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Linking crop productivity, market participation and technology use among smallholder farmers: Evidence from Uganda

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ABSTRACT

In this paper, we establish the link between crop productivity, crop market participation and agricultural technology use among smallholder farmers. We take advantage of the latest four waves of the Uganda National Panel Survey – 2013/14, 2015/16, 2018/19, and 2019/20. First, we test for complementarity of agricultural technology use among smallholder farmers, and we do not find evidence for the combined effect of organic and inorganic fertilizers as well as pesticides and organic fertilizers on crop yields, which implies that there is lack of complementarity. More precisely, smallholder farmers mostly use these agricultural technologies in isolation. However, we find strong individual effect of organic fertilizers on cassava, beans, and coffee yields. Second, we use a two-step factor analysis to construct four technology sub-indexes for improved seeds, pesticides, organic, and inorganic fertilizers in the first step and the overall agricultural technology index in the second step. We run crop-specific models and the results re-affirm a positive effect of agricultural technology use on both cassava and coffee yields. Third, when we attempt to measure crop productivity as farm productivity, we find that a unit increase in inorganic fertilizers used increases farm crop productivity by 69%. We do not see this strong effect of inorganic fertilizers on our partial measure of crop productivity – crop yields – which implies that the way we measure crop productivity matters. We therefore conclude that of the four agricultural technologies, inorganic fertilizers have the strongest individual effect on farm productivity of smallholder farmers. Fourth, we employ the Heckman two-step technique to correct the selection bias in crop market participation outcomes. We do not find strong evidence of the effect of agricultural technology use on crop market participation, but we find that it is rather crop yields that are most critical for market participation. Therefore, a farmer's crop productivity is arguably the most critical facilitator or inhibitor of their market participation. More precisely, to boost crop market participation among smallholder farmers, increasing their productivity is a necessary condition.

Keywords: Crop productivity, market participation, agricultural technology, smallholder farmers
JEL Classifications: Q00, Q10, Q13, Q12

EXECUTIVE SUMMARY

The majority of the population in sub-Saharan Africa still derive their livelihood from agriculture. For instance, in Uganda the agriculture sector employs over 68.1 percent of the working population. Considering its numerous links with other sub-sectors of the economy such as agro-processing, agribusiness, and high value-added agro-industry, it is therefore critical to invest more in agriculture to improve productivity and farmers' incomes. Given its absorptive capacity, the sector provides the most likely entry point for creating inclusive growth and improving livelihoods in the region.

However, productivity and market participation has stagnated over the years, rendering the sector less attractive overtime. The slow growth directly affects agro-industrialization, which in turn has implications on the employment viability in the dominant agro-industry. Agricultural technology has been thought of as a remedy that can bridge the gap between the different stages of the agricultural value chain - from production up to marketing. We hypothesize that agricultural technology (such as improved seeds, fertilizers, and pesticides) adoption leads to higher crop productivity and consequently crop market participation. The main proposition is that a household that adopts technology will experience enhanced crop yields and crop sales and vice versa.

This paper leverages the recent four waves of the Uganda National Panel survey (i.e., 2013/14, 2015/16, 2018/19 and 2019/20) to link agricultural technology use, crop productivity, and crop market participation among smallholder farmers. The study is relevant for a couple of reasons. First, unlike most papers in literature that often analyze only crop productivity and agricultural technology or crop market participation and agricultural technology, we attempt to link agricultural technology to both crop productivity and crop market participation and then crop productivity to crop market participation. Second, we can observe smallholder farmers in a sub-Saharan African context over time with the use of a nationally representative longitudinal dataset. Third, we contribute to the growing literature on priorities of smallholder farmers and what is critical for them to participate in the crop market in a bid to expand the money economy and reduce the subsistence sector.

Findings of the study indicate that as we move from rudimentary implements such as hoes and pangas to more advanced machinery such as tractors and weeders, the percentage of smallholder farmers using the respective farm implement gradually reduces. In addition, we do not find evidence of complementarities in the use of improved seeds, pesticides, organic, and inorganic fertilizers among smallholder farmers. It is rather that farmers use them in isolation.

For a comparative analysis we leverage a farm level measure of crop productivity aside the partial measure of productivity – crop yields – which may not be an informative measure of crop productivity, especially among farmers that practice multi- and inter-cropping that is typical of Ugandan smallholder farmers. Results show that a unit increase in inorganic fertilizers increases farm crop productivity by 69%. We do not see this strong effect of inorganic fertilizers on crop yields – which implies that the way we measure crop productivity matters. We therefore conclude that of the four agricultural technologies considered in this study, inorganic fertilizers have the strongest individual effect on farm crop productivity among smallholder farmers.

Lastly, we do not find strong evidence of the effect of agricultural technology use on crop market participation, but we find that it is crop yields that are most critical for market participation. Therefore, a farmer's crop productivity is arguably the most critical facilitator or inhibitor of their market participation. More precisely, to boost crop market participation among smallholder farmers, increasing their productivity is a necessary condition.

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ACRONYMS AND ABBREVIATIONS

Acronym	Definition
AGRA	Alliance for a Green Revolution in Africa
EPRC	Economic Policy Research Centre
FAO	Food and Agriculture Organization
HUMA	Institute for Humanities in Africa
IFPRI	International Food Policy Research Institute
IMR	Inverse Mills Ratio
LSMS-ISA	Living Standards Measurement Survey-Integrated Survey on Agriculture
MAAIF	Ministry of Agriculture, Animal Industry and Fisheries
NAADS	National Agricultural Advisory Services
OLS	Ordinary Least Squares
UBOS	Uganda Bureau of Statistics
UGX	Ugandan Shilling
USD	United States Dollar
UNPS	Uganda National Panel Survey
USAID	United States Agency for International Development

I. Introduction

Improving agricultural productivity and market participation is a key development priority for most sub-Saharan African countries (USAID, 2013). In Uganda, the agriculture sector employs 68.1 percent of the working population (UBOS, 2020) and has numerous links with other sub-sectors of the economy such as agro-processing, agribusiness, and high value-added agro-industry. Given its absorptive capacity, the sector provides the most likely entry point for creating inclusive growth and improving livelihoods (Yeboah et al., 2018), especially among the rural population (AGRA, 2015; Magelah and Ntambirweki-Karugonjo, 2014).

Despite the significance of the sector in providing employment and being a source of livelihood, productivity and market participation has stagnated over the years, rendering the sector less attractive overtime (Ripoll et al., 2017). The slow growth directly affects agro-industrialization, which in turn has implications on the employment viability in the dominant agro-industry (Guloba et al., 2021). The low productivity and market participation is partly blamed on the low uptake of agricultural technology (such as improved seeds, fertilizers, pesticides, and herbicides) among farmers, yet improved crop output enhances both crop market participation and performance (Donkor, Onakuse, & Bogue et al., 2019).

Technology bridges the gap between the different stages of the agricultural value chain - from production up to marketing (Gebeyehu, 2016). For instance, mobile phones and internet access provide easy access to information on better agricultural practices, and consequently create opportunities for smallholder farmers (Kosec et al., 2018). The use of improved technology is associated with higher earnings which reduces household poverty (Kassie et al, 2011; Minten et al, 2007). Despite the numerous documented advantages, the adoption rate for improved agricultural technologies in Uganda and many other sub-Saharan African countries has lagged other regions (Kasirye, 2013; World Development Report, 2008). Additionally, the agriculture sector is known to play a key role in the green revolution success experienced in Asian countries (Ravallion and Chen, 2004). Therefore, this paper establishes the link between crop productivity, crop market participation and agricultural technology use among smallholder farmers in a sub-Saharan country context using the most recent four waves – 2013/14, 2015/16, 2018/19, and 2019/20 – of the Uganda National Panel Survey data.

First, we test for the complementarity of agricultural technology use among smallholder farmers by investigating whether there is any combined effect of selected agricultural technologies on crop yields. We do not find evidence for the combined effect of organic and inorganic fertilizers as well as pesticides and organic fertilizers on crop yields, which implies that there is lack of complementarity. More precisely, smallholder farmers mostly use agricultural technologies in isolation. However, we find a strong individual effect of organic fertilizer usage on cassava, beans, and coffee yields. Since organic fertilizers can relatively be accessed easily compared to inorganic fertilizers or improved seeds, it presents an opportunity for smallholder farmers to boost their yields, but overall usage of organic fertilizers must improve from the current adoption rate of about 8%.

Second, we use a two-step factor analysis to construct four technology sub-indexes for improved seeds, pesticides, organic, and inorganic fertilizers in the first step and the overall agricultural technology index in the second step. We then run crop-specific models and results re-affirm a positive effect of agricultural technology use on both cassava and coffee yields. Although insignificant, we find the same positive effect on maize, beans, and banana food yields.

Third, for a comparative analysis we leverage another measure of crop productivity by measuring productivity at a farm level. Recent literature has emphasized that crop yields – a partial measure of productivity – may not be an informative measure of crop productivity, especially among farmers that practice multi- and inter-cropping (Aragon et al., 2022) which is typical of Ugandan smallholder farmers. We find that a unit increase in the usage of inorganic fertilizers increases farm crop productivity by 69%. We do not see this strong effect of inorganic fertilizers on crop yields – which implies that the way we measure crop productivity matters. We therefore conclude that, of the four agricultural technologies considered in this study, inorganic fertilizers have the strongest individual effect on farm crop productivity among smallholder farmers.

Fourth, we employ the Heckman two-step technique to correct for selection bias in crop market participation outcomes. In the first step we estimate probit models of market participation in the Banana, Cassava, Maize, Beans, and Coffee market. In the second step we estimate pooled ordinary least squares on the value of crop sales for all the five respective crops. The model required the identification of exclusion restrictions or auxiliary variables. Those are variables that can predict market participation, but may not explain the value of crop sales, for example, agricultural extension services may influence the farmers' decision to participate in the crop market but may not directly affect the value of crop sales. So, such variables are included in the first step regressions only. Our analysis does not find strong evidence on the effect of agricultural technology use on crop market participation, but we unearth the fact that it is rather crop yields that are most critical for crop market participation – this is true for banana and cassava. More precisely, the amount of the crop output produced by the farmer has a big influence on their market participation outcomes. We argue that it could be partly attributed to the pressing food needs faced by smallholder farmers and the fact that such food needs must be met before a farmer decides to sell their harvest on the crop market. Failure to satisfy these food needs may lead to non-participation in the crop market.

Unlike most studies in literature that often analyze the nexus between crop productivity and agricultural technology or crop market participation and agricultural technology, we take another approach in this paper. Firstly, by linking agricultural technology to both crop productivity and crop market participation and then crop productivity to crop market participation we attempt to establish the relationship between agricultural technology use and crop yields as well as farm crop productivity. Secondly, we can observe changes in agricultural technology adoption among smallholder farmers in a sub-Saharan African context over time with the use of a nationally representative longitudinal dataset. Thirdly, we contribute to the growing literature on the importance of crop productivity measurement – by comparing both partial and total factor productivity measures.

The rest of the paper is organized as follows. Section 2 explores the existing literature on crop productivity, crop market participation and agricultural technology use. Section 3 advances the conceptual framework that links agricultural technology use to crop productivity and market participation. It also highlights the estimation strategy, models, and gives a description of the data. Section 4 highlights the results and the discussion of our findings, whereas section 5 concludes.

II. Link between crop productivity, market participation, and agricultural technology use

Crop productivity and technology use nexus

The majority of the population in sub-Saharan Africa has agriculture as their main source of livelihood and there is an increasing interest in agricultural investment to improve productivity and rural incomes. Agricultural productivity can simply be defined as the volume measure of production (output) divided by the volume measure of inputs. The most common forms of productivity are mainly land productivity (volume of output / planted area) and labor productivity (volume of output / units of labor employed). In addition, output can be defined as the number of animals by species, livestock production by product in quantities and values whereas inputs include the total area of land planted for each crop, the share of land used for pasture, among others (FAO, 2017).

South Asia and Africa, being the home for most of the poor, have experienced a relative stagnation in agriculture productivity in recent decades. This is due to the low adoption of improved technologies for sustainable farming systems among farmers, for example, the demand for extension services, agri-business, and the use of fertilizers among others. This underscores the need for new innovations to improve farmers' livelihoods.

To boost the agricultural sector productivity, there is a need to adopt and use a wide range of evolving technology. Technology greatly contributes to fostering sustainable improvements in the physical, social, and economic well-being of individuals and society (Fuglie et al, 2020; MAAIF, 2019; Kilimani et al., 2020). In addition, Chavas and Nauges (2020) conclude that technology adoption leads to economic growth through improved food security and improved farm productivity (Griliches 1957, Evenson and Gollin 2003; Pingali 2012; Qaim 2009; Wieczorek and Wright 2012, Acemoglu, 2002).

Despite all the benefits associated with technology adoption, it is still adoption is still low especially in developing countries like Uganda. For instance, most farmers don't use improved seeds, fertilizers and do not receive extension support, which presents an enormous productivity challenge (Odokonyero and Mbowa, 2019). Notably, some of the existing technologies such as the internet are mainly used for social networking (83.6%) and rarely for business (16.5 %), or research on agriculture (UBOS, 2021). Yet, forms of technology like the use of mobile phones, audio conferencing and portable external loudspeakers have also been found to enable farmers to access advice and link them with agricultural extension workers (FAO, 2014). This presents an opportunity to enhance productivity among crop farmers in countries like Uganda, where agriculture is the backbone of the economy. For example, Pan et al (2018) concludes that access to extension services is a big contributor to food security as well as agricultural productivity among Ugandan farmers. Notably, the decision to improve crop productivity by adopting improved production techniques is dependent on several factors. Plainly, it is easy to conclude that adoption of technology improves crop productivity. However, there is a need to take into consideration the requirements and/or conditions under which farmers will adopt and use the technology.

Given the heterogeneity among farmers, adoption of a given technology to improve agricultural productivity is highly dependent on the existing farmer knowledge of the technology, and how easy it is to learn how to use it (Marra et al, 2003; Abdulai & Huffman 2005). Thus, farmers who are familiar with the technology tend to be the earlier adopters and users, while those who need time to learn tend to adopt at a later stage. In addition, the spread in the adoption is faster for farmers who are organized in farmer groups compared to those operating individually (Beaman et al. 2018; Pan et al. 2018; Sulaiman 2018; BenYishay and Mobarak 2019; Omotilewa, Ricker-Gilbert, and Ainembabazi 2019).

Furthermore, a farmer is more likely to adopt technology that is less costly in comparison to the marginal gain from using it. Omotilewa et al (2019) showed that subsidizing an entirely new agricultural technology (hermetic storage bags for maize and other grains) increased adoption among smallholders in Uganda, both directly and indirectly through spillover effects.

Crop market participation and technology use nexus

The key drivers of economic growth have been identified to be through agriculture and natural resources (World Bank, 2017) which in recent times have been revamped through technological innovation and the adoption of new technology basically in the agriculture sector – the backbone of many developing countries (Chavula, 2014). Therefore, improving the sector market participation and performance is a priority of many governments. Agricultural market participation and performance involves activities that enable a producer to find new buyers, build and maintain relationships with current buyers, and access market research to manage supply, anticipate demands and establish prices (USAID, 2013).

New and emerging technologies like smart phones and the use of internet more broadly have been found to enhance agricultural market participation but also help to diversify market options (Mwesigye et al, 2020). Hamill (2017) postulates that market information services, mainly those based in mobile phones and tablets, can enhance crop farmer’s ability to access markets which in turn helps them to match consumers’ demand and this not only improves information flow, but also decreases transaction costs. Crop farmers use mobile phone technology to build a network of contacts, draw on wider expertise to obtain critical information more rapidly, and make better decisions, particularly related to transportation and logistics, price and location, supply and demand, diversification of their products base, and access to inputs among others. Based on the commendable role played, many smallholder crop farmers have recently embraced different technologies to enhance their access to agricultural markets (Ogutu et al., 2014; Okello et al., 2010) hence dealing with market failure (Merfeld, 2020; Barrett, 2008). Such technologies are seen as important tools to enhance farmers' access to better paying agricultural markets and perhaps avoid market failure (Katengeza et al., 2011).

Following the outbreak of the COVID-19 pandemic that disrupted the global supply chains (including agriculture), many farmers have continued to embrace technology. In Uganda the banning of movements and physical contacts during the lockdown led farmers to embrace digital technologies to markets their products and be able to receive supply of inputs. In addition, many have joined social media platforms which has led to the rise of internet use to 64% in 2021 and out of which 16.5% use it for marketing of their businesses (UBOS, 2021). This presents an opportunity to leverage technology to create more market opportunities for agricultural produce and bridge the existing gap in the value chain, particularly between crop production and marketing. The evolving world presents an opportunity to conduct a study that tries to link crop productivity, crop market participation and agricultural technology use among smallholder farmers.

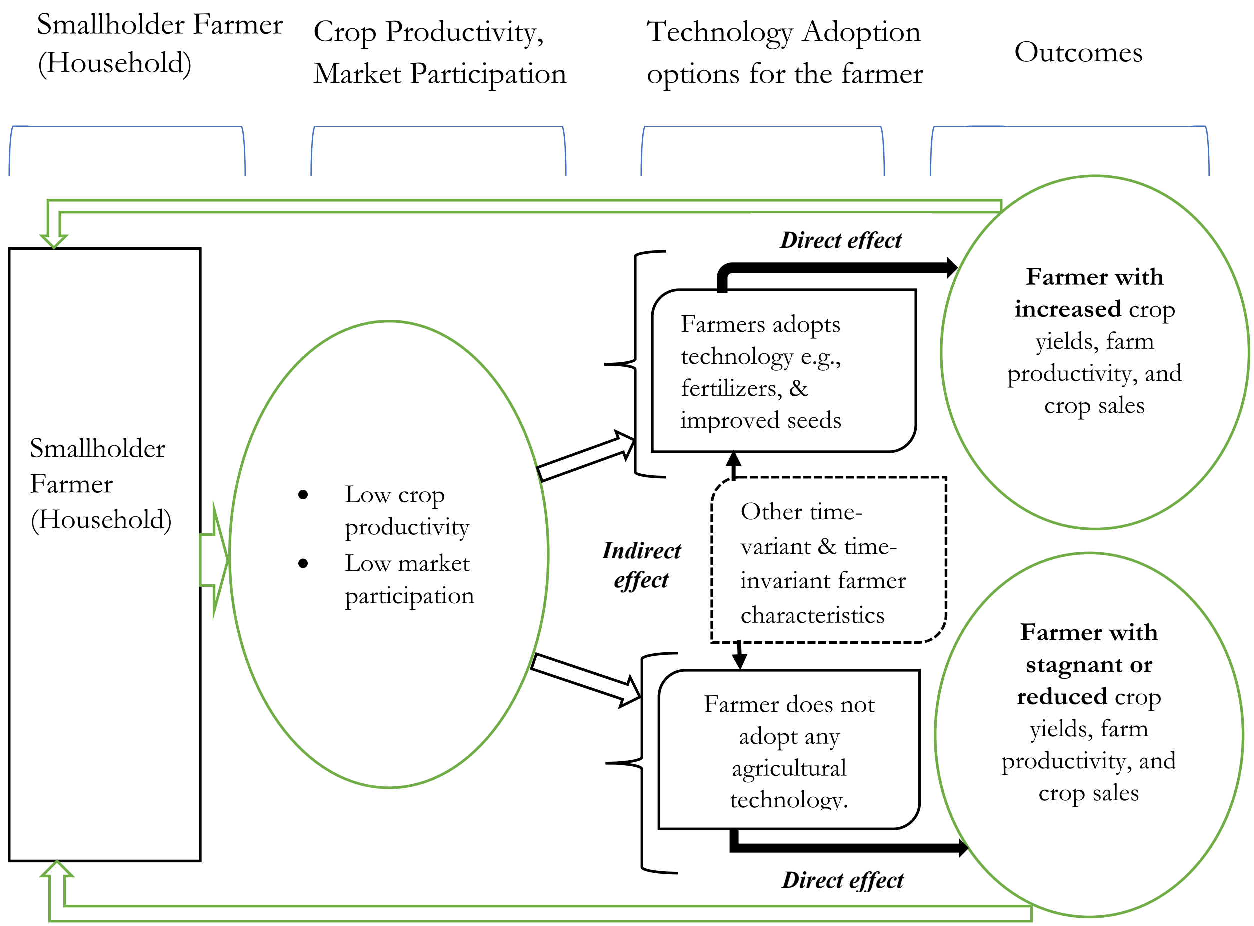
III. Methodology

In this section, we present the different methods and techniques that were adopted to achieve the study objectives. We present the conceptual and theoretical framework, the empirical strategy, and describe the data used.

Conceptual framework

To understand the effect of technology use on crop productivity and market participation, we conceptualize a model of households (smallholder farmers) while differentiating those that adopt the agricultural technology from those that do not. We expect that the two groups experience two different outcomes as summarized in Figure 1. The main proposition here is that a farmer that uses technology is expected to experience higher crop productivity through increased yields and farm productivity as well as higher market participation.

Figure 1: Crop productivity, market participation and technology use nexus



Source: Authors' own construction based on the ideas of Mpuuga, Bulime & Ogwang (2023)

We hypothesize that technology adoption leads to higher crop productivity and higher crop market participation. We recognize the possibility of a bidirectional causality between technology adoption and market participation as well as crop productivity and the selection bias of crop market participation outcomes. Moreover, Benfica et al (2017) postulate that agricultural productivity and market participation intensity have a bidirectional causality. The main proposition is that a household that adopts technology will experience enhanced crop yields and crop sales and vice versa.

Just like Muyanga and Jayne (2014), here the smallholder farmer (household) and the firm are interdependent, whereby some farm inputs like inorganic fertilizers, pesticides, and improved seeds are purchased, and some outputs are sold in the markets. More precisely, a household is both a producer and consumer.

Empirical strategy

This section describes the econometric approaches and techniques applied to achieve the study objectives. It explicitly highlights how each variable was measured.

Crop productivity

To examine the effect of technology use on crop productivity we use firstly, household-level crop yields calculated in kilograms of output per acre – land productivity using quantity produced of a single crop. We estimate the following equation, where the unit of observation is household i in year t. $AgricTechn_{it}$ is the single or a combination of agricultural technologies adopted by household i at time t, and X is a vector of socioeconomic and demographic characteristics which may directly or indirectly affect crop yields. The general model is specified as follows:

$$LogYields_{it} = \alpha + \beta AgricTechn_{it} + X'_{it}\theta + \varepsilon_{it} \quad (1)$$

The composite error component $\varepsilon_{it} = \mu_i + \lambda_t + u_{it}$, where μ_i is the unobservable individual-specific effect, λ_t is the unobservable time-specific effect, u_{it} is the remainder of the disturbance. Since our outcome is continuous, we run a Hausman test after estimating random effects and fixed effects models for each of the five crops – Banana, Cassava, Maize, Beans, and Coffee – to choose the best model. The null hypothesis is that the preferred model is random effects, and the alternate hypothesis is that the fixed effects model is better. Essentially, the test looks to see if there is a correlation between the unique errors and the regressors in the model. We transform the outcome variable by taking its logarithm (*LogYields* = logarithm of yields in kilograms of crop output per acre). The agricultural technologies under consideration are improved seeds, pesticides, organic, and inorganic fertilizers, and robust standard errors are reported in all our models.

For comparative purposes, we construct an alternative measure of crop productivity at a farm level. The idea is to measure agricultural output and input use for each farm in each period. Recent literature has emphasized that crop yields, which is a partial measure of productivity may not be an informative measure of crop productivity, especially among farmers that practice multi- and inter-cropping (Aragon et al., 2022). This is typical of smallholder farmers in Uganda where many crops can be grown on the same parcel or plot thus making it almost impossible to attribute land, labor, and other inputs to individual crops.

More precisely, we aggregate the crop output produced of all crops grown by the household from all its parcels which make up the household farm. This is the farm crop out for the two seasons in a year (panel wave). We also calculate the unit value in Ugandan shillings (price per kilogram) for each crop grown in a given household parcel each year. We use the median unit value (median price per kilogram) for each crop in a given year and the farm crop output to get the real farm crop output for each household. For the land and labor inputs, first, we calculate the total area cultivated in acres by summing up all the parcels cultivated whether the farmer owns or has user rights like renting and the data is available as GPS and farmer-reported size. Noteworthy, GPS data has several missing values and so we leverage farmer-reported sizes to fill up the missing data. Secondly, following Aragon et al (2022) we also measure labor as the total number of person-days on the farm – both family and hired labor. For the 2018/19 and 2019/20 waves where some family labor is not reported and only hired labor data is available, we use the median person-days (both family and hired labor) within a district for the 2013/14 wave to fill up these gaps for consistence in the measurement of inputs – we acknowledge this data limitation. Therefore, the real farm crop productivity model follows a similar structure as the crop yields model and is specified as follows:

$$FarmProductivity_{it} = \alpha + \beta AgricTechn_{it} + X'_{it}\theta + \varepsilon_{it} \tag{2}$$

Construction of the technology index

To complement our measure of agricultural technology, we construct a technology index $Tindex$ using factor analysis considering the four agricultural technologies – organic fertilizer, inorganic fertilizer, pesticides, and improved seeds. The factor analysis technique finds the correlation between factors and calculates factor loadings for multiple common factors. These factor loadings are then used to identify exactly which common factors represent the concept measured. Consequently, the loadings are used to calculate the index as a weighted average (Sunday et al., 2022). More precisely, the technological index is being proposed as an estimation of four sub-indices, based on the four agricultural technologies adopted for this study. To produce factors that are not inter-correlated, we report rotated factor loads since they provide a clearer pattern and result in orthogonal factors. This is important as we want to identify variables to create indexes. More precisely, the sub-indexes of the agricultural technologies used by farmers are defined as: organic fertilizer sub-index (OFI) = index based on the dummy variable that is 1 or 0 if a farmer uses organic fertilizers; inorganic fertilizer sub-index (IFI) = index based on the dummy variable that is 1 or 0 if a farmer uses inorganic fertilizers; improved seeds sub-index (ISI) = index based on the dummy variable that is 1 or 0 if a farmer uses improved seeds; and pesticides sub-index (PI) = index based on the dummy variable that is 1 or 0 if a farmer uses pesticides.

We construct the four sub-indexes for each panel wave separately to be able to compare agricultural technology usage over time. In addition, this enables us to understand the percentage contribution of each individual technology to the overall index over the four waves. The overall agricultural technology index is specified as follows;

$$Tindex \quad = \quad \beta_1 OFI + \beta_2 IFI + \beta_3 ISI + \beta_4 PI \tag{3}$$

Where the β parameters are the respective factor analysis coefficients estimated using inter-correlations among our four sub-indexes. These are weights that represent the strength of the correlation of individual agricultural technologies with the overall index. Following Jayne et al (2009) and Sunday et al (2022), we normalize our index to vary from 0 to 100 as follows;

$$Tindex_{norm} = \left(\frac{t - min_t}{max_t - min_t}\right) \text{x } 100 \tag{4}$$

Where $Tindex_{norm}$ is the normalized technology index, t is the value of the index before normalizing, whereas min_t and max_t are the minimum and maximum values of the index, respectively. We treat 0 and 100 as extreme points within the sample and the respective econometric model is specified as follows;

$$LogYields_{it} = \alpha + \beta Tindex_{norm_{it}} + X'_{it}\theta + \varepsilon_{it} \tag{5}$$

Crop market participation

For crop market participation, a farmer is faced with a discrete choice of whether to participate in the crop market or not. Consequently, the discrete participation decision affects the performance. We measure a farmer's market participation by the value of the individual crop sales in Ugandan Shillings (UGX) which implies that the market participation sub-sample exhibits non-randomness and eventually introduces sample selection bias. Heckman (1979) suggests a remedy in his two-step approach that recommends regressing the discrete choice model with a probit model – selection model – followed by an ordinary least squares (OLS) model in the second step for the continuous outcome of value of sales, while controlling for the Inverse Mills Ratio (IMR) commonly known as the Heckman lambda (λ). The significancy of the IMR justifies the importance of selection and the need to run a Heckman two-step model. Otherwise, with a non-significant IMR, the OLS model is enough. Following Boughton, Mather, Barret et al (2007), we first estimate probit models of market participation in the Bananas, Cassava, Maize, Beans, and Coffee market. As discussed earlier, the model requires the identification of exclusion restrictions /auxiliary variables, i.e., variables that can predict market participation decision, but not the value of crop sales. For example, extension services from the National Agriculture Advisory Services (NAADS) can influence the farmers' decision on whether to participate in the crop market but may not directly affect the value of crop sales. For such a variable we include it only in the first step of our regression. Other auxiliary variables in our model are usage of oxen to plough.

From Puhani (2000) we estimate selection models by running a probit regression on the crop market participation $Market_{it}$ outcome of farmer i at time t. Secondly, we run pooled OLS models for the main outcome model $ValueCS_{it}$ – value of crop sales in Ugandan Shillings (UGX) at time t. We are interested in the value of crop sales, but we do not observe crop sales of farmers who do not participate in the crop market. We assume that farmers that are only able to achieve a comparatively low value of sales given their level of technology adoption will decide not to participate in the market. The respective models are summarized as follows:

Selection Model - Probit:

$$Market_{it} = \alpha + \beta AgricTechn_{it} + X'_{it}\theta + \varepsilon_{it} \tag{6}$$

Main Model - OLS:

$$ValueCS_{it} = \alpha + \beta AgricTechn_{it} + X'_{it}\theta + \varepsilon_{it} \tag{7}$$

Where $Market_{it}$ is a dichotomous outcome of 1 if a farmer i participates in the crop market, at time t, and 0 otherwise. $ValueCS_{it}$ is the value of crop sales in UGX by farmer i at time t. X represents other regressors besides technology $AgricTechn$ whereas, ε_{it} is the error term that captures every factor that is not directly included in the model. For us to capture seasonality and year-specific effects, we include year dummies, considering that the study utilizes four panel waves. By controlling for time effects in the model we set out to get the true and non-spurious relationship between the dependent and independent variables. Although modelling time is not the primary concern, time dummies greatly contributed to the reliability and parsimony of our results.

Data

The study utilizes data from the most recent four waves of the Uganda National Panel survey (i.e., 2013/14, 2015/16, 2018/19 and 2019/20), which is collected under the World Bank's Living Standards Measurement Survey – Integrated Survey on Agriculture (LSMS-ISA) project. The UNPS data spans seven waves, but due to the sample refresh that happened with the 2013/14 wave (wave 4) where one-third of the initial sample was refreshed to balance the advantages and shortcomings of panel surveys, we use the 2013/14 wave and the subsequent three waves to mitigate the problem of attrition. The panel data is nationally representative and contains information relevant for our study, including data on household landholdings, investments on land, types of crops produced, type of seeds grown by farmers, use of organic and chemical fertilizers, pesticides, agricultural labor inputs, harvest and produce marketing as well as crop sales. Agricultural data is collected through two household visits – six months apart – to account for the two agricultural seasons experienced in most parts of Uganda. Although the agricultural module provides details up to plot level, we do not perform plot level analysis due to data limitations that make it impossible to construct a panel of plots.

For this study we concentrate mainly on the five crops of Banana-food, Cassava, Maize, Beans, and Coffee. Table 1 highlights how the five most grown crops in Uganda have evolved overtime and results indicate that the number of maize farmers grew steadily from 11.8% in 2013/14 to 15.5% in 2018/19 but suddenly dropped to 6.3% in 2019/20. The huge drop in the proportion of maize farmers is a reason to worry since maize doubles as a cash and food crop, yet it takes a few months to harvest. We explore a couple of possibilities that could explain this reduction. First, we limit our sample to only farmers who were there in 2013/14 and are still in the sample in 2019/20 just so we can rule out any unbalanced panel anomalies. We find that the proportion of maize farmers slightly increases to 9.2% whereas those growing Banana-food further reduces to 11.5% in 2019/20. This implies that for maize, there is still a huge drop from 15.5% in 2018/19 to 9.2% in 2019/20. We then delve into maize market conditions between 2018/19 and 2019/20. The question we ask ourselves is whether it could be that maize farmers were responding to the prevailing market conditions to cut production. We find that maize suffered one of the lowest prices ever in 2018/19 where a kilogram of maize grain was being sold at only 200[1] Ugandan Shillings (0.06 USD) which was a huge decline from about 900 Ugandan Shillings (0.24 USD) in 2017. It is possible that in the subsequent season(s), farmers relocated their land and effort to other lucrative crops considering that maize which matures in barely four months can easily be substituted for other crops such as beans. In mid-2022 the price of maize grain per kilogram had increased to over 1600 Ugandan Shillings (0.47 USD) per kilogram in most local markets in Kampala.[2] Relatedly, the reduction in Banana growers is mainly attributed to the Banana wilt disease which ravaged the country around the same period[3].

[1] Barungi, M. (August 2018). Maize prices drop miserably: Implications and the need for price stabilizers. https://eprcug.org/blog/maize-prices-drop-miserably-implications-and-the-need-for-price-stabilisers/

[2] Advocacy Coalition for Sustainable Agriculture (June 2022). Maize price soaring higher as less supply gets to the market | Week 22, 2022. https://acsa-ug.org/maize-price-soaring-higher-as-less-supply-gets-to-the-market-week-22-2022/

[3] CGTN Africa (September 2018). Ugandan farmers struggle with banana wilt disease. https://www.youtube.com/watch?v=1e7cxp5zYfY

Table 1: Percentage of households growing the five most popular crops in Uganda (UNPS 2013/14 – 2019/20)

Crop	2013/14	2015/16	2018/19	2019/20	N	pooled sample (%)
Banana Food	23.7	22.9	14.7	12.5	1224	18.5
Cassava	17.6	15.6	12.9	23.3	1172	17.7
Maize	11.8	12.6	15.5	6.3	740	11.2
Beans	13.3	10.6	15.8	12.8	860	13.0
Coffee	8.7	9.0	7.9	13.3	654	9.9
Other crops	25.0	29.0	33.0	32.0	1958	30.0
N	1794	1618	1345	1851	6608	≅*100*

Notes: Other crops grown include, Wheat, Rice, Finger Millet, Sorghum, Field Peas, Cow Peas, Pigeon Peas, Groundnuts, Soya Beans, Sunflower, SimSim, Cabbage, Tomatoes, Onions, Pumpkins, Eggplants, Sugarcane, Cotton, Tobacco, Irish Potatoes, Sweet Potatoes, Yam, Coco Yam, Oranges, Pawpaw, Pineapples, Banana Beer, Banana Sweet, Mango, Avocado, Passion Fruit, Cocoa, Tea, etcetera.

IV. Results

Our results are both descriptive and empirical. We present the descriptive analysis where we investigate any possible differences among rural and urban farmers in Uganda. We further delve into farmers' usage of farm implements and machinery analysis while investigating the complementarity of agricultural technology usage among the farmers. We later empirically examine the effect of agricultural technology use on both crop productivity and crop market participation leveraging a range of different outcomes.

Descriptive analysis

The overall sample – with all crops grown in Uganda – consists of 88.4% rural framers and 11.6% urban farmers. In Table 2, we summarize rural farmers separately from the overall sample to ascertain whether there are differences in farmer characteristics. We do not find big differences between rural farmers and overall farmers in a pooled sample and thus for subsequent analyses we do not separate the sample.

Table 2: Summary Statistics (UNPS 2013/14 – 2019/20)

	Rural farmers		Overall sample	
Variable	**Mean**	**Std. dev.**	**Mean**	**Std. dev.**
Household and farm characteristics				
HoH is female	0.37	0.48	0.36	0.48
HoH can read and write	0.49	0.50	0.51	0.50
Household size	6.27	3.07	6.28	3.06
Area planted (acres)	0.78	1.52	0.78	1.46
Land owned- GPS (acres)	1.01	2.97	0.96	2.87
Land owned - farmers' estimate (acres)	2.51	6.32	2.49	6.45
Freehold land tenure	0.46	0.50	0.47	0.50
Leasehold land tenure	0.02	0.15	0.03	0.16
Mailo land tenure	0.03	0.17	0.03	0.17
Customary land tenure	0.49	0.50	0.48	0.50
Rain-fed parcel	0.98	0.13	0.98	0.13
HH received NAADS extension services	0.96	0.21	0.95	0.21
Use of organic fertilizer	0.07	0.25	0.07	0.26
Use of inorganic fertilizer	0.02	0.14	0.02	0.13
Use of improved seeds	0.07	0.26	0.08	0.26
Use of pesticides	0.06	0.23	0.06	0.23
Use of Ox plough	0.18	0.39	0.17	0.38
Crop productivity				
Overall Crop yields (kgs per acre)	1664.8	7155.9	1683.6	7284.4
Maize yields (kgs per acre)	1569.0	5313.5	1495.7	5006.6
Beans yields (kgs per acre)	1577.7	4985.2	1729.7	6134.2
Cassava yields (kgs per acre)	1072.1	4672.4	1130.8	4794.2
Banana yields (kgs per acre)	2517.4	11316.7	2461.8	11074.6
Coffee yields (kgs per acre)	2371.8	5190.2	2295.9	5008.7
Log farm crop productivity	8.82	3.04	8.83	3.02
Crop market participation				
Market participation (sold any of the harvest)	0.39	0.49	0.38	0.49
Overall value of crop sales (UGX)	190,981	812,589.5	208,221	1,203,976
Maize value of sales (UGX)	207,061	721,358.8	203,911	767,240
Beans value of sales (UGX)	119,356	413133.5	133,616	438,257.8
Cassava value of sales (UGX)	93,551	315,975	94,713	321,361
Banana value of sales (UGX)	213,104	648,550.9	237,761	684754.3
Coffee value of sales (UGX)	239,234	620,458.4	258,344	641,592.4

Notes: We restrict our sample to crop farming households. Rural farmers represent 88.4% (5,836) of the entire sample and only 11.6% (772) are urban farmers. Not all parcels were captured using GPS and thus for some parcels farmers' size estimates are reported and considered. To capture total household land in acres, we add all parcels provided under that household all HH parcels. NAADS = National Agricultural Advisory Services, HoH = Household head, and HH = Household.

Descriptive results in Table 2 indicate that only 39% of rural farmers participated in the crop market, whereas overall 38% participated in the crop market. We notice that yields vary across crops which justifies crop level analysis considering that different crops weigh differently and need distinct area of land to grow, for instance, Bananas need large parcels of land compared to beans and maize that are planted one plant close to each other. The majority of the land is owned customarily and approximately 98% of all farmers' parcels rely on rain as a source of water for crops. We measure crop productivity as land productivity (or yields), but for comparative purposes we also leverage farm productivity measures – total factor productivity. Crop market participation on the other hand is the value of the individual crop sales in UGX. From the results, we notice that the use of agricultural technology by farmers is very low i.e., on average less than 10% of farmers use organic fertilizers, improved seeds, inorganic fertilizers, or pesticides and only 17% use oxen to plough their land for planting. Inorganic fertilizers are the least used at only 2% for both rural farmers separately and rural and urban combined.

In Table 3, we analyze farmers' usage of different farm implements and machinery, both rudimentary and advanced machinery. We find that as we move from rudimentary implements such as hoes and pangas to more advanced machinery such as tractors and weeders, the percentage of smallholder farmers using the respective farm implement reduces. More precisely, descriptive results indicate that 99.8% of farmers use hoes whereas only 0.3% use tractors. This has direct implications on crop productivity and crop market participation.

Table 3: Farmers' usage of farm implements and machinery

Farm implement/machinery	% farmers using implement
Hoe	99.8
Pangas	93.1
Slashers	44.8
Spade	37.8
Sprayer	31.3
Pruning knives	23.0
Ox-plough	17.3
Wheelbarrows	16.0
Fork hoe	14.9
Watering cans	10.4
Ploughs	4.5
Pail	3.5
Pruning saws	1.2
Harrow/cultivator	0.9
Tractor	0.3
Sheller	0.3
Weeder	0.2
Chain/band saws	0.2
Trailer	0.03

Source: Authors' computation using UNPS data (2013/14 – 2019/20)

Complementarity of agricultural technology use

We then attempt to find out whether there is complementarity of technology usage among smallholder farmers. First, by simply describing our data we attempt to find out whether farmers view these agricultural technologies as substitutes or rather as complements. We look at the four technologies (inputs) i.e., organic fertilizer, inorganic fertilizer, improved seeds, and pesticides. The most used technology is improved seeds (7.7%), followed by organic fertilizers (6.9%), pesticides (5.6%) and the least being inorganic fertilizers at only 1.8 percent (see Table 4).

Anecdotally, the higher usage of organic fertilizers could be attributed to the ease of access as well being less costly compared to inorganic fertilizers and pesticides. For example, some of the crop farmers are also engaged in livestock farming which provides manure that is consequently used as an organic fertilizer.

Looking at the percentage usage of combinations of these inputs, we can conclude that most farmers use these technologies in isolation. This is so because only 0.9% use a combination of organic fertilizers and pesticides, 0.5% use both improved seeds and inorganic fertilizers, and 0.4 % use organic and inorganic fertilizers. This is contrary to what is recommended by agronomists whereby for a farmer to attain greater yields improved seeds should be supplemented with inorganic fertilizers. This observation is in line with what Sheahan and Barret (2017) postulate. Generally, it is believed that using only one form of technology limits the gain in yield, given that the different technology types serve relatively similar, but sometimes different purposes. In addition, Roba (2018) highlights that, although organic fertilizers improve physical and biological soil activities, they are low in nutrients, whereas inorganic fertilizers are directly accessible by plants and contain all necessary nutrients. Consequently, appropriate application of a combination of organic and inorganic fertilizers increases productivity compared to using organic and inorganic fertilizers individually.

Table 4: Complementarity of technology use

Agricultural Technology	*Usage by Households (%)*	
	Rural farmers	**Overall sample**
Organic fertilizer	6.60	6.9
Inorganic fertilizer	1.85	1.8
Organic + Inorganic fertilizer	0.35	0.4
Improved seeds	7.63	7.7
Improved seed + Inorganic fertilizer	0.52	0.5
Pesticide	5.71	5.6
Organic fertilizer + Pesticide	0.94	0.9

Source: Authors' computation using UNPS data (2013/14 – 2019/20)

We further analyze the complementarity of agricultural technology use, empirically, while controlling for year effects. We run pooled ordinary least squares, random effects and fixed effects models and use the *hausman* test to choose between the fixed and random effects model. We fail to reject the null hypothesis at 5% level of significance and then proceed to report random effects models for the respective five crops of Banana, Cassava, Coffee, Maize, and Beans (see table 5).

Our outcome for the five models is land productivity transformed by taking its logarithm (Log Yields [kgs per acre]). Due to data limitations, we test for a combination of organic and inorganic fertilizers as well as organic fertilizer and pesticides only. In both cases as reported in Table 5 and 6 respectively, we do not find any significant combined effect on all the five crops which re-affirms the results from the descriptive analysis. More precisely, there is no complementarity in technology usage which explains the prevailing low levels of crop yields in Uganda. Individually, we find a strong and positive effect of organic fertilizer usage for Cassava and Beans, but positive and not significant for Banana, Coffee, and Maize. In addition, we do not find any significant effect of inorganic fertilizer usage on crop productivity. We note that it might be due to the extremely low uptake of inorganic fertilizers in the country and thus little or nothing of the growth or reduction in crop yields can be attributed to adoption or non-adoption of inorganic fertilizers. This should not be interpreted conclusively as if inorganic fertilizers do not impact crop yields.

Table 5: Combined effect of organic and inorganic fertilizer usage on crop productivity

	Log Crop Yields (Kgs per acre)				
Variables	**Banana**	**Cassava**	**Coffee**	**Maize**	**Beans**
Organic fertilizer	0.237	3.774***	0.181	0.189	1.052**
	(0.256)	(0.578)	(0.370)	(0.619)	(0.411)
Inorganic fertilizer	1.368	1.897	0.0554	-0.253	0.327
	(1.000)	(2.241)	(0.723)	(0.748)	(0.794)
Organic x Inorganic fertilizer	-1.550		1.212	0.909	0.280
	(1.877)		(1.309)	(3.296)	(1.788)
Year dummies	Yes	Yes	Yes	Yes	Yes
Constant	6.951***	4.510***	6.442***	6.104***	6.459***
	(0.158)	(0.180)	(0.239)	(0.216)	(0.200)
Number of HHs	843	864	487	635	712
Observations	1,219	1,159	648	771	846

Notes: For the outcome of Log Crop Yields (Kgs per acre) = Logarithm of yields (kilograms of crop output per acre) we run random effects models for the respective five crop of Banana, Cassava, Maize, Beans, and Coffee. Robust standard errors are reported in parentheses. < 0.10, ** p < 0.05, *** p < 0.01 (10%, 5%, 1% level of significance respectively). HH = Household.

In Table 6, we also do not find any combined effect of organic fertilizer and pesticide usage on crop yields. Although pesticide usage is relatively higher than inorganic fertilizers' uptake, we still do not find any significant combined effect with organic fertilizers. However, there is a significant individual effect of organic fertilizer on both Cassava and Beans yields which further confirms lack of complementarity of agricultural technology usage among smallholders.

Table 6: Combined effect of organic fertilizer and pesticide usage on crop productivity

	Log Crop Yields (Kgs per acre)				
Variables	**Banana**	**Cassava**	**Coffee**	**Maize**	**Beans**
Organic fertilizer	0.162	3.506***	0.128	-0.0315	1.112**
	(0.261)	(0.618)	(0.383)	(0.695)	(0.434)
Pesticide	0.912*	0.191	0.358	0.300	0.0930
	(0.513)	(0.695)	(0.518)	(0.482)	(0.433)
Organic fertilizer x Pesticide	0.545	1.889	0.874	0.779	-0.248
	(1.104)	(1.846)	(1.029)	(1.447)	(1.142)
Year dummies	Yes	Yes	Yes	Yes	Yes
Constant	6.937***	4.506***	6.408***	6.082***	6.465***
	(0.159)	(0.180)	(0.241)	(0.217)	(0.200)
Number of HHS	843	864	487	635	712
Observations	1,219	1,159	648	771	846

Notes: For the outcome of Log Crop Yields (Kgs per acre) = Logarithm of yields (kilograms of crop output per acre) we run random effects models for the respective five crops of Banana, Cassava, Maize, Beans, and Coffee. Robust standard errors are reported in parentheses. < 0.10, ** $p < 0.05$, *** $p < 0.01$ (10%, 5%, 1% level of significance respectively). HH = Household.

Effect of agricultural technology usage on crop productivity

Controlling for factors such as area planted in acres, source of water for the farmers' parcels, and other socioeconomic and demographic farmer characteristics, we find a positive and significant effect of organic fertilizer use on cassava, beans, and coffee yields. The fact that organic fertilizers can relatively be accessed easily compared to inorganic fertilizers or improved seeds presents an opportunity for smallholder farmers to boost their yields.

Unfortunately, overall usage of organic fertilizers is still below 10% in Uganda which partly explains the persistent low levels of crop productivity among smallholder farmers. We then, use an area planted quadratic specification and confirm a non-linear relationship. More precisely, smallholder farmers in Uganda exhibit lower crop yields compared to relatively largescale farmers as shown by the negative sign on area planted, but a positive sign on its squared term. Aragon, Restuccia, and Rud (2022) also find that small farms are not necessarily more productive compared to large farms in a sub-Saharan African context which is contrary to conventional literature on agricultural productivity. We can partly attribute this to the low capacity of technology adoption as well knowledge gaps among smallholder farmers in most sub-Saharan African countries.

Table 7: Effect of organic fertilizer usage on crop productivity

	Log Crop Yields (Kgs per acre)				
Variables	**Banana**	**Cassava**	**Maize**	**Beans**	**Coffee**
Organic fertilizer	0.205	3.753***	-0.263	1.101***	0.623*
	(0.260)	(0.608)	(0.618)	(0.395)	(0.359)
Area planted	-0.279**	0.0422	-1.734***	0.0331	-0.556*
	(0.129)	(0.153)	(0.308)	(0.158)	(0.332)
Area planted x Area planted	0.0105*	-0.000167	0.257***	-0.000498	0.121
	(0.00584)	(0.00228)	(0.0584)	(0.00202)	(0.0793)
Rain fed parcels	-0.502	-0.0378	-1.555*	0.303	1.056
	(0.689)	(0.746)	(0.822)	(0.850)	(0.813)
Age	-0.00214	-0.00473	0.00814	-0.00753	-0.00585
	(0.0045)	(0.0047)	(0.0064)	(0.0055)	(0.0055)
HH size	0.00459	0.00882	-0.0382	-0.00374	-0.104**
	(0.0327)	(0.0370)	(0.0380)	(0.0370)	(0.0416)
Constant	7.675***	4.581***	8.717***	6.329***	6.430***
	(0.748)	(0.821)	(0.886)	(0.922)	(0.906)
Year dummies	Yes	Yes	Yes	Yes	Yes
Number of HHs	824	839	604	674	474
Observations	1,171	1,111	721	798	620

Notes: For the outcome of Log Crop Yields (Kgs per acre) = Logarithm of yields (kilograms of crop output per acre) we run random effects models for the respective five crops of Banana, Cassava, Maize, Beans, and Coffee. Robust standard errors are reported in parentheses. < 0.10, ** p < 0.05, *** p < 0.01 (10%, 5%, 1% level of significance respectively). HH = Household.

Before running regressions for the normalized agricultural technology index – $Tindex_{norm}$ – as our main independent variable, we present a summary of the factor analysis communality together with the percentage contribution of each technology, in Table 8. Communality in this case is the proportion of each variable's variance that can be explained by the factors. More precisely, it is the sum of squared factor loadings for the variables. The results indicate that there are variations in the contributions of the respective agricultural technologies to the overall agricultural technology index overtime with the contribution of organic fertilizers reducing gradually over the years. Communality values from the pooled sample suggest that inorganic fertilizers and pesticides if left alone would explain an average of 55% and 58% of the variation in the technology index, respectively. Considering all the four technologies together, improved seeds, pesticides, organic, and inorganic fertilizers contribute 8.4%, 41.7%, 10.1%, and 39.8%, respectively to the overall agricultural index. Implying that inorganic fertilizers and pesticides contribute the highest to the overall agricultural technology index.

Table 8: Factor analysis communality and percentage contribution of each agricultural technology over the four panel waves

Year	Variable	Factor 1	Factor 2	Communality	% contribution
2013/14	Organic fertilizer	-0.013	0.900	0.809	33.734
	Inorganic fertilizer	0.765	0.055	0.588	24.493
	Pesticides	0.571	0.426	0.507	21.132
	Improved seeds	0.663	-0.236	0.495	20.641
2015/16	Organic fertilizer	0.273	-0.485	0.309	13.080
	Inorganic fertilizer	0.786	0.029	0.619	26.150
	Pesticides	0.811	0.033	0.659	27.840
	Improved seeds	0.080	0.879	0.779	32.930
2018/19	Organic fertilizer	0.020	0.971	0.943	39.459
	Inorganic fertilizer	0.782	-0.108	0.623	26.056
	Pesticides	0.755	0.208	0.613	25.655
	Improved seeds	0.436	-0.144	0.211	8.831
2019/20	Organic fertilizer	0.514	-	0.264	18.193
	Inorganic fertilizer	0.713	-	0.509	35.100
	Pesticides	0.729	-	0.531	36.612
	Improved seeds	0.383	-	0.146	10.096
Pooled sample	Organic fertilizer	0.375	-	0.140	10.142
	Inorganic fertilizer	0.742	-	0.550	39.774
	Pesticides	0.759	-	0.577	41.719
	Improved seeds	0.340	-	0.116	8.364

Notes: Factor loadings are the weights and correlations between each variable and the factor. The higher the load the more relevant in defining the factor's dimensionality. A negative value indicates an inverse impact on the factor. A factor is retained if it has an eigenvalue of over 1, otherwise it is dropped or not reported. The greater 'communality' the higher the relevance of the variable in the factor model. We report rotated factor loads since they provide a clearer pattern and result into orthogonal factors which are not correlated to each other.

When we run our four crop yield regressions with the normalized agricultural technology index – $Tindex_{norm}$ – as our main regressor, we see relatively similar results for coffee and cassava as when we regress with only organic fertilizer. Results re-affirm a positive effect of agricultural technology use on both cassava and coffee productivity among smallholder farmers in Uganda. The direction of the effect is the same for the rest of the crops – maize, beans, and banana food – although not statistically significant.

Table 9: Effect of agricultural technology usage on crop productivity

	y = Log Crop Yields (Kgs per acre)				
Variables	**Maize**	**Beans**	**Banana**	**Coffee**	**Cassava**
Technology Index	0.0142	0.00175	0.0398	0.0747*	0.0681**
	(0.0279)	(0.0266)	(0.0358)	(0.0411)	(0.0313)
Area planted	1.172	0.725	-0.198	-0.471	0.813
	(1.311)	(0.603)	(0.334)	(0.930)	(1.133)
Area planted x Area planted	-0.338	-0.00953	0.00691	0.0917	-0.366
	(0.299)	(0.00753)	(0.0126)	(0.205)	(0.416)
Rain fed parcels	-3.841*	-3.234	2.832	0.491	1.510
	(2.193)	(2.976)	(2.016)	(2.964)	(1.736)
Age	0.0171	-0.00808	-0.00240	0.0160	0.000231
	(0.0182)	(0.0169)	(0.0101)	(0.0137)	(0.00977)
Household size	0.116	-0.0608	0.0905	-0.0242	0.288**
	(0.198)	(0.209)	(0.159)	(0.162)	(0.132)
Constant	8.905***	10.14***	4.634**	5.503*	2.084
	(2.649)	(3.281)	(2.298)	(3.157)	(2.472)
Year dummies	Yes	Yes	Yes	Yes	Yes
Number of HHs	604	673	755	438	807
Observations	721	797	1,066	562	1,062

Notes: For the outcome of Log Yields (Kgs per acre) = Logarithm of yields (kilograms of crop output per acre) we run fixed effects models for the respective five crops of Banana, Cassava, Maize, Beans, and Coffee. Standard errors are reported in parentheses. < 0.10, ** p < 0.05, *** p < 0.01 (10%, 5%, 1% level of significance respectively). HH = Household.

We run separate models to ascertain the effect of each of the four respective agricultural technologies (inorganic fertilizers, pesticides, organic fertilizers, and improved seeds) on farm crop productivity as our alternative measure of crop productivity. Results indicate that a unit increase in inorganic fertilizers applied in the soil increases farm crop productivity by 69%. The application of pesticides, organic fertilizers, and improved crop seeds are not statistically significant on farm crop productivity, but both organic fertilizers and pesticides have a positive effect on farm crop productivity (see Table 10).

This finding confirms that the measurement of crop productivity matters. More precisely, we find that our partial measure of crop productivity – crop yields – gives somewhat different results from the total factor crop productivity – farm crop productivity. Recent literature shows that yields may not be so informative especially among smallholder farmers (Aragon et al., 2022). The fact that most smallholder farmers in Uganda often grow many crops on the same parcels exacerbates the challenge of attributing inputs to individual crops, which increases the measurement error. In addition, amidst a remarkably clear consensus concerning the low usage of these agricultural technologies, Sheahan and Barrett (2017) confirm that there are noticeable within-country differences in the levels of input use reported which also suggests the presence of measurement errors and the fact that the rate of inorganic fertilizers usage is perhaps higher than what we document in this study.

Table 10: Effect of agricultural technology usage on farm crop productivity

	y = Log Farm Crop Productivity			
Variables	**M (1)**	**M (2)**	**M (3)**	**M (4)**
Area planted	0.402***	0.406***	0.403***	0.334***
	(0.0683)	(0.0685)	(0.0687)	(0.119)
Area planted x Area planted	-0.0301***	-0.0305***	-0.0305***	-0.0299
	(0.0105)	(0.0105)	(0.0105)	(0.0210)
Rain fed parcels	-0.258	-0.279	-0.281	-0.278
	(0.311)	(0.309)	(0.309)	(0.480)
Age	-0.00165	-0.00172	-0.00168	0.000119
	(0.00156)	(0.00156)	(0.00156)	(0.00238)
Household size	-0.0498***	-0.0496***	-0.0495***	-0.0305**
	(0.0104)	(0.0105)	(0.0104)	(0.0151)
Inorganic fertilizer	0.688***			
	(0.199)			
Organic fertilizer		0.0153		
		(0.101)		
Pesticides			0.107	
			(0.158)	
Improved seeds				-0.238
				(0.168)
Constant	6.771***	6.798***	6.798***	6.645***
	(0.324)	(0.322)	(0.322)	(0.506)
HH agric. asset controls	Yes	Yes	Yes	Yes
Number of HHs	2,207	2,207	2,207	1,439
Observations	3,614	3,614	3,614	1,977

Notes: For the outcome of Log Farm Crop Productivity = Logarithm of farm crop productivity. Standard errors are reported in parentheses. < 0.10, ** p < 0.05, *** p < 0.01 (10%, 5%, 1% level of significance respectively). HH = Household. HH agric. asset controls include Ox-plough usage, tenure of land owned.

Effect of agricultural technology use on crop market participation

We measure crop market participation outcome by the value of crop sales in Ugandan shillings. Crop sales are observed only for farmers who decide to participate in the crop market which implies that we are faced with a sample selection problem which will bias our outcome estimates. To mitigate the impact of selection bias on our estimates, we use the Heckman two-step technique described earlier. In the first step, we run selection probit models on the discrete outcome of crop market participation and the subsequent step we run pooled ordinary least squares regressions on a transformed continuous outcome of market participation – value of crop sales. More precisely, we run the logarithm of value of crop sales in the second step.

Restrictions in our models are based on whether the variable is considered auxiliary or not, i.e., an exclusion restriction. As discussed earlier, those are variables that can predict missingness but are not interesting for the main model of value of crop sales. We include extension services from the National Agriculture Advisory Services (NAADS) that can influence the farmers' decision of whether to participate in the crop market may not directly affect the value of crop sales. Other auxiliary variables in our model are usage of oxen to plough and whether a farmer's parcels depend on rain as a source of water for crops i.e., rain-fed crops.

Additionally, we include yields in our step-one models but exclude it in the second stage because of the simultaneity between the values of sales and yields. We try as much as possible to avoid endogeneity considering that although the Heckman two-step model duly solves sample selection bias, it does not duly mitigate endogeneity caused by simultaneity of the outcome and the regressor. Our Inverse Mills Ratios (IMR) are negative and highly significant for all the models except for Beans. The significancy of the IMR further confirms that we cannot just run pooled OLS because selection is important.

From Table 11, we do not find strong evidence of the usage of the selected agricultural technologies on crop market participation. We, however, discover that it is crop yields that are critical for market participation. We argue that for food crops (such as Banana-food and Cassava) this this might partly be explained by the fact that smallholder farmers are often faced with pressing food needs in their households that must be met before a farmer decides to sell their harvest. Failure to satisfy these food needs implies that the farmer will not wholly participate in the market. Therefore, a farmer's crop productivity (crop yields) is critical for their market participation. More precisely, to boost crop market participation and performance among smallholder farmers, enhancing their crop productivity (crop yields) is a necessary condition. This means that they can meet their food needs and spare produce for the market (see Figure 2 in the Appendix for a visual relationship between crop yields and crop market participation).

Table 11: Effect of agricultural technology use on crop market participation

	Banana		*Cassava*		*Maize*		*Beans*		*Coffee*	
Variables	**Market part**	**Sales value**	**Market part**	**Sales value**	**Market part**	**Sales value**	**Market part**	**Sales value**	**Market part**	**Sales value**
Area planted	0.0811***	0.589*	0.0970***	-0.284	0.116***	0.581	0.125***	1.251*	0.0384	0.618
	(0.0309)	(0.350)	(0.0233)	(0.370)	(0.0437)	(0.564)	(0.0389)	(0.681)	(0.0418)	(0.469)
NAADS ext. svs.	-0.639***		-0.251		0.560***		-0.755***		0.596***	
	(0.0178)		(0.286)		(0.0321)		(0.0204)		(0.0316)	
Organic fertilizer	0.0325	0.313	0.00944	1.133	0.0944	0.832	-0.0499	-0.505	-0.0608	-0.818
	(0.0487)	(0.567)	(0.0924)	(1.384)	(0.126)	(1.478)	(0.0748)	(0.985)	(0.0918)	(0.944)
Customary tenure	-0.0244	-1.498***	-0.0495	1.017*	0.0224	0.276	0.0981**	0.0489	-0.0685	-1.625**
	(0.0483)	(0.515)	(0.0424)	(0.576)	(0.052)	(0.572)	(0.0496)	(0.628)	(0.0683)	(0.702)
Ox plough use	0.271**		-0.0920*		0.11		-0.0784		0.221	
	(0.133)		(0.0539)		(0.104)		(0.111)		(0.211)	
Rain fed parcels	0.267***		-0.115		0.261**		0.212*		-0.0607	
	(0.0792)		(0.158)		(0.122)		(0.125)		(0.243)	
Sex	0.0593*	-0.659	0.0226	0.0247	0.0116	0.121	-0.0133	0.0125	-0.113*	-0.179
	(0.036)	(0.433)	(0.0341)	(0.413)	(0.0493)	(0.540)	(0.0462)	(0.544)	(0.060)	(0.633)
Able to read & write	0.0142	-0.382	0.0815**	-1.642***	0.0903*	-0.233	-0.00678	0.318	-0.00559	0.119
	(0.0387)	(0.440)	(0.034)	(0.496)	(0.0496)	(0.662)	(0.0487)	(0.566)	(0.0627)	(0.635)
Age	-0.00048	0.00786	-0.00128	0.00933	-0.00367**	-0.0019	-0.00117	-0.00143	-0.00201	-0.00811
	(0.0009)	(0.0106)	(0.0009)	(0.0109)	(0.0014)	(0.0213)	(0.0013)	(0.0148)	(0.0014)	(0.0144)
HH size	-0.00634	0.0215	-0.0127**	0.0885	-0.0195**	0.00776	-0.0129	0.00769	0.00136	0.0496
	(0.0062)	(0.0764)	(0.0064)	(0.0893)	(0.0091)	(0.119)	(0.0080)	(0.1070)	(0.0113)	(0.119)
Banana yields	0.0193***									
	(0.0068)									
Cassava yields			0.0175***							
			(0.0055)							
Maize yields					0.00101					
					(0.0092)					
Beans yields							0.0116			
							(0.0093)			
Coffee yields									-0.0183	
									(0.012)	
IMR (λ)		-4.884***		-7.794***		-5.364**		-0.835		-1.948***
		(1.200)		(1.060)		(2.395)		(1.443)		(0.536)

Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant		11.23***		16.56***		11.00***		5.343***		9.919***
		(1.528)		(1.912)		(2.704)		(1.951)		(1.214)
Number of HHs		618		521		386		377		260
Observations	740	740	603	603	423	423	406	406	294	294

Notes: The first stage entails the selection model where we run probit models for the farmers' discrete choice of participation in the crop market i.e., Market part. For the outcome of the value of sales in Ugandan Shillings, we run pooled ordinary least squares for the respective five crop of Banana, Cassava, Maize, Beans, and Coffee. Robust standard errors are reported in parentheses. < 0.10, ** $p < 0.05$, *** $p < 0.01$ (10%, 5%, 1% level of significance respectively). HH = Household. IMR = Inverse Mills Ratio. NAADS ext. svs. = National Agriculture Advisory Services (NAADS) extension services. Area planted is in acres.

V. Conclusion

In this paper we establish the link between agricultural technology use, crop productivity, and crop market participation among smallholder farmers. We take advantage of the most recent four waves of the Uganda National Panel survey (i.e., 2013/14, 2015/16, 2018/19 and 2019/20) data which is collected under World Bank's Living Standards Measurement Survey– Integrated Survey on Agriculture (LSMS-ISA) project. We provide descriptive statistics for rural farmers separately from the overall sample to ascertain whether there are differences in farmer characteristics, but we do not find big differences between rural farmers and overall farmers in a pooled sample.

We analyze farmers' usage of different farm implements and machinery – both rudimentary and advanced – and we find that as we move from rudimentary implements such as hoes and pangas to more advanced machinery such as tractors and weeders, the percentage of smallholder farmers using the respective farm implement gradually reduces. In addition, considering four main inputs of improved seeds, pesticides, organic, and inorganic fertilizers, we examine first, whether there is any complementarity in the usage of these agricultural technologies. We do not find evidence of complementarities in the use of these agricultural technologies among smallholder farmers. It is rather that farmers use them in isolation.

We go a step beyond descriptive analysis to test for complementarity of agricultural technology use empirically. Due to data limitations, we test for only two combinations i.e., organic and inorganic fertilizers as well as organic fertilizers and pesticides and for both scenarios we do not find evidence for any combined effect on crop yields, which confirms the lack of complementarity as documented by Sheahan and Barret (2017). However, this does not mean that a combination of organic and inorganic fertilizers or pesticide and organic fertilizers has no effect on crop productivity. On the other hand, we find a strong and positive effect of organic fertilizer usage on Cassava, Beans, and Coffee yields. Since organic fertilizers are relatively easier to access compared to inorganic fertilizers or improved seeds, it presents a tremendous opportunity for smallholder farmers to boost their crop yields. For that to happen, overall usage of organic fertilizers must improve from the current 8% of farmers. We acknowledge the fact that while these might be mere correlations, they provide us with a strong intuition on what could be behind the persistent low levels of crop productivity in Uganda. When we attempt to measure crop productivity as farm productivity, we find that a unit increase in inorganic fertilizers applied in the soil increases farm crop productivity by 69%. This finding is different from what we see when we investigate the effect of inorganic fertilizer on the partial measure of crop productivity – crop yields – which implies that the way we measure productivity matters. We therefore conclude that, of the four agricultural technologies, inorganic fertilizers have the strongest effect on farm productivity among smallholder farmers in Uganda.

Furthermore, we do not find strong evidence of the effect of the selected agricultural technology on crop market participation. However, we unearth the fact that it is crop yields which is the most critical for crop market participation – this is the case for Banana and Cassava. In simple terms, the amount of the crop output produced by the farmer has a big influence on their market participation. For instance, we argue that since smallholder farmers often have pressing food needs, their crop productivity has to be high enough to meet the food needs for them to also participate in the crop market. Therefore, a farmer's crop productivity (crop yields) is arguably the most critical facilitator or inhibitor of market participation. More precisely, to boost crop market participation among smallholder farmers, increasing their crop yields is a necessary condition.

This paper is relevant for a couple of reasons. First, unlike most papers in literature that often analyze only crop productivity and agricultural technology or crop market participation and agricultural technology, we take another approach by linking agricultural technology to both crop productivity and crop market participation and then crop productivity to crop market participation. Second, we can observe smallholder farmers in a sub-Saharan African context over time with the use of a nationally representative longitudinal dataset. Third, we contribute to the growing literature on priorities of smallholder farmers and what is critical for them to participate in the crop market in a bid to expand the money economy and reduce the subsistence sector.

Whereas we get closer to understanding the link between agricultural technology use, crop productivity and market participation among smallholder farmers, we do not explicitly delve into the causal mechanisms behind the correlations we find. We believe that further research can concentrate on unearthing the causal mechanisms behind some of our results. In addition, due to data limitations we do not perform plot level analysis to find out the nitty gritty of how technology adoption evolves with different crops grown on those plots over time.

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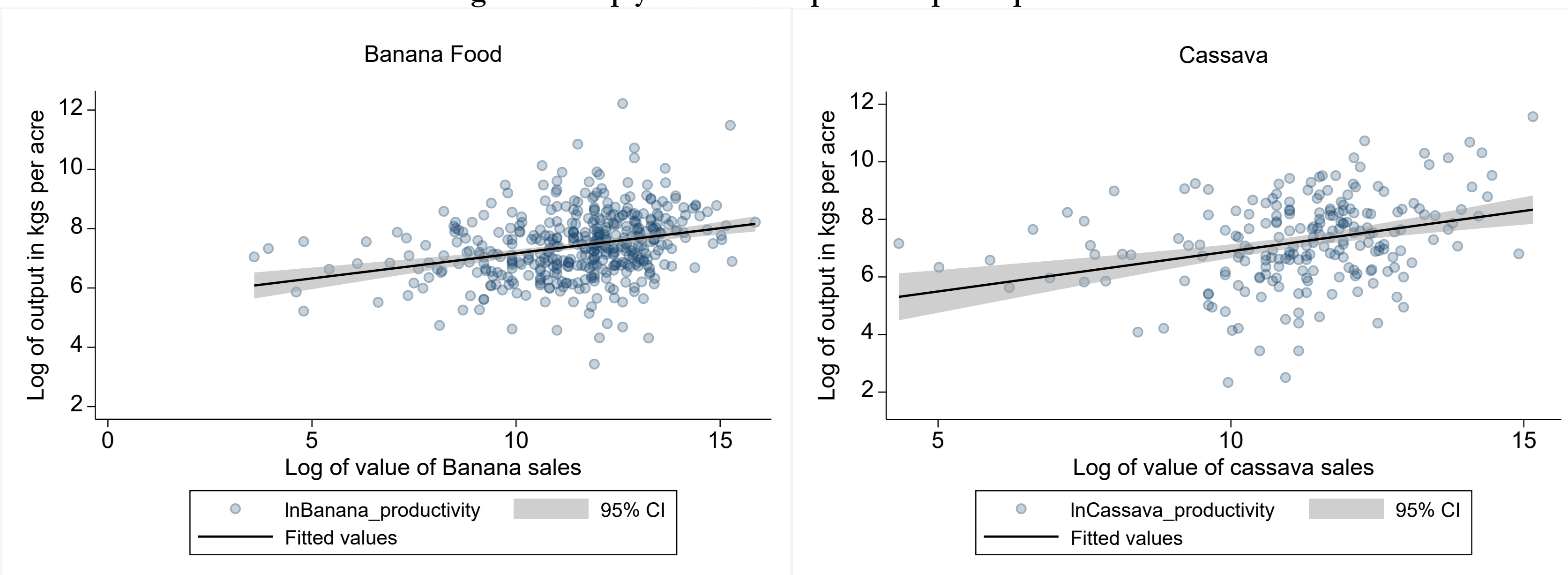
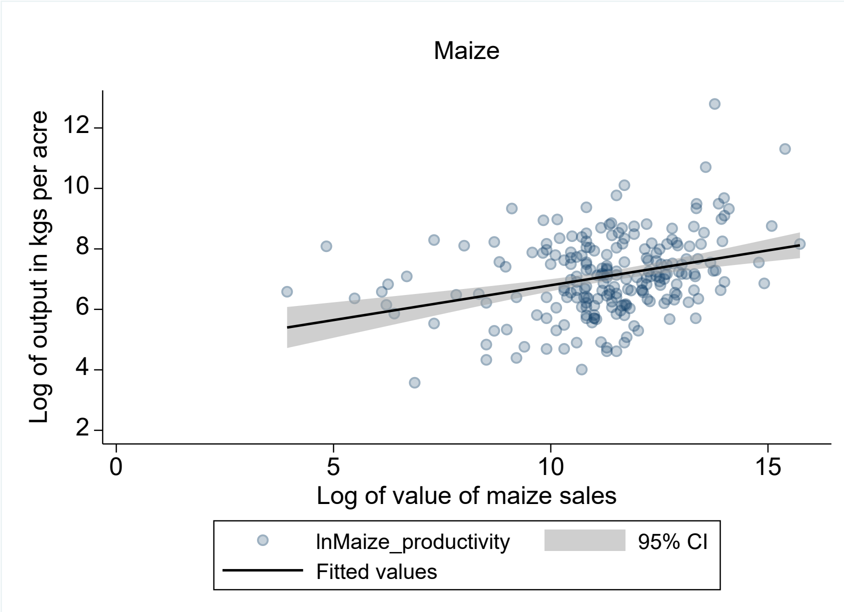
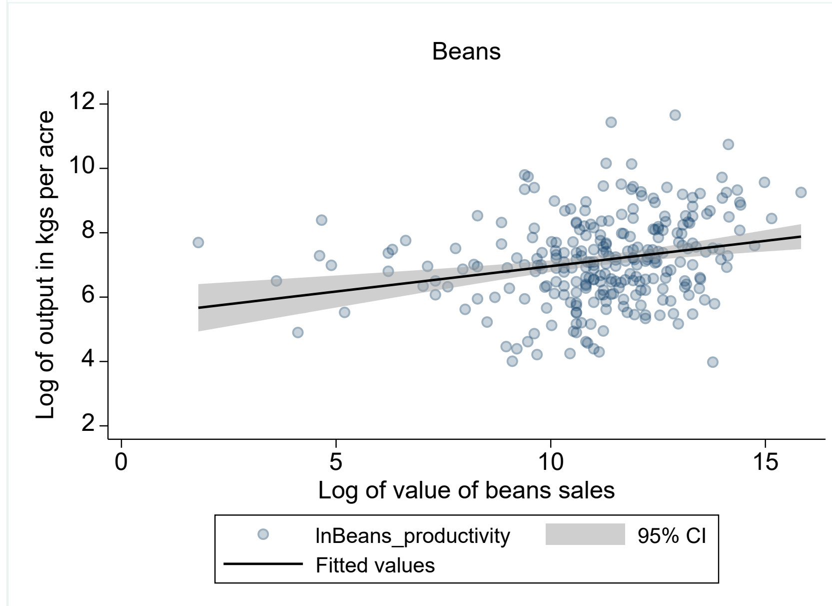
VII. Appendix

The relationship between crop yields and crop market participation is a direct and positive one. This signifies how critical yields are for a smallholder farmer to decide whether they will participate in the market or not. Considering that such farmers must first meet food needs before participating in the crop market, yields must be over and above the household food requirements. The cash crop – coffee – exhibits a relatively similar relationship although we cannot explain it similarly.

Figure 2: Crop yields and crop market participation nexus




Maize
Log of output in kgs per acre
2
4
6
8
10
12
0
5
10
15
Log of value of maize sales
lnMaize_productivity
95% CI
Fitted values


Beans
Log of output in kgs per acre
2
4
6
8
10
12
0
5
10
15
Log of value of beans sales
lnBeans_productivity
95% CI
Fitted values

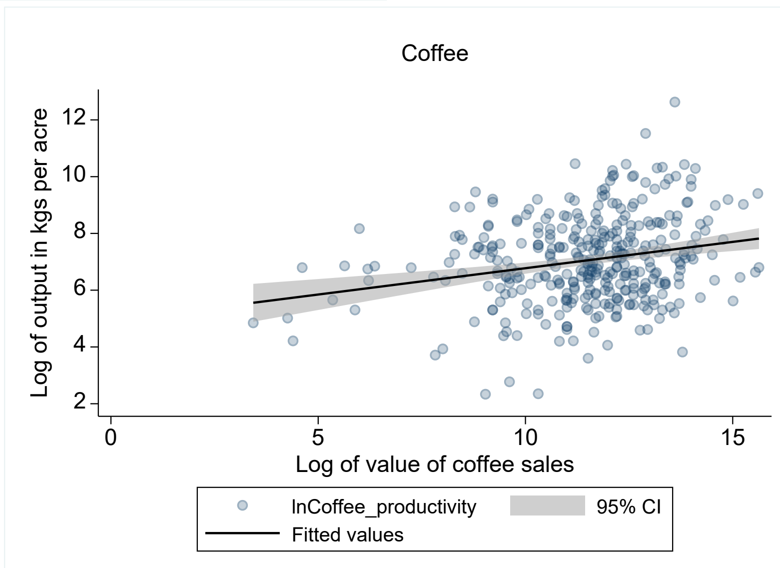

Coffee
Log of output in kgs per acre
2
4
6
8
10
12
0
5
10
15
Log of value of coffee sales
lnCoffee_productivity
95% CI
Fitted values

Table 12: Technology usage by sex of decision maker, crop type and land tenure

	Organic fertilizer (%)	*Inorganic fertilizer (%)*	*Improved seed (%)*	*Pesticide (%)*	*Organic + Inorganic fertilizer (%)*	*Improved seed + Inorganic fertilizer (%)*	*Organic fertilizer + Pesticide (%)*
Panel A: Technology use by sex of decision maker							
Female head	5.89	1.38	6.94	2.55	0.21	0.38	0.43
Male head	7.22	1.99	10.75	6.28	0.46	1.01	1.30
Panel B: Technology use by crop type							
Maize	3.7	2.2	12.2	6.7	0.01	0.9	1.3
Coffee	13.5	3.9	16.4	7.6	1.3	2.2	2.6
Banana food	14.2	1.1	2.8	3.8	0.4	0.0	0.7
Cassava	3.3	0.3	8.0	2.2	0.0	0.0	0.1
Beans	7.4	3.0	1.8	7.8	0.5	0.36	1.3
Panel C: Land tenure and technology use							
Freehold	9.4	1.8	4.0	5.4	0.5	0.4	1.0
Leasehold	11.1	1.5	7.0	4.4	0.8	0.0	0.0
Mailo	18.0	5.2	9.8	14.5	2.2	4.8	6.1
Customary	3.9	1.5	11.3	4.7	0.2	0.5	0.4

Source: Authors' computation using UNPS data (2013/14 – 2019/20)

Low complementarity of technology use is evident irrespective of the sex of the decision maker, but female headed households exhibit relatively lower complementarity compared to male headed households. In addition, there are differences in technology use among the four main forms of land tenure in the country with farmers possessing land customarily exhibiting the least adoption of organic and inorganic fertilizers at 3.9% and 1.5% respectively. The results are in line with the overall low levels of technology adoption in the country since close to 50% of land in Uganda is owned customarily – characterized by unsecure ownership rights by the farmer compared to freehold tenure where land is owned in perpetuity. Often, the lack of secure land ownership rights creates a disincentive to adopt sustainable agricultural technologies among farmers (see Table 12).

Table 13: Individual effect of organic fertilizer usage on crop productivity

	Log Crop Yields (Kgs per acre)				
Variables	**Banana**	**Cassava**	**Coffee**	**Maize**	**Beans**
Organic fertilizer	0.220	3.769***	0.309	0.217	1.084***
	(0.253)	(0.578)	(0.353)	(0.607)	(0.399)
Year dummies	Yes	Yes	Yes	Yes	Yes
Constant	6.959***	4.509***	6.436***	6.099***	6.470***
	(0.158)	(0.180)	(0.238)	(0.215)	(0.199)
Number of HHs	843	864	487	635	712
Observations	1,219	1,159	648	771	846

Notes: For the outcome of Log Yields (Kgs per acre) = Logarithm of yields (kilograms of crop output per acre) we run random effects models for the respective five crops of Banana, Cassava, Maize, Beans, and Coffee. Robust standard errors are reported in parentheses. < 0.10, ** p < 0.05, *** p < 0.01 (10%, 5%, 1% level of significance respectively). HH = Household.