel B: Excluding Spillovers from the sample				
Productivity (Kg/ Hectare)	208.836***	107.707***	229.043***	194.239***
	(71.573)	(3.899)	(4.118)	(5.502)
	1,483	1,483	1,483	1,483
Volume marketed (Kg/ Hectare)	155.359***	191.141***	237.613***	107.623***
	(63.619)	(5.601)	(4.148)	(4.128)
	1,483	1,483	1,483	1,483
Share of output marketed	0.050*	0.074***	0.200***	0.073***
	(0.030)	(0.001)	(0.002)	(0.005)
	1,491	1,491	1,491	1,491
Revenue (UGX/Hectare)	0.339***	0.281***	0.387***	0.170***
	(0.107)	(0.010)	(0.007)	(0.007)
	1,469	1,469	1,469	1,469

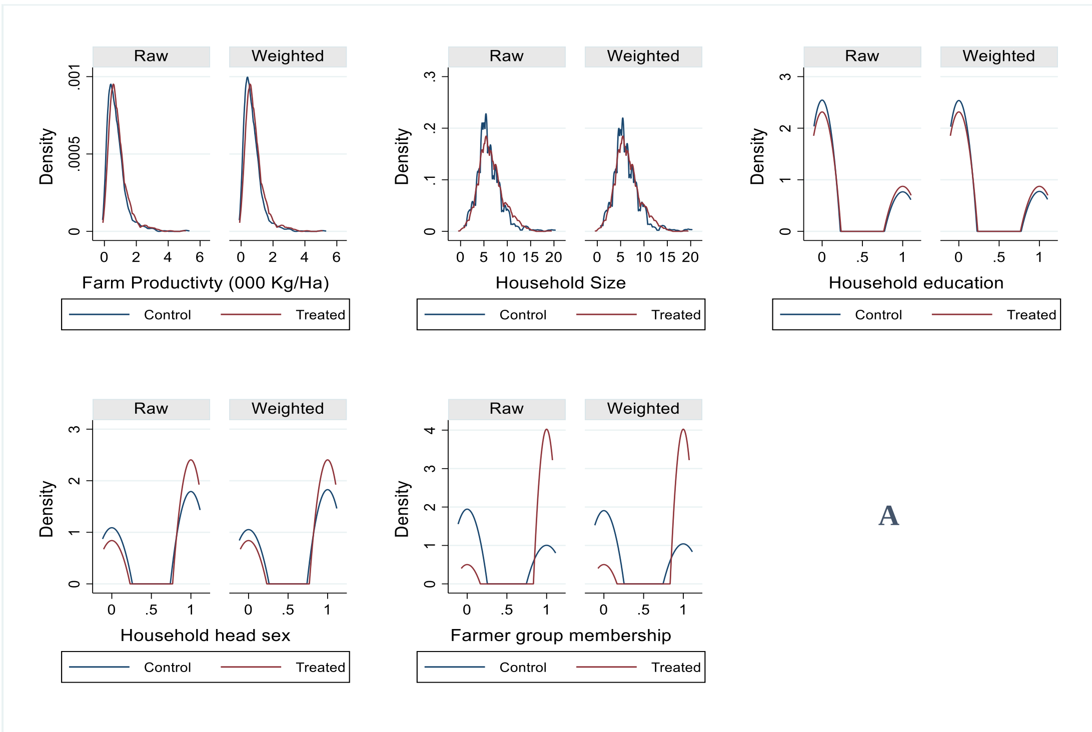
Standard errors are in parentheses. * p<0.1; ** p<0.05; *** p<0.01. The model is controlled for household head sex, education of head, household size, and farmer group membership. Results in column 2 to 4 are based on seemly unrelated regressions estimates in panel setting. Here, “near treatment effects” or spillovers are not incorporated into the model as a robustness check of the observed estimates in the chapter’s main sections.

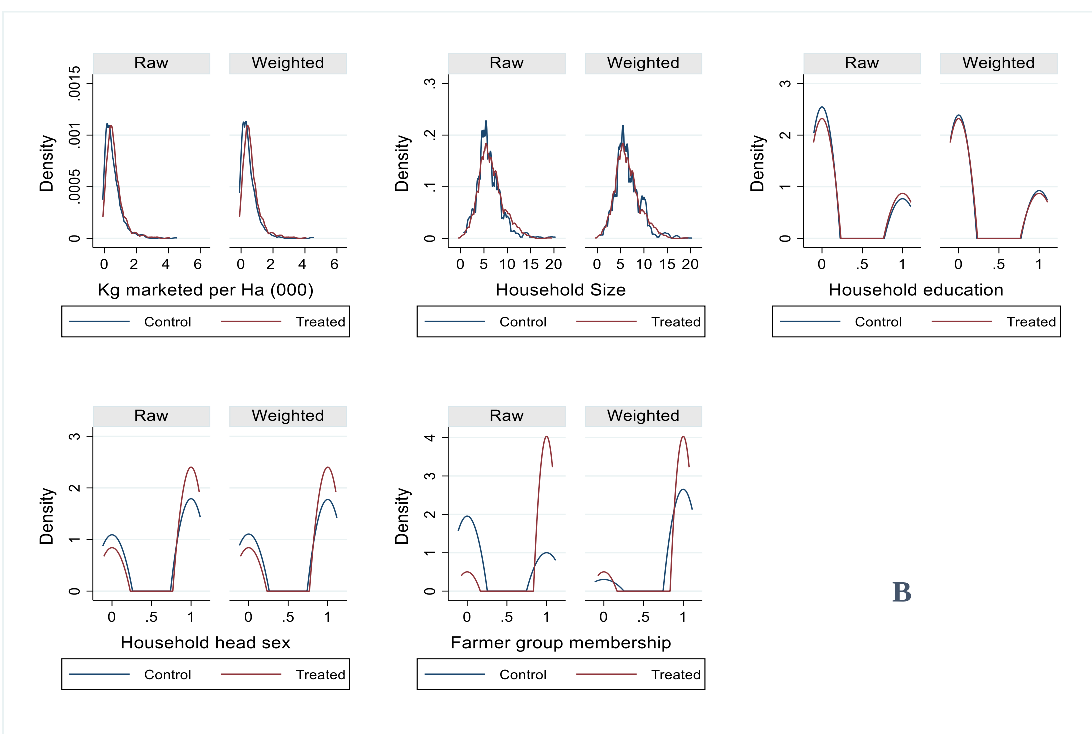
Table 4-20: Other Baseline summary statistics

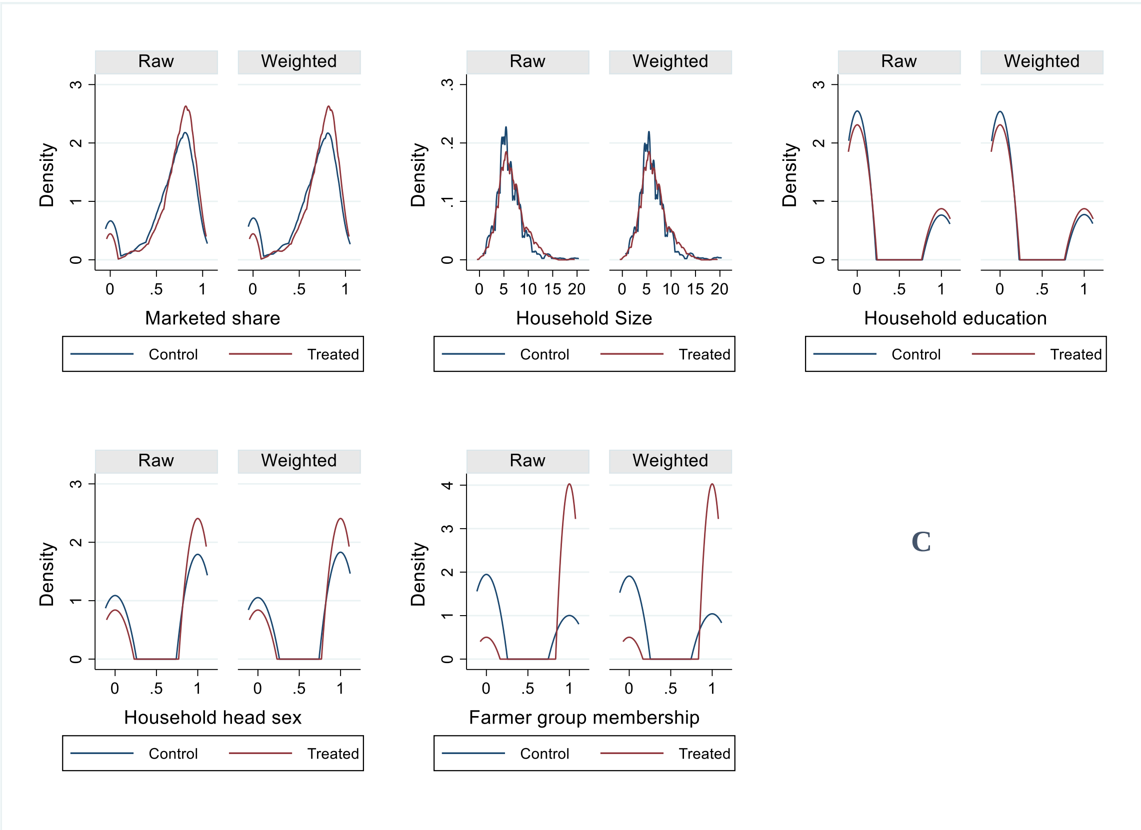
Variables	Baseline Treated group (n=266)	Baseline control group (n=333)	PPP-farmers (n=599)		Seed credit Transfer (n=599)		Market Transfer (n=599)		Knowledge Transfer (n=599)	
	Mean	**Mean**	**Coef.**	**p-value**	**Coef.**	**p-value**	**Coef.**	**p-value**	**Coef.**	**p-value**
(1)	**(2)**	**(4)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**
Produced improved varieties (1=yes)	0.65	0.45	0.202	0.001	0.357	0.000	0.061	0.478	0.338	0.000
Produced PPP varieties (1=yes)	0.35	0.20	0.149	0.003	0.355	0.000	0.058	0.362	0.337	0.000
Used pesticides (1=yes)	0.38	0.26	0.121	0.025	0.089	0.141	0.159	0.018	0.084	0.157
Used fertilizer (foliar/solid) (1=yes)	0.34	0.20	0.143	0.004	0.069	0.287	0.230	0.000	0.060	0.291
Used PPP bean variety home saved seed (1=yes)	0.11	0.09	0.016	0.514	0.122	0.003	0.050	0.200	0.093	0.045
Used improved bean variety home saved seed (1=yes)	0.25	0.22	0.032	0.424	0.484	0.293	0.099	0.121	0.014	0.759

C.2 Additional Figures

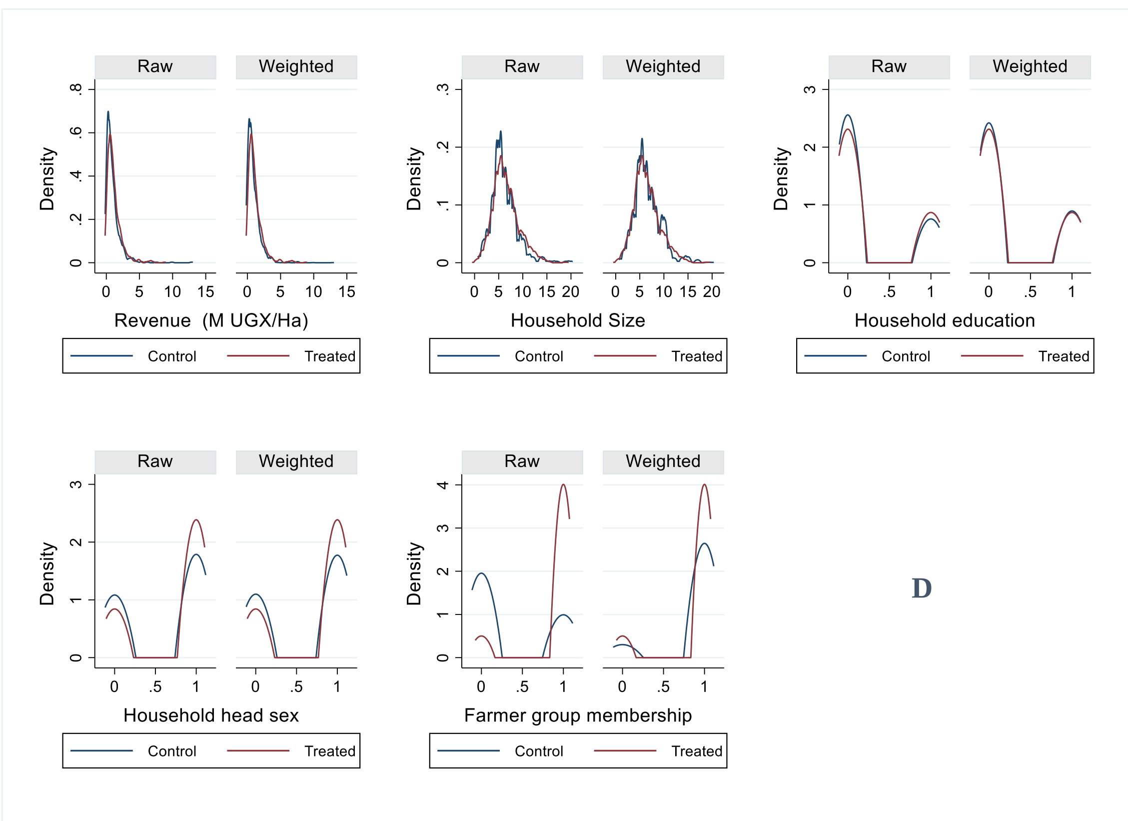
Figure 4-2: Treatment effects balance density plots for estimated IPWRA models with PPP membership as the treatment: Productivity (A), Marketed volume (B), Marketed share (C) and Revenues (D)






Raw
Weighted
Density
Marketed share
Household Size
Household education
Household head sex
Farmer group membership
Control
Treated

C


Raw
Weighted
Density
Revenue (M UGX/Ha)
Household Size
Household education
Household head sex
Farmer group membership
Control
Treated

D

C.3 Definitions of abbreviations used

ATE – Average Treatment Effect

ATET – Average Treatment Effect on Treated

CAPI - Computer Assisted Personal Interviewing

CEDO - Community Enterprises organization

CIAT - Center for International Tropical Agriculture

DID – Difference in Difference

FAO - Food and Agriculture Organization of the United Nations

GDP - Gross Domestic Product

IPWRA – Inverse Probability Weighted Regression Adjustment

KT – Knowledge Transfer

MAAIF - Ministry of Agriculture Animal Industry and Fisheries

NaCRRI - National Crops Resources Research Institute

NARO - National Agricultural Research Organization

NGO – Non-Governmental Organization

PABRA- Pan Africa Bean Research Alliance

POM - Potential Outcome Mean

PPP - Public-Private partnerships

RA – Regression Adjustment

SC – Seed Company

SCM – Seed Credit Model

TASAI - The African Seed Access Index

TOT's - Trainers of Trainers

UBOS - Uganda Bereau of Statistics

UGX – Uganda Shillings

UNISDR - UN Office for Disaster Risk Reduction

USD – US dollars

VEAs - Village Extension Agents

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Chapter 5 - Summary of Research

Given the enormous potential of small-scale farmers to service agro industries, support growing food demand and generate foreign exchange, paramount interest should be placed in understanding conditions under which such farmers operate, and to identify factors that could hasten their role as key contributors to the agricultural sector in the developing world. This dissertation assesses these issues by: (1) examining output allocation strategies and their determinants, (2) quantifying threshold levels for farm production and non-farm income that could encourage market participation, and (3) assessing the economic benefits of interventions adopted to promote market participation, food security and poverty reduction.

The first essay analyzes the ex-post decision when output is known with certainty to assess how small holder farms allocate production, and to determine factors that affect the choice of allocation strategies. It finds that levels of self-provisioning are about 66% of produced output and commercialization stands at 27%. The study's empirical findings show that household food sufficiency, crop diversification, off-farm incomes, value of production, farm liquidity and policy all affect choice of allocation strategies for farm output. An analysis implemented by dividing farms by farm size, to check if farm size may alter allocations mixes, and by distress categorization, to assess if behavior changes given distressing events, showed no major differences in choice of allocation strategies. However, while the direction of a range of factors was the same, their significance and size varied within farms.

In the second essay, the conditions that are necessary to motivate farmers to supply larger output levels to the market were analyzed. The estimation results show that the effects of policy outcomes may be incongruous with farmer needs and production circumstances if detailed and in-depth procedures are not considered in policy formulation, implementation, and analysis. The study found income and production thresholds are much higher than earned annual average non-farm incomes and farm production. While both farm and nonfarm income were positively associated with Household Food Sufficiency, thus market participation, the study found that the farm income effect was dominant. This finding suggests that implementing farm-level-based interventions may provide superior results relative to nonfarm interventions in securing food security and indirectly market participation in developing countries. Furthermore, because the study did not find a point at which proportions marketed were positively associated with household food sufficiency, the study results show that; some farmers could be giving up food sufficiency for reasons such as alleviating farm liquidity constraints to buy non-food items, services, or other calories, and may be trading more calorie-dense food for less calorie-dense foods.

The third essay investigated the economic value to farmers, created by an Ag-PPP to common bean producers in Uganda. Findings of this essay show that by leveraging the potential to create synergies among actors, the PPP created positive outcomes for farmers and stimulated increased production from targeted interventions. The study found evidence of a significant increase in sales and sales revenue due to increases in bean production. For example, the PPP farmers were likely to report about 230kg/ha higher than non-PPP farmers. Also, PPP farmers that chose from different interventions were more likely to report positive quantities of marketed produced, share of produce allocated to markets, revenues and higher productivity.