Ecology of scope and the productivity of small-scale farming

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Abstract

The lack of specialization in developing countries is commonly seen as a cause of inefficiency and a consequence of absent or malfunctioning markets. A large ecology literature in contrast finds a positive relationship between diversity and ecosystem productivity. In this paper we study the economics of crop diversity. Using plot level data from Uganda, we show that the high levels of crop diversity are neither explained by risk exposure nor by a lack of market access but rather by the befits of crop diversity for production ('ecology of scope'). Guided by a microeconomic farming model, we estimate that a 10 percent increase in farm size and a 10 percent increase in farm labor increases crop diversity by 1.6 and 1.8 percent, respectively, consistent with the presence of both ecology of scope and economies of scale. Holding labor and land constant, a 10 percent increase of crop diversity at the farm level increases revenues by 3 percent. The estimated benefits of crop diversity are even larger at the plot level, suggesting that ecological interactions drive our results. Our results show further that the private benefits of crop diversity decline with agricultural modernization leading to a loss of crop diversity and its external benefits.

Keywords: Crop diversity; biodiversity; ecosystem services; agriculture; economic development

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1 Introduction

Households in developing countries rarely specialize and farmers in Africa are no exception. They grow substantially more crop varieties than their counterparts in developed countries (Waha et al. 2018). A lack of specialization is often seen as indicative for inefficiency (Romer 1987; Banerjee and Duflo 2007) resulting from malfunctioning or absent markets for financial services, inputs or outputs. Based on this view, policies to support specialization would increase agricultural productivity in Africa.

In contrast, a large ecological literature that studies the role of biodiversity for ecosystem functioning, finds that diversity increases ecosystem productivity. This is because different species are complementary in their utilization of niches, i.e., they use different combinations of ecological resources or the same combination of resources but at different points in time (Hooper et al. 2005; Harpole and Tilman 2007; Cardinale et al. 2012; Duffy et al. 2017; Eisenhauer et al. 2018). In agriculture, this may not only apply to ecological resources such as nutrients, space or light, but also to other inputs such as labor and capital. Different crops require labor and capital inputs at different points in time, therefore increasing the effective labor and capital endowments of a farm. This ecological concept is closely related to economies of scope in the economic literature (Panzar and Willig 1981). According to this view, utilizing 'ecology of scope' with high crop diversity enhances productivity, whereas policies that promote specialization would reduce agricultural productivity.

In this study we explore the drivers and consequences of crop diversity for small-scale farming in Africa using a microeconomic farming model and plot level data from Uganda. Like many African countries, Uganda is predominantly rural and the majority of households depend on local agriculture for incomes and food. Despite the relative importance of agriculture, agricultural productivity in Africa is low and the gaps between the observed yields and the potential yields under improved nutrients and water management are large (Mueller et al. 2012). The low use of agricultural inputs such as fertilizer and irrigation also imply that African farmers still largely rely on ecosystem services for their agricultural production. Here we discuss the importance of crop diversity for the low input agriculture of Sub-Saharan Africa using Uganda as a typical example.

In the first step of our analysis, we explore the empirical relationships between crop diversity and variables that are commonly associated with diversification or specialization. Although farmers in Uganda perceive droughts and floods as the most important reason for income shortfalls, we find no evidence that variations in rainfall risk explain the observed crop diversity pattern. We also find no evidence that market access plays an important role in explaining crop diversity. In contrast, we do find evidence for the production benefits of crop diversity as well as evidence for crop specific fix costs and productivity differences between crops as the basis for returns to specialization.

Next, we propose a new microeconomic farming model based on these empirical observations. The model combines the economic theory of gains from specialization with the benefits of diversification suggested by the ecology literature. In line with the ecological literature (Harpole and Tilman 2007) the importance of the ecological complementarities between crop

species depends on the ability of the farmer to control the environmental factors of production. In other words, the ability to homogenize the environment – e.g. through irrigation to regulate the water supply, application of fertilizer to regulate nutrients or greenhouses to regulate temperature – reduces the number of ecological niches and thus the benefits of crop diversity.

Our theory predicts that crop diversity increases with farm size and labor. This positive relationship between farm size, labor and crop diversity results from the interplay between the ecology of scope and the economies of scale. While the benefits of crop diversity increase with farm size and farm labor, the mechanisms that underlay the economies of scale remain constant. However, this relationship between farm size and crop diversity weakens with the increasing ability of the farmer to control the environment. Our theory predicts further that crop diversity increases productivity as a consequence of the complementarities between crop types. Similar to the first prediction, the this relationship weakens with the farmer's increasing control over the environment.

In a third step, we then test these predictions using the plot-level data from the living standard measurement survey of Uganda. The main advantage of these data is that they contain observations of most crop types grown individually (monocultures) and in combination with other crops (intercropping). This allow us to distinguish between different mechanism that are responsible for the benefits of crop diversity. Farmers in Uganda have limited control over environmental factors. They rarely use fertilizer, irrigation systems, pesticides and other strategies to control the environment. We therefore focus on the model predictions for the low-input agriculture of Africa.

Our empirical results show that crop diversity increases with farm size and farm labor in line with the prediction of our model. A 10 percent increase in farm size increases crop diversity by 1.6 percent in our preferred regression specification. Farm labor has a similarly positive effect. Increasing farm labor by 10 percent increases crop diversity by 1.7 percent in our preferred regression specification. These results remain unchanged when using household composition and land inheritance as instruments for labor and land respectively as well as using the GPS land measurements to correct for land measurement error. The variation of labor and land alone explains 22 percent of the variation in crop diversity after controlling for farmer, season and years specific differences.

Further, we find that crop diversity increases productivity. Every thing else equal, a 10 percent increase in crop diversity at the farm level increases revenues at the farm level by 3.3 percent. However, this result could be biased if crop diversity is correlated with the average farm level plot size and harvest from smaller plots is systematically overreported. Estimating this relationship at the plot level allows us to control for the impact of plot size on the outcomes. Additionally, while the benefits of crop diversity due to increased labor and capital use efficiency materialize at the farm level, the ecology of scope from reduced crop competition between crops through niche partitioning is only relevant at the plot level. In a second approach we therefore estimate the impact of crop diversity at the plot level. The results suggest that a 10 percent increase of crop diversity at the plot level increases revenues by 4.2 percent. We interpret this result as evidence for the importance of ecological interaction for the low input agriculture of Sub-Saharan Africa.

Our study is related to the literature that studies the economic consequences of crop diversity. Weitzman (2000) studies the trade-off between the benefit from agricultural specialization and the risk of catastrophic infection in a theoretical framework. The main focus of his paper is the trade-off between individual gains from specialization through increased revenues and the contribution of individual specialization to the probability of aggregate agricultural collapse. Similarly, Brock and Xepapadeas (2003) assume that the benefit of crop diversity results from the impact of crop diversity on crop failure but their main focus is on developing a theoretical framework to evaluate this benefit.[1] Bellora and Bourgeon (2019) add the externalities from pesticide use as well as the gains from specialization due to comparative advantages to these trade-offs. In the theory proposed in this paper, we add the input complementarities or imperfect competition which is central to the ecological literature (e.g. Vandermeer 1992) as well as the returns to specialization from the economics literature.

Empirically, our paper builds on the work by Smale et al. (1998), Di Falco and Chavas (2009) and Bellora et al. (2017) who study the impact of crop diversity on the level and stability of crop production in Pakistan, Ethiopia and South Africa respectively.[2] Similarly, Fiszbein (2017) studies the impact of agricultural diversity on economic development. In contrast to these studies, we do not take crop diversity levels as given but focus on the mechanism explaining diversification in agriculture. This mechanistic understanding of the drivers and implications of crop diversity allows us to make counterfactual predictions about the impact of economic development and market integration on the value of crop diversity.

The main contribution of our paper is to combine the proposed drivers for specialization and diversification from the economic and the ecology literature in one unified theoretical framework based on empirical facts from agriculture in Uganda. The empirical tests of our predictions support the underlying assumptions. Our main finding is that the high levels of crop diversity in Uganda result from the interplay between economies of scope, largely due to ecological interactions and reduced competition, and the economies of scale of crop production.

The rest of the paper is organized as follows. In Section 2, we present our data and in Section 3 we derive stylized facts as the basis for our model. Our model is developed in Section 4. The statistical methods to estimate model predictions are explained in Section 5 while Section 6 presents the empirical results. Section 7 quantifies the value of crop diversity and discusses counterfactual simulations. The final section contains the discussion and conclusion.

2 Data

Similar to many African countries, agriculture in Uganda is characterized by low levels of inputs and high levels of crop diversity. Crop production in Uganda is not only diverse within farms but also within fields as intercropping (planting a mix of crops on one plot) are common

[1] Gollin et al. (2000) study the value of gene banks for developing pest are disease resistant crop varieties.

[2] Auffhammer and Carleton (2018) address a similar research question using district level data from India. Michler and Josephson (2017) and Tesfaye and Tirivayi (2020) take a very different approach estimating the direct impact of crop diversity on poverty and consumption respectively. On global scale, Renard and Tilman (2019) estimate the impact of crop diversity on output variance.

practice. Observing the same crop planted as monoculture and in combination with other crops allows us to isolate ecological interactions from economic mechanisms that operate at the farm level. Throughout this article we use plot level data from the Living Standards Measurement Study - Integrated Surveys on Agriculture (LSMS-ISA) from Uganda. Self-reported data have their limitations. However, for highly diverse small-scale agriculture with rampant intercropping they may still be the best source of information. We discuss how we address potential biases of self reported data below.

2.1 Household data

The data from LSMS-ISA is representative at the national level, the urban and rural level and the regional level (North, East, West and Central regions). The survey is composed of structured interviews of 3,200 households from the stratified random sample of the Uganda National Household Survey in 2005/06. Interviews were conducted in five rounds between 2009/10 and 2015/16 with visits in each of the two growing seasons per year. Households were tracked over time, but a share of the sample was replaced in 2012 by a new random sample of households based on the updated sample frames developed for the Population and Housing Census. We include an initial Uganda National Household Survey of 2005/06 as well, but exclude the urban stratum to focus on the rural production, which results in a sample of about 45,000 complete plot and about 18,000 complete household level observations. The survey design is described in detail on the LSMS-ISA web page. The data contains plot-level information on seasonal crop production including data on crop type, inputs and other production practices, and yields. In the following we discuss the measurement of our key variables.

Land: We measure land (farm size, plot size, and crop area) based on the area planted with crops. Farmers in Uganda may not know the exact size of their plot. In fact, farmers in Uganda systematically over-report the size of small plots and small farms while they under-report the size of large plots or farms (Carletto et al. 2013; Dillon et al. 2019). However, 60 % of the plots were also measured using GPS. To test for potential bias in self-reported plot sizes we estimate

$$\log(\text{land gps}_{it}) = \theta \log(\text{land reported}_{it}) + \varepsilon_{it}$$

where land gps_{it} is the plot size measured by GPS signal and land reported_{it} is the plot size reported by the farmer. We then predict plot size based on this estimated relationship for all self-reported values. In a robustness test, we use this predicted land size measure bootstrapping standard errors across both levels of estimation. In addition, previous studies show that measurement error is larger on small plots Burke and Lobell (2017). We therefore exclude all crop stands under 100 m^2 and all farms below 0.1 ha in all regression specifications.

Land is measured in three levels of aggregation. The lowest level of aggregation is the *crop-plot level* or the *crop stand*. This is the share of a plot which is occupied by one crop. While the size of the crop stand equals the plot size for monocultures it diverges when multiple crops are planted in combination on the same plot. We use the crop cover percentages reported by the farmer to allocate the plot area to individual crops. The next level of aggregation is the

plot level. A plot or field is a piece of land that is managed as one unit. It could be managed as monocultures with one crop type or in intercropping with several crop types. The GPS measurements are at the plot level. Lastly, *farm size* is the sum of cultivated plots. The measure excludes farm land under fallow, rangelands or native vegetation.

Labor: Labor is recorded on plot level in person days. Here, we combine family labor and hired labor. However, hired labor plays a minor role in the agriculture of Uganda (see table 1). We allocate plot level labor to individual crops according to the crop shares discussed above.

Revenues and yields: Production is recorded in local physical units. We convert these units to kilograms (kg) using the median district level conversion factors from the survey. To aggregate outputs across different crops we use crop prices. Only a small fraction of the crops are sold (see Table 1). We therefore use median crop prices on year, season and district level from the survey to convert physical quantities to revenues. Although crop prices probably play a minor role in the planting decisions of farmers we still consider them a good proxy for marginal utility from consumption. We exclude all observations with less than 1 kg harvest or more than 10,000 kg harvest per plot to address misreporting and influential outliers.

Crop diversity: There are many different measures of diversity in ecology. Most of these measures combine the number of species and their relative abundance. The most commonly used diversity measures (Simpson index, Shannon index and species richness) are variations of the effective number of species defined by

$$D = \left(\sum_{i=1}^{n} a_i^{\alpha} \right)^{\frac{1}{1-\alpha}}$$

where $\alpha \geq 0$, n is the number of species or crop types, and a_i is the relative abundance of species i (Hill 1973). The main difference between the specific indices is the weight placed on abundance compared to mere presence-absence information. For $\alpha = 0$ the index equals species richness i.e. the number of species or crops that are present in a sample, for $\alpha \to 1$ the index equals the Shannon index, while for $\alpha = 2$ the index equals the inverse Simpson index. We use crop richness in our theoretical approach and main empirical specification and use the Simpson index as a robustness check.[3]

To measure relative abundance, we use the area planted with a crop relative to the total cropping area. The advantage of using area planted compared to measures based on outcomes in the harvesting season (e.g. revenues or area harvested) is that the area planted is independent of weather events during the growing cycle as well the impact of crop diversity on the outcome itself.

2.2 Weather data

We use weather data as controls in our regression specifications and to measure production risk. Farmers reported drought as the single most important reason for income shortfalls followed by floods as the second most important reason for income shortfalls (see Figure 6).

[3]Note that the Simpson index is equivalent to the Herfindahl–Hirschman Index of market concentration widely used in economics.

Both are directly related to weather events. We use three different gridded data sets to measure positive and negative precipitation deviations that may cause droughts and floods. The first precipitation data set is the combined data from the Tropical Rainfall Measuring Mission (TRMM) and the Global Precipitation Mission (GMP) which was produced by a joint space mission between NASA and the Japan Aerospace Exploration Agency to measure tropical rainfall (Huffman et al. 2007).[4] The data product combines measurements from precipitation radar, microwave imager, visible infrared scanner, clouds & earths radiant energy system and lightning imaging sensor. The data set starts in 1998 and has a 0.25° spatial resolution. We use this data set to measure rainfall.

The second data set is the Standardized Precipitation Evapotranspiration Index (SPEI) based on CRU TS 3.24 weather data and the FAO-56 Penman-Monteith estimation of potential evapotranspiration.[5] The index combines temperature and precipitation data to measure the difference between the temperature dependent potential evapotranspiration and the measured precipitation level (Vicente-Serrano et al. 2010). The spatial resolution is 0.5°.

The third weather data set are terrestrial air temperature and precipitation data from Willmott and Matsuura of the University of Delaware (UDEL).[6] We use this data set mainly for comparison.

We calculate district level average monthly weather and merge these data to the household data using the district name as identifier.

2.3 Summary statistics

Table 1 provides the summary statistics of our household data. Overall, gross crop revenues per farm are low and farms are small. The mean value of the complete harvest (revenues) are 616 USD per year [7] or 1,777 in international PPP adjusted dollars while the mean farm size is 1.1 hectare (ha). In contrast to the small farm size, labor is abundant. The mean farm labor per season is 141 days combining family labor and hired labor. However, the share of hired labor is low, with 1.4 % on average. This low level of market participation is also apparent in the harvest, with only about 20 % of harvest sold on markets. Crop diversity in contrast is high, both within and across plots. The median share of the farm land that is allocated to intercropping (defined as growing several crops on one plot at the same time) is 44 % and farms grow on average more than four crops on their land.

3 Patterns of crop diversity and farming in Uganda

In this section we relate crop diversity to variables that the literature commonly associates with diversification. Specifically we focus on risk, market functioning and returns to scale from the economic literature as well as resource complementarities or ecology of scope from the ecological literature. Here, we do not aim at establishing causal relationships but rather

[4] `https://gpm.nasa.gov/data/directory`

[5] `https://spei.csic.es/database.html`

[6] `http://climate.geog.udel.edu/~climate/html_pages/download.html`

[7] This includes the share of the harvest that is consumed by the farmer as well as the share that is sold. We use median district level prices to compute total revenues.

Table 1: Summary Statistics

Statistic	Mean	St. Dev.	Median	Q25	Q75	Min	Max
Revenues [2018 US $/year]	615.8	2,982.6	260.3	110.2	576.3	2.4	189,418.1
Revenues [2018 Int.$/year]	1,776.5	8,603.6	750.8	318.0	1,662.4	6.9	546,393.8
Share sold [%]	20.0	20.8	16.7	0	33.3	0	100
Farm size [ha]	1.1	2.1	0.7	0.4	1.2	0.1	82.6
Share inherited [%]	64.4	44.6	100.0	0.0	100.0	0.0	100.0
Labor [days per year]	276.9	253.9	214	120	352	2	6,074
Share hired [%]	1.4	7.6	0	0	0	0	100
Number of crops	4.3	1.9	4	3	5	1	16
Share intercropping [%]	44.1	37.9	50.0	0.0	75.0	0.0	100.0

The table reports the mean (Mean), the standard deviation (St. Dev.), the median (Median), the lowest (Q25) and highest (Q75) quartile as well as the minimum value (Min) and the maximum value (Max) of the 17,838 household level observations. 'Share sold' is the share of the harvest that is sold. The remaining part is consumed by the household. 'Farm size' is the sum of area of cultivated plots. 'Share inherited' is the share of the land that was inherited by the household. 'Labor' is the sum of labor across all plots cultivated by the household. 'Share hired' is the share of this labor that was hired. 'Number of crops' is the mean number of crops grown by a household per season while 'share intercropping' is the share of the household's plots with intercropping.

to explore empirical relationships as the basis for our theoretical framework. Before we relate crop diversity to risk, markets, increasing returns and ecology of scope, we describe the general cropping pattern.

Figure 1: Typical farm landscape and intercropping of banana, beans, cassava and taro in Western Uganda (photo: Frederik Noack)

3.1 Cropping pattern

Uganda is located at the equator experiencing uniform warm and humid climate throughout the year. There are two cropping seasons, the first season from January to June, the second season from July to December. The tropical climate not only allows for almost continuous cultivation but it also supports a wide variety of crops. Figure 1 illustrates a typical agricultural landscape and intercropping of beans, cassava, bananas and taro in Western Uganda. Figure 2

shows the frequency and the co-occurrence of the 10 most common crops in our data set. The shading of the antidiagonal elements represent the number of plot level observations of crops in our data set while the off-antidiagonal elements indicate the number co-occurrence with other crop types. The figure suggests that crop production in Uganda is diverse and not dominated by a few crops.It also shows that there is a smooth transition of shading, suggesting that most crop combinations are commonly observed.

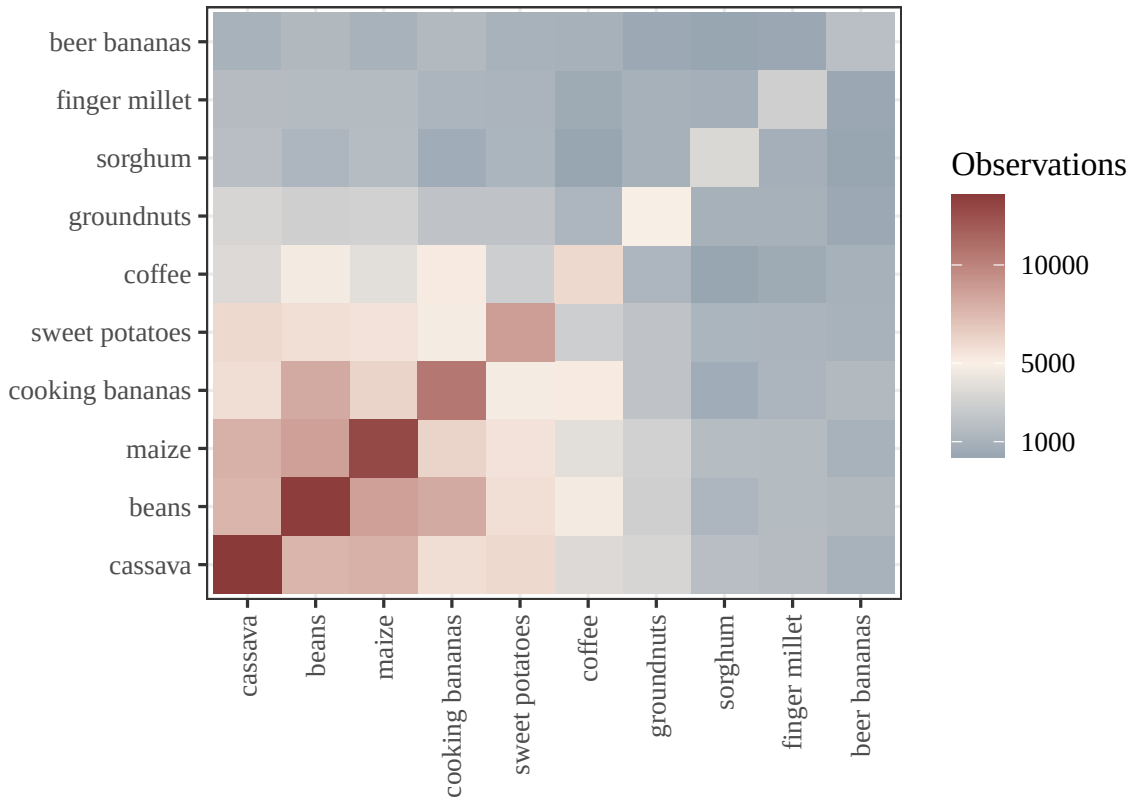

Figure 2: Co-occurrence of the main crop types within farms

The focus of Figure 2 is on-farm crop diversity. In contrast, Figure 3 illustrates the planting system by crop type. Monoculture refers to cultivation of only one crop type per plot at the same time, while intercropping refers to the mix of at least two crops per plot. The bars represent the total area planted with the 10 most common crop types in monocultures and intercropping. For intercropping we use the share of the plot that is allocated to the specific crop (see data section). The figure shows that all common crop types are planted in both monocultures and intercropping systems making direct comparison of yields between both systems possible.

Cropping pattern not only vary across space but also over time. Figure 4 shows the mean annual crop number per season and the mean absolute deviation of crop numbers for a balanced panel of households between the years 2009 and 2015.[8] Households plant on average 4.3 different crops per season but the actual number of crops is on average about one crop dif-

[8]We use the annual mean of seasonal crop diversity to focus on the inter-annual variation. We further drop the 2004/05 data from the figure because of the time gap between 2005 and 2009. In the further analysis we use seasonal crop diversity and include 2004/05.

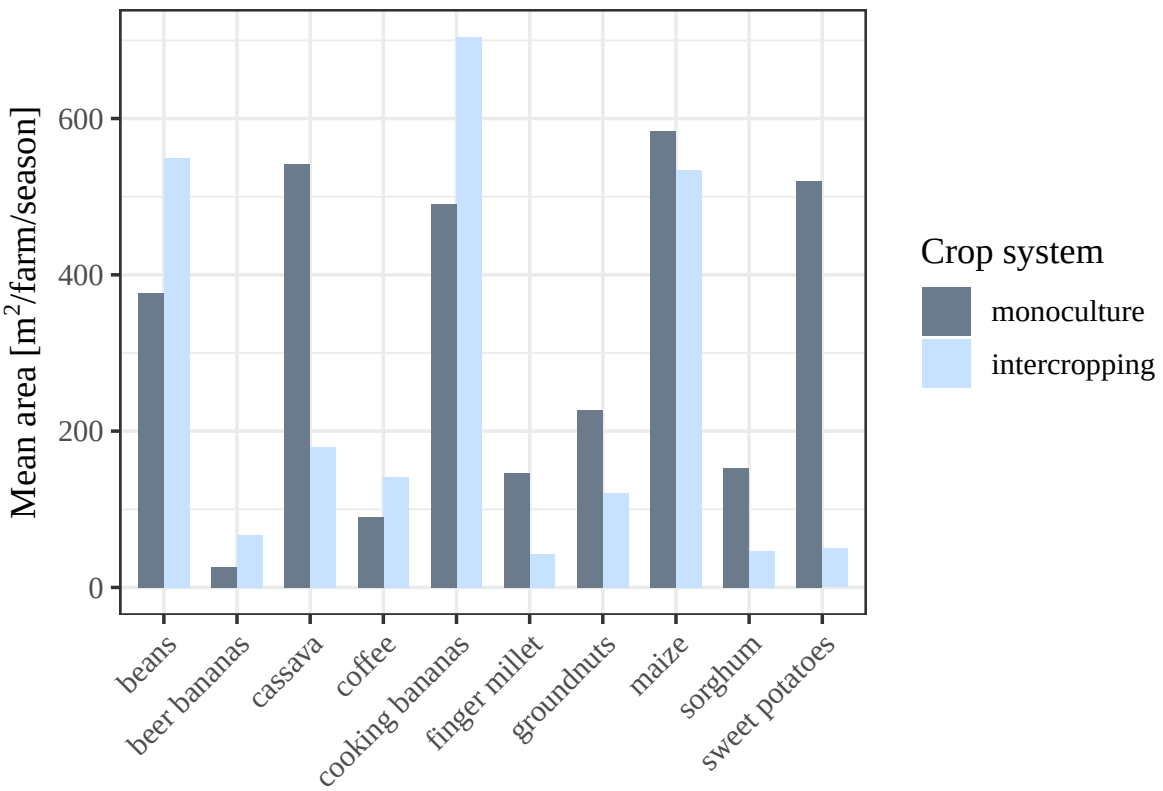

Figure 3: Area planted with the ten most common crop types by cropping system

ferent from this expected value. In other words, there is considerable inter-annual variation in crop diversity within individual farms.

Figure 5 depicts the spatial distribution of crop diversity. The number of crops per farm is relatively evenly distributed within Uganda. The average number of crops per farm is higher than average in Central and Western Uganda and lower in Northern Uganda (Figure 5). Since the survey is not representative at the district level and new districts were created during the time of the survey, extreme values of individual districts may not be informative.

However, some spatial pattern of crop numbers per farm become apparent. A clear relationship between rainfall risk and crop numbers seems unlikely because farms in Northern Uganda have low levels of crop diversity but are exposed to relatively dry weather with frequent droughts while the southern part of Uganda enjoys a relatively stable and humid climate. However, the southern parts of Uganda are also more densely populated making a relationship between market access and crop diversity possible. We explore the relationship between crop diversity and risk, markets, prices and costs in the following.

3.2 Crop diversity and risk

Diversification is often associated with risk-management (e.g. Eeckhoudt et al. 2005) and crop diversity is no exception (Di Falco and Chavas 2009; Auffhammer and Carleton 2018; Chuang 2019). Farmers in Uganda are facing high levels of income risk with little access to financial services to mitigate these shocks. By far the most common reason for income shortfalls in rural

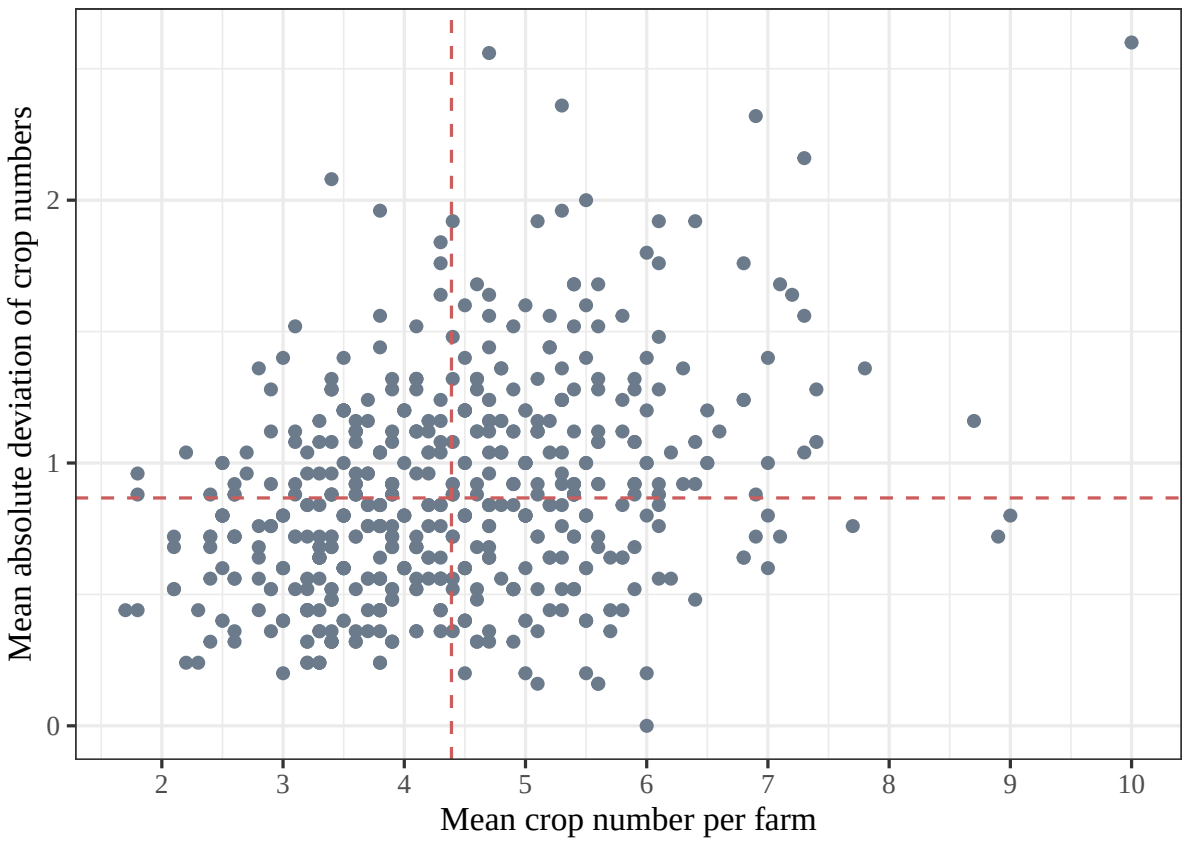

Figure 4: Mean number of planted crops and mean absolute deviation of crop numbers for a balanced panel of households between 2009 and 2015. The red lines are sample means.

Uganda are droughts followed by floods (Figure 6). Droughts as well as floods are directly related to rainfall patterns.

The attempt to cope with the risk of droughts and floods may therefore seem to be a plausible explanation for the high levels of crop diversity in Uganda. To explore the relation between risks and crop diversity, we plot the number of crops against deciles of the coefficient of variation of annual district level rainfall between 1998 and 2016 based on the TRMM/GPM data.[9]

Figure 7 does not reveal any clear relation between crop diversity and rainfall risk. Although we find a positive correlation between rainfall and crop diversity in the Appendix C, rainfall levels and rainfall riskiness only explain about 6% of the variations in crop diversity. Further, we find no clear relationship between current and past weather shocks and crop diversity (Appendix C). We therefore conclude that rainfall risk is not the major determinant of crop diversity in Uganda. Although this finding seems surprising at first it can be explained by the high correlation of crop responses to weather shocks. Diversification is important to mitigate the risk of uncorrelated returns such as gambles (Gollier 2001). However, reducing the expected response to a highly correlated shock such as droughts may imply choosing the crop with the least response to weather extremes. In other words we expect a change in the

[9]We use the coefficient of variation instead of the standard deviation or variance because it corrects for mean precipitation levels which could affect crop diversity levels also directly. Uganda is located directly at the equator with a 12 months growing period. We therefore use annual precipitation levels. Appendix A shows the correlation of the TRMM data with the UDEL precipitation data from Willmott and Matsuura as a reference. It also shows the relationship between crop diversity and rainfall risk based on the UDEL data.

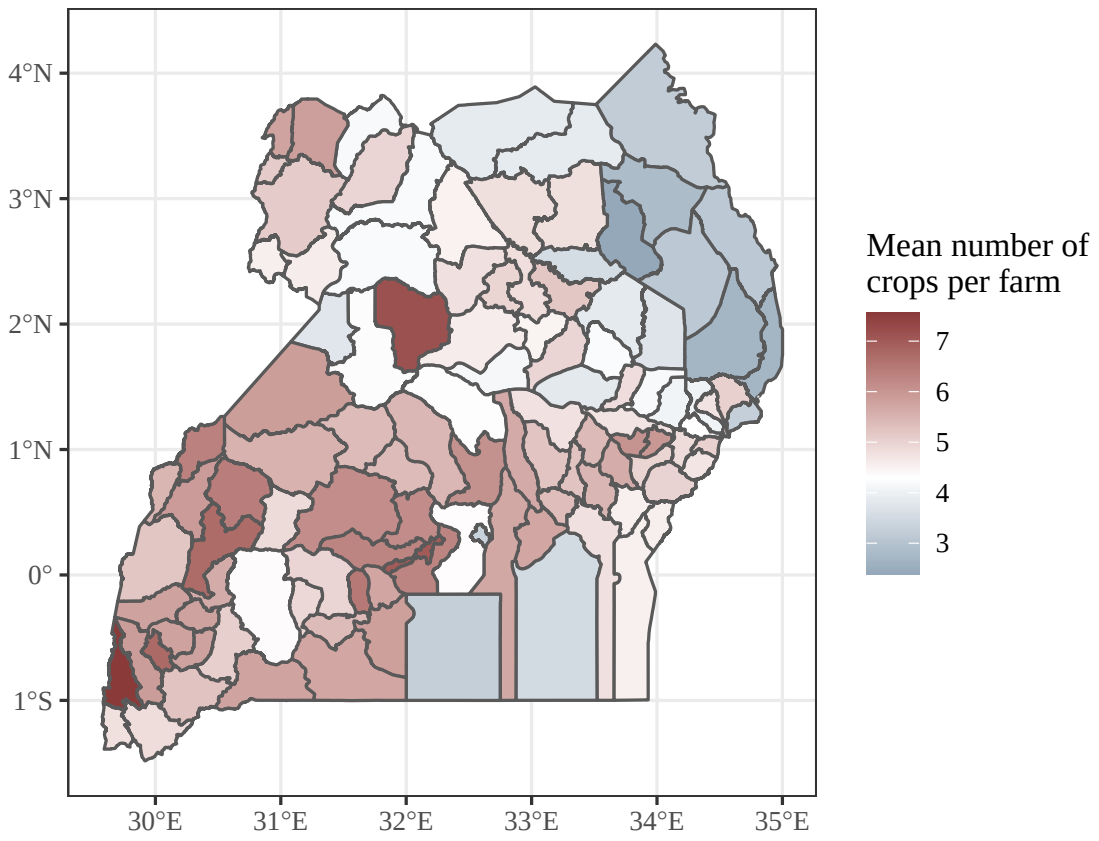

Figure 5: Spatial distribution of crop diversity

crop identity or crop selection but not necessarily a response in crop diversity.

3.3 Crop diversity and markets

Crop diversity may also be high to cater preferences for variety in consumption (e.g. Dixit and Stiglitz 1977, Quaas and Requate 2013) in the absence of markets. Most farms in Uganda are subsistence farms, consuming the largest share of their production (Table 1). In consequence, if farmers have a preference for variety they may wish to produce a variety of crops. It therefore seem plausible that households grow a large number of crops because of their preference for diversity in consumption. In contrast to farmers in Uganda, farmers in developed countries sell most of their harvest. They often specialize according to their comparative advantage and use the revenues to buy the desired variety of consumption goods. Based on these arguments, we would expect that crop diversity declines with market participation, because households become less dependent on their own production for consumption. Figure 8 shows the level of crop diversity in relation to market participation. Farms in the lowest market participation bin consume their complete harvest while farms in the highest market participation bin sell 90 % of their harvest or more. While the survey contains observations for each market participation bin, observations exceeding 50 % market participation are rare. However, the figure suggests that crop diversity declines with market participation.

Market participation is endogenous while market access is more exogenous to the individual household. We therefore investigate the relationship between crop diversity and market

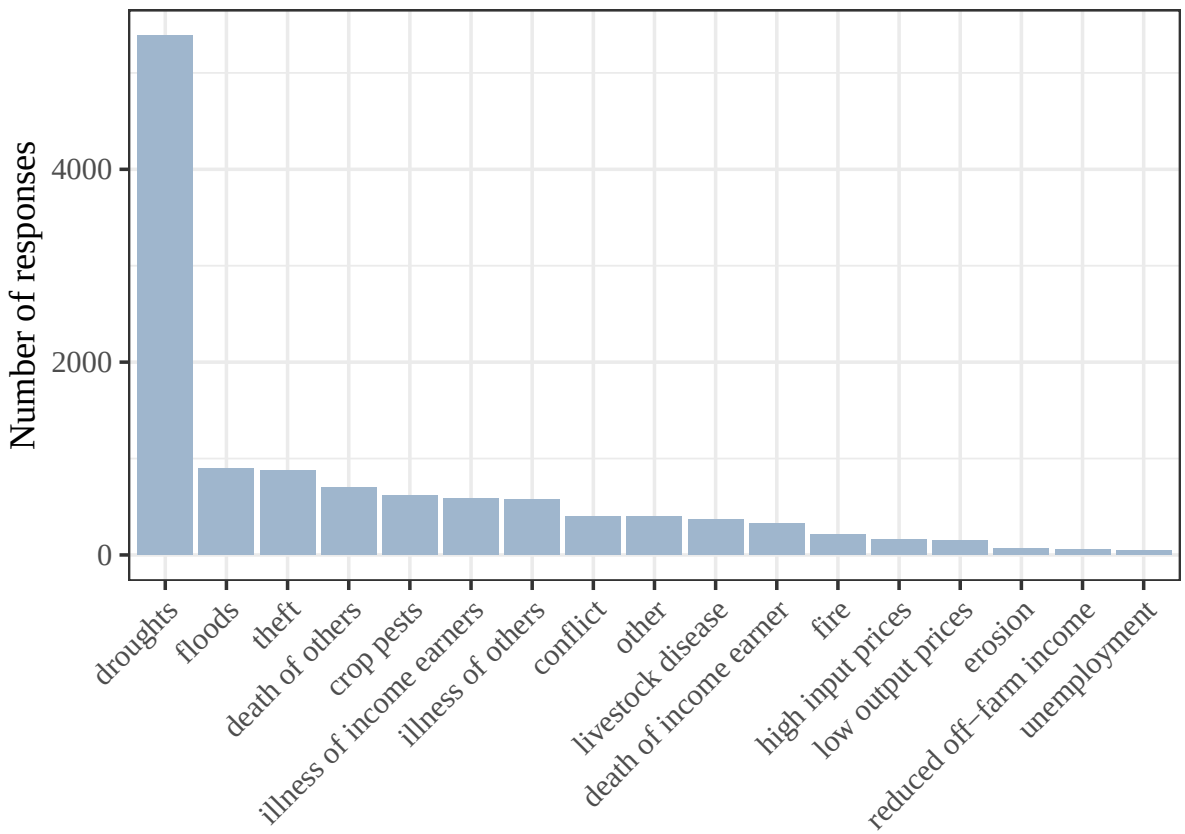

Figure 6: Reasons for income shortfalls.

access in Appendix D. However, we find no clear relationship between market access and crop diversity, partly because market access is mostly unrelated to market participation in Uganda. In contrast, the agricultural suitability for cash crops does explain output market participation. Using the agricultural suitability for coffee and cotton (the two main cash crops in Uganda) as instruments for market participation, we find a nonlinear relationship between crop diversity and market participation similar to Figure 8. Participation in output markets explains about 10 % of the variation of crop diversity in Uganda (see Appendix D).

3.4 Crop diversity and increasing returns

A major reason for returns to specialization are increasing returns to scale due to fixed costs (e.g. Romer 1987). In agriculture, specific crop types may need specific inputs such as machinery, but also knowledge or just the additional preparation time and effort to carry out crop-specific tasks such as planting, weeding or harvesting. These costs induce increasing returns to scale in profits and can be the driver for specialization.[10] While these fixed costs are difficult to observe directly, we can indirectly infer about their presence. Optimal land allocations across crops may include very small values such as several square centimeters or meters. However, we would not observe these small allocations in the presence of fixed costs. We discuss this argument further in the theoretical section of this paper. Figure 9 shows the land that

[10]Other reasons for increasing returns to scale such as increasing returns to scale in production seem unlikely based on the large farm size literature (e.g. Noack and Larsen 2019).

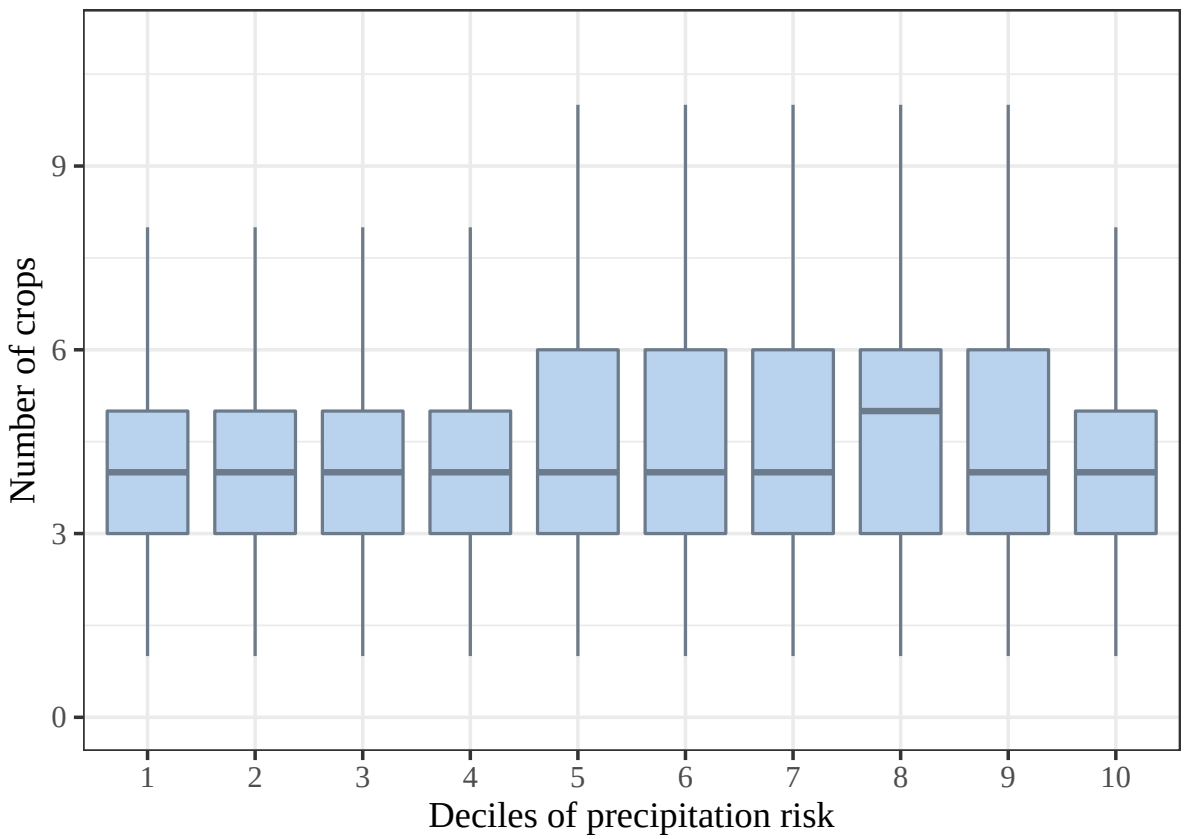

Figure 7: Farm level crop diversity and deciles of rainfall risk. Rainfall risk is measured by the coefficient of variation (CV) of annual district level rainfall between 1998 and 2016 based on the TRMM data.

is allocated to individual crops per farm. The median crop area per farm is 1,518 m^2 (black line) while only 2.5 % of the observations are below 100 m^2. Although these values are small according to developed country standards it is relatively large compared to the small farm sizes in Uganda. We interpret this finding as indicative for the presence of fixed costs.

3.5 Crop diversity and economies of scope

The main mechanism suggested by ecologists to explain the positive impact of biodiversity on productivity in natural ecosystems is the complementarity of species' resource use (Hooper et al. 2005). In other words, different "... species use different resources, or the same resources but at different times or different points in space..." (Hooper et al. 2005). In agriculture this is likely to occur for resources such as nutrients, water and light but also for other inputs such as labor. For example, if crops require labor inputs at different points in time (e.g. they have different planing and harvesting cycles) then dividing labor among more crops would increase the effective labor units of a household. Intercropping, i.e. growing several crops on one plot, is a common practice in Uganda. If ecological complementaries between crops were important, we would observe higher productivity on plots with intercropping compared to monocultures. Figure 10 shows the output per unit of land for the ten most common crops in our data sets. The figure shows that median crop yields are higher on plots with intercropping compared to

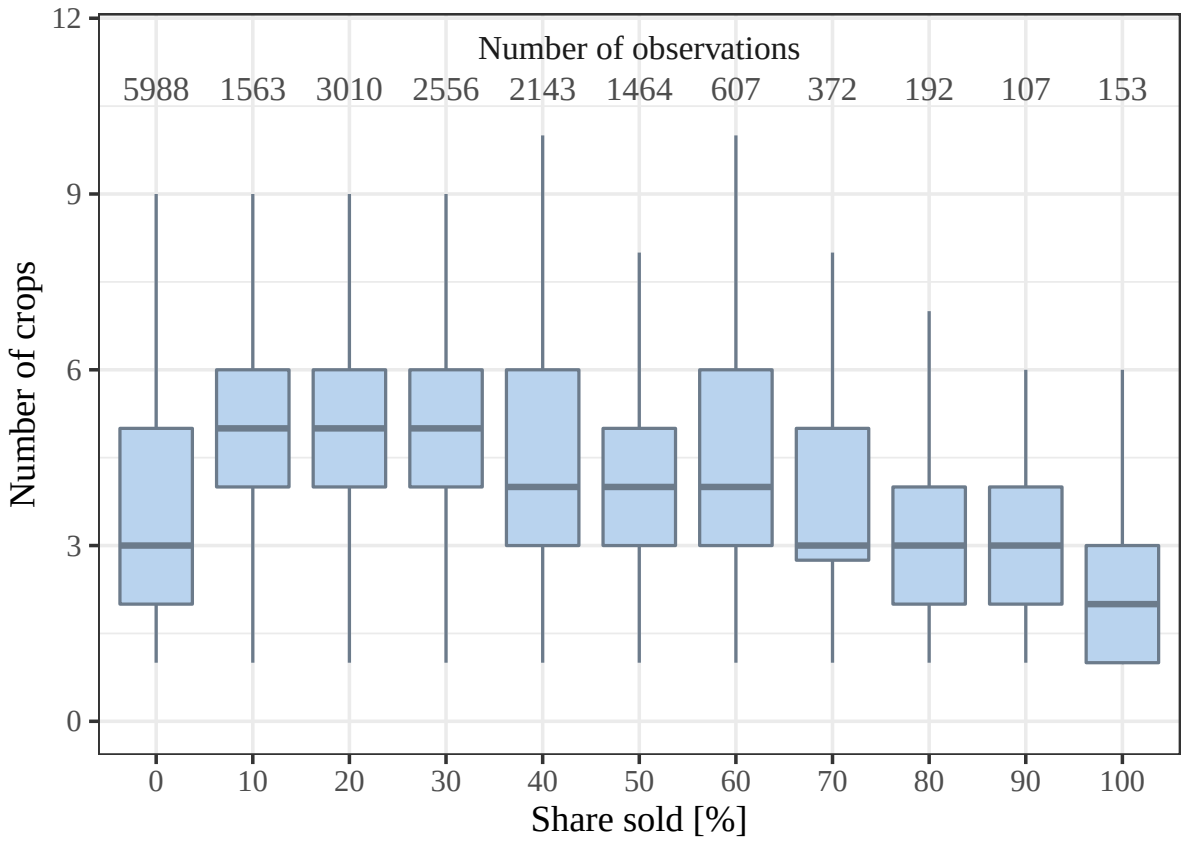

Figure 8: Market participation and crop diversity. Market participation is measured in the share of the total harvest that is sold. Market participation bins are defined as 0: 0 %, 10: 1 % to 10 %, 20: 11 to 20 %,.. 100: 91 % to 100 %. The number of observations within each bin is shown above each boxplot.

monocultures.

However, the complementarities between crops only increase productivity if the gains form crop complementarities in production outweigh the losses from allocating resources away from the most productive crops to a less productive crop. Figure 11 compares the revenues per unit of land across different crops grown in monocultures and intercropping. Using revenues to measure productivity, the figure suggests that the productivity differences between the same crop grown in monoculture and in intercropping are often larger than the productivity differences across different crops grown in the same system.

These observation suggests that there are direct benefits of crop diversity. However, the net benefits of crop diversity may change once we account for the cost of other inputs such as labor. We address this problem in the main empirical section of this study (Section 6).

The benefit of intercropping differs between crops. While yields are substantially higher in intercropping compared to monoculture for beans, bananas and coffee, there is hardly any difference in yields between both systems for e.g. millet and sweet potatoes. We therefore expect that sweet potatoes and millet are less frequently planted in intercropping compared to beans, bananas and coffee. This pattern is confirmed by Figure 3. In addition to the individual suitability of crops for itercropping, some specific crop combination may be more beneficial than others. The analysis of these pattern is, however, complicated by the fact that less bene-

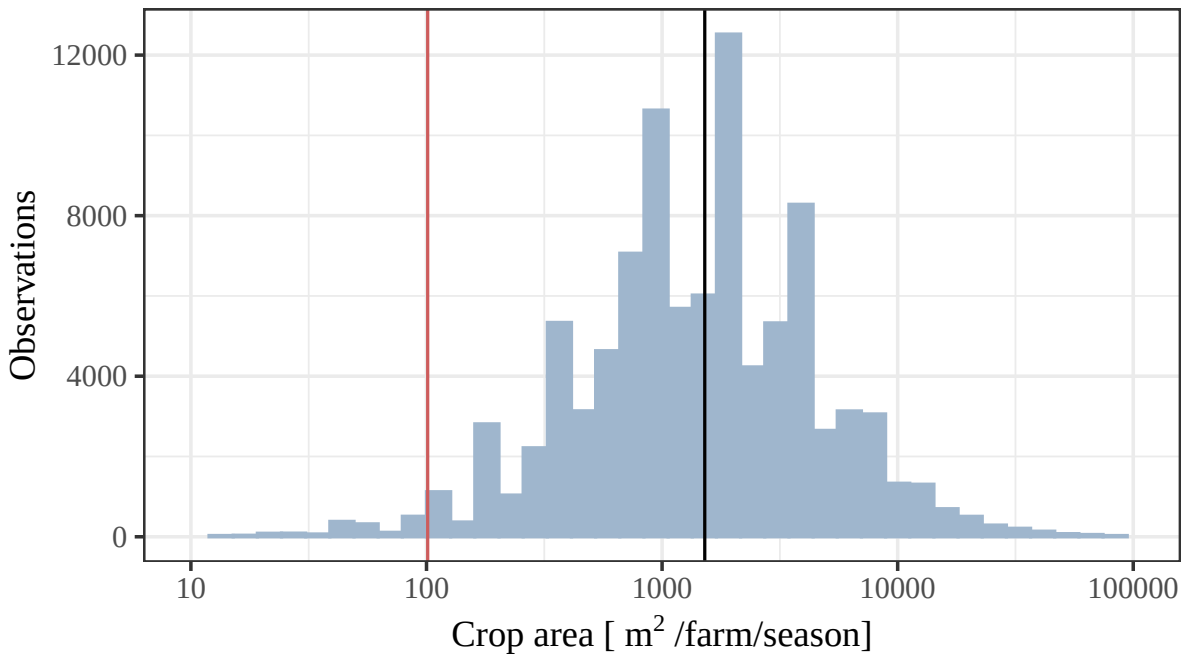

Figure 9: Farm area allocated to individual crops. The red line is the 2.5th percentile, the black line is the 50th percentile.

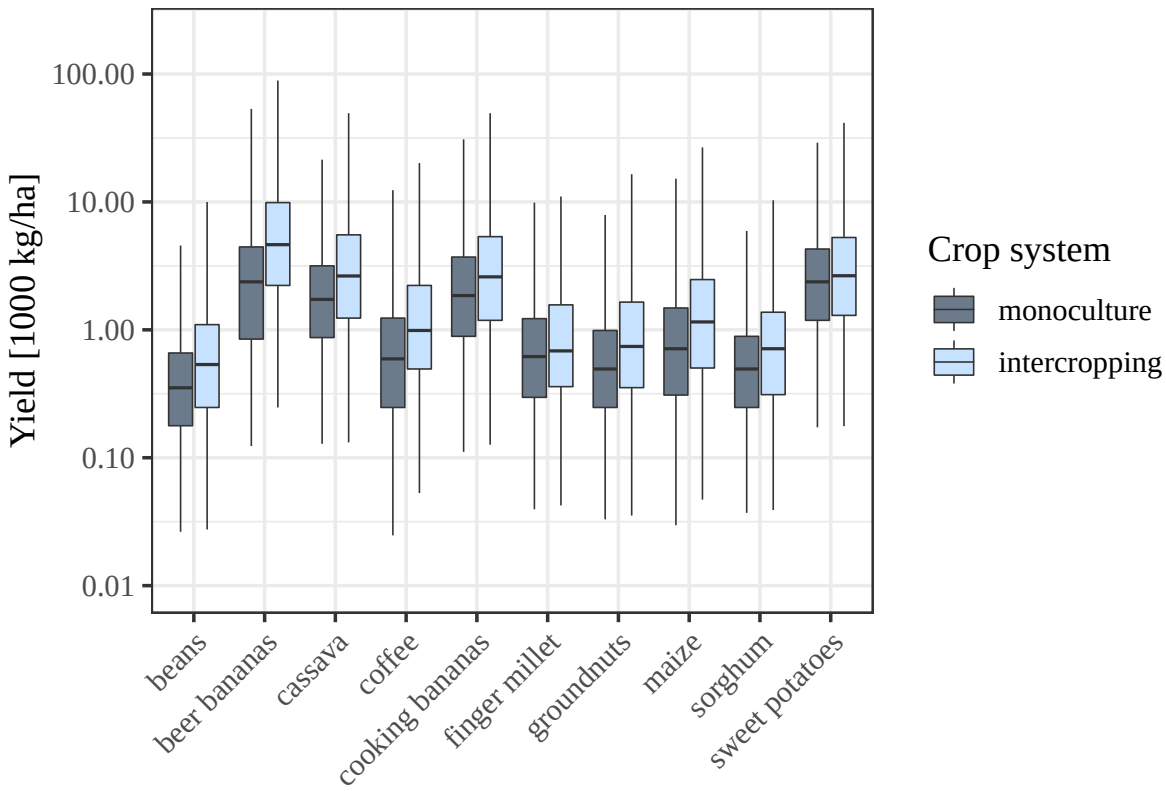

Figure 10: Yields and cropping systems. Land on plots with interacrooping is allocated to individual crops according to the percentage shares of individual crop covers.

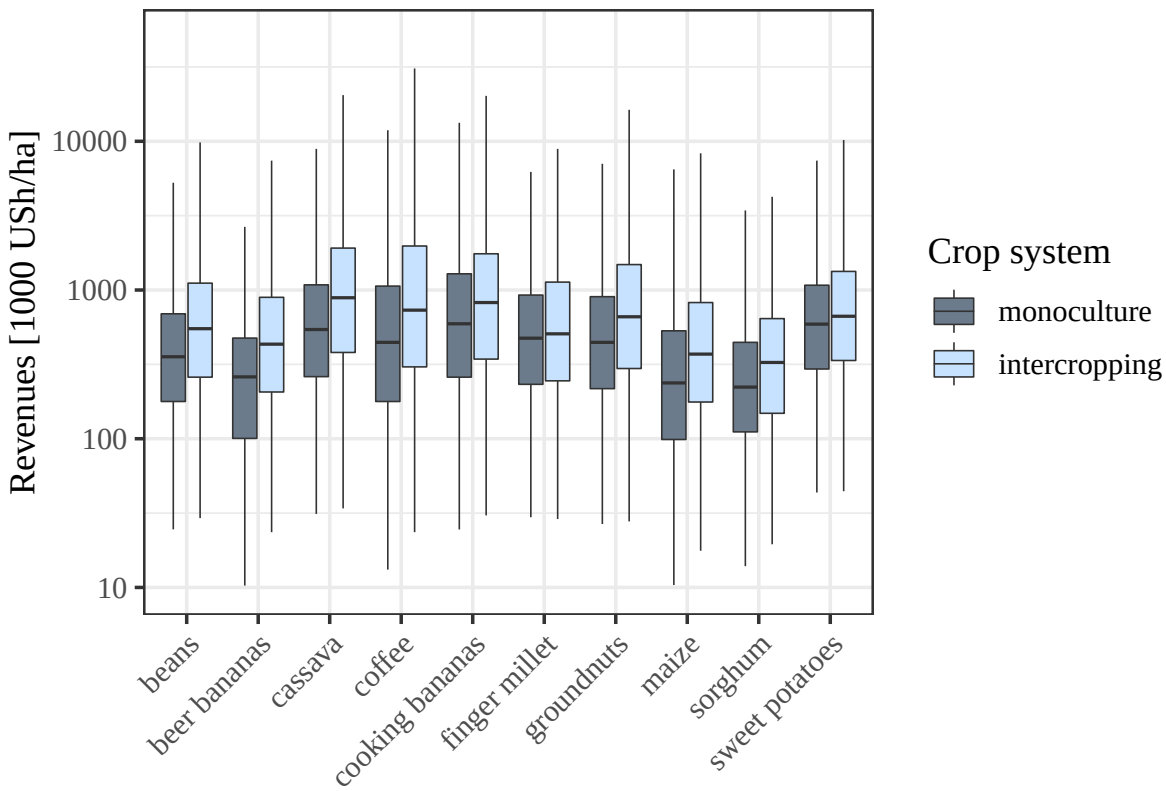

Figure 11: Revenues and cropping systems. Land on plots with interacrooping is allocated to individual crops according to the percentage shares of individual crop covers.

ficial combinations are less frequently observed. Appendix B compares the frequency of crop combinations with their yield differences compared to monocultures. Generally, we find that more beneficial combinations are more frequently observed (Appendix B).

4 Microeconomic farming model

In this section we develop a simple microeconomic farming model based on the observations of the previous section. We then derive testable predictions about the drivers and consequences of crop diversity which we then test empirically in the following section.

Following Foster and Rosenzweig (2017) we describe agricultural production by a constant-returns-to-scale production function g with the inputs land (a) and nutrients (e) effectively available to the plants. Foster and Rosenzweig (2017) think of plant nutrient availability as produced by labor and machinery, for example used to remove weeds that compete with crops for nutrients. We also include these processes in our model by considering labor as an input that enhances nutrient availability for plants. Additionally, the overall amount of nutrients effectively available to the plants may depend on numerous other factors as well. Plants need multiple nutrients to grow in composition specific to the particular crops. Soil composition, soil structure, water availability, microbe communities, and shading are some of these factors, or regulating ecosystem services, that influence the composition and amount of nutrients available to the plant. These factors can be determined by natural processes and thus largely given

to the farmer, or they can be modified artificially by application of fertilizers, tillage, irrigation, fungicides, etc. Moreover, all these factors are complementary to each other, at least to some degree. A parsimonious and tractable specification that captures these aspects of agricultural production is the Cobb-Douglas production function for crop k:

$$y_k = a_k^{\alpha}\, e_k^{1-\alpha} = a_k^{\alpha}\, l_k^{\beta}\, \exp\left(\int_0^{\mu} \gamma\, \ln(x_{ik})\, di + \int_{\mu}^{1} \gamma\, \ln(e_{ik})\, di\right), \tag{1}$$

where a_k is land and l_k is labor allocated to crop k. We further denote the environmental regulating services that cannot be controlled by the farmer $e_{ik} > 0$ while x_{ik} are the environmental regulating services that can be controlled at marginal costs q. For analytical tractability, we consider a continuum of non-labor inputs into effective nutrient production and assume that their output elasticities (γ) are identical. Non-controlled regulating ecosystem services are indexed in increasing order, i.e. $de_{ik}/di > 0$. The fraction $\mu \in (0,1)$ of these is considered fixed. This continuum of environmental regulating services which is only partly controlled by the farmer is the main mechanisms for the ecology of scope.

The marginal products for all inputs is positive but decreasing, $\alpha, \beta, \gamma \in (0,1)$, with $\alpha + \beta + \gamma = 1$ due to constant returns to scale in production.

The farmer chooses land and labor allocation as well as nutrients inputs across crops in order to maximize profits[11]

$$\max_{\{a_k, l_k, x_{ik}\}} \int_0^N \left(p_k\, y_k - \int_0^{\mu} q\, x_{ik}\, di\right) dk \quad \text{subject to} \int_0^N a_k dk = A \text{ and } \int_0^N l_k dk = L. \tag{2}$$

For analytical tractability, we consider a whole continuum of crops. He we also assume that the total land endowment (A) and labor endowment (L) are given but we consider the case of a labor market in Appendix G.

Using λ to denote the Lagrangian multiplier for land, and ω for labor, the first-order conditions read

$$\alpha\, p_k\, \frac{y_k}{a_k} = \lambda \tag{3a}$$

$$\beta\, p_k\, \frac{y_k}{l_k} = \omega \tag{3b}$$

$$\gamma\, p_k\, \frac{y_k}{x_{ik}} = q \qquad \text{for } i \in [0, \mu]. \tag{3c}$$

In Appendix F we show that this implies

$$\frac{a_k}{A} = \frac{l_k}{L} = \frac{p_k^{\frac{1}{(1-\mu)\gamma}}\, r_k\, q^{-\frac{\mu}{1-\mu}}}{\int_0^N p_k^{\frac{1}{(1-\mu)\gamma}}\, r_k\, q^{-\frac{\mu}{1-\mu}}\, dk} = \frac{p_k^{\frac{1}{(1-\mu)\gamma}}\, r_k}{\int_0^N p_k^{\frac{1}{(1-\mu)\gamma}}\, r_k\, dk} \tag{4}$$

i.e. the share of land (and labor) allocated to crop k depends on the value p_k of that crop relative to some generalized mean value of all N crops the farmer chooses to grow. In that ratio, and

[11] In the absence of output markets, farmers may maximize the nutritional value of crop production. The interpretation of p_k would be e.g. caloric values in this case.

in the generalized mean, the value of each crop is taken to the power $1/(1-\mu\,\gamma) > 1$, which distorts the land allocation in favor of the more valuable crops. The closer μ comes to one, i.e. the larger the fraction of environmental supporting services that the farmer controls, the larger is the fraction of land and labor allocated to the most valuable crop. This result suggests the lack of control over environmental conditions as the driver of crop diversity in low input agriculture.

In Appendix F we show further that aggregate profit on a farm with N crops is given by

$$Y = \int_0^N \pi_k \, dk = (1-\mu\,\gamma)\, A^{\frac{\alpha}{1-\mu\,\gamma}}\, L^{\frac{\beta}{1-\mu\,\gamma}} \left(\int_0^N p_k^{\frac{1}{(1-\mu)\,\gamma}}\, r_k \, dk \right)^{\frac{(1-\mu)\,\gamma}{1-\mu\,\gamma}} \left(\frac{\gamma}{q} \right)^{\frac{\mu\,\gamma}{1-\mu\,\gamma}}. \tag{5}$$

The number of crops, however, is an endogenous choice of the farmer, that depends on farm size and labor endowment. Although farmers may grow all possible crops on their land as a result of the optimization process they would only allocate insignificant fractions of their land and labor endowments to the least valuable crops. In the previous section we established that this is rarely the case. We therefore introduce crop-specific fixed costs $F_k > 0$ similar to Romer (1987). This fix cost could be crop specific machinery but also crop specific knowledge or the additional effort to carry out a crop specific task. For simplicity we assume that this fix costs is constant across crops such that $F_k = F$. This crop specific fix cost of production is responsible for the returns to specialization. The optimal number of crops is therefore determined by

$$\frac{\partial Y}{\partial N} = F. \tag{6}$$

In order to further explore the farmer's choice of crop diversity, we need to specify the distribution of marginal crop values p_k. We think of p_k as a general measure of marginal value, for example in terms of market price of the respective crop, or in terms of caloric value. We assume that the marginal value of crops differ, and that p_k is described by a Pareto distribution of marginal crop values

$$p_k = p_1\, k^{-\varphi}. \tag{7}$$

The value or price differences between crops is the second mechanism that drives the returns to specialization in our model. Motivated by the observation of similar revenues across crops from the previous section we assume a rather 'flat' distribution of values, i.e.

$$\varphi < (1-\mu)\,\gamma. \tag{8}$$

Assumption (8) implies that the benefit of specialization – due to the high marginal value of some crops – is limited compared to the benefit of diversification – due to decreasing marginal returns on controlled inputs, captured by the term $(1-\mu)\,\gamma$. Borrowing from the New Economic Geography literature (Krugman 1991), we refer to Assumption (8) as the 'no black hole condition'. If (8) is violated, the farmer optimally chooses to allocate all resources – land, labor, and all nutrients – to the most valuable crop only, i.e. the problem to choose the optimal crop number collapses into the corner solution of just growing the most valuable crop. Note that

the model implies such a corner solution for $\mu = 1$, i.e., for the case that the farmer fully controls environmental conditions of crop production. This shows again that the model explains a large number of crops as the consequence of the farmer's dependency of regulating services provided by the ecosystem.

Furthermore, we assume that the distribution of e_{ik} is independent of k, which implies $r_k = \bar{r}$ for all k. Thus,

$$\int_0^N p_k^{\frac{1}{(1-\mu)\gamma}} r_k \, dk = \bar{r} \int_0^N p_1^{\frac{1}{(1-\mu)\gamma}} k^{\frac{\varphi}{(1-\mu)\gamma}} \, dk = \frac{\bar{r}\, p_1^{\frac{1}{(1-\mu)\gamma}}}{1 - \frac{\varphi}{(1-\mu)\gamma}} N^{1-\frac{\varphi}{(1-\mu)\gamma}} \tag{9}$$

Under the given specification, the relative allocation of land to the crops (equation 4) simplifies to (in logarithmic form)

$$\ln\left(\frac{a_k}{A}\right) = \frac{\varphi}{(1-\mu)\gamma} \ln(k) - \left(1 - \frac{\varphi}{(1-\mu)\gamma}\right) \ln(N), \tag{10}$$

and the aggregate output is explicitly given as a function of crop number, land and labor endowments as

$$Y = \left(\Omega\, N^{(1-\mu)\gamma-\varphi}\, A^{\alpha}\, L^{\beta}\right)^{\frac{1}{1-\mu\gamma}} \tag{11}$$

where

$$\Omega := \frac{(1-\mu\gamma)^{1-\mu\gamma}\, \bar{r}\, p_1}{\left(1 - \frac{\varphi}{(1-\mu)\gamma}\right)^{(1-\mu)\gamma}} \left(\frac{\gamma}{q}\right)^{\mu\gamma} \tag{12}$$

depends on the model parameters only. Taking logs of (11), we obtain

$$\ln(Y) = \ln\left(\frac{\Omega}{1-\mu\gamma}\right) + \frac{(1-\mu)\gamma - \varphi}{1-\mu\gamma} \ln(N) + \frac{\alpha}{1-\mu\gamma} \ln(A) + \frac{\beta}{1-\mu\gamma} \ln(L) \tag{13}$$

We can estimate this model using the farm data from Uganda. In particular, the coefficient estimate for $((1-\mu)\gamma - \varphi)/(1-\mu\gamma)$ gives the percentage change of output with crop number, and $((1-\mu)\gamma - \varphi)/(1-\mu\gamma)\, Y$ is an estimate of the value of crop diversity for the farms in Uganda.

The crop number N in (13) is endogenous, however, and in particular it depends on the farm's endowments with land A and labor L. From (6) we obtain the following condition that characterizes the optimal number of crops:

$$\ln(N) = \ln(C) + \frac{\alpha}{\alpha+\beta+\varphi} \ln(A) + \frac{\beta}{\alpha+\beta+\varphi} \ln(L), \tag{14}$$

where $C > 0$ is some positive constant that depends on the model parameters. Equation (14) shows that the optimal crop number positively depends on the farm size both in terms of land and labor endowments. This relationship results from the interplay of the economies of scope that scale with farm size and the economies of scale based on the farm size independent

fix costs. We can also estimate this equation directly using the data from Uagnda. In our regression equation we include farm fixed effects that capture differences in technology and ecological resources across farms. Note that the coefficients for land and labor are independent of these differences, so all effects related to technology choice and resource endowments are adequately captured by the fixed effects.

5 Estimation strategy

In this section we test the model predictions. We are especially interested in the drivers of crop diversity and its private benefits. Both questions are closely related, because large private benefits would incentivize high levels of crop diversity.

One key prediction of our model is that crop diversity increases with land and labor inputs; while the gains from the ecology of scope increase with land and labor inputs, the fixed costs that determine the economies of scale remain constant. Equation (14) specifies this relationship. However, farms may differ with respect to their physical and economic environment which could determine the amount of labor and land for crop production in addition to crop diversity. Seasonal and yearly weather fluctuations could further affect agricultural productivity as well as crop diversity. We therefore include, household, year and season fixed effects. These fixed effects absorb the composite parameters of equation (14):

$$\ln(N_{ist}) = \frac{\alpha}{\alpha+\beta+\varphi}\ln(A_{ist}) + \frac{\beta}{\alpha+\beta+\varphi}\ln(L_{ist}) + \eta_i + \theta_t + \nu_s + \varepsilon_{ist}. \tag{15}$$

Here N_{ist} is the number of crops grown per farm, A_{ist} is the land used for crop production, L_{ist} is the labor used for crop production and Y_{ist} are the revenues of farm i in season s in year t. The last four terms are farmer fixed effects, year fixed effects, seasonal fixed effects and the error term that we cluster at the district level to account for the two stage sampling process of the survey (Abadie et al. 2017).

In addition to the estimation on household level, we also report results for (14) on plot level. All household level variables are replaced in this case by plot level measurements of the same variables. For example, crop diversity in this specification is measured by the number of crops that are grown together on one plot. Although our measure of crop diversity is directly derived from our theory section, we also present results using the inverse Simpson (Herfindahl–Hirschman) index to measure crop diversity. The number of crop types (crop richness) is one extreme of the common diversity indices placing no weighs on the allocation of inputs among crops. In that sense, the Simpson index is another extreme of the common diversity indices, placing more weight on the allocation of inputs than other common measures of diversity including the Shannon index.

The land variable in our baseline specification is based on self-reported land size. However, in a robustness check we use GPS corrected land measurement based on the description in the Data Section. In this case, the land variable is an estimated regressor based on the estimated relationship between GPS measured and farmer-reported land size for a sub-sample of the observations. We therefore bootstrap our standard errors across both stages of the estimation

using 500 bootstrap replicates.

Labor and land may be endogenous, and simultaneously determined with crop diversity. We therefore use land inheritance and household composition as instruments for farm size and labor respectively. Land inheritance is by far the most common form of land transfers in Uganda and one third of the households in our sample inherited land during the survey period. We argue here that land inheritance is exogenous to the household. In contrast to land inheritance, family size is not exogenous. However, the timing of the changes in the household composition may be exogenous because the individual contributions to the household labor force are age specific and age changes exogeneously. We therefore use the OECD measure of adult equivalent units (Haughton and Khandker 2009) as instrument for labor inputs in combination with household fixed effects.

Droughts are a major concern of farmers in Uganda (see Figure 6). Droughts may also affect crop diversity directly (e.g. farmers may not plant drought sensitive crops in dry years) or indirectly (e.g. farmers who experienced droughts may adjust their crop portfolio). We therefore present results using different drought measures as additional controls in Appendix C. We regard the estimated impact of lagged droughts on crop diversity as an extension of the discussion on crop diversity and risk from Section 3.

Although the estimates from (15) support our theoretical predictions they do not allow us to draw direct conclusions about the magnitude of the economy of scale and the economies of scope. In contrast to (14) estimating (13) allows us to identify the crop specific fixed costs as well as the input complementarities.

Estimating a causal effect of crop diversity on productivity would require exogeneous variation in crop diversity. Crop diversity varies largely between farms and within farms but over time (e.g. Figure 4). However, our descriptive analysis shows that this variation cannot be explained by observed variations in market access (Appendix D), land heterogeneity (Appendix E), rainfall risk (Section 3) or past weather shocks (Appendix C).[12] We therefore treat the variation in crop diversity as random and estimate the relationship between crop diversity and agricultural productivity using a differences-in-differences approach. After introducing household, year and seasonal fixed effects, (13) becomes

$$\ln(Y_{ist}) = \frac{(1-\mu)\,\gamma - \varphi}{1-\mu\,\gamma}\,\ln(N_{ist}) + \frac{\alpha}{1-\mu\,\gamma}\,\ln(A_{ist}) + \frac{\beta}{1-\mu\,\gamma}\,\ln(L_{ist}) + \eta_i' + \theta_t' + \nu_s' + \varepsilon_{ist}'. \tag{16}$$

Here, Y_{ist} are the revenues of farm i in season s in year t, N_{ist} is the number of crops grown per farm, A_{ist} is the farm size and L_{ist} is the labor used for crop production. The last four terms are farmer fixed effects, year fixed effects, seasonal fixed effects and the error term that we cluster at the district level. In addition to our specifications on farm level we also estimate (16) on plot level. In this specification we can directly control for plot size and farm size to address concerns that crop diversity and output measurement error may both be correlated with plot size.

In equation (16) we cannot use the instruments for labor and land because crop diversity

[12] Although some pattern seem apparent, none of these variables have enough predictive power for an instrumental variable approach.

is a function of labor and land according to (14). Using instruments for labor and land would increase the measurement error of labor and land and therefore biases the coefficient estimate of crop diversity.

The parameter estimate of crop diversity in (16) has several interpretations. First, for the production environment of Uganda with little control over environmental factors, it equals the net benefit of crop diversity ($\gamma - \varphi$) i.e. the complementarities in crop production minus the price difference between crops. Second, equation (6) also suggests that the marginal productivity of crop diversity equals the crop specific fix costs. We can therefore use the results of equation (16) to calculate the fix costs parameter F.

6 Empirical Results

Table 2 presents the results on the impact of farm size and farm labor on crop diversity. The baseline specification (1) with district, season and year fixed effects suggests that a 10 percent increase in the farm size increases crop diversity by 1.4 % while a 10 percent increase of labor increases crop diversity by 1.8 %. Adding household fixed effects (specification 2) changes these estimates to 1.6 % and 1.7 % respectively. Using predicted farm size based on GPS measurements to measure farm size (specification 3) has little impact on the results. Also, using household composition and inherited land as instruments for labor and land (specifications 4 to 6) leaves the results largely unchanged. The F statistic for inherited land and household composition is 89 and 78 respectively in specification (6). Lastly, measuring crop diversity by the Simson index does not affect the results qualitatively but increases the contribution of labor relative to the contribution of land to crop diversity. Simpson diversity puts more weight on the allocation of inputs, suggesting that crop diversity may play and important role for labor smoothing.

In addition to these household level results, we present results on plot level in the Appendix H. Although the impact of land and labor on crop diversity at the plot level is reduced, the qualitative results are similar: Larger plots and higher labor inputs are associated with more crops types planted in combination on one plot.

Overall, these results confirm the predictions from the theoretical section that crop diversity increases with farm size and farm labor. The rural surplus labor in Uganda therefore partly explains the high crop diversity in Uganda. The suggested underlying mechanisms for these results are the economies of scope in crop production in combination with crop specific fixed costs. The next results allow us to quantify these two mechanisms.

Table 3 summarizes the results for the impact of crop diversity on revenues. The baseline specification with district, season and year fixed effects suggests an output elasticity of land and labor of 0.52 and 0.24 respectively. The results show further that a 10 % increase in crop diversity increases output by 2.8 %. However, these estimates are based on the differences in revenues across farms within districts which may be partly driven by differences in farmer and land characteristics. Including household fixed effects in specification (2) reduces the estimated output elasticity of land substantially suggesting that farm size is correlated with land quality. In contrast to the changes in the estimated contribution of land to production, the estimated

Table 2: Farm level crop diversity, farm size and labor

	Ln(number)						Simpson
	(1) OLS	(2) OLS	(3) ER	(4) IV	(5) IV	(6) IV	(7) OLS
ln(Farm size)	0.138***	0.158***	0.166***	0.137***	0.175***	0.170***	0.147***
	(0.007)	(0.011)	(0.007)	(0.033)	(0.044)	(0.050)	(0.032)
ln(Labor)	0.184***	0.171***	0.171 ***	0.217***	0.167***	0.185***	0.414***
	(0.009)	(0.010)	(0.006)	(0.069)	(0.019)	(0.061)	(0.026)
Observations	17,837	17,837	17,837	17,837	14,587	14,587	17,837
Within R^2	0.260	0.216	0.216	0.210	0.214	0.214	0.094
Instruments				Labor	Land	Labor & Land	
Fixed effects	District	Household	Household	Household	Household	Household	Household

The specifications are: (1) district fixed effects, (2) household fixed effects, (3) similar to specification (2) but with predicted land size and bootstrap standard errors, (4) similar to (2) but using household adult equivalent units as instrument for labor, (5) similar to (2) but using inherited land as instrument for farm size, (6) similar to (2) but using both instruments simultaneously, (7) similar to (2) but measuring crop diversity with Simpson diversity. All models include year and season fixed effects. Standard errors are clustered at the district level except for specification (3). Significance levels are $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. The number of observations for specification (5) and (6) are reduced due to missing data on land acquisition.

output elasticities of crop diversity and labor remain relatively stable. In specification (3) we replace self-reported land size with predicted land size, using 500 bootstrap replications across both levels of estimation to correct standard errors but the results remain largely unchanged. In specifications (4) and (5) we further control for precipitation levels in the current and the previous season using precipitation data from the TRMM/GPM and the SPEI drought index respectively. However, the results remain largely unchanged. Lastly, we test the robustness of our results with respect to the diversity measure. In specification (7) we replace the log of the number of crops of specification (2) with the Simpson diversity index. Again, the results are qualitatively similar.

Although the results for the differences-in-differences specifications presented in Table 3 suggest a relationship between crop diversity and revenues, we present further evidence in Table 4 based on plot level data. In this specification we measure crop diversity as the number of crops grown in combination on one plot. In contrast to crop diversity at the farm level, crop diversity at the plot level takes the direct competition of crops for resources into account. The specifications are otherwise similar to the specification reported in Table 3 but all variables except for farm size are measured at the plot level. Additionally, we include farm size as a control to take correlations between farm size and plot size, plot size and crop diversity as well as between farm size and agricultural productivity into account. The results are very similar to the results on farm level but the estimated impact of crop diversity is increased. This is no surprise because our measure of crop diversity captures the ecological complementarities between crops more directly. The estimated impact of farm size on plot level productivity is negative, in line with the large literature on farm size and agricultural productivity.

Additionally, we estimate the impact of crop diversity on agricultural productivity at the

Table 3: Revenues and crop diversity at the household level

	Ln(Revenues)					
	(1) OLS	(2) OLS	(3) ER	(4) OLS	(5) OLS	(6) OLS
Diversity	0.276***	0.328***	0.328***	0.331***	0.323***	0.097***
	(0.032)	(0.041)	(0.025)	(0.041)	(0.041)	(0.010)
ln(Farm size)	0.522***	0.271***	0.285***	0.269***	0.270***	0.309***
	(0.019)	(0.018)	(0.017)	(0.018)	(0.018)	(0.017)
ln(Labor)	0.239***	0.210***	0.210***	0.210***	0.214***	0.227***
	(0.016)	(0.019)	(0.014)	(0.019)	(0.019)	(0.017)
Precipitation				−0.0002***	0.035***	
				(0.0001)	(0.008)	
Lag precipitation				−0.0001	0.061***	
				(0.0001)	(0.009)	
Observations	17,838	17,838	17,838	17,812	17,838	17,838
Within R^2	0.278	0.122	0.122	0.123	0.125	0.119
Diversity	Ln(Number)	Ln(Number)	Ln(Number)	Ln(Number)	Ln(Number)	Simpson
Fixed effects	District	Household	Household	Household	Household	Household
Precipitation data				TRMM	SPEI	

Results for regression equation (16) *at the household level. The specifications include (1) district fixed effects, (2) household fixed effects, (3) similar to specification (2) but with predicted land size and bootstrap standard errors, (4) similar to specification (2) but with precipitation in the current and the previous season using TRMM data, (5) similar to (4) but using the SPEI index to measure precipitation, (6) similar to (2) but measuring crop diversity with Simpson diversity. All models include year and season fixed effects. Standard errors are clustered at the district level except for specification (3). Significance levels are* $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

crop stand or crop-plot level. In this approach we compare the crop specific output per unit of input directly between intercropping and monoculture. Estimating the impact of crop diversity on the crop stand level has the advantage that we can measure output directly in physical units without conversion to revenues. However, since labor and land are measured at the plot level and the farmer only reports the share of land that is allocated to individual crops within the plot, there is increased measurement error of crop specific land and labor inputs in interacrooping compared to monoculture. This additional measurement error may bias our crop diversity estimates. We therefore only report the estimates as a robustness test in Appendix I. The results are, however, qualitatively similar.

Overall, our results provide strong evidence for the productivity supporting role of crop diversity for agriculture in Uganda. They also suggest that the main mechanism of this productivity supporting role of crop diversity is the direct interaction of crops at the plot level.

7 Agricultural development and the value of crop diversity

What is the value of crop diversity for production? How does this value change with agricultural development? The theoretical framework in combination with the empirical results

Table 4: Revenues and crop diversity at the plot level

	Ln(Revenues)					
	(1) OLS	(2) OLS	(3) ER	(4) OLS	(5) OLS	(6) OLS
Diversity	0.398***	0.426***	0.426***	0.429***	0.423***	0.267***
	(0.046)	(0.048)	(0.014)	(0.048)	(0.048)	(0.028)
ln(Plot size)	0.422***	0.406***	0.433***	0.405***	0.406***	0.416***
	(0.020)	(0.023)	(0.01)	(0.023)	(0.023)	(0.024)
ln(Labor)	0.200***	0.192***	0.192***	0.193***	0.192***	0.193***
	(0.011)	(0.012)	(0.009)	(0.012)	(0.011)	(0.012)
ln(Farm size)	0.083***	−0.153***	−0.163***	−0.152***	−0.153***	−0.161***
	(0.018)	(0.022)	(0.012)	(0.022)	(0.023)	(0.024)
Precipitation				−0.00004	0.009	
				(0.0001)	(0.009)	
Lag precipitation				0.0001*	0.029***	
				(0.0001)	(0.009)	
Observations	44,774	44,774	44,774	44,686	44,774	44,773
Within R^2	0.170	0.133	0.133	0.134	0.135	0.129
Diversity	Ln(Number)	Ln(Number)	Ln(Number)	Ln(Number)	Ln(Number)	Simpson
Fixed effects	District	Household	Household	Household	Household	Household
Precipitation data				TRMM	SPEI	

Results for regression equation (16) *at the plot level. The specifications include (1) district fixed effects, (2) household fixed effects, (3) similar to specification (2) but with predicted plot and farm sizes and bootstrap standard errors, (4) similar to specification (2) but with precipitation in the current and the previous season using TRMM data, (5) similar to (4) but using the SPEI index to measure precipitation, (6) similar to (2) but measuring crop diversity with Simpson diversity. All models include year and season fixed effects. Standard errors are clustered at the district level except for specification (3). Significance levels are* $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

allow us to answer these questions.

Similar to the wage share we can estimate the value of crop diversity based on the output elasticity. Our parameter estimates suggest an output elasticity of crop diversity of 0.33 in Table 3. Using the PPP adjusted GDP for 2018 of 93.2 billion constant 2018 international dollars and the agricultural contribution to GDP of 24 % from the National Population and Housing Census of 2014 yields a value of agricultural production of 22.4 billion 2018 international dollars and subsequently a value of crop diversity of 7.4 billion 2018 international dollars.

However, this approach uses the current marginal value of crop diversity to evaluate non-marginal changes in crop diversity. An alternative approach is to compare the current value of agricultural production with a production based on monocultures (Brock and Xepapadeas 2003). To compute the difference in revenues we predict the individual outcomes based on specification (2) of Table 3 for current crop diversity levels and for a counterfactual with only one crop per farm. The results suggest a reduction of total revenues by 39 % or an average reduction of 35 % per farmer. Based on the value of agricultural production in Uganda this calculation suggests a value of crop diversity of 8.7 billion 2018 international dollars.

These results focus on the revenues and neglect costs. Based on our theoretical results we propose that the crop specific fix costs equal the marginal productivity of crop diversity. We can quantify these crop-specific fixed costs as $F = \frac{(1-\mu)\gamma-\varphi}{1-\mu\gamma}\frac{Y}{N}$ where $\frac{(1-\mu)\gamma-\varphi}{1-\mu\gamma}$ is the output elasticity of crop diversity. Using the mean values of revenues and crop diversity from Table 1 yields $\frac{Y}{N} = \frac{615.8}{4.3} = 143.2$ 2018 international dollar. Based on the output elasticities of crop diversity of 0.33 in Table 3, the fixed cost per crop are equivalent to 47.3 international dollar. According to the Uganda Annual Agricultural Survey there were 7.4 million farms in 2018, suggesting that the total aggregate cost of crop diversity equals 1.2 billion international dollar.[13] These figures therefore suggest that the net aggregated value of crop diversity in Uganda based on comparison with monocultures is 8.7 - 1.2 = 7.5 billion international dollars. However, here we neglect the opportunity ocst of time and the positive externalities of crop diversity.

The value of crop diversity also depends on the control over the environment (μ) and the price differences across crops (φ). Increased control over the environment results for example from irrigation and drainage to regulate water availability, fertilizer to regulate nutrients, pesticide to reduce biological interaction and greenhouses to control the growing climate. Increased control of the environment is closely related to agricultural development. In contrast to the environment, prices cannot be controlled by the farmer but are determined by markets. The price parameter in our theoretical framework is a combination of prices in a strict sense and total factor productivity. Reduced trade costs may increase the price or productivity differences across crops (φ) and would therefore induce specialization.

To visualize the relationships between the value of crop diversity, price differences, and the control over the environment we plot the output elasticity of crop diversity against μ and φ. The output elasticity also depends on the parameter γ which we set equal to $\gamma = 0.835$ (see Appendix J). Figure 12 suggests that crop diversity is a valuable input in the low input agriculture of Uganda with small price differences across crops. However, it also shows that the value of crop diversity declines with increasing control over the environment (μ) and increasing price differences across crops (φ). For production environments with sufficient control over the environment and large price or productivity differences across crops, the elasticity becomes negative and monocultures prevail.

8 Discussion and Conclusion

Farms are diverse in Uganda, growing on average more than four crops per hectare. In this article we propose that this high level of crop diversity is the result of a trade-off between ecology of scope and economies of scale resulting from crop specific fixed costs. Based on our estimates we can quantify the value of crop diversity for agricultural production in Uganda. Our estimates suggest that the total annual value of crop diversity in Uganda equals 7.8 billion dollar. This value captures only the private benefits of crop diversity. The actual economic value may be even higher, as crop diversity additionally generates positive externalities (Weitzman 2000, Larsen and Noack 2017, Noack et al. 2019).

[13] $(4.3 - 1) \times 47.5 \times 7.4 = 1160$ Million

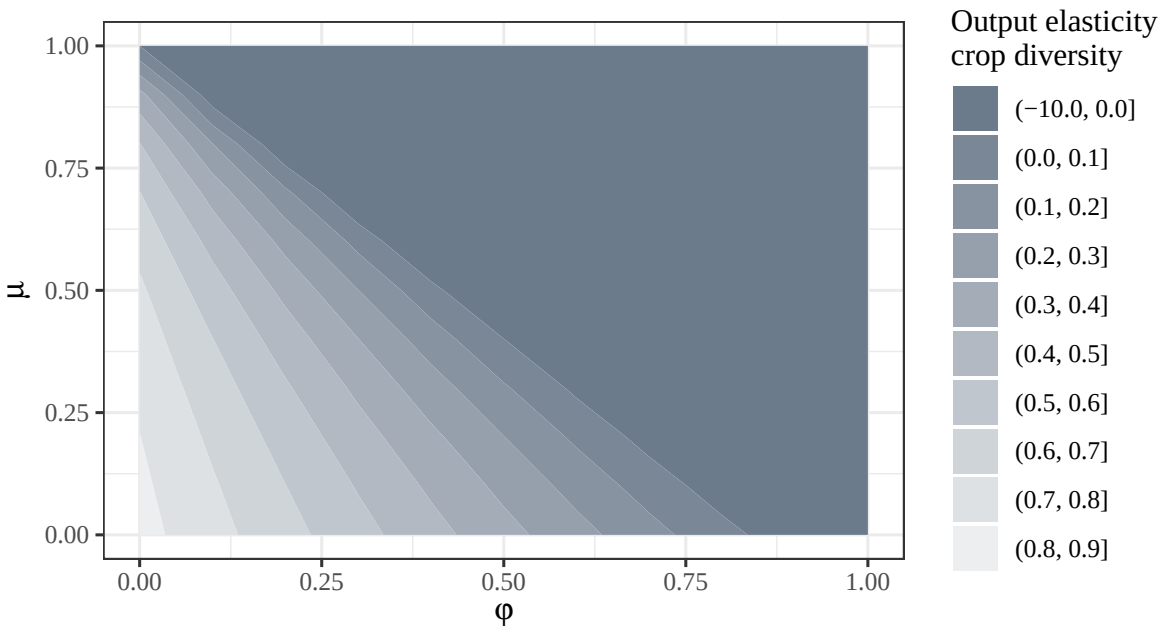

Figure 12: Output elasticity of crop diversity in response to the farmer's control over the environment (μ) and price differences across crops (φ).

Our results show that the high levels of crop diversity in Uganda partly result from the rural surplus labor. Rural to urban migration and structural change is closely related to the process of economic development. During this process, labor is typically reallocated from agriculture to manufacturing and the service sector. Our results therefore predict a loss of crop diversity with economic development and the declining rural labor force.

Similarly to Benin et al. (2004) we find that crop diversity increases with farm size. The impact of farm size on aggregate crop diversity is, however, difficult to predict since it also depend on the similarity of crop portfolios across farms. We leave this interesting question for future research.

Our analysis suggests further that the private benefits of crop diversity largely depend on the ability of the farmer to control the production environment including irrigation and drainage to control water supply, fertilizer to regulate nutrients, glasshouses to stabilize temperatures, pesticides to reduce biological damages etc. Control over the production environment typically increases with economic development. Although this process generally improves the economic productivity of agriculture, our findings also show that it reduces the private benefits of crop diversity and therefore incentivizes specialization. The increase in inputs such as fertilizer and pesticides with the simultaneous loss of crop diversity can lead to a loss of ecosystem services and the state of agriculture in developed countries that makes it to one of the largest contributors to global biodiversity loss, water pollution and climate change (Tilman et al. 2017; Poore and Nemecek 2018; Springmann et al. 2018; IPBES 2019). The loss of crop diversity excercerbates this process further, increasing the need for further environmental control (Larsen and Noack 2017, 2020) to prevent a catastrophic agricultural collapse (Weitzman 2000).

A Precipitation data

Figure A1 compares the seasonal precipitation levels from the TRMM/GPM data set and the data set from Willmott and Matsuura of the University of Delaware (UDEL) for each year-season-household level observation from the LSMS household data. The correlation coefficient is 0.73. The precipitation levels in the TRMM data are generally higher than in the UDEL data.

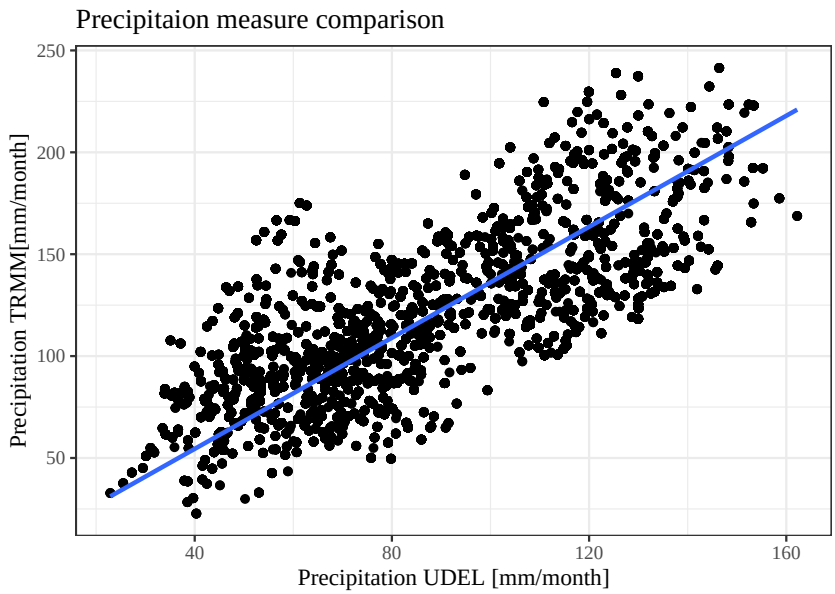

Figure A1: Correlation of TRMM and UDEL precipitation for each LSMS household observation. The correlation coefficient is 0.73.

Figure A2 repeats the visualization of rainfall risk and crop diversity from the main text (Figure 7) but using UDEL data. The pattern are very similar, however.

B Crop combinations

Figure A3 shows the frequency of occurrence and the yield difference to monocultures of crop combinations for the ten most common crop types. For these figures, we exclude all crop combinations with less than 100 observations and all plots with intercropping of more than two different crops. Panel B shows the revenue differences to monocultures of one crop (y-axis) if it is planted in combination with a second crop (x-axis), controlling for labor, land, season, year and district. The values are semi-elasticities, e.g. a value of 0.3 for the hypothetical combination of crop i and j would indicate that the yield of crop i is 30 % higher in combination with crop j compared to monocultures, everything else equal.[14] Note that while panel A is symmetric, panel B is not because it shows the impact of intercropping on yields of the crops on the y-axis with the crops on the x-axis. Grey shaded areas are combinations with less than

[14]We estimate the following regression separately for each of the ten most common crop types: $\ln(y_{ihst}) = \ln(l_{ihst}) + \ln(a_{ihst}) + \sum_{j=1}^{10} \tau_{jihst} + \delta_h + \theta_t + \nu_s + \varepsilon_{ihst}$ where y_{idst} is the yield in kg on plot i, of household h, in season s, and in year t, l is labor allocated to the specific crop on that plot, a is the land allocated to the specific crop on plot i and τ_{jidst} are dummies for the ten most common crops that indicate whether this crop was planted on the same plot. The remaining variables are household, year and season fixed effects and the error term.

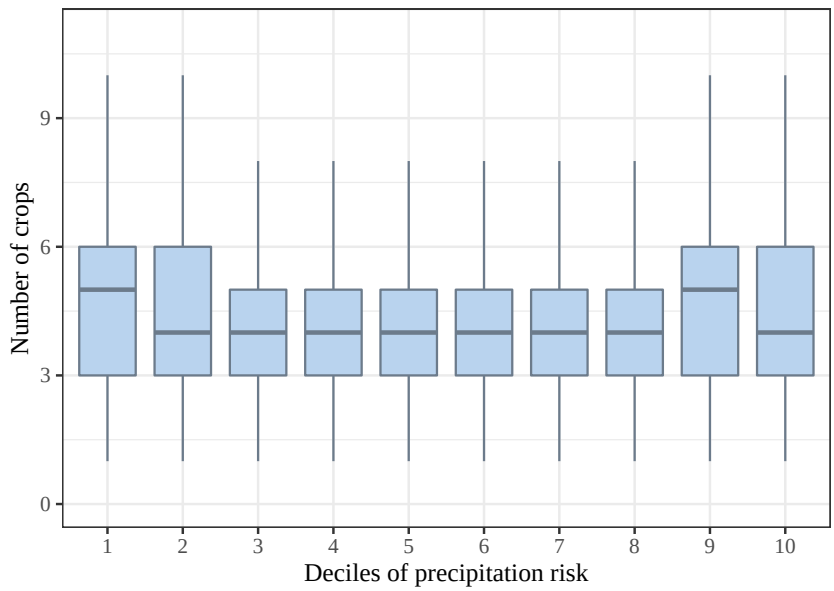

Figure A2: Number of crops per farm and rainfall risk. Rainfall risk is measured by the coefficient of variation of annual district level rainfall between 1980 and 2016 using the UDEL data.

100 observations or the effect of the crop on itself. While some common combinations such as maize and beans or beans and cooking bananas seem to be mutually beneficial, other combinations such as sweet potatoes and cassava seem to be less beneficial. Overall, the figure shows that the most common combinations tend to be mutually beneficial.

Figure A3: Frequency and benefits of crop combinations. Panel A shows the frequency of plot level crop combinations. Panel B shows the impact of crop combinations on yields while controlling for crop level labor and land as well household, season and year fixed effects.

C Crop diversity, climate and droughts

In this section we explore the relationship between climate, weather and crop diversity. Climate can affect crop diversity either through the resource base (e.g. humid climates with more

precipitation can support more species than dry climates) or through the households' efforts to mitigate the impact of climate risk. Table A1 summarizes the results based on the mean and the coefficient of variations (CV) of precipitation in the reference period from 1998 to 2016 for the TRMM/GPM data and from 1986 to 2016 for the UDEL data.

The first column of Table A1 presents the relationship between crop diversity and precipitation based on the TRMM/GPM data. We measure crop diversity with the log number of crops to be consistent with the results in the main empirical section of this paper. Both, the mean and the coefficient of variation have a positive and significant impact on crop diversity. All specifications include season and year fixed effects. Introducing additionally region fixed effects in column (3) reduces the climate parameter estimates but has no impact on the qualitative results. Using the mean and the CV of precipitation from the UDEL data yields qualitatively similar results. Although these result suggest that precipitation pattern contribute to the high level of crop diversity in Uganda, the explanatory power of our precipitation variables is small. The two precipitation variables combined explain about 1 to 6 % of the variation in crop diversity.

Our model of Section 4 predicts that crop diversity increases with farm size and farm labor. Although we test these predictions formally in Section 5 we reproduce some baseline results here for comparison. The results in column (5) suggest that farm size and labor combined explain about 26 % of the variation of crop diversity in Uganda.

Table A1: Crop diversity and climate

	Dependent variable:				
	log(number)				
	(1)	(2)	(3)	(4)	(5)
Mean precipitation	0.001***	0.001***	0.002***	0.001***	
	(0.0001)	(0.0001)	(0.0002)	(0.0003)	
CV precipitation	1.242***	0.600*	1.608***	0.505	
	(0.448)	(0.328)	(0.430)	(0.669)	
Ln(Farm size)					0.107***
					(0.008)
Ln(Labor)					0.222***
					(0.011)
Observations	17,812	17,812	17,812	17,812	17,838
Within R^2	0.060	0.016	0.055	0.01	0.257
Location fixed effects		Region		Region	
Precipitation data	TRMM	TRMM	UDEL	UDEL	

All specifications include year and season fixed effects. Standard errors are clustered at the district level. Significance levels are $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

In contrast to these results based on the cross-sectional variation of rainfall pattern of Table A1, the result in Table A2 are based on the intertemporal variation of precipitation. Column (1)

repeats the results for crop diversity from column (5) of Table A1 but with households, season and year fixed effects.

In the next column we introduce precipitation in the current growing season, the previous growing season (6 months), the same growing season but in the previous year (12 month) etc. The results suggest that more rain in the current season is associated with more crop diversity while precipitation in the previous season reduces crop diversity. The next two columns (3 and 4) convert these continuous rainfall variables into dummies for extreme events. Here we define a drought as a season with more than one standard deviation less precipitation than the seasonal mean and a flood as a season with more than one standard deviation more precipitation than the seasonal mean. The results are, however, inconclusive. The next three columns (5 to 7) repeat the analysis of the previous columns (2 to 4) but with SPEI water balance data. The results based on the SPEI data partially contradict the results based on the TRMM/GMP data. Overall, no clear pattern becomes apparent. Also, the additional explanatory power of land, labor and rainfall pattern for predicting crop diversity. After controlling for household, year and season with fixed effects, land and labor explain 22 % of the variation in crop diversity. Adding the rainfall variables does not improve the performance of the model.

D Crop diversity and markets

Figure A4 shows the relationship between crop diversity and market access based on self reported proxies for market access from the LSMS-ISA community questionnaire. Roads are the major mode of transportation in Uganda since railroads and transportation on water ways is largely undeveloped. Panel A therefore relates crop diversity to the main road access of the village. Type A roads are main (trunk) roads with asphalt (A1) or gravel surfaces (A2). Type B and C roads are feeder roads and community roads respectively. No villages without road access were surveyed. Although crop diversity seems to be higher in villages that are only connected through community roads the low number of observations makes an interpretation of this pattern unreliable. Panel B shows crop diversity in relation to different levels of self-reported access to agricultural markets. While median crop diversity is higher on farms with no market access, there is no difference in median crop diversity between households with agricultural markets within the same village or within neighboring villages. Panel C shows the crop diversity distribution for deciles of distance to the nearest market for agricultural inputs and/or outputs. No clear pattern becomes apparent. We report the mean time to travel to those agricultural markets above each boxplot. We use infinity for those households with no market access.

Table A2: Crop diversity, droughts and floods

	Ln(Number)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Ln(Farm size)	0.158***	0.157***	0.158***	0.157***	0.158***	0.158***	0.157***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Ln(Labor)	0.171***	0.169***	0.171***	0.171***	0.170***	0.171***	0.168***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Precipitation		0.0001***			−0.004		
		(0.00004)			(0.005)		
Precipitation (6 months)		−0.0001**			0.013**		
		(0.0001)			(0.006)		
Precipitation (12 months)		0.0001			−0.017***		
		(0.0001)			(0.005)		
Precipitation (18 months)		−0.00003			−0.005		
		(0.0001)			(0.004)		
Precipitation (24 months)		0.0001*			−0.021***		
		(0.00005)			(0.005)		
Drought			−0.019	−0.034**		0.169***	0.139*
			(0.012)	(0.016)		(0.061)	(0.071)
Flood			0.004	0.009		−0.004	−0.013
			(0.017)	(0.018)		(0.008)	(0.013)
Drought (-1 season)				−0.040*			−0.312***
				(0.024)			(0.102)
Flood (-1 season)				−0.030*			0.065***
				(0.017)			(0.018)
Drought (-2 seasons)				−0.030			0.056*
				(0.023)			(0.031)
Flood (-2 seasons)				0.026			0.030
				(0.026)			(0.019)
Drought (-3 seasons)				0.018			−0.073***
				(0.032)			(0.026)
Flood (-3 seasons)				−0.022			0.003
				(0.020)			(0.017)
Drought(-4 seasons)				−0.002			−0.026
				(0.019)			(0.021)
Flood (-4 seasons)				0.023			−0.060***
				(0.018)			(0.013)
Observations	17,838	17,812	17,812	17,812	17,812	17,812	17,812
Within R^2	0.216	0.222	0.216	0.219	0.223	0.216	0.225
Precipitation data		TRMM	TRMM	TRMM	SPEI	SPEI	SPEI

*The specifications are: (1) baseline, the same specification as (2) of Table 2, (2) with TRMM precipitation in mm, (3) with TRMM precipitation drought and flood dummies, (4) with TRMM precipitation drought and flood dummies for the current and past seasons, (5) with SPEI precipitation data in standard deviations, (3) with SPEI precipitation drought and flood dummies, (4) with SPEI precipitation drought and flood dummies for the current and past seasons. We define a drought as seasonal precipitation of one standard deviation below the seasonal mean. We define a flood as seasonal precipitation of one standard deviation above the seasonal mean. There are two cropping seasons per year in Uganda i.e. precipitation with one lag (-1 season) is for a different cropping season but in the same year while precipitation with two lags (-2 seasons) is precipitation for the same cropping season but in the previous year. All specifications include household, year and season fixed effects. Standard errors are clustered at the district level. Significance levels are *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.*

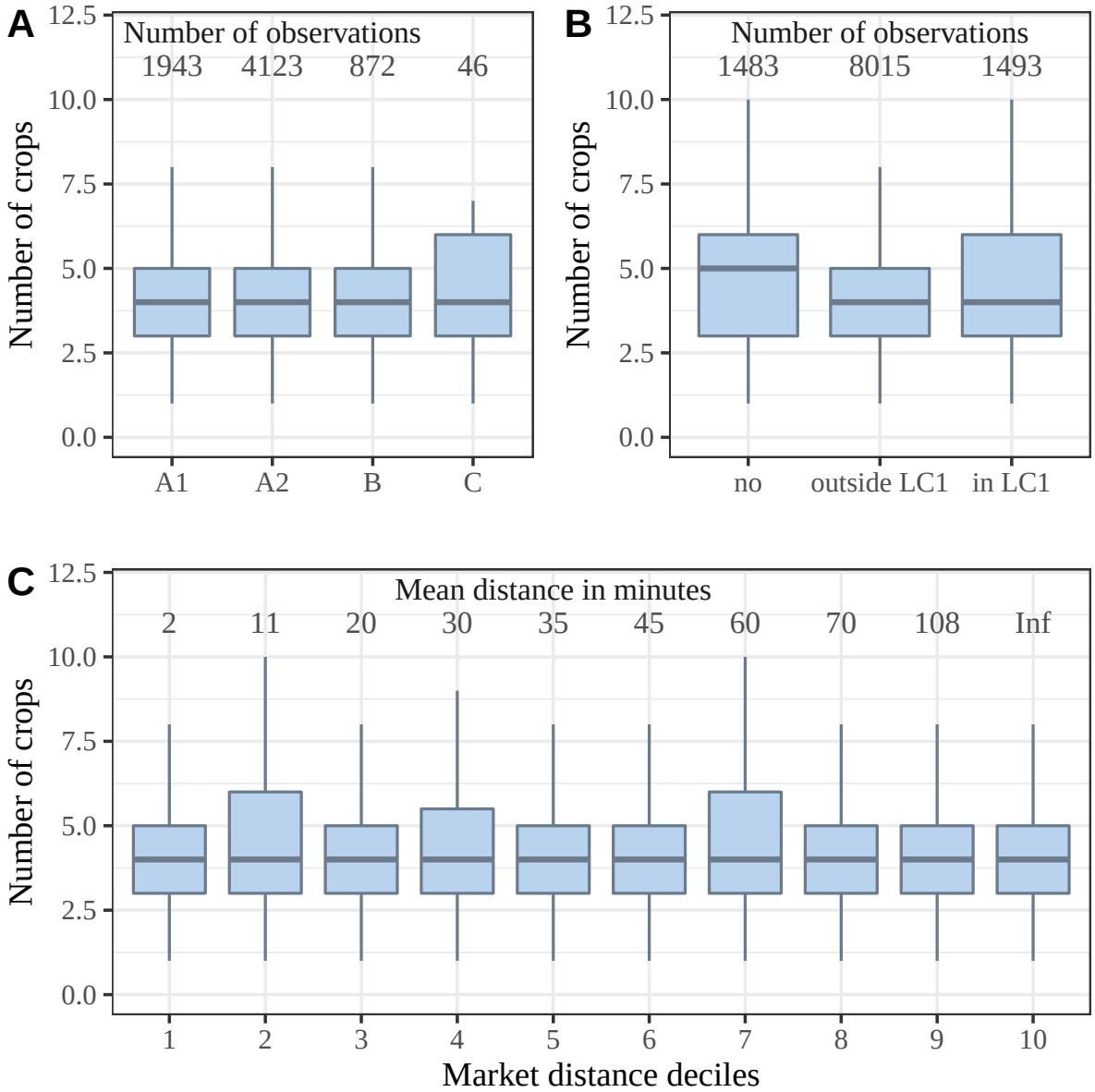

Figure A4: Boxplot of crop diversity and self reported market access. Panel A shows the distribution of crop diversity with respect to the main road access of the village. A1 are main (trunk) roads with asphalt surfaces, A2 are main (trunk) roads with gravel surfaces, B are feeder roads, C are community roads. Panel B shows the distribution of crop diversity with respect to access to self-reported access to agricultural markets. The number of observations are displayed above each boxplot. LC1 refers to local council 1 (enumeration area). Panel C shows crop diversity with respect to self-reported market distance declies. The mean travel time in minutes for each decile is displayed above the boxplots. The number of observations may differ from the analysis in the main text because of missing market access data.

Overall, market access and market participation seem largely unrelated in Uganda. Figure A5 shows a map of market participation in Uganda. It shows that farmers next to Kampala (the capital in the southern center of Uganda) sell similar shares of their harvests than farmers in the more remote North-West of the country. However, areas with high market participation coincide with areas in which coffee (South-West) or cotton (belt from East to North-West) are grown. Coffee and cotton are the main cash crops in Uganda partly because they are easy to

transport and to store.

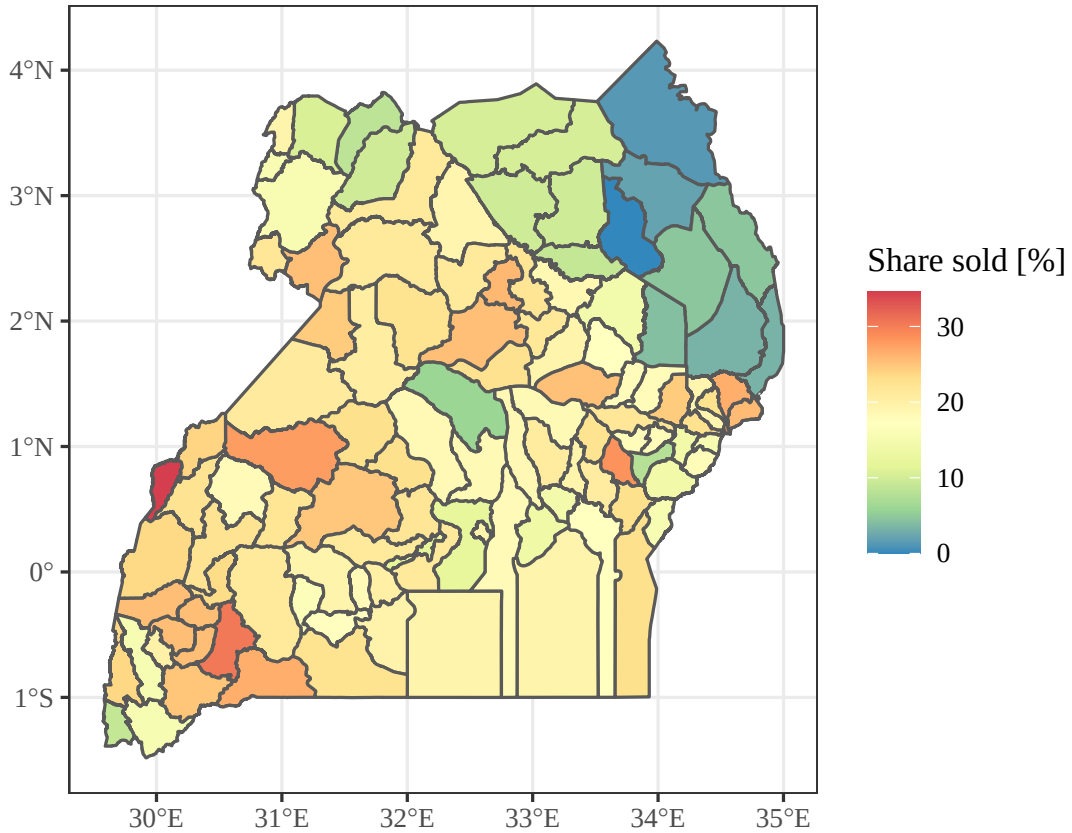

Figure A5: Mean share of the harvest that is sold.

Table A3 summarizes the relationship between market participation and crop diversity using a simple OLS and IV regressions. We measure crop diversity as the log number of crop grown per farmer and season and market participation as the share of the harvest that is sold. We include market participation in linear and squared form as suggested by Figure 8. The results show that crop diversity increases initially with market participation until it reaches a maximum around 6 % and then starts declining again. This relationship is unaffected by including region fixed effects (column 2) or household fixed effects (column 3). However, market participation is endogenous. We use the share of households within a district that grow coffee and the share of households that grow cotton as an instrument for market participation while excluding the focal household in these shares. The F-statistic for the instrument is 26. Although the curvature increases in the IV specification compared to the OLS regression, the turning point remains unchanged.

The regressions also suggest that market participation explains a larger faction of the variation in crop diversity compared to precipitation, ranging between 6 and 10 %.

E Land heterogeneity and crop diversity

Figure A6 plots the distribution of crop diversity against different measures of land heterogeneity. Panel A shows the distribution of crop diversity for different levels of land fragmen-

Table A3: Crop diversity and market participation

	Dependent variable:			
	Ln(Number)			
	(1) OLS	(2) OLS	(3) OLS	(4) IV
Ihs(Share sold)	0.321^{***}	0.289^{***}	0.224^{***}	2.382^{***}
	(0.015)	(0.012)	(0.014)	(0.695)
Ihs(Share sold)^2	-0.063^{***}	-0.057^{***}	-0.048^{***}	-0.467^{**}
	(0.003)	(0.003)	(0.003)	(0.166)
Observations	26,465	26,465	26,465	23,471
Within R^2	0.097	0.081	0.056	-
Location fixed effects	-	Region	Household	-

All specifications include year and season fixed effects. Standard errors are clustered at the district level. Significance levels are $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

tation. We measure land fragmentation as the number of distinct time intervals to reach the individual land parcel of the farm. The LSMS-ISA records five different time intervals to reach a specific parcel (Less than 15 minutes, 15 to 30 minutes, 30 to 60 minutes, 60 to 120 minutes, more than 120 minutes). Although the number of crops increases with the number of unique time intervals to reach the farm's parcels, there are very few observations with more than three unique time intervals. Panel B plots the distribution of crop diversity against the number of unique soil types within the farm. The LSMS-ISA distinguishes between four different soil types (Sand loam, Sandy clay loam, Black clay and Other). Similar to panel A there seem to be a positive relationship between land heterogeneity and crop diversity although there are very few observations with more than two distinct soil types. Panel C plots crop diversity against the number of distinct soil quality classes within a farm. The LSMS-ISA records three different soil qualities (Good, Fair, Poor). There is no obvious relationship between soil quality diversity and crop diversity. Panel D plots the distribution of crop diversity against the number of distinct topographic classes per farm. There are six different topographic classes (Hilly, Flat, Gentle slope, Steep slope, Valley, Other). No distinct pattern becomes apparent.

Table A4 estimates the relationship between land heterogenity and crop diversity in a regression framework using the same land heterogenity measures as in Figure A6. There is a positive relationship between crop diversity and land heterogenity in all specifications but the explanatory power is low ($R^2 < 1\%$). In addition, land heterogenity may be correlated with farm size, which we will address in the main empirical section of this paper.

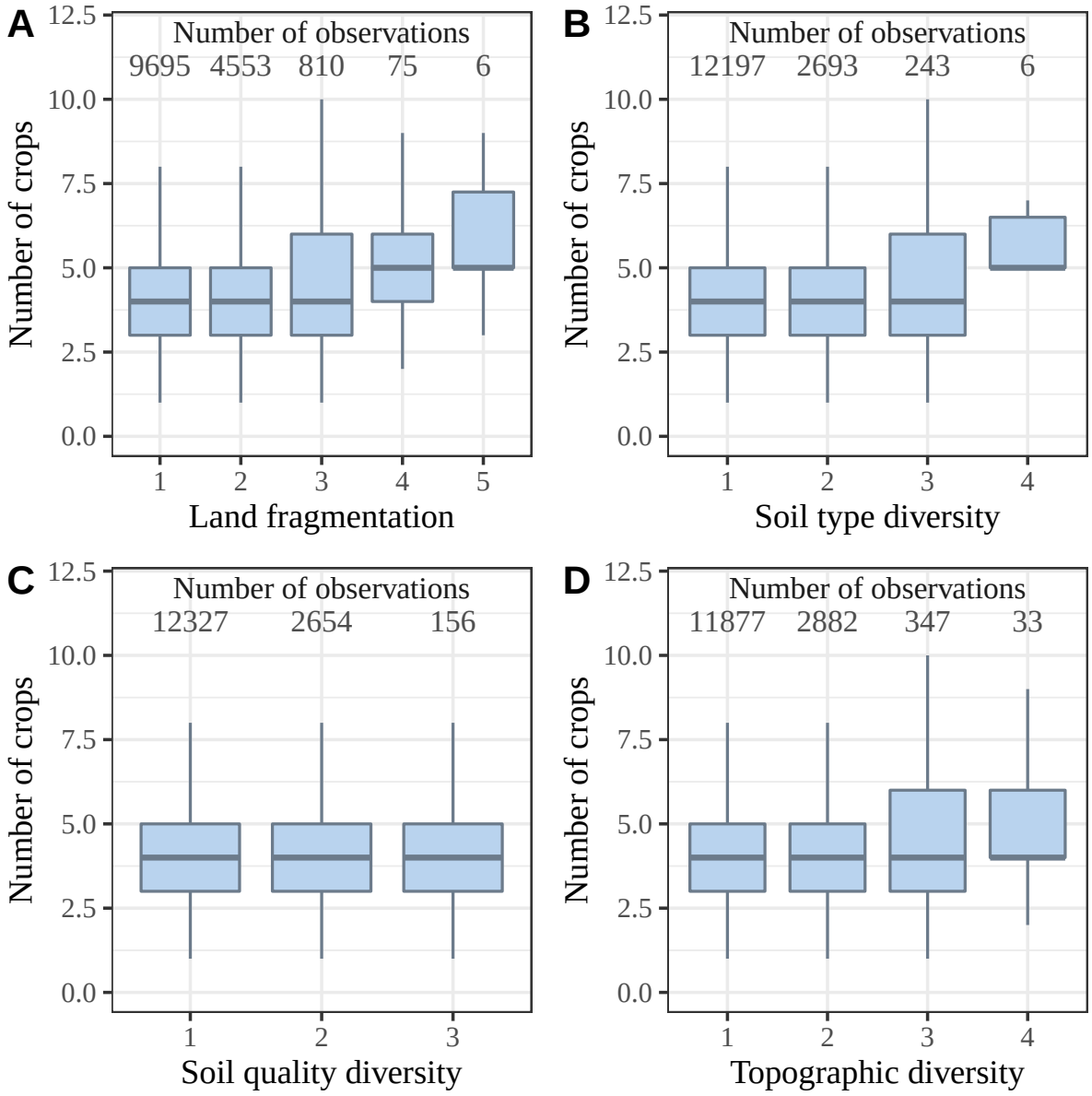

Figure A6: Land heterogeneity and crop diversity. Panel A plots crop diversity against land fragmentation. We measure land fragmentation as the number of distinct distance bins to reach the individual land parcels of the farm. Panel B plots crop diversity against soil diversity. We measure soil diversity as the number of distinct soil types contained within the farm. Panel C plots crop diversity against the heterogeneity of soil quality. We measure soil quality heterogeneity as the number of distinct soil quality classes within the farm. Panel D plots crop diversity against the number of distinct topographic classes of the farm.

F Proofs

Dividing (3a) by (3b), and (3a) by (3c),

$$l_k = \frac{\beta}{\alpha}\frac{\lambda}{\omega}a_k \tag{17}$$

$$x_{ik} = \frac{\gamma}{\alpha}\frac{\lambda}{q}a_k \tag{18}$$

Table A4: Crop diversity and land heterogeneity

	Dependent variable:							
	log(number)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Land fragmentation	0.047***	0.049***						
	(0.011)	(0.010)						
Soil type diversity			0.032**	0.046***				
			(0.015)	(0.013)				
Soil quality diversity					0.044***	0.040***		
					(0.015)	(0.014)		
Topographic diversity							0.071***	0.023**
							(0.015)	(0.010)
Fixed-effects								
Season	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household		Yes		Yes		Yes		Yes
Observations	15,139	15,139	15,139	15,139	15,139	15,139	15,139	15,139
Within R^2	0.0036	0.0032	0.0009	0.0019	0.0014	0.0014	0.0051	0.0005

Standard errors are clustered at the district level. Significance levels are $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

plugging into (3a)

$$\alpha\, p_k\, a_k^{\alpha-1} \left(\frac{\beta}{\alpha}\,\frac{\lambda}{\omega}\, a_k\right)^{\beta} \left(\frac{\gamma}{\alpha}\,\frac{\lambda}{q}\, a_k\right)^{\mu\,\gamma} \underbrace{\exp\left(\int_{\mu}^{1} \gamma\, \ln(e_{ik})\, di\right)}_{=:\, r_k^{(1-\mu)\,\gamma}} = \lambda. \tag{19}$$

Rearranging,

$$a_k^{1-\alpha-\beta-\mu\,\gamma} = \alpha^{1-\beta-\mu\,\gamma}\, \beta^{\beta}\, \gamma^{\mu\,\gamma}\, p_k\, r_k^{(1-\mu)\,\gamma}\, \lambda^{\beta+\mu\,\gamma-1}\, \omega^{-\beta}\, q^{-\mu\,\gamma} \tag{20}$$

Integrating over crops, and using $\gamma = 1 - \alpha - \beta$, we obtain with positive constants Ω_A and Ω_L

$$A = \Omega_A \int_0^N p_k^{\frac{1}{(1-\mu)\,\gamma}}\, r_k\, q^{-\frac{\mu}{1-\mu}}\, dk \tag{21}$$

$$L = \Omega_L \int_0^N p_k^{\frac{1}{(1-\mu)\,\gamma}}\, r_k\, q^{-\frac{\mu}{1-\mu}}\, dk \tag{22}$$

Using this in (20), we obtain (4).

The aggregate output of crop k is obtained by plugging (4) in the production function (1)

as

$$y_k = A^\alpha\, L^\beta \left(\frac{p_k^{\frac{1}{(1-\mu)\,\gamma}}\, r_k}{\int_0^N p_k^{\frac{1}{(1-\mu)\,\gamma}}\, r_k\, dk} \right)^{\alpha+\beta} \exp\left(\int_0^\mu \gamma \ln\left(\frac{\gamma\, p_k\, y_k}{q} \right) di + \int_\mu^1 \gamma \ln(e_{ik})\, di \right) \tag{23}$$

$$= A^\alpha\, L^\beta \left(\frac{p_k^{\frac{1}{(1-\mu)\,\gamma}}\, r_k}{\int_0^N p_k^{\frac{1}{(1-\mu)\,\gamma}}\, r_k\, dk} \right)^{\alpha+\beta} \left(\frac{\gamma\, p_k\, y_k}{q} \right)^{\mu\,\gamma} r_k^{(1-\mu)\,\gamma} \tag{24}$$

Solving yields (25):

$$y_k = A^{\frac{\alpha}{1-\mu\,\gamma}}\, L^{\frac{\beta}{1-\mu\,\gamma}} \left(\frac{p_k^{\frac{1}{(1-\mu)\,\gamma}}\, r_k}{\int_0^N p_k^{\frac{1}{(1-\mu)\,\gamma}}\, r_k\, dk} \right)^{\frac{\alpha+\beta}{1-\mu\,\gamma}} \left(\frac{\gamma\, p_k}{q} \right)^{\frac{\mu\,\gamma}{1-\mu\,\gamma}} r_k^{\frac{(1-\mu)\,\gamma}{1-\mu\,\gamma}} \tag{25}$$

Using the previous results, we also find the optimized profit per crop k as:

$$\pi_k = p_k\, y_k - \int_0^\mu q\, x_{ik}\, di = p_k\, y_k - \mu\,\gamma\, p_k\, y_k = (1-\mu\,\gamma)\, p_k\, y_k \tag{26}$$

$$= (1-\mu\,\gamma)\, A^{\frac{\alpha}{1-\mu\,\gamma}}\, L^{\frac{\beta}{1-\mu\,\gamma}} \left(\frac{p_k^{\frac{1}{(1-\mu)\,\gamma}}\, r_k}{\int_0^N p_k^{\frac{1}{(1-\mu)\,\gamma}}\, r_k\, dk} \right)^{\frac{\alpha+\beta}{1-\mu\,\gamma}} \left(\frac{\gamma}{q} \right)^{\frac{\mu\,\gamma}{1-\mu\,\gamma}} r_k^{\frac{(1-\mu)\,\gamma}{1-\mu\,\gamma}}\, p_k^{\frac{1}{1-\mu\,\gamma}} \tag{27}$$

$$= (1-\mu\,\gamma)\, A^{\frac{\alpha}{1-\mu\,\gamma}}\, L^{\frac{\beta}{1-\mu\,\gamma}} \frac{p_k^{\frac{1}{(1-\mu)\,\gamma}}\, r_k}{\left(\int_0^N p_k^{\frac{1}{(1-\mu)\,\gamma}}\, r_k\, dk \right)^{\frac{\alpha+\beta}{1-\mu\,\gamma}}} \left(\frac{\gamma}{q} \right)^{\frac{\mu\,\gamma}{1-\mu\,\gamma}} \tag{28}$$

Aggregate profit thus is (5).

G Labor markets

Efficient labor markets require $\frac{dY}{dL} = w$ where Y are the farm level revenues, L is farm level labor and w is the wage rate. Using equation (11) we can solve for L

$$\frac{dY}{dL} = \frac{\beta}{1-\mu\,\gamma} \left(\Omega\, N^{(1-\mu)\,\gamma-\varphi}\, A^\alpha \right)^{\frac{1}{1-\mu\,\gamma}} L^{\frac{\beta}{1-\mu\,\gamma}-1} = w$$

$$\Longleftrightarrow$$

$$L = \left[\frac{w(1-\mu\,\gamma)}{\beta} \left(\Omega\, N^{(1-\mu)\,\gamma-\varphi}\, A^\alpha \right)^{\frac{1}{\mu\,\gamma-1}} \right]^{\frac{1}{1-\frac{\beta}{1-\mu\,\gamma}}}$$

Next we solve for w using the labor constraint

$$\bar{L} = \sum_i \left[\frac{w(1-\mu\,\gamma)}{\beta} \left(\Omega\, N_i^{(1-\mu)\,\gamma-\varphi}\, A_i^{\alpha} \right)^{\frac{1}{\mu\,\gamma-1}} \right]^{\frac{1}{1-\frac{\beta}{1-\mu\,\gamma}}}$$

$$\Longleftrightarrow$$

$$w = \left[\bar{L}^{-1} \frac{(1-\mu\,\gamma)}{\beta} \sum_i \left(\Omega^{\frac{1}{\mu\,\gamma-1}} N_i^{\frac{(1-\mu)\,\gamma-\varphi}{\mu\,\gamma-1}} A_i^{\frac{\alpha}{\mu\,\gamma-1}} \right)^{\frac{1}{1-\frac{\beta}{1-\mu\,\gamma}}} \right]^{\frac{\beta}{1-\mu\,\gamma}-1}$$

where $\bar{L}$ is the aggregate rural labor supply, i is the individual farm. We use the survey year 2015/16 as baseline with $\bar{L} = 448952$. Using the parameter values of column (2) from Table 2 and 3 yields $\frac{1-\mu\,\gamma}{\beta} = 4.807692$ or $\frac{\beta}{1-\mu\,\gamma} = 0.208$ and $\Omega^{\frac{1}{\mu\,\gamma-1}} N_i^{\frac{(1-\mu)\,\gamma-\varphi}{\mu\,\gamma-1}} A_i^{\frac{\alpha}{\mu\,\gamma-1}} = \frac{Y_i}{L^{\frac{\beta}{1-\mu\,\gamma}}}$.

H Crop diversity at the plot level

Table A5 reports the results for the impact of plot size and plot labor on plot level crop diversity. It shows that larger plots and higher labor inputs are associated with intercropping. In other words, farmers plant more different crops on larger plots and they also allocate more labor towards those plots with intercropping. However, because we do not have an instrument for labor and land at the plot level, the results lack causal interpretation.

Table A5: Crop diversity at the plot level

	ln(Number)			Simpson
	(1) OLS	(2) OLS	(3) ER	(4) OLS
ln(Plot size)	0.072***	0.106***	0.106***	0.141***
	(0.007)	(0.009)	(0.009)	(0.011)
ln(Labor)	0.045***	0.056***	0.056***	0.083***
	(0.005)	(0.004)	(0.004)	(0.006)
Observations	44,780	44,780	44,780	44,779
Fixed effects	District	Household	Household	Household

The specifications are: (1) district fixed effects, (2) household fixed effects, (3) similar to specification (2) but with predicted land size and bootstrap standard errors, (4) similar to (2) but measuring crop diversity with Simpson diversity. All specifications include year and season fixed effects. Standard errors are clustered at the district level except for specification (3). Significance levels are $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

I Crop diversity and productivity at the crop level

Table A6 reports the results on crop diversity and harvest quantities on the crop-plot level. The baseline result with district fixed effects suggests that planting a crop in combination with one

other crop increases yields by 9 % compared to monocultures everything else equal. Including household fixed effects increases the estimate to 14 percent. This estimate remains largely unaffected by using the GPS corrected crop patch size measurement (3) or by adding precipitation levels as controls (Column 4 and 5). In column (6) we measure crop diversity with the Simpson index.

Table A6: Revenues and crop diversity at the crop level

	ln(Harvest)					
	(1) OLS	(2) OLS	(3) ER	(4) OLS	(5) OLS	(6) OLS
Diversity	0.088**	0.139***	0.139***	0.139***	0.139***	0.136***
	(0.035)	(0.037)	(0.037)	(0.037)	(0.037)	(0.036)
ln(Crop area)	0.323***	0.344***	0.344***	0.344***	0.344***	0.328***
	(0.030)	(0.029)	(0.029)	(0.029)	(0.029)	(0.024)
ln(Labor)	0.196***	0.187***	0.187***	0.187***	0.187***	0.187***
	(0.013)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
ln(Plot area)	0.067**	0.028	0.028	0.029	0.028	0.047**
	(0.026)	(0.025)	(0.025)	(0.025)	(0.025)	(0.020)
ln(Farm size)	0.087***	−0.127***	−0.127***	−0.127***	−0.127***	−0.128***
	(0.013)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Precipitation				0.00004	0.001	
				(0.0001)	(0.009)	
Lag precipitation				−0.00004	−0.005	
				(0.0001)	(0.009)	
Observations	66,790	66,790	66,790	66,686	66,790	66,790
Diversity	Ln(Number)	Ln(Number)	Ln(Number)	Ln(Number)	Ln(Number)	Simpson
Fixed effects	District	Household	Household	Household	Household	Household
Precipitation data				TRMM	SPEI	

Results for regression equation (16) *at the crop-plot level. The specifications include (1) district fixed effects, (2) household fixed effects, (3) similar to specification (2) but with predicted crop area, plot area and farm size as well as bootstrap standard errors, (4) similar to specification (2) but with precipitation in the current and the previous season using TRMM data, (5) similar to (4) but using the SPEI index to measure precipitation, (6) similar to (2) but measuring crop diversity with Simpson diversity. All models include year and season fixed effects. Standard errors are clustered at the district level except for specification (3). Significance levels are* $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

J Parameters for Figure 12

The output elasticity of crop diversity is a function of the control over the environment (μ), the productivity (price) differences between crops (φ) and the output elasticity of ecosystem services or nutrients (γ). To visualize the relation of the output elasticity of diversity, μ and ϕ we need to quantify γ. However, to determine γ we first need to estimate φ.

The results reported in column (2) of Table A6 use crop specific fixed effects in addition to household fixed effects, year fixed effects and season fixed effects. The estimated crop fixed effects equal $\varphi \log(k)$ while $\log(p_1)$ is absorbed by the other fixed effects. Table A7 reports the

estimated crop fix effects for crops with more than 100 observations. The table also provides the standard errors, the number of observations (n) and the rank (k). The column 'Price' reports the exponential of the crop fixed effects for a regression through the origin without the other fixed effects ($p_k = p_1 k^{-\varphi}$).

Table A7: Crop prices (including total factor productivity)

Crop name	Estimate	Standard error	Price	n	k
Rice	1.102	0.171	2384.679	290	1
Tomatoes	0.891	0.149	2348.585	311	2
Cotton	0.693	0.146	1472.506	160	3
Irish Potatoes	0.499	0.156	1560.803	1057	4
Banana Food	0.443	0.139	1414.644	12382	5
Cassava	0.437	0.12	1239.502	6287	6
Onions	0.412	0.176	1521.088	139	7
Coffee All	0.395	0.141	1152.09	2046	8
Sweet Potatoes	0.25	0.121	1019.774	5976	9
Finger Millet	0.152	0.136	986.608	1450	10
Simsim	0.118	0.136	921.008	673	11
Sugarcane	0.102	0.196	848.207	169	12
Groundnuts	0.071	0.135	912.676	3338	13
Pumpkins	0.05	0.151	812.393	123	14
Yam	0.016	0.13	782.335	333	15
Pigeon Peas	-0.002	0.164	888.928	220	16
Beans	-0.038	0.122	811.262	13224	17
Sunflower	-0.052	0.206	680.74	207	18
Other	-0.135	0.179	611.025	186	19
Field Peas	-0.177	0.146	620.714	339	20
Sorghum	-0.295	0.143	505.46	1608	21
Maize	-0.414	0.125	535.427	12373	22
Soya Beans	-0.457	0.176	561.578	412	23
Banana Sweet	-0.464	0.138	548.784	643	24
Banana Beer	-0.481	0.164	571.949	1237	25
Cow Peas	-0.581	0.164	437.8	105	26

The price includes the total factor productivity as explained in Section 4

Figure A7 plots the estimated crop fixed effects against the log rank from Table A7. The slope of the linear regression is $\varphi = 0.5$.

Assuming no control over the environment ($\mu = 0$) simplifies the output elasticity of crop diversity to $\gamma - \varphi$. Using the estimate from the main specification (2) of Table 3 yields $\gamma = 0.835$.

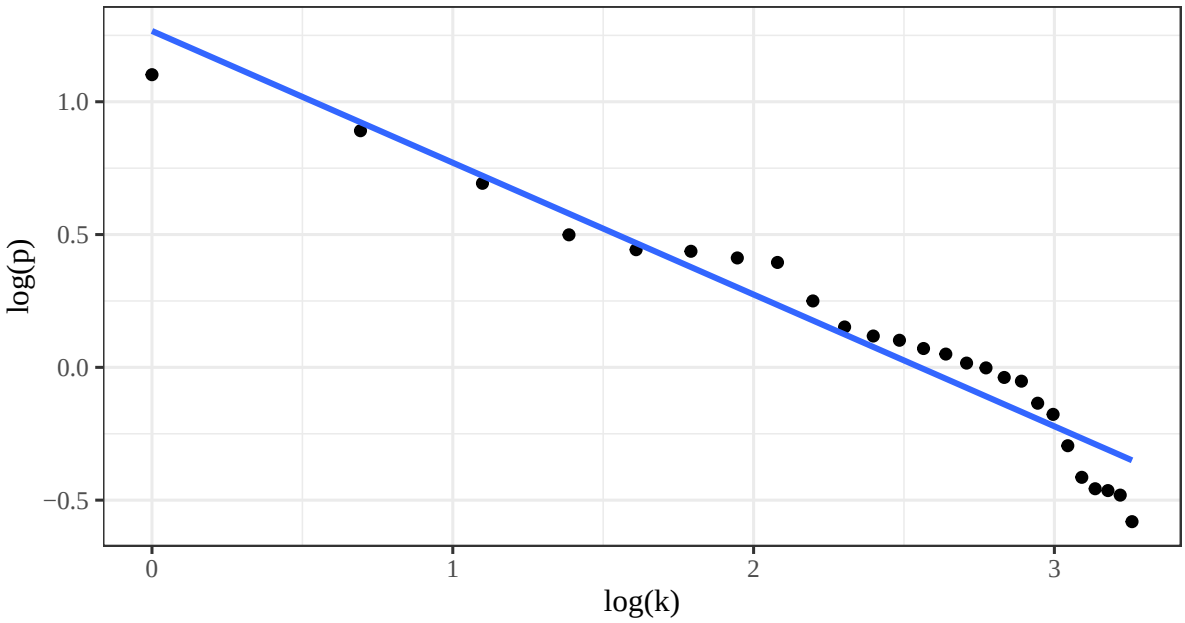

Figure A7: Crop price (p_k) and crop rank ($\log(k)$). The blue line is a linear regression with slope $\varphi = -0.5$.

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