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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 a link between crop productivity, crop market participation and agricultural technology use among smallholder farmers. We utilise the latest four waves of the Uganda National Panel Survey – 2013/2014, 2015/2016, 2018/2019, and 2019/2020. First, we test for the complementarity of agricultural technology use among smallholder farmers, but we find no evidence for the combined effect of organic and inorganic fertilisers, as well as pesticides and organic fertilisers, on crop yields, which depicts a lack of complementarity. However, we find a strong individual effect of organic fertilisers 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 fertilisers in the first step, and the overall agricultural technology index in the second step. The results reaffirm the positive effect of agricultural technology use on cassava and coffee yields. Third, when we measure crop productivity as farm productivity, we find that a unit increase in inorganic fertilisers increases farm productivity by 69%. However, we do not see this strong effect of inorganic fertilisers on our partial measure of crop productivity – crop yields. Lastly, we show that crop yields are the most critical for market participation.

Key words: crop productivity, market participation, agricultural technology, smallholder farmers

1. 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 about 68% of the working population (UBOS 2020) and has numerous links to 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 (Magelah & Ntambirweki-Karugonjo 2014; AGRA 2015).

Despite the significance of the sector in providing employment and being a source of livelihood, productivity and market participation have stagnated over the years, rendering the sector less attractive over time (Ripoll *et al*. 2017). The slow growth directly affects agro-industrialisation, which in turn has implications for the employment viability in the dominant agro-industry (Guloba *et al*. 2021). The low productivity and market participation are blamed partly on the low uptake of agricultural technology (such as improved seeds, fertilisers, pesticides and herbicides) among farmers, yet improved crop output enhances both crop market participation and performance (Donkor *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 reduce household poverty (Minten *et al*. 2007; Kassie *et al*. 2011). Despite the numerous documented advantages, the adoption rate for improved agricultural technologies in Uganda and many other sub-Saharan African countries has lagged behind that of other regions (World Bank 2007; Kasirye 2013). In addition, the agriculture sector is known to play a key role in the green revolution success experienced in Asian countries (Chen & Ravallion, 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 four most recent waves – 2013/2014, 2015/2016, 2018/2019 and 2019/2020 – of the Uganda National Panel Survey data.

First, we tested for the complementarity of agricultural technology use among smallholder farmers by investigating whether there was any combined effect of the selected agricultural technologies on crop yields. We did not find evidence for the combined effect of organic and inorganic fertilisers, as well as pesticides and organic fertilisers, on crop yields, which implies that there is a lack of complementarity. More precisely, smallholder farmers mostly use agricultural technologies in isolation. However, we found a strong individual effect of organic fertiliser usage on cassava, bean and coffee yields. Since organic fertilisers can be accessed easily compared to inorganic fertilisers or improved seeds, it presents an opportunity for smallholder farmers to boost their yields.

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

Third, for a comparative analysis, we leveraged another measure of crop productivity by measuring productivity at the farm level. Recent literature has emphasised 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 found that a unit increase in the usage of inorganic fertilisers increased farm crop productivity by 69%. We did not see this strong effect of inorganic fertilisers 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 fertilisers have the strongest individual effect on farm crop productivity among smallholder farmers.

Fourth, we employed the Heckman two-step technique to correct for selection bias in crop market participation outcomes. In the first step, we estimated probit models of market participation in the banana, cassava, maize, bean and coffee markets. In the second step, we estimate pooled ordinary least squares on the value of crop sales for all five respective crops. Our analysis did not find strong evidence of the effect of agricultural technology use on crop market participation, but we unearthed the fact that it is rather crop yields that are most critical for crop market participation – this was true for bananas 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 attributed partly 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 in the crop market. Failure to satisfy these food needs may lead to non-participation in the crop market.

Unlike most studies in the literature, which often analyse the nexus between crop productivity and agricultural technology or crop market participation and agricultural technology, we took 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 attempted to establish the relationship between agricultural technology use and crop yields, as well as farm crop productivity. Secondly, we could 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 organised as follows. Section 2 synthesises 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 and models, and describes the data. Section 4 highlights the results and their discussion, whereas Section 5 concludes.

2. Previous related literature

2.1 Crop productivity and technology use

Since the majority of the population in sub-Saharan Africa has agriculture as its main source of livelihood, there is an increasing interest in agricultural investment to improve productivity and rural incomes. Notably, the most common forms of productivity are land productivity (volume of output per planted area) and labour productivity (volume of output per unit of labour employed) (FAO 2017). Generally, technology contributes greatly to fostering sustainable improvements to the physical, social and economic well-being of individuals and society (Fuglie *et al*. 2019; 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; Acemoglu, 2002; Evenson & Gollin 2003; Qaim 2009; Pingali 2012; Wieczorek & Wright 2012).

Despite all the benefits associated with technology, adoption is still low in sub-Saharan countries like Uganda. For instance, most farmers do not use improved seeds or fertilisers, and do not receive extension support, which presents an enormous productivity challenge (Odokonyero & Mbowa 2019). Yet Pan *et al*. (2018), for instance, conclude that access to extension services is a big contributor to food security, as well as agricultural productivity, among Ugandan farmers. Other forms of technology, such as 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). Notably, the decision to improve crop productivity by adopting improved production techniques is dependent on several factors. It is easy to conclude that the 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, the adoption of a given technology to improve agricultural productivity is highly dependent on the existing farmer's 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 of the adoption is faster among farmers who are organised into farmer groups compared to those operating individually (Beaman *et al*. 2018; Pan *et al*. 2018; Pan *et al*. 2018; BenYishay & Mobarak 2019; Omotilewa *et al*. 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) show that subsidising 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.

2.2 Crop market participation and technology use

The key drivers of economic growth have been identified to be agriculture and natural resources (World Bank 2017), which in recent times have been revamped through technological innovation and the adoption of new technology in the agriculture sector – the backbone of many developing countries (Chavula 2014). Therefore, improving market participation in the sector is a priority for many governments. Agricultural market participation involves, among others, 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 smartphones and the use of the internet more broadly, have been found to enhance agricultural market participation and also help to diversify market options (Mwesigye *et al*. 2020). Hamill (2017) postulates that market information services, mainly those based on mobile phones and tablets, can enhance crop farmers' ability to access markets, which in turn helps them to match consumers' demands, 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 product base and access to inputs, among others. Based on the commendable role played, many smallholder farmers have recently embraced different technologies to enhance their access to agricultural markets (Okello *et al*. 2014; Ogutu *et al*. 2014), thereby dealing with market

failure (Barrett 2008; Merfeld 2020). Such technologies are seen as important tools to enhance farmers' access to better-paying agricultural markets (Katengeza *et al*. 2011).

Following the outbreak of the Covid-19 pandemic, which disrupted global supply chains, many farmers embraced technology. The curtailing of movements and physical contact led farmers in most sub-Saharan countries to embrace digital technologies to market their products and be able to receive inputs. For instance, in Uganda, many farmers leveraged social media platforms to market their produce (UBOS 2021). Thus, it is critical and opportune to investigate the linkage between crop productivity, crop market participation and agricultural technology use among smallholder farmers.

3. Methodology

3.1 Conceptual framework

To understand the effect of technology use on crop productivity and market participation, we conceptualised a model of households (smallholder farmers) while differentiating between those who adopted agricultural technology and those who did not. We expected that the two groups experienced two different outcomes, as summarised in Figure 1. The main proposition here is that a farmer who uses fertilisers (organic and/or inorganic), improved seeds and pesticides will experience higher crop productivity through increased yields and farm productivity, and consequently participate in the market.

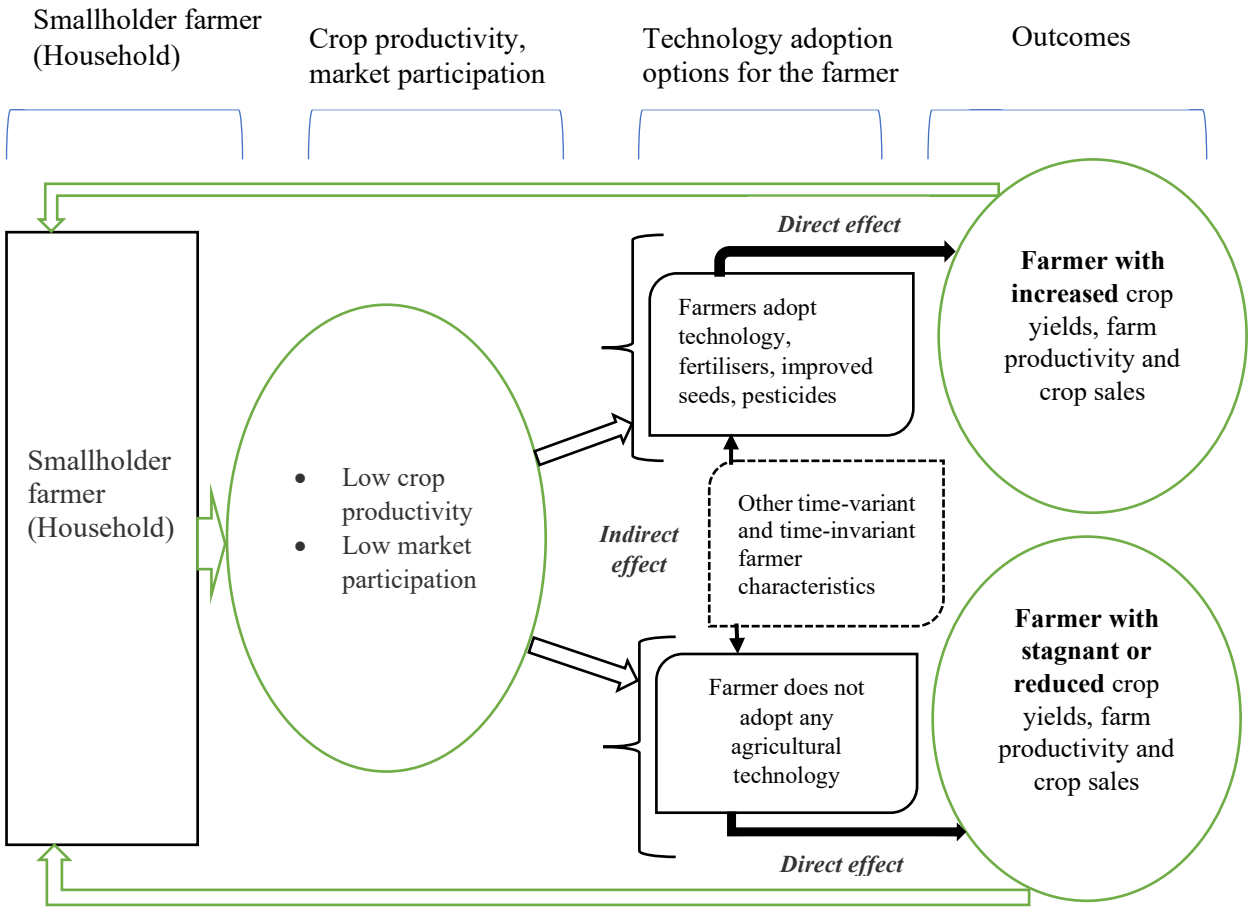

Figure 1: Crop productivity, market participation and technology use nexus
Source: Authors' construction, based on the ideas of Mpuuga *et al*. (2021)

More precisely, we hypothesise that technology adoption leads to higher crop productivity and higher crop market participation. We recognise the possibility of bidirectional causality between technology adoption and market participation, as well as crop productivity and the selection bias of crop market participation outcomes. Moreover, agricultural productivity and market participation intensity have bidirectional causality (Benfica *et al*. 2017).

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

3.2 Empirical strategy

3.2.1 Crop productivity

To examine the effect of technology use on crop productivity we firstly used household-level crop yields calculated in kilograms of output per acre – using the quantity produced of a single crop. We estimate Equation (1), where the unit of observation is household i in year t. $AgricTechn_{it}$ is the single agricultural technology, or a combination of agricultural technologies, adopted by household i at time t, and X is a vector of household 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, and u_{it} is the remainder of the disturbance. Since our outcome is continuous, we ran 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 examines whether there is a correlation between the unique errors and the regressors in the model. We transformed the outcome variable by taking its logarithm (*LogYields*). The agricultural technologies under consideration are improved seeds, pesticides, organic and inorganic fertilisers, and robust standard errors are reported in all our models.

For comparative purposes, we constructed an alternative measure of crop productivity at a farm level. The idea was to measure agricultural output and input use for each farm in each period. Recent literature has emphasised that crop yields, which is a partial measure of productivity, may not be an informative measure of crop productivity, especially among farmers who 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, labour and other inputs to individual crops.

More precisely, we aggregated the crop output produced of all crops grown by the household from all its parcels that make up the household farm. This is the farm crop output for the two seasons in a year (panel wave). We also calculated the unit value in Ugandan shillings (price per kilogram) for each crop grown in a given household parcel each year. We used 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 labour inputs, we first calculated the total area cultivated in acres by summing 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. What was noteworthy was that the GPS data had several missing values, and so we leveraged farmer-reported sizes to fill in the missing data. Second, following Aragon *et al*. (2022), we also measured labour as the total number of person-days on the farm – both family and hired labour. For the 2018/2019 and 2019/2020 waves, where some family labour was not reported and only hired labour data was available, we used the median person-days (both family and hired labour) within a district for the 2013/2014 wave to fill in these gaps for consistency in the measurement of inputs. Therefore, the real farm crop productivity model follows a similar structure as the crop yields model, and is specified as follows:

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

3.2.2 Construction of the technology index

To complement our measure of agricultural technology, we constructed a technology index, $Tindex$, using factor analysis considering the four agricultural technologies – organic fertiliser, inorganic fertiliser, pesticides and improved seeds. The factor analysis technique finds the correlation between factors and calculates factor loadings for multiple common factors. These factor loadings were then used to identify exactly which common factors represent the concept measured. Consequently, the loadings were 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 fertiliser sub-index (OFI) = index based on the dummy variable that is 1 or 0 if a farmer uses organic fertilisers; inorganic fertiliser sub-index (IFI) = index based on the dummy variable that is 1 or 0 if a farmer uses inorganic fertilisers; 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 constructed the four sub-indexes for each panel wave separately to be able to compare agricultural technology usage over time. In addition, this enabled us to understand the percentage contribution of each individual technology to the overall index over the four waves. The overall agricultural technology index can be specified as follows:

$$Tindex = \beta_1 OFI + \beta_2 IFI + \beta_3 ISI + \beta_4 PI, \quad (3)$$

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

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

where min_t and max_t are the minimum and maximum values of the index, respectively. We treated 0 and 100 as extreme points within the sample and the respective econometric model was specified as follows:

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

3.2.3 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 measured 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 – a 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 significance 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 *et al*. (2007), we first estimated probit models of market participation in the banana, cassava, maize, bean and coffee markets. The model requires the identification of exclusion restrictions/auxiliary variables, i.e., variables that may predict the market participation decision, but not the value of crop sales. For example, extension services by the National Agriculture Advisory Services (NAADS) can influence the farmers' decision 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. Another auxiliary variable in our model is the use 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, $ValueCS_{it}$ – the 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 the crop sales of farmers who do not participate in the crop market. We assume that farmers who 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 summarised as follows:

Selection Model – Probit:

$$Market_{it} = \alpha + \beta AgricTechn_{it} + X'_{it}\theta + \varepsilon_{it}, \quad (6)$$

and

Main Model – OLS:

$$ValueCS_{it} = \alpha + \beta AgricTechn_{it} + X'_{it}\theta + \varepsilon_{it}, \quad (7)$$

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 $AgricTechn$, 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 three year dummies, considering that the study utilises 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 contributed greatly to the reliability and parsimony of our results.

3.3 Data sources

The study utilises data from the four most recent waves of the Uganda National Panel Survey (i.e., 2013/2014, 2015/2016, 2018/2019 and 2019/2020), which is collected under the World Bank's Living Standards Measurement Survey – Integrated Survey on Agriculture (LSMS-ISA) project. The

Uganda National Panel Survey (UNPS) data spans seven waves, but due to the sample refresh that happened with the 2013/2014 wave (wave 4), where one-third of the initial sample was refreshed to balance the advantages and shortcomings of panel surveys, we use the 2013/2014 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 fertilisers, pesticides, agricultural labour 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 did not perform plot level analysis due to data limitations that make it impossible to construct a panel of plots (Mpuuga *et al*. 2021).

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 over time, and the results indicate that the number of maize farmers grew steadily – from 11.8% in 2013/2014 to 15.5% in 2018/2019 – but suddenly dropped to 6.3% in 2019/2020. The huge drop in the proportion of maize farmers is a cause for concern, since maize doubles as a cash and food crop, yet it takes a few months to harvest. We explored a couple of possibilities that could explain this reduction. First, we limited our sample to only farmers who were there in 2013/2014 and were still in the sample in 2019/2020 just so that we could rule out any unbalanced panel anomalies. We found that the proportion of maize farmers increased slightly to 9.2%, whereas those growing banana-food further reduced to 11.5% in 2019/2020. This implies that, for maize, there was still a huge drop – from 15.5% in 2018/2019 to 9.2% in 2019/2020. We then delved into maize market conditions between 2018/2019 and 2019/2020. The question we asked 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 2018/2019, when a kilogram of maize grain was being sold at only 200 Ugandan shillings (0.06 USD) (Barungi 2018), 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 four months – can easily be substituted for crops such as beans. In mid-2022, the price of maize grain per kilogram had increased to over 1 600 Ugandan shillings (0.47 USD) per kilogram in most local markets in Kampala (Advocacy Coalition for Sustainable Agriculture 2022). Similarly, the reduction in banana growers is attributed mainly to the banana wilt disease that ravaged the country around the same period (CGTN Africa 2018).

Table 1: Percentage of households growing the five most popular crops in Uganda (UNPS 2013/2014 to 2019/2020)

Crop	2013/2014	2015/2016	2018/2019	2019/2020	N	Pooled sample (%)
Banana Food	23.7	22.9	14.7	12.5	1 224	18.5
Cassava	17.6	15.6	12.9	23.3	1 172	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	1 v958	30.0
N	1 794	1 618	1 345	1 851	6 608	≅ *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.

4. Results and discussion

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

4.1 Descriptive statistics

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

The 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. It can be noticed that yields vary across crops, which justifies a crop-level analysis, considering that different crops weigh differently and need a distinct land area to grow, for instance bananas need large parcels of land compared to beans and maize, which are planted 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 measured crop productivity as land productivity (or yields), but for comparative purposes we also leveraged farm productivity measures – as in total factor productivity. Crop market participation, on the other hand, is the value of the individual crop sales in UGX. From the results it can be noticed that the use of agricultural technology by farmers is very low, viz., less than 10% of farmers on average use organic fertilisers, improved seeds, inorganic fertilisers or pesticides, and only 17% use oxen to plough their land for planting. Inorganic fertilisers are the least used, at only 2%.

In Table 3, we analyse farmers' usage of different farm implements and machinery – both rudimentary and advanced machinery. We found that, as we moved from rudimentary implements such as hoes and pangas to more advanced machinery, such as tractors and weeders, the percentage of farmers using the respective farm implement reduces. More precisely, 99.8% of farmers use hoes, whereas only 0.3% use tractors.

4.2 Complementarity of agricultural technology use

We then attempted to find out whether there was any complementarity of technology usage. First, by simply describing our data we attempted to discover whether farmers use these agricultural technologies as substitutes or as complements. The most used technology was improved seeds (7.7%), followed by organic fertilisers (6.9%) and pesticides (5.6%), with the least being inorganic fertilisers, at only 1.8% (see Table 4). Anecdotally, the higher usage of organic fertilisers could be attributed to its ease of access, in addition to being less costly compared to inorganic fertilisers 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 fertiliser.

Table 2: Summary statistics (UNPS 2013/2014 to 2019/2020)

	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 fertiliser	0.07	0.25	0.07	0.26
Use of inorganic fertiliser	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 (kg per acre)	1 664.8	7 155.9	1 683.6	7 284.4
Maize yields (kg per acre)	1 569.0	5 313.5	1 495.7	5 006.6
Beans yields (kg per acre)	1 577.7	4 985.2	1 729.7	6 134.2
Cassava yields (kg per acre)	1 072.1	4 672.4	1 130.8	4 794.2
Banana yields (kg per acre)	2 517.4	11 316.7	2 461.8	11 074.6
Coffee yields (kg per acre)	2 371.8	5 190.2	2 295.9	5 008.7
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	413 133.5	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	684 754.3
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's parcels. NAADS = National Agricultural Advisory Services, HoH = head of household, and HH = household.

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 (2013/2014 to 2019/2020)

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

Table 4: Complementarity of technology use

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

Source: Authors' computation using UNPS data (2013/2014 to 2019/2020)

We further analysed the complementarity of agricultural technology usage, empirically, while controlling for year effects. We ran pooled ordinary least squares, random effects and fixed effects models and used the Hausman test to choose between fixed and random effects models. We failed to reject the null hypothesis and then proceeded to report random effects model estimates for the five respective crops (see Table 5).

Our outcome for the five models is *LogYields* in kg per acre. Due to data limitations, we tested for a combination of organic and inorganic fertilisers, as well as organic fertilisers and pesticides only. In both cases, as reported in Tables 5 and 6, we did not find any significant combined effect on crop yields, which reaffirms results from the descriptive analysis. More precisely, there is no complementarity in technology usage. Individually, we find a strong positive effect of organic fertilisers on cassava and bean yields, but a positive insignificant effect on banana, coffee and maize yields. In addition, we did not find any significant effect of inorganic fertilisers on crop yields. We argue that this might be due to the low uptake of inorganic fertilisers 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 fertilisers by smallholder farmers. Since crop yields are a partial measure of productivity, this result does not conclusively imply that inorganic fertilisers do not influence crop productivity.

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

	Log crop yields (kg per acre)				
Variables	**Banana**	**Cassava**	**Coffee**	**Maize**	**Beans**
Organic fertiliser	0.237	3.774***	0.181	0.189	1.052**
	(0.256)	(0.578)	(0.370)	(0.619)	(0.411)
Inorganic fertiliser	1.368	1.897	0.0554	-0.253	0.327
	(1.000)	(2.241)	(0.723)	(0.748)	(0.794)
Organic x Inorganic fertiliser	-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 (kg per acre) = Logarithm of yields (kilograms of crop output per acre) we ran random effects models for the five respective crops of banana, cassava, maize, beans and coffee. Robust standard errors are reported in parentheses. ** $p < 0.05$, *** $p < 0.01$ (5% and 1% level of significance respectively). HH = household.

In Table 6, we also do not find any combined effect of organic fertilisers and pesticide usage on crop yields. Although pesticide usage is relatively higher than the uptake of inorganic fertilisers, we still do not find any significant combined effect with organic fertilisers. However, there is a significant individual effect of organic fertilisers on both cassava and bean yields, which further confirms the lack of complementarity of agricultural technology usage among smallholders. Recent work by Li *et al*. (2025) and Wang *et al*. (2024) confirms the importance of organic amendment input on soil quality, and consequently on overall crop productivity.

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

	Log crop yields (kg per acre)				
Variables	**Banana**	**Cassava**	**Coffee**	**Maize**	**Beans**
Organic fertiliser	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 fertiliser 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 (kg per acre) = Logarithm of yields (kilograms of crop output per acre) we ran random effects models for the five respective crops of banana, cassava, maize, beans and coffee. Robust standard errors are reported in parentheses. ** $p < 0.05$ and *** $p < 0.01$ (5% and 1% level of significance respectively). HH = household.

4.3 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 found a positive and significant effect of organic fertilisers on cassava, bean and coffee yields. The fact that organic fertilisers can be accessed easily compared to inorganic fertilisers or improved seeds presents an opportunity for smallholder farmers to boost their yields.

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

Before running regressions for the normalised agricultural technology index, $Tindex_{norm}$, we present a summary of the factor analysis communality together with the percentage contribution of each technology (see 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 show variations in the contributions of the respective agricultural technologies to the overall agricultural technology index over time, with the contribution of organic fertilisers gradually reducing over the years. Communality values from the pooled sample suggest that, if left alone, inorganic fertilisers and pesticides would explain an average of 55% and 58% of the variation in the technology index, respectively. Considering all four technologies together, improved seeds, pesticides, organic and inorganic fertilisers contribute 8.4%, 41.7%, 10.1% and 39.8% respectively to the overall agricultural index. This implies that inorganic fertilisers and pesticides contribute the highest to the overall agricultural technology index.

Table 7: Effect of organic fertiliser usage on crop productivity

	Log crop yields (kg per acre)				
Variables	**Banana**	**Cassava**	**Maize**	**Beans**	**Coffee**
Organic fertiliser	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 (kg per acre) = Logarithm of yields (kilograms of crop output per acre) we ran random effects models for the five respective crops of banana, cassava, maize, beans and coffee. Robust standard errors are reported in parentheses. * < 0.10, ** p < 0.05 and *** p < 0.01 (10%, 5% and 1% level of significance respectively). HH = household.

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**
2013/2014	Organic fertiliser	-0.013	0.900	0.809	33.734
	Inorganic fertiliser	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
2015/2016	Organic fertiliser	0.273	-0.485	0.309	13.080
	Inorganic fertiliser	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
2018/2019	Organic fertiliser	0.020	0.971	0.943	39.459
	Inorganic fertiliser	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
2019/2020	Organic fertiliser	0.514	-	0.264	18.193
	Inorganic fertiliser	0.713	-	0.509	35.100
	Pesticides	0.729	-	0.531	36.612
	Improved seeds	0.383	-	0.146	10.096
Pooled sample	Organic fertiliser	0.375	-	0.140	10.142
	Inorganic fertiliser	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 it is in defining the factor's dimensionality. A negative value indicates an inverse impact on the factor. A factor was retained if it had an eigenvalue of over 1, otherwise it was dropped or not reported. The greater the '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 with each other.

When we ran our four crop yield regressions, the results reaffirmed a positive effect of agricultural technology use on cassava and coffee productivity. The direction of the effect was 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 (kg 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 (kg per acre) = Logarithm of yields (kilograms of crop output per acre), we ran fixed effects models for the five respective crops of banana, cassava, maize, beans and coffee. Standard errors are reported in parentheses. * < 0.10, ** p < 0.05 and *** p < 0.01 (10%, 5% and 1% level of significance, respectively). HH = household.

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

This finding shows that the measurement of crop productivity matters. 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 has shown that yields may not be so informative, especially among smallholder farmers (Aragon *et al*. 2022). The fact that most smallholder farmers often grow different crops on the same parcels of land exacerbates the challenge of attributing inputs to individual crops, which increases the measurement error. There are noticeable within-country differences in the levels of input use among most sub-Saharan countries, but also the rate of inorganic fertilisers usage is perhaps higher than what is often documented (Sheahan & Barrett 2017).

4.4 Effect of agricultural technology use on crop market participation

To mitigate the impact of selection bias in our measure of crop market participation – the value of crop sales – we used the Heckman two-step technique, as elucidated earlier. In the first step, we ran selection probit models on the discrete outcome of crop market participation and, in the subsequent step, we ran pooled ordinary least squares regressions on the logarithm of the value of crop sales. In addition, we included yields in our step-one models, but excluded them in the second stage because of the simultaneity between the values of sales and yields. The inverse Mills ratios (IMR) were negative and significant for all the models except for beans, which shows that we cannot just run a pooled OLS model 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 discover, however, that it is crop yields that are critical for market participation. We argue that, for food crops (such as banana and cassava) 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 might not participate in the market. Therefore, a farmer's crop yields are critical for their market participation. To boost crop market participation among smallholder farmers, a necessary condition is enhancing their crop productivity. In this way, they can meet their food needs and spare produce for the market (see Figure A in the Appendix for the relationship between crop yields and market participation).

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 fertiliser	0.688***			
	(0.199)			
Organic fertiliser		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. ** $p < 0.05$ and *** $p < 0.01$ (5% and 1% level of significance respectively). HH = household. HH agric. asset controls include ox-plough usage, tenure of land owned.

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. system	-0.639***		-0.251		0.560***		-0.755***		0.596***	
	(0.0178)		(0.286)		(0.0321)		(0.0204)		(0.0316)	
Organic fertiliser	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*** (1.200)		-7.794*** (1.060)		-5.364** (2.395)		-0.835 (1.443)		-1.948*** (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 ran 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 ran pooled ordinary least squares for the five respective crops of banana, cassava, maize, beans and coffee. Robust standard errors are reported in parentheses.* < 0.10, ** p < 0.05 and *** p < 0.01 (10%, 5% and 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.

5. Conclusions

We established the link between agricultural technology use, crop productivity and crop market participation among smallholder farmers by taking advantage of the most recent four waves of the Uganda National Panel survey (i.e., 2013/2014, 2015/2016, 2018/2019 and 2019/2020) data. We provide descriptive statistics for rural farmers separately from the overall sample to ascertain whether there are significant differences in farmer characteristics, but we did not find big differences among the two kinds of farmers.

When we analysed farmers' usage of different farm implements and machinery, we discovered that the majority of the farmers still use rudimentary implements such as hoes and pangas but, most importantly, we did not find evidence of complementarities in the usage of improved seeds, pesticides, and organic and inorganic fertilisers.

We went a step beyond descriptive analysis to test for the complementarity of agricultural technology use empirically, but there still was no evidence for any combined effect on crop yields. These findings partly explain the prevailing low levels of crop productivity among smallholder farmers. On the other hand, we found a strong, positive individual effect of organic fertilisers on cassava, bean and coffee yields. Since organic fertilisers are relatively easier to access compared to inorganic fertilisers or improved seeds, the provide an opportunity for smallholder farmers to boost their crop yields by enhancing their adoption of organic fertilisers.

In our attempt to measure crop productivity as farm productivity, we found that a unit increase in inorganic fertilisers applied to the soil increases farm crop productivity by 69%. This finding is different from what we see when we investigate the effect of inorganic fertilisers on the partial measure of crop productivity. The implication is that the way we measure crop productivity matters. Thus, we argue that, of the four respective agricultural technologies considered in this study, inorganic fertilisers have the strongest effect on farm productivity. Furthermore, we unearth the fact that crop yields are very critical for the crop market participation of smallholder farmers – this is the case for banana and cassava. We argue that, since smallholder farmers often have pressing food needs, their crop productivity has to be high enough to meet their food needs for them to participate in the crop market.

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

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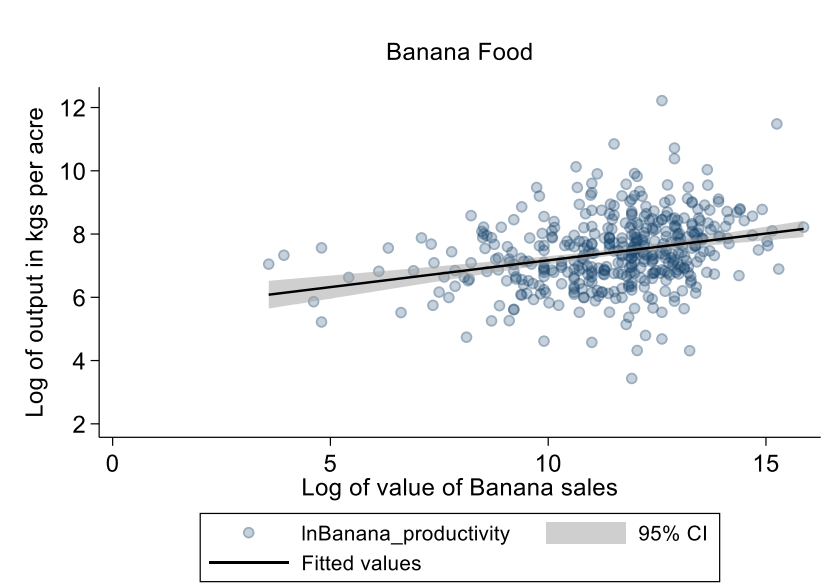
Appendix

The relationship between crop yields and crop market participation is both direct and positive. This signifies how critical yields are for smallholder farmers' participation in the market. Specifically, yields should at least satisfy household food requirements. The cash crop – coffee – exhibits a relatively similar relationship.



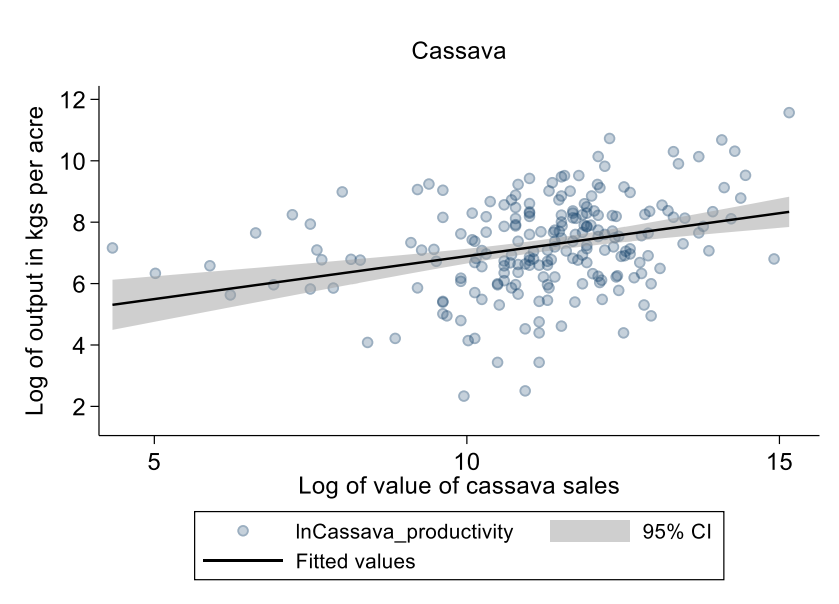
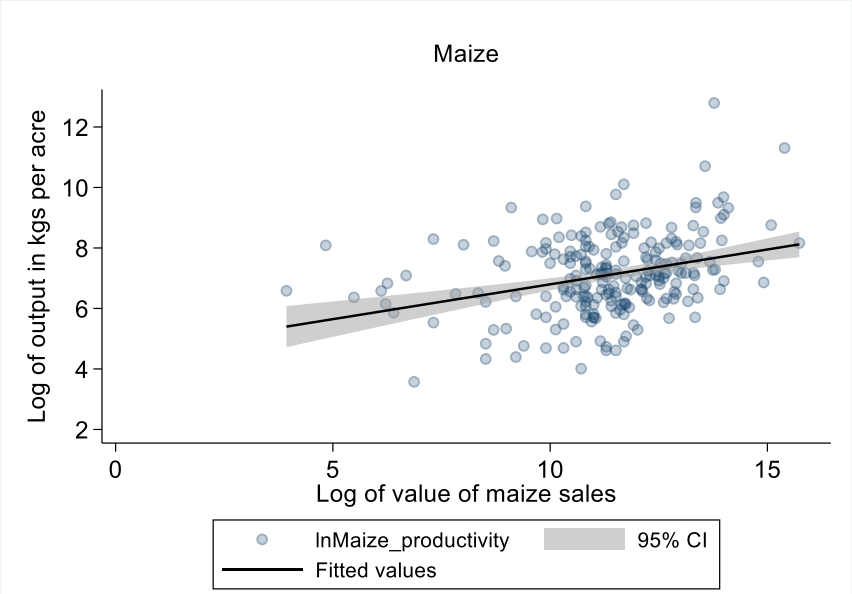
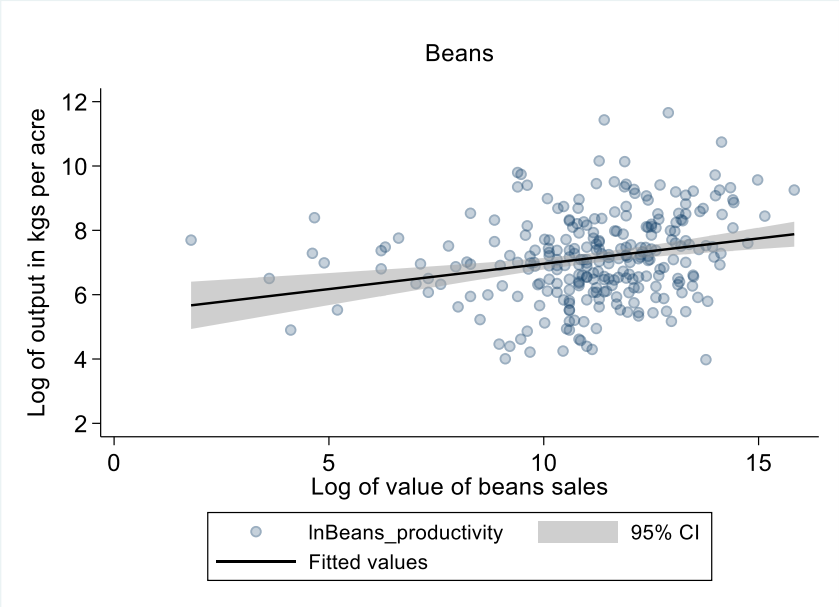


Figure A: Nexus between crop yields and crop market participation (continued on next page)





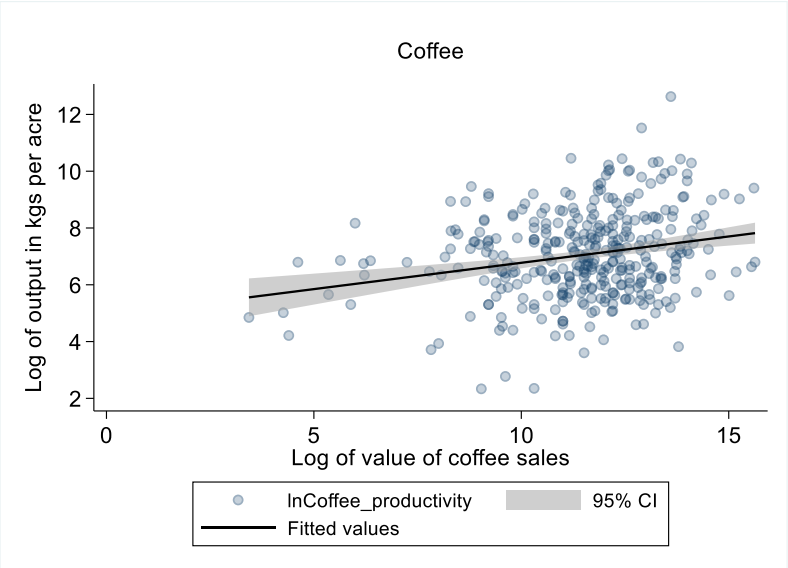


Figure A: Nexus between crop yields and crop market participation (continued)