Benefits of diversification in agriculture: Evidence from Malawi

Draft

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Abstract

We use data from a farmers' survey in Malawi to compare two agricultural technologies: monoculture maize and crop diversification (maize-legume intercrop). We match farmers locations with data on rainfall and air temperature to test whether more biodiverse agriculture is better at absorbing weather shocks, and hence adaptation to the climate change. The data make it possible to compare variation not only over time, but also over different plots within the same time period, which helps reduce omitted variable bias. The instrumental variable method is used to eliminate rainfall measurement error. For a number of specifications, and controlling for fertilizer use, crop diversification is both more productive than monoculture maize and more resistant to weather shocks. Although I am not able to identify the average population effect, I build a model to show that the effect I identify is likely to prevail if the Malawian government decides to shift the focus of its agricultural subsidy at the margin from fertilizer to legume seeds and education. In particular, a reform that cuts fertilizer

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use by 10% (e.g. reducing the price subsidy) would be yield-neutral, but more sustainable, if agricultural land used for maize-legume intercrop is expanded by about nine percentage points.

Keywords: agricultural productivity, diversification, technology adoption, biodiversity, sustainability, resilience, input subsidy, climate change

JEL-classification: O13, Q01, Q12, Q18, Q16, Q54

1 Introduction

People in Sub-Saharan Africa (SSA) are extremely food-insecure. In 2011-13 25% of the SSA population were undernourished, down only eight percentage points from 1990. The region has been a laggard in meeting the Millennium Development Goals (UN, 2014).

Improvements in food security in SSA have been pushed off track by frequent and severe weather shocks. Because over 90% of the region's cropland is rain-fed, and insurance markets are underdeveloped, yields and hence food security are highly dependent on rainfall. Droughts and dry spells during a short growing season can have dreadful consequences. Sporadic rainfall in the 2001-02 growing season in Malawi brought on a severe food crisis, which caused as many as several thousand hunger-related deaths (ActionAid, 2006).

An additional risk is that agriculture in SSA relies on a supply of cheap fertilizer, which is not always available. Many countries in the region offer fertilizer subsidies, which are expensive for the government budget and the country's external position, and often require financial aid from international donors. In 2012 about 10% of government spending went to Malawi's Farm Input Subsidy Program; of the total 12% was directly covered by foreign aid (Chirwa and Dorwards, 2014). Fertilizer prices are extremely volatile: annual swings of 20-30% are not uncommon. This undermines either the sustainability of subsidy programs or adequate supply of fertilizer to the field.

In many SSA countries monoculture maize has been the dominant technology used by smallholder farmers. In Malawi its share of agricultural land increased from 27% in 2004 to 37% in 2009, despite slow long-run growth in productivity and vulnerability to weather and fertilizer supply shocks. Many scholars hail intensive monoculture as the only viable path to satisfy the ever-growing demand for food (Borlaug, 2000; Morris et al., 2007; Tilman et al., 2011). Economists mainly deal with questions like effectiveness of subsidy programs (Rickert-Gilbert et al., 2010; Dorwards and Chirwa, 2011), or why smallholder farmers do not take up fertilizer or new hybrid seeds on a large scale (Duflo et al., 2011; Suri, 2011).

Given Africa's poor soils and dry climate, an often-proposed alternative way to improve food security is crop diversification: growing different crops together on one plot. In Malawi the often suggested technology is an intercrop of maize and legumes. Farm trials and participatory farming demonstrate that even with less fertilizer this technology can be as productive as monoculture maize (Searle et al., 1981; Snapp et al., 2010; Sileshi et al., 2010; One Acre Fund, 2015). The technology now has the attention of the Gates Foundation and the Malawian Government, which decided in 2013 to subsidize legume seeds as well as maize seeds and fertilizer. The question that remains is how crop diversification performs against monoculture maize in real life conditions of smallholder farmers on a large scale, and whether crop diversification is better at absorbing shocks confronting farmers.[1] [2]

This paper uses data on Malawian rural households to test whether crop diversification, in particular maize-legume intercropping, is indeed more productive and resilient than monoculture maize. I match farmers' locations with multiple weather measures, which makes it possible to use the IV method to reduce measurement error. Also, the unique structure of the dataset allows me to observe not only farmers over time but also the performance of both technologies managed by the same farmer at a single point in time. This is important for reducing the omitted variable bias, though it is still not possible to identify an average population effect. However, I build a model of farmer's optimal technology portfolio choice, and show that the effect which I do identify is likely to prevail if the government decides to shift the subsidy focus at the margin from maize seeds and fertilizer to legume seeds and education about crop diversification.

Controlling for the use of fertilizer, I find crop diversification to be more productive than monoculture maize. This result is robust to variety of estimation specifications and variable definitions, although for some of them the result is not statistically significant. According to the preferred specifi-

[1] As shown by Duflo et al. (2016), controlled experiments are not always informative about the policy implications in real life

[2] In few studies crop diversification is included as one of the regressors, and is shown to improve yields. See Sheahan et al. (2013). The variable is, however, never the focus of the study, and its interaction with weather and fertilizer shocks is not explored

cation, a ten percentage points shift in land use from maize to maize-legume intercrop is likely to raise average calorie yield by 2.4 percent. The better performance of the maize-legume intercrop seems to be driven by high productivity of legumes and the fact that they do not seem to interfere much with the growth of maize even when planted densely together. At the same time, on average the intercrop is not more productive than maize-legume rotation.

I also find that Malawian farmers are highly vulnerable to fertilizer supply and weather shocks, and that more biodiverse agricultural technology likely works as a shock absorber, although again the results lose significance in some specifications. A half historical standard deviation negative shock to rainfall is expected to reduce the average historical calorie yield by almost four percent. It would cost government about 0.9 percent of GDP to compensate the losses to farmers at 2013 maize price and the exchange rate. A ten percentage points increase in land used for maize-legume intercrop is likely to reduce the yield loss to 3.5 percent, which is equivalent to a reduction in the compensation cost of 0.1 percent of GDP. A similar pattern is observed for rainfall variance, temperature, and fertilizer supply shocks. Reforming the subsidy program by reducing fertilizer use by 10 percent and increasing use of maize-legume intercrop by nine percent would be yield-neutral but would make Malawi's agriculture more resilient and more sustainable. Finally, I find that maize-legume intercrop is also more weather-resistant than maize-legume rotation or growing maize and legume separately.

2 Background

2.1 About Malawi

Malawi is a land-locked country in SSA. Despite sustained economic growth of about 7% per year for the past five years, the country's GDP per capita in 2010 was only 925 PPP units, which was in the lowest 5% of the world's distribution. Malawi's population is 13 million people, 40% of which were living on less than USD 1.25 per day in 2010. Farmers represent 78% of the population. According to Dorwards et al. (2010), only 10% of them are net sellers, i.e. produce surplus over their own consumption. Maize is by far the main staple crop in the country: it is grown by 97% of the farmers, and it accounts for 60% of total calorie consumption in the country.

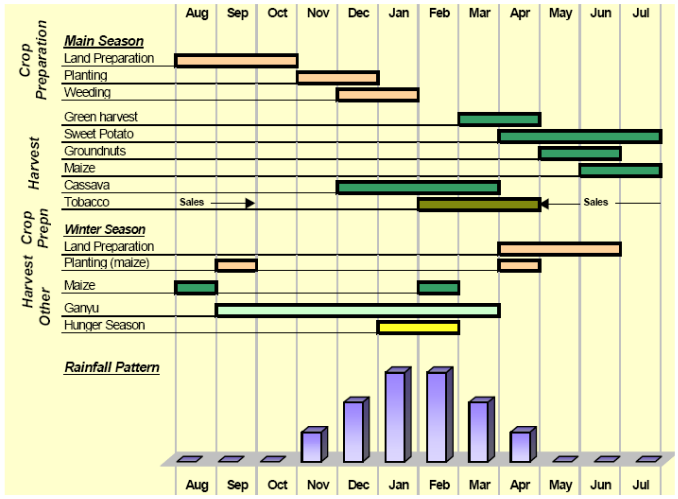


Figure 1: Usual cropping season of a Malawian household

Note Copied from MNVAC (2005)

2.2 A year in life of Malawian subsistence farmer

Maize is grown in Malawi without irrigation during the single rainy season between October and April. The usual cropping season is depicted on Figure 1. Weather can cause significant fluctuations of maize harvest. The plant has relatively shallow root system, which makes it dependent on soil moisture and consequently regular rainfall. Low precipitation between January and March is harmful to the harvest. High rainfall variation is damaging as well. Especially dangerous are dry spells of more than a week in January to March during maize's flowering and early grain filling. For example, the Malawian aggregate maize harvest decreased by about 40% in 2004/05 most likely as a result of two weeks without rain in February. In addition, Lobell et al. (2011) provides empirical evidence on negative impact of (too) high temperature on maize productivity (up to 1.7% decrease for each day above 86F (30C)). At the same time, moderate increases in temperature are expected to affect the harvest favorably.

2.3 Legumes and maize-legume intercrop

In addition to being vulnerable to rainfall shocks maize can deplete soils of nutrients - in particular carbon and nitrogen - if grown continuously without fallow periods. Nitrogen is an essential component of a plant's nutrition. Without sufficient quantity of nitrogen in the soil, yields can fall significantly. One solution to this problem is to use inorganic fertilizer. An alternative is to intercrop (grow at the same time) or rotate (grow one after another) maize with nitrogen-fixing plants, such as legumes.

Even though the supply of nitrogen in nature is practically boundless, most of it is contained in our atmosphere (70% of its volume). Most plants are not able to fix nitrogen directly from the atmosphere. They use ammonia (NH_3) in the soil, which is being produced by bacteria using air. Legumes are able to attract these bacteria on their roots by supplying them other nutrients. In exchange the bacteria fix nitrogen from the atmosphere and produce ammonia for the plant.

Growing legumes with maize in an intercrop can affect average yield in several ways (see Figure 2 for a photo of a plot with maize-legume intercrop). Since legumes fix nitrogen, it can increase nitrogen available for maize too (so-called nitrogen sharing). It can also improve the soil quality over the long term.[3] Intercropping also allows for denser planting (f.e. a row of legume between two regular rows of maize), and hence more efficient use of land, nutrients and water. A field with more diversified agriculture is likely to attract less insect pests (Wetzel et al., 2016). At the same time, planting maize and legumes in close proximity to each other may lead to inter-species competition (so called competition depression), but given that the plants have different height, root systems and growing cycles, the impact of this competition on yield is likely to be limited.

Additional potential benefit of growing maize and legumes together is that the system may become more resistant to weather shocks. Legumes provide more cover for the ground. They also shed leaves, which improves the organic matter of the soil. Together these factors increase the capacity of soil to store water. Most legumes also have deeper root systems than maize, which makes them more weather-resistant. The usual risk diversification argument is also at work here - since the plants have different growing cycles, weather shocks are likely to have differential impact on the yields, and hence more diversified system is likely to be more stable. Even though this argument

[3]This argument also works for the maize-legume rotation

Figure 2: A plot with the maize-legume intercrop

Note Taken from www.cirad.fr. Accessed October 20, 2016.

works in general for growing more than one crop in one season (f.e. maize and legume on different plots), intercropping gives an additional momentum to it. In case of an adverse weather shock, a failure of one of the crops would reduce inter-species competition on the plot and hence increase the yield of the other crop.

2.4 Agricultural Input Subsidy Programs

Malawian agricultural input subsidy was first implemented in 2005/06 after poor harvest season of 2004/05, and then every year afterward. It consisted of distribution of vouchers to roughly 50% of farmers to receive fertilizers for maize production at a 90% discount, and further distribution of vouchers for improved maize seeds and fertilizer for tobacco.

According to the Malawian government, the main objectives of the input subsidy are national and personal food self-sufficiency and food security, as well as income increase among the poorest. Poverty and food insecurity are seen as major market failures and causes for other negative externatilities, thus warranting government intervention. An additional reason for input subsidy is potential information externality. It is frequently argued that farmers do not realize the full payoff to the fertilizer, and therefore they need to be encouraged to use it and learn.

Information externality argument also applies to maize-legume intercropping. While the technology is not new, [4] it has not been traditionally used in all regions of the country, and it has been gradually crowded out by monoculture maize in recent decades, not least due to maize seed subsidy and government extension. Besides with climate rapidly changing and becoming more prone to droughts, farmers increasingly need to learn how to cope with the weather shocks. Maize-legume intercrop is one of the strategies. At the same time, some recent studies suggest that farmers likely do not fully realize the potential benefits of this technology. For example, after on-farm trials by the One Acre Fund in Kenya the adoption rate of the maize-legume intercrop increased by up to 40 percentage points (One Acre Fund, 2015). Another example, a so-called On-Farm Cropping Verification Trial - a 1998-2000 experiment of planting and educating Malawian farmers about six different technologies - demonstrated that of those who did not use the maize-pigeon pea intercrop before, 67% decided to use it after being shown how to properly use it.[5]

An additional potential obstacle to the wider spread of the maize-legume intercropping is the absence of necessary infrastructure. For example, in 2009 pigeon pea was being sold only in 25% of the villages, the rest of the farmers had to walk long distances to purchase the seeds.

At the same time, the technology could be more labor and seed intensive than monocropped maize, which would also stall its dissemination, and it would be the case against the subsidy. However, field trials suggest that the labor requirements are not too different among the two technologies, at least for legume species that are grown in Malawi (Snapp et al., 2003). Intercrop may require more labor at seeding and harvesting, but then it may require less weeding in between. Even if the intercrop is more seed and labor intensive, but its yield is sufficiently high, the government might still be interested in subsidizing it, since it would increase agricultural productivity per unit of scarce arable land.

The input subsidy is costly, however. For example, 2008/09 subsidy program accounted for 15% of country's budget. Therefore, if it is to be con-

[4] Growing maize and legumes together has been practiced as early as 3000 years ago in Americas - a system known as "the three sisters" along with squash.

[5] See Gilbert et al. (2002), and also Kerr et al. (2007)

tinued, it is of utmost importance to maximize the program's efficiency, i.e. yielding maximum food security and minimizing the risks at the smallest cost possible. This includes the choice of inputs to subsidize, as well as the choice of extension activities.

3 Data

I use a panel of three surveys of Malawian households, which were implemented and used to track the progress of agricultural input subsidy programs in 2006-2009. The first wave - Integrated Household Survey Round 2 (IHS2) - was conducted from March 2004 to March 2005, and served as a baseline survey for the subsequent waves. A total of 9494 households were asked about a wide variety of topics, such as health, expenditures, time use, agricultural practices, etc. The next two waves - Agricultural Input Subsidy Survey 2007 (AISS07) and AISS09 - were conducted in May-July 2007 and February-July 2009 correspondingly. Due to the resource constraints these surveys were of much smaller scale than IHS2: only 3169 and 1918 households were surveyed correspondingly, and the set of questions was restricted mainly to such topics as agricultural practices, and in particular fertilizer use. In all three waves, the households were randomly sampled by district (tier 1 of Malawian local government), traditional authority of sub-chief unit (tier 2), and enumeration area (local sampling unit - EA), and most of the attrition between wave 1 and waves 2 and 3 comes from the random jettisoning of entire EA's. The number of observations and the attrition rates are given in Table 1. Note that the actual number of households participating in the three surveys is higher than the one reported and used in this paper, as I dropped those households, which did not participate in agricultural activity during the last cropping season, and households, which did not report their harvest.

A unique and useful feature of the data is that, where applicable, it is disaggregated by plot for each household. Plot is an area in which a uniform, consistent crop management system is used. The household-plot disaggregated data includes inputs and outputs of farming: use of fertilizer, seeds, number and timing of weeding, harvest by each crop grown on a plot.[6]

[6]Data on seeds and weeding are not available for all waves of surveys. Also data on seeds are not reported by crop

Table 1: Malawian households survey: Available observations and attrition

Indicator	Wave 1 (IHS2)	Wave 2 (AISS07)	Wave 3 (AISS09)
N households, total	9753	3184	1918
N households, all waves	1242	1242	1242
N households, at least two waves	2752	2935	1489
N households, common with prev. wave	n.a.	2720	1457
Attrition from previous wave	n.a.	71%	54%
Exogenous attrition (due to sampling design),% of attrition	n.a.	92%	81%
N households replaced/dropped	n.a.	557	320
N plots, total	19703	5195	5022

Note Abbreviations: IHS2 - Integrated Household Survey Round 2 (1994-1995), AISS07 - Agricultural Input Subsidy Survey Round 1 (2007), AISS09 - Agricultural Input Subsidy Survey Round 2 (2009). Population of households is restricted to those engaged in agricultural activity (growing crops) and who reported their harvests. Definitions of indicators: *N households, total* - total number of interviewed households in a current wave of survey; *N households, all waves* - number of households, which were interviewed in all three waves; *N households, at least two waves* - number of households in a current wave, which were interviewed in at least one additional wave; *N households, common with prev. wave* - number of households, which were interviewed in current and previous waves; difference with the previous indicator is that some households were interviewed in Wave 1 and Wave 3 only; *Attrition from previous wave* - households which were not interviewed in a current wave but were interviewed in a previous wave, as a percentage of total number of interviewed households in a previous wave; *Exogenous attrition (due to sampling design)* - households from enumeration areas, which were jettisoned in a current wave, but were sampled in a previous wave, as a percentage of total number of households subject to attrition; *N households replaced/dropped* - number of households from EAs, which were sampled in both current and previous waves, but were subject to attrition in a current wave; *N plots, total* - number of plots owned by households interviewed in a current wave

General information about each household is also reported: demographic structure, alternative sources of income, etc.

The final dataset represents a "two-dimensional" panel of Malawian households. First, as in usual panel, I am able to observe farming households over time, which allows me to control for time-constant characteristics of the households. The second dimension is geographical - within one period I am able to observe farmers using different technologies at different plots. This allows me to control for all characteristics, including the time-changing ones, which are common to plots cultivated by the same household. I am not able to identify plots across years, as farmers numbered them differently during each wave, but I do track the technology use over time.

3.1 Measuring crop diversification: agricultural technologies in Malawi

As much as 50 different crops were grown in Malawi in 2003-2009. They are listed in Table 14 in Appendix. Some crops are allocated a separate plot, some are grown together on the same plot. Farmers were asked to name up to five most important crops for each plot. On average, 1.76 crops are reported per each plot. Fifty two percent of plots in the sample grow only one crop, 25% grow two crops, 14% - three, 6% - four. Only 2.6% plots grow five crops, so the upper boundary does not seem too binding. Altogether 2109 different combinations of crops are grown.

Local maize and hybrid maize are the most popular crops. Either one of them is grown on 62% of all plots in the sample. The group of legumes includes groundnut, ground bean, bean, soybean, pigeon pea, peas, cow peas, mucuna, and hyacinth bean. At least one of the legumes is grown on 44% of the plots. Non-food crops, tobacco and cotton, which are primarily grown to get cash, comprise 8% of the plots. Other popular crops are sorghum, nkhwani, cassava, sweet potato.

The summary of the most popular agricultural technologies is presented in Table 2. For each technology I list shares of plots used by it - total and for each wave separately.

Two technologies that I compare in my main specifications are maize (M) and maize-legume intercrop (ML). A technology is M if at least one of the crops listed on the plot is local maize, hybrid maize or open pollinated variety (OPV) maize, and no legumes are grown on the plot. A technology is ML if both maize and at least one of the legumes are grown on the plot. Thirty percent of the plots use intercrop of maize with one of the legumes, maize without legumes is cultivated on 32% of plots.

I chose to take the broadest definition for M and ML in my main specifications. In particular, other crops except maize and legumes are allowed to grow on both M and ML plots. Also, even if very little legume or maize is grown on a plot, it would still make it to the estimation.[7] I opt for the broadest definition for two reasons. First, even though I am likely to pick up some noise in the data, I am also sure not to dismiss any relevant observations. As Table 3 shows, in absolute majority of ML plots harvest shares of maize and legumes are dominant (average is 96%). However, if one goes too strict and requires only maize and legumes grown on ML plots, one would loose 34% of observations. Second, even though one could base the definition on certain thresholds of maize and legume harvest shares, any such definition would be arbitrary and potentially could dismiss relevant observations. For example, Table 3 shows that there are many plots with a small (less than 5%) harvest share of legumes. This could be because legumes are simply not dominant crops on these plots, in which case the plots are not maize-legume intercrops. But this could also be due to a failure of a dominant crop, and one of the advantages of crop diversification is that it provides insurance against such failure (harvest of the other dominant crop). Hence, one would want to include these plots in the sample.[8] Finally, even though M plots include few intercrops of maize with non-legume plants, I do want to separate out intercrops of maize and legumes for the reasons listed in Section 2.3.

As a robustness check, I also check other definitions of M and ML: maize and intercrop when maize and legumes are listed among three most important crops, maize and intercrop without any other crops on the plot, maize and intercrop only on plots with significant harvest shares of both. I also check specifications with dummies for plots with only maize or legumes to see presence of other crops significantly affects my results. Finally, I also apply a "X vs. 100-X" rule, which requires the harvest share of legumes on ML plots to be at least X%, and the harvest share of maize on M plots to be at

[7] As a result, some of the ML plots could, in some sense, be "less intercropped" than some M plots. For example, a plot with 96% maize and 4% cassava (non-legume plant) would be considered M plot, while a plot with 97% maize and 3% pigeon pea would be considered ML

[8] I do not observe seed input or area seeded by crop, so I cannot use these to define ML

Table 2: Technology use by Malawian farmers, shares by plots

Technology	Definition	wave 1 (IHS2)	wave 2 (AISS07)	wave 3 (AISS09)	total
M	maize, no legume	28.68	40.51	37.06	32.26
H	hybrid maize, no legume	16.38	21.79	18.98	17.8
ML	maize and legume	25.58	39.26	34.65	29.61
M13	maize - one of 3 most important crops	28.68	40.51	37.06	32.26
ML13	maize and legume - one of 3 most important crops	23.52	38.23	33.87	27.96
M only	maize - single crop on plot	21.61	31.07	21.35	23.26
ML only	maize and legume - single crops on plot	12.92	22.28	17.48	15.39
MPp	maize and pigeon pea	12.51	21.11	15.43	14.56
MB	maize and beans	9.21	8.56	11.64	9.52
MGn	maize and ground nuts	6.63	13.29	9.63	8.35

Note Abbreviations: IHS2 - Integrated Household Survey Round 2 (1994-1995), AISS07 - Agricultural Input Subsidy Survey Round 1 (2007), AISS09 - Agricultural Input Subsidy Survey Round 2 (2009). Legumes include groundnut, ground bean, bean, soybean, pigeon pea, peas, cow peas, mucuna, hyacinth bean. Maize include local maize, OPV and hybrid. The numbers in the table are shares of corresponding plots in total.

least (100-X)%.[9] Qualitatively the results are similar, although as expected due to reduced number of observations, some of them become statistically insignificant. [10]

Figure 3 breaks down the M and ML plots by crops. Both local and hybrid (supposedly more productive) maize are used to almost equal extent on monoculture and intercropped plots. Quite a few plots mix the two, both M and ML. Most popular legumes are pigeon pea, bean and ground nut.

An important feature of the agriculture technology use in Malawi is that many farmers apply two and more technologies (on different plots) within one growing season. Table 4 reports the distribution by wave. Most farmers still use only one technology, but as much as 800 of them over three waves use two. Low number for Wave 1 is because the harvests in the IHS2 survey

[9] This rule makes sure that in some sense M plots are not more "intercropped" than ML plots. For example, under the broad definition, a plot with 95% maize and 5% cassava (non-legume crop) would be defined as M plot. A plot with 97% maize and 3% legume would be defined as ML plot. In this case, the M plot is actually more diversified than the ML plot, which would be desirable to avoid, even though I do want to specifically test for maize-legume intercrops because of their peculiar properties (see Section 2.3). I test the rules with X=3 and X=5

[10] The results are reported in Tables 20 - 24

Table 3: Maize (M) and maize-legume intercrop (ML): Harvest shares by crops

crop	mean	sd	p(10)	p(25)	p(50)	p(75)	p(90)
M plots, harvest shares of ...							
Maize	0.97	0.12	0.96	1	1	1	1
ML plots, harvest shares of ...							
Maize	0.73	0.24	0.36	0.6	0.79	0.92	0.98
Legumes	0.23	0.23	0.01	0.06	0.15	0.33	0.58
Maize + Legumes	0.96	0.1	0.85	0.97	1	1	1

Note Legumes include groundnut, ground bean, bean, soybean, pigeon pea, peas, cow peas, mucuna, hyacinth bean. Maize include local maize, OPV and hybrid. Harvest shares are calculated based on the caloric value of crops.

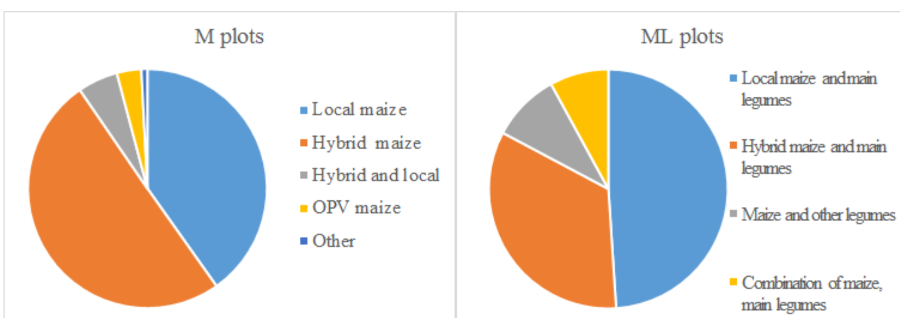


Figure 3: Composition of M and ML plots by crops

Note Main legumes: pigeon pea, bean, ground nut. Included are only the plots used in the estimation.

Table 4: Technology use and diversification by Malawian farmers, number of households

wave 1 (IHS2)

	M	ML
M	4183	208
ML		3656

wave 2 (AISS07)

	M	ML
M	1261	217
ML		1266

wave 3 (AISS09)

	M	ML
M	694	414
ML		707

Note Abbreviations of technologies: M - maize, ML - maize-legume intercrop. Diagonals are numbers of households using only one corresponding technology at a given year. Above diagonals are numbers of households using two corresponding technologies at a given year. Reported numbers are after all adjustments (i.e numbers used in estimation).

are reported only as aggregates across all plots. So, even though types of crops grown on each plot are reported, I cannot differentiate between the two technologies in my estimation if they involve same crops.[11] Plots, where it is impossible to identify harvests, are dropped from the estimation.

3.2 Measuring output

My objective in this paper is to measure real agricultural output, as relates to the food security. This is not straightforward when several crops are harvested. Therefore I use several measures.

My main measure is the total energy output of the plot. The unit of measurement is kilo calorie. The measure makes sense since both maize and legumes are staple crops, and it is their nutritional value that the farmers look up to. Besides food security is primarily defined as the access to a minimum required number of calories per day (FAO, 2008). I use data from Food Composition Tables of Food and Agriculture Organization of United Nations (FAO) to transform multi-crop harvest into its energetic value. The conversion rates are reported in Table 14.

I use four additional measures in my estimations. The first one is similar to the real GDP of a country: it is cash value of harvests of all crops at 2007 (constant) national prices. National price of a crop is defined as the

[11]For example, if a farmer grows local maize on one plot, and local maize plus some legume on another then harvests by plots are impossible to identify. At the same time, some M and ML combinations are possible to identify, as I observe harvests by each variety of maize, and I do observe types of crops grown by plot. For example, if a farmer grows hybrid maize on one plot, and local maize plus some legume on another then I can identify harvests by plots

Table 5: Measures of harvest and fertilizer: Summary statistics

	count	mean	sd	p10	p50	p90
energy yield, mln kCal/ha	12606	2.89	2.65	0.55	2.05	6.28
cash yield, thousand MK/ha	12606	10.98	11.84	1.99	7.85	23.69
maize eqiuv. yield (Liu-Myers), tonnes/ha	12606	1.21	1.45	0.16	0.76	2.79
grain yield, tonnes/ha	12606	0.83	0.76	0.16	0.60	1.83
protein yield, kg/ha	12606	85.34	79.26	15.14	62.52	183.11
maize yield, tonnes/ha	12606	0.71	0.71	0.11	0.46	1.61
fertilizer applied, tonnes/ha	12606	0.08	0.11	0	0.04	0.25

Note: All summary statistics are calculated at a household level. Only farmers who use M or ML (or both) are included. Exchange rate as of 2007 is 141MK per USD.

median of the crop's price distribution over the whole country, as reported in community surveys, which were conducted parallel to the household surveys during each wave. The prices that I used are reported in Table 14. The second measure is similar. It was proposed by Liu and Myers (2009) and is defined as the cash value of the harvest in current prices divided by the current price of maize. The measure takes into account the relative change of maize price, but it is not clear why should it be used if maize productivity is not sole focus of the research. The third measure is the amount of grain produced - both maize and legume in case of intercrop. In other words, this is just the weight of harvest. It is directly observable by farmers, and probably best understood by them. Finally, the fourth measure is the total protein output measured in grams. Again, I use FAO's conversion rates for transformation.

All measures of output are converted into yields per hectare. On household level (over all plots) yields are computed as geometrical averages of yields by plots, where weights are the corresponding land shares. [12] Yields summary statistics are reported in Table 5.

3.3 Measuring weather conditions

I match farmers' locations on TA (traditional authority - third tier of government) level with the measurements of several weather conditions, which are likely to affect maize and legumes harvest - rainfall, rainfall variation, and temperature. All weather conditions are measured during the growing season (January to March or April).

[12]The rationale for geometric average are explained in section on Identification

Table 6: Weather indicators dataset: Descriptions

Name	Full name	Provider	Measured indicators	Method	Cover.	Resolution	Start. from	Freq.
CMAP	Climate Prediction Center Merged Analysis of Precipitation	NOAA/OAR/ESRL PSD, Boulder, Colorado, USA	Precipitation	Satellite	world	2.5x2.5 degrees	1979	5 days
RFE	Rainfall Estimate	FEWS NET (Famine Early Warning System Network)	Precipitation	Satellite	SSA	8x8 km	1995	10 days
math	Mathematica WeatherData	Wolfram's Mathematica	Precipitation, temperature	Weather stations	world	17000 weather stations	1949	0.1-10 days

Note: Web-addresses: CMAP - *www.esrl.noaa.gov/psd/*, RFE - *earlywarning.usgs.gov/fews/index.php*, math - *reference.wolfram.com/language/ref/WeatherData.html*

Measurement of historical rainfall (and hence rainfall variation) in SSA is not a trivial undertaking, as the weather stations are sparse and using outdated equipment, and so most measurements are proxies and interpolations. To reduce the influence of a measurement error in my regressions, I collect three rainfall measures: CMAP, RFE, and MATH. They are described in Table 6. CMAP and RFE use satellite-based data and algorithms to derive the precipitation data (see Xie and Arkin (1997) for more details), while MATH uses the data from weather stations. To measure rainfall and rainfall variation at a traditional authority X I take the corresponding indicators from the data point (point in the grid for CMAP and RFE, weather station for MATH), which is the closest to the geographical center of X.[13]

The summary statistics for the weather indicators are reported in Table 7. The average rainfall in Malawi in 2003-09 is around 180 mm per month from January to March, and the average temperature is around 23°C. The correlations between all three rainfall measures are positive, which is reassuring, but never greater than 0.4, which suggests non-trivial measurement error. Indeed, CMAP and RFE rely on indirect rainfall measurement, and their grid is relatively coarse. MATH relies on often untrustworthy data from the weather stations, which are also very scarce in the region. For instance, the mean distance from a TA to the closest weather station is 28 km (the distance to the closest CMAP grid data point is 95 km). Combining several weather indicators measures helps to reduce the effect of the measurement error in the estimation, as one can see in the next sections.

[13]The coordinates of geographical center of X are derived as: latitude=(max(latitude)+min(latitude))/2; longitude=(max(longitude)+min(longitude))/2

Table 7: Weather indicators: Summary statistics

	count	mean	sd	p10	p50	p90
CMAP rainfall, January-March, mm per day	18293	5.75	0.91	4.44	5.68	6.76
CMAP rainfall variance, January-March	18293	4.56	1.17	3.41	4.55	6.36
RFE rainfall, January-March, mm per day	18293	6.44	1.13	4.78	6.70	7.76
RFE rainfall variance, January-March	18293	3.91	1.04	2.75	3.84	5.35
math rainfall, January-March, mm per day	18293	6.44	1.39	4.93	5.96	8.98
math rainfall variance, January-March	18293	3.07	1.26	1.65	2.84	4.92
math temperature, January-April, C	18293	22.38	2.48	20.18	21.38	27.46

Note: All summary statistics are calculated at a household level. For the rainfall and temperature - the average over the indicated period; for the rainfall variance - the variance over the indicated period.

4 Identification strategy

4.1 General framework

Assume, the general production function of an average Malawian subsistence farmer is Cobb-Douglas with two essential factors needed for non-zero output - labor and (seeded) land:

$$Y_{ixt} = A_{ixt} L_{ixt}^{\gamma_1} D_{ixt}^{\gamma_2} \mathrm{e}^{\epsilon_{ixt}}, \tag{1}$$

where Y_{ixt} is the output of household i using technology x at time t, L is labor, and D is land. A is the total factor productivity, which includes all the other factors that may affect output, including use of fertilizer and weather conditions. $\mathrm{e}^{\epsilon_{ixt}}$ is the multiplicative productivity shock, which is independent of other factors.

Dividing both sides of (1) by D we get the production function in per unit of area terms. Taking logarithm and denoting per unit of area terms by the corresponding small letters, and assuming that the production function is constant returns to scale, we get:

$$\log y_{ixt} = \log A_{ixt} + \gamma_1 \log l_{ixt} + \epsilon_{ixt} \tag{2}$$

Assume $\log A_{ixt}$ has the following form:

$$\log A_{ixt} = \beta_0 + \beta_1 T_{ix} + \beta_2 V_{ixt}^{(2)} + \beta_3 V_{it}^{(3)} + \beta_4 V_{ix}^{(4)} + \beta_5 V_i^{(5)}, \tag{3}$$

where T is the technology dummy - monoculture maize vs. crop diversification. Technologies use varies by farmer. Also, farmers can use both technologies at the same time (on different plots).[14] $V_{ixt}^{(2)}$ represents factors that vary by time and by technology for each household: fertilizer use, farmer's experience and knowledge about the technology, etc. $V_{ixt}^{(2)}$ can also include interactions of T_{ixt} with variables like weather or fertilizer. $V_{it}^{(3)}$ represents a wide group of factors that vary by household and by time, but not by technology: current farmer's abilities and education, health, demography of a household, preference for consumption and leisure, current wealth and credit constraints, weather conditions, soil quality, geology, and in general any contemporary farmer's or environment characteristics. $V_{ix}^{(4)}$ and $V_i^{(5)}$ represent factors that are time-constant, and only vary by household and technology, or only by household: for instance, technology's labor or capital intensity, its other time-constant characteristics (potential for drought resistance, needs for certain composition of soil, etc.)

Many of the factors included in V's are not measured in the dataset, or simply not observable, and can be correlated with the farmer's choice of technology. "Two-dimension" panel structure of the dataset - the fact that I observe farmers both over time and over multiple technologies - helps to put many potential biases in check.

First, since we observe same farmers using different technologies at the same time, we can include household-time fixed effects to effectively control for $V_{it}^{(3)}$ and $V_i^{(5)}$ - a wide set of technology-constant but potentially time-changing factors. In the household-time fixed effects regression the yields are compared across plots using different technologies, within the same household and year.

Second, we can also include household-technology fixed effects, which will allow us to control for $V_{ix}^{(4)}$ - the set of factors, which vary by household and technology but constant over time. Note that the technology dummy T_{ix} in (3) is one of these factors, so β_1 cannot be identified if we include household-technology fixed effects. Only farmers who use both technologies at the same time and for more than one period would be included in a regression with both household-time and household-technology fixed effects.

An alternative way to control for $V_{ix}^{(4)}$, but not for $V_{it}^{(3)}$, is to use household fixed effects in a traditional "one-dimension" household-year panel, where all plots of the household are assembled and analyzed as a single field.

[14] In the data there are cases when same technology is used on more than one plot. Since I cannot identify plots over time, I simply join all plots that use the same technology into a single plot-technology observation.

4.2 Main specification and summary of identification issues

The main specification that I use for (3) is the following:

$$\log y_{ixt} = \beta_0 + \beta_1 T_{ix} + \beta_{31} * W_{it} + \beta_{21}(T_{ix} * W_{it}) + \\ + \beta_{22} * F_{ixt} + \beta_{23}(T_{ix} * F_{ixt}) + \epsilon_{ixt} \quad (4)$$

Here x is either maize (M) or maize-legume intercrop (ML), see definition in Section 3.1. y is yield as defined in Section 3.2. T is one if x is ML, and zero otherwise. W is a vector of weather indicators: rainfall, rainfall variation within growing season, temperature, temperature squared, and temperature cubed. All weather indicators are demeaned using the sample averages (reported in Table 7).[15] The latter two indicators are added to test possible non-linearities in the response of maize yield to temperature, as recently argued in Lobell et al. (2011).[16][17] $T * W$ is the interaction of the technology dummy and weather indicator. F is a vector of fertilizer use indicators: fertilizer applied and fertilizer applied squared to reflect possibility of diminishing returns. This variable is also demeaned using the sample average (reported in Table 5).[18] The demeaning of weather and fertilizer indicators is done to provide for a reasonable interpretation of β_1 - an effect of using ML versus M when weather and fertilizer use are at the sample averages (because at the sample averages W*T=F*T=0).

The coefficients of interest are β_1, β_{21}, and β_{23}. If $\beta_1 > 0$ then it means that, everything else equal, maize-legume intercrop is more productive than maize. If ML is also more weather shocks-absorbing than M then I expect that β_{21} and β_{31} would have the opposite signs, and $\beta_{21} < \beta_{31}$.[19] For example, rainfall is likely to affect yield positively. For M the effect is $\beta_{31} > 0$, while

[15] Sample averages are very close to historical average in 2001-2010

[16] Temperature indicator is first demeaned and then squared and cubed, so that temperature squared and temperature cubed are both zero at sample average

[17] As a robustness check, I also try non-linear (quadratic and cubic) specifications of rainfall and rainfall variance. The results are qualitatively similar to the main specification, even though I do find statistically significant non-linear effects of rainfall and its variance on the yields. In this paper I decided to stick to conventional specifications from the literature, while exploring the non-linearities in more detail is left for further research

[18] Like with the temperature, fertilizer indicator is first demeaned and then squared, so that $F^2 = 0$ at the sample average

[19] Generally speaking, β_{21} and β_{31} are (1x5) vectors. The conjecture is that this relationship between the coefficients holds element by element

for ML the effect is $\beta_{31} + \beta_{21}$. It is also positive but smaller than β_{31}, which means that ML is less responsive to the weather shocks. The interpretation is similar in case of fertilizer use.

I run (4) using three different estimation techniques. The first one is pooled OLS: the unit of observation is household-technology, and no fixed effects are included. It means that household X growing maize and the same household growing maize-legume intercrop are considered two independent observations. The next two techniques are household-time FE and household-time and household-technology FE as described in the section above. There again the unit of observation is household-technology (i.e. up to two observations per household per year), but with the corresponding fixed effects included. [20]

I also use an auxiliary specification in a traditional "one-dimensional" household-year panel, where the observations are identified over household and year, and technologies (plots) are lumped together:

$$\log y_{it} = \alpha_0 + \alpha_1\theta_{it} + \alpha_{31} * W_{it} + \alpha_{21}(\theta_{it} * W_{it}) + \\ + \alpha_{22} * F_{it} + \alpha_{23}(\theta_{it} * F_{i1t}) + \epsilon_{it} \quad (5)$$

The specification is similar to (4), but instead of technology dummy T_{ix} there is a land share of ML - θ_{it}. y_{it} is a total yield of a household i at year t. To make α's in (5) be directly comparable with the β's in (4) y should be a geometric average of yields by the two technologies, and the weights are the corresponding land shares. [21]

Specification (5) is run using two estimation techniques. The first is traditional household FE. Now the unit of observation is household-year, all plots within the same household-year are lumped together. Household FE allow comparing same households over time. The second estimation

[20] Household-time FE are run the following way. The dataset is declared a panel with cross-section dimension identified by household-year i.d., and "time" dimension identified by technology. Then a simple FE regression is run. The household-time and household-technology FE are more complicated to run. First, I demean each variable by technology, i.e. I manually remove household-time fixed effects. For any variable a, denote $\ddot{a}$ its demeaned value, where mean is taken by technology for each household and year. Then $\ddot{a}_{ixt} = a_{ixt} - \sum_x a_{ixt}$. Households at any given year are dropped if they used only one technology at that year. Second, I declare the dataset of the demeaned variables to be a household-technology/year panel, and then run the FE regression. The standard errors are correct since I cluster them by household in every regression

[21] For details, see Section A.2 in Appendix

method is Arellano-Bond GMM,[22] is added to reduce the bias in case the strict exogeneity assumption is violated in the household FE. The chances are that this assumption is indeed violated as most farmers in Malawi are credit constraint and the harvest they collect likely affects the next year's harvest through health, productivity, and ability to buy inputs.[23] Note that these factors are taken care of in household-time FE as they are common to all technologies used by the farmer within one year.

Table 8 summarizes the possible factors that affect yield and how various estimation methods cope with controlling for these factors. There are two threats to the identification of betas in (4) and (5). First, even though some estimation methods, especially household-time FE and household-technology FE, allow to control for plenitude of factors, none of the methods does it all. Factors like (potentially time changing) technology-specific education, experience, labor and seed input are likely to be correlated both with the yield and with the choice of technology. The second threat is that the household-time FE and household-technology FE, the two most robust methods, are by definition applied only to a sample of farmers, which use both technologies at the same time. The number of such farmers in the sample is quite large, but they are still minority and they could be a special crowd, which raises concerns about the sample selection bias.

In what follows I provide few remedies to the issues above. First, the five estimators that I use allow to control for different sets of factors, and hence potentially yield different magnitudes and directions of biases. So if all estimators produce similar results then the biases are likely to be small-scale.

Second, in the next section I build a model of farmers choosing which technologies to use. The model disentangles the sample selection bias and how it links to the technology-specific factors, which I do not control for in my regressions - education, experience, labor, seeds. None of the methods I use consistently estimates the average treatment effect. But the model shows that, even if I do not control for some technology-specific factors, household-time fixed effects regression consistently estimates the likely effect of government policy changes (e.g. technology-specific education or input subsidy) if the changes are small. This is because the likely compliers to such policy are those who already use both technologies (e.g. the sample for household-time fixed effects regression) or those who are "close" to using the

[22]See Arellano and Bond (1991) for more details
[23]See Foster and Rosenzweig (2010)

Table 8: Summary of estimation techniques: Identification and potential biases

Est. method:	pooled OLS	hhold-time FE	hhold-time & techn. FE	hhold FE	GMM
	Identification comes from comparing...				
	plots	plots over hholds	plots over hholds and time	hholds over time	hholds over time
	Factors (potential biases):				
Technology	+	+	+	+	+
Weather	+	+	+	+	+
Fertilizer	+	+	+	+	+
Geology	-/+[a]	+[b]	+	+	+
General abilities, education	-	+	+	-/+[c]	-/+[c]
Technology-specific education, experience	-	-	-/+[c]	-/+[c]	-/+[c]
Labor	-	-/+[d]	-/+[c,d]	-/+[c]	-/+[c]
Seed[e]	-	-/+[d]	-/+[c,d]	-/+[c]	-/+[c]
Credit constraints	-	+	+	-	+
Selection bias	no	yes	yes	no	no

"+" - controlled for; "-" - not controlled for; "-/+" - partially controlled for

[a] To the extent geology is similar within region (when regional dummies are included)

[b] To the extent that farmers do not systematically subject one of the technologies to better local conditions. The (sparse) evidence from the surveys is that they are not. See Table 17 in Appendix

[c] Only time-constant factors are controlled for

[d] Only factors common to both technologies: preference for leisure, labor supply

[e] I do have data on seed input by plot, but this data is likely unreliable. See Section 7 for details

two.

For large policy changes my results are less reliable. The actual effect will depend on specific policies, and on systemic difference in labor and seeds requirements between the two technologies. In Section 2.4 I argue that the requirements are not too different. In addition, I control for the seed input as one of the robustness checks, and I find no qualitative change in results.[24] The time-constant labor and seed technology requirements are also controlled for in household-time and technology fixed effects, but this specification is not the main, because it does not allow to estimate β_1, and the estimation sample is too small to yield any statistically significant results.

4.3 Technology choice by farmers: A model

The objectives of the model are threefold. The first objective is to show in which direction the technology-specific omitted variables, in particular education and experience, but also labor and seed input (further - TSE), affect the estimates of β_1 in (4). The second objective is to check whether the sample selection bias introduced by the household-time FE mitigates the TSE bias or exacerbates it. Finally, the third objective is to show how the choice of technology is likely to be affected if the government alters its policies, e.g. cost of agricultural inputs and provision of technology-specific education.

The main results are the following. First, the TSE bias can tilt β_1 in either direction, or it can also be zero. This is true both for pooled OLS and household-time FE, so β_1 is likely to be an inconsistent estimate of the average population effect. Second, under a plausible assumption about the TSE distribution, the TSE bias is smaller in household-time FE compared to pooled OLS. Third, if the government reduces cost of one of the technologies or provides more TSE the likely compliers with such a reform would be the farmers, which are similar to those selected by the household-time FE. So the effect of the reform is likely to be the effect estimated by the household-time FE.

[24] Seed input is not used in the main specification as the data is incomplete and likely unreliable. See Section 7

4.3.1 Optimal portfolio of technologies

There are N farmers, each owns one unit of land. Each farmer chooses shares of his/her land to be used for certain agricultural technologies. There is only one period in the model, and the choice is between two technologies, e.g. maize and maize-legume intercrop. The first technology gives an average yield of f_{1i} for farmer i, and costs c_{1i}, the yield and cost of the second technology are f_{2i} and c_{2i} correspondingly. For simplicity, I assume that both technologies are take-it-or-leave-it - there is no choice on how much fertilizer or seeds to use, the farmer either buys the necessary inputs and uses the technology or does not buy the inputs and gets a return of 0. First technology is subject to weather (or other kinds of) risks. When the weather is bad, with probability 0.5, the yield is $f_{1i} - \epsilon$. With probability 0.5 the weather can also be good, and the yield is $f_{1i} + \epsilon$. The cost does not depend on the weather. The second technology is assumed to be riskless.[25]

The farmer i chooses α_i - a share of his/her land to be used for the technology 1. The rest of the land, $1 - \alpha_i$, would go for the technology 2. The farmer is risk-averse. He/she maximizes the following utility function with respect to α_i:

$$\max_{\alpha_i} 0.5U(L) + 0.5U(H), \tag{6}$$

where $L = \alpha_i(f_{1i} - \epsilon - c_{1i}) + (1 - \alpha_i)(f_{2i} - c_{2i})$, $H = \alpha_i(f_{1i} + \epsilon - c_{1i}) + (1 - \alpha_i)(f_{2i} - c_{2i})$; and $U' > 0,\ U'' < 0$. The choice of optimal α_i is no different from the choice of optimal portfolio of two risky assets in finance.

The optimal α_i should satisfy the following first-order condition:

$$\frac{U'(H)}{U'(L)} \geq -\frac{f_{1i} - \epsilon - c_{1i} - f_{2i} + c_{2i}}{f_{1i} + \epsilon - c_{1i} - f_{2i} + c_{2i}} \tag{7}$$

For farmer i if $f_{1i} - \epsilon - c_{1i} > f_{2i} - c_{2i}$ - i.e. technology 1 is more profitable than technology 1 even in the bad state - then $\alpha_i = 1$. If $f_{1i} - c_{1i} < f_{2i} - c_{2i}$ - i.e. technology 1 is less profitable than technology 1 on average - then $\alpha_i = 0$. This follows from the fact that in (7) $\frac{U'(H)}{U'(L)}$ is always smaller than one, because $U'' < 0$, and $H > L$. The right hand side of (7) is smaller than one if and only if $f_{1i} - c_{1i} > f_{2i} - c_{2i}$. Risk-averse users would always prefer less risky asset if

[25] The fact that only one technology is risky is a simplification without the loss of generality. I can assume both technologies to be risky, it will just introduce extra parameters and lengthier calculations without any benefits

the expected return is the same. Finally, if $f_{1i} - \epsilon - c_{1i} < f_{2i} - c_{2i} < f_{1i} - c_{1i}$ then α_i is between 0 and 1.

We can sort farmers by $f_{1i} - c_{1i} - f_{2i} + c_{2i}$, from the largest to the smallest. Then there are two thresholds, k_1 and k_2, such that:

$$\forall\ i = 1, .., k_1\ \alpha_i = 1 \tag{8}$$

$$\forall\ i = k_1 + 1, .., k_2\ 0 < \alpha_i < 1 \tag{9}$$

$$\forall\ i = k_2 + 1, .., N\ \alpha_i = 0. \tag{10}$$

The punchline is that it is natural to hedge productivity risks by diversifying if two or more technologies are available. The reason why it often does not happen is that for some farmers the difference in net returns between the technologies is too large - either they know very little how to use one of the technologies, or its cost is prohibitively high. Such situation is not uncommon in Malawi. See Section 2.4.

4.3.2 TSE bias: Arbitrary direction

In the sample of N farmers, k_1 of them use only technology 1, $N - k_2$ use only technology 2, and $k_2 - k_1$ use both technologies. Besides the technology use, we only observe their yields f_{1i} or f_{2i}, or both if farmer i uses both technologies - a total of $N + k_2 - k_1$ observations. We want to find out which technology is more productive, and so we run a regression:[26]

$$f_i = c + \gamma T_i + \xi_i, \tag{11}$$

where f_i is the yield , T_i is one if technology 2 is used, and zero otherwise.

Since T_i is a dummy, the OLS estimate of γ is simply: $\hat{\gamma} = \bar{f}_2 - \bar{f}_1$, where $\bar{f}_j$ is a corresponding average over all those who use technology j.[27] If the true data generating process for f's were $f_j = c + \gamma T_j + \xi$, where ξ is a random error with zero mean, then $\hat{\gamma}$ were a consistent estimator of true γ:

$$\text{plim}\hat{\gamma} = \text{plim}\left(\bar{f}_2 - \bar{f}_1\right) = \gamma(T_2 - T_1) = \gamma. \tag{12}$$

Now suppose that the true data generating process for f's depends not only on T_j but also on general abilities/education (E) and technology-specific ed-

[26] In this model, for simplicity, I concentrate only on β_1 from (4), not the other coefficients of interest. The reasoning for these coefficients is similar

[27] See the proof in Appendix, Section A.3.1

ucation/experience (TSE):[28]

$$f_{ji} = c + \gamma T_{ji} + \lambda_1 E_i + \lambda_2 TSE_{ji} + \xi_{ji}, \tag{13}$$

where, to remind, j is the technology index, i is the farmers' index.

With (13), $\hat{\gamma}$ is no longer, in general, a consistent estimator of the true γ:

$$\hat{\gamma} = \bar{f}_2 - \bar{f}_1 = \gamma + \lambda_1(\bar{E}_2 - \bar{E}_1) + \lambda_2(T\bar{S}E_2 - T\bar{S}E_1). \tag{14}$$

The last two terms constitute a bias, the last term is a TSE bias. The sign and the magnitude of these biases are arbitrary. They depend on the distribution of the education and experience among the technology users. For example, if technology 1 users have more education and experience then $\hat{\gamma}$ underestimates γ. If the education levels are approximately equal then the bias is zero. Note that the general education bias is reduced due to the fact that parts of $\bar{E}_2$ and $\bar{E}_1$, those of the farmers who use both technologies, cancel out.

The next question is whether the bias changes if instead of pooled OLS we restrict the sample to only those farmers who use both technologies.

4.3.3 TSE bias: Smaller for household-time FE

Suppose now instead of pooling all farmers together we restrict our sample only to those who use both technologies - $2(k_2 - k_1)$ observations. The relationship between $\hat{\gamma}$ and γ is still (14), but the averages are taken over (k_1, k_2) farmers. This procedure with our simple specification is equivalent to running the household-time FE in (11).[29]

The general education bias - the second term in (14) - is zero if we restrict the sample. This is because $\bar{E}_2$ and $\bar{E}_1$ are taken over the same sample, and the general education does not depend on technology.

The technology-specific education bias - the third term in (14) - is not zero even if we restrict the sample. Even though they all use both technologies,

[28] There could be more factors, and the factors could be different. The main distinction here is between the factors that are "common" to both technologies (e.g. E), and the factors that are "'technology-specific"' (e.g. TSE)

[29] By definition, household-time FE estimator is OLS on demeaned values of variables from (11), where the demeaning is performed by technology. The demeaned value of f_{1i} is $(f_{1i} - f_{2i})/2$, that of f_{2i} is $(f_{2i} - f_{1i})/2$, that of T_{1i} is -0.5, and that of T_{2i} is 0.5. So OLS on these demeaned values means regressing $(f_{2i} - f_{1i})/2$ on 0.5, which yields $\hat{\gamma} = \bar{f}_2 - \bar{f}_1$

farmers can still have systematically different experience or education related to these technologies. Intuitively though the difference between TSE_{2i} and TSE_{1i} should not be too large for those who use both technologies. Otherwise farmers would specialize in only one of them.

Whether the technology-specific education bias in the household-time FE is always smaller in absolute value than the one in pooled OLS depends on the distribution of TSE. The following proposition shows that this is the case if TSE is normally distributed.

Proposition 4.1 *Let* $TSE_1 \sim N(\mu_1, \sigma_1)$ *and* $TSE_2 \sim N(\mu_2, \sigma_2)$. *Then*

$$|E(TSE_2 - TSE_1)|_{pooled\ OLS} > |E(TSE_2 - TSE_1)|_{hhold-time\ FE} \tag{15}$$

Proof See Appendix, Section A.3.2.

4.3.4 Effect of government subsidy

The previous two sections show that neither pooled OLS nor household-time FE consistently identify the average population effect of technology on yield. Sample selection and technology-specific biases are not removed. A question one may ask though is whether we actually need to identify the average population effect if our goal is to analyze government policies that intend to affect the current state of technology use. To assess the results of such government policy we need to identify the effect only on compliers with this policy rather then on the whole population. Unless the government can directly force particular farmers to use this or other technology, the set of compliers will also be subject to selection bias.

Suppose the government wants to induce farmers to use more of technology 2, and it has two types of reforms in its mind. First, it can reduce/subsidize the cost of the second technology, which will automatically increase its net returns $(f_2 - c_2)$ for each farmer. Second, the government can provide technical assistance/education on the second technology. This reform raises TSE_2 for each farmer and thus f_2. Both reforms will affect (increase) share of land used for the technology 2 for those farmers who already use both technologies. Moreover, they can also affect k_1 and k_2 - the thresholds at the technology selection: some farmers, who used only technology 1 before, may join the group of diversifiers; other farmers may switch to specializing only in technology 2.

Suppose government provides the cost subsidy for technology 2, such that the aggregate share of land used for the technology increases by δ. Such subsidy affects the selection of farmers into technologies, but it does not affect farmers' productivity in each particular technology (e.g. f_{1i} and f_{2i}).

Denote the new land share of technology 1 by α_i^*, and the new technology use thresholds by k_1^* and k_2^*. Then:

$$\forall i = 1, .., k_1^* \ \alpha_i^* = \alpha_i = 1 \tag{16}$$

$$\forall i = k_1^*, .., k_1 \ 0 < \alpha_i^* < 1 \text{ and } \alpha_i = 1 \tag{17}$$

$$\forall i = k_1, .., k_2^* \ 0 < \alpha_i^* < 1 \text{ and } 0 < \alpha_i < 1 \tag{18}$$

$$\forall i = k_2^*, .., k_2 \ \alpha_i^* = 0 \text{ and } 0 < \alpha_i < 1 \tag{19}$$

$$\forall i = k_2, .., N \ \alpha_i^* = \alpha_i = 0 \tag{20}$$

The change in f - average aggregate agricultural productivity of the country - as a result of the subsidy is the following:

$$\Delta f = \frac{1}{N}\sum_{i=1}^{N}\left(f_{2i} + \alpha_i^*\left(f_{1i} - f_{2i}\right)\right) - \frac{1}{N}\sum_{i=1}^{N}\left(f_{2i} + \alpha_i\left(f_{1i} - f_{2i}\right)\right) =$$
$$= \frac{1}{N}\sum_{i=1}^{N}\left(\alpha_i - \alpha_i^*\right)\left(f_{2i} - f_{1i}\right) = \frac{1}{N}\sum_{i=k_1^*}^{k_2}\left(\alpha_i - \alpha_i^*\right)\left(f_{2i} - f_{1i}\right). \tag{21}$$

Using (13), equation (21) can be rewritten:

$$\Delta f = \gamma\frac{1}{N}\sum_{i=k_1^*}^{k_2}\left(\alpha_i - \alpha_i^*\right) + \lambda_2\frac{1}{N}\sum_{i=k_1^*}^{k_2}\left(\alpha_i - \alpha_i^*\right)\left(TSE_{2i} - TSE_{1i}\right) \tag{22}$$

Further assume $\Delta\alpha$ and ΔTSE are not correlated, which is not unreasonable: $\Delta\alpha = 0$ for small ΔTSE, at k_1^* it starts to increase, reaches its maximum and goes back to zero at k_1, when ΔTSE is large.[30] Then (22) turns into:[31]

$$\Delta f = \left(\bar{\alpha} - \bar{\alpha^*}\right)\left(\gamma + \lambda_2(T\bar{S}E_2 - T\bar{S}E_1)\right), \tag{23}$$

[30] In general, the correlation depends on the risk-aversion of the farmers and their utility. Theoretically, it can be non-zero, but it is likely to be small. See below the discussion on the model simulation

[31] Equation 23 follows from the fact that for any two random variables x and y $E(xy) = cov(x, y) + E(x)E(y)$

where in $\bar{TSE}_j$ the average is taken over $i \in (k_1^*, k_2)$. By assumption, $\bar{\alpha} - \bar{\alpha^*} = \delta$. The second multiplier of (23) - name it the effect of the cost subsidy - looks very similar to $\hat{\gamma}$ - the estimator of γ that we obtain in household-time FE regression. The difference is that the TSE bias in (23) is over $i \in (k_1^*, k_2)$ rather than over $i \in (k_1, k_2)$. The compliers of the cost subsidy are those, for whom the change in technology cost matters. These are the farmers with moderate ΔTSE - those that already use both technologies or those that were on the margin before the subsidy was introduced. That is why it is their productivity rather than productivity of an average farmer in the population that is important at identifying the effect of the reform.

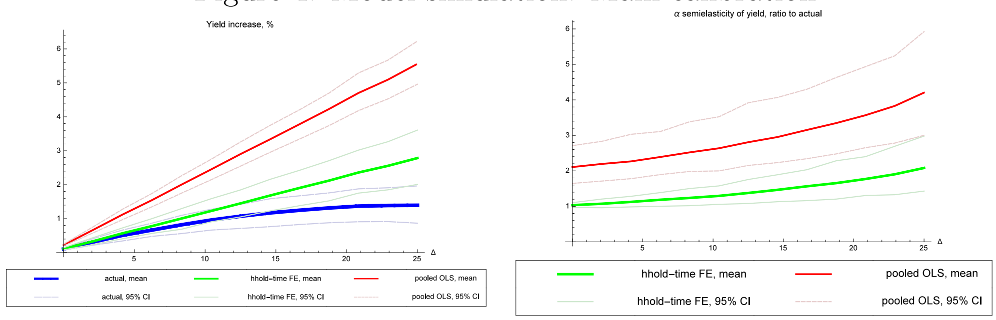
How large is the difference between the TSE bias in (23) and the TSE bias at household-time FE? For a small subsidy most of the compliers, and hence most of the land use change, are in the group (k_1, k_2), and so the difference is small. For instance, if the subsidy is so small that it only induces land use change among existing users of technology 2, and no new users, then the difference is zero, and household-time FE consistently estimates the effect of the subsidy. If the new users of technology 2 do appear, then household-time FE would generally overestimate the true effect of the subsidy, but the bias would be small for small subsidies. For instance, if the distribution of TSE is uniform, and the number of new compliers is proportional to the subsidy-induced land use change then the bias is a quadratic function of δ.[32]

To support the above considerations I numerically compute the model and demonstrate the difference between the actual effect of the cost subsidy and the effect, which is estimated by household-time FE and pooled OLS. In the main calibration the farmers' utility is logarithmic, and the technology-specific education is distributed uniformly. The values for the parameters are chosen so that the simulated technology use pattern resembles the actual one in Malawi: around 50-60% of farmers use M, 50-60% use ML, and 10-15% use both M and ML.

Figure 4 shows results of the main calibration. The left panel demonstrates the yield increase as a result of Δ percent reduction in c_2 for each farmer. Blue line is the actual yield as implied by the model, green line is the estimate of the yield according to household-time FE, and red line is the

[32]Suppose $k_1 - k_1^* = \delta(k_2 - k_1)$ - share of newcomers is proportional to the induced land use change. Then the difference between household-time FE TSE bias and subsidy-induced TSE bias is $\Delta \bar{TSE}_{(k_1,k_2)} - \Delta \bar{TSE}_{(k_1^*,k_2)} = \delta \left(\Delta \bar{TSE}_{(k_1,k_2)} - \Delta TSE_{k_1} \right)$. Therefore, $\Delta f = \delta \hat{\gamma} - \delta^2 \left(\Delta \bar{TSE}_{(k_1,k_2)} - \Delta TSE_{k_1} \right)$.

Figure 4: Model simulation: Main calibration



Note: Specification of the model is outlined in Section 4.3. The following assumptions and values for parameters are used: farmers' utility is logarithmic, TSE_1 is fixed at 5, c_1 is fixed at 2, TSE_2 is distributed uniformly between 3 and 6.5, c_2 is fixed at 3, ϵ=1.2, ξ $N(0, 0.5)$, $\gamma = 1$, $\lambda_1 = 0$, $\lambda_2 = 1$. Parameters are selected so that the simulated technology use pattern resembles the one observed in Malawi: around 50-60% of farmers use M, 50-60% use ML, and 10-15% use both M and ML. Δ is the assumed percent reduction in c_2 - the cost of ML. CI means confidence interval. At each datapoint the sample comprises 1000 farmers, and 500 simulations are run to account for weather (ϵ) and general (ξ) uncertainty .

estimate according to pooled OLS. The right panel shows the α semielasticity of yield[33] for each Δ - the one implied by household-time FE (green line) and the one implied by pooled OLS (red line). Both semielasticities are expressed as ratios to the actual semielasticity as implied by the model. Hence, the closer is their value to one the more accurate is the estimate. Both panels show that household-time FE performs better than pooled OLS for any Δ. Consistent with the discussions above, for small Δ's household-time FE produces estimates, which are very close to the actual. When Δ is less than 5%, the projected and the actual effects are practically identical. The difference starts to appear at $\Delta = 10\%$, but becomes statistically significant only when Δ is 20-25%.

Appendix A.4 shows various robustness checks to the main calibration of the model. I first relax assumption of the uniform distribution of TSE_2, and use normal instead. Then instead of log-utility I apply general constant relative risk aversion (CRRA) utility, and check different values of risk aversion coefficient. I also check what happens if I use different values for γ, TSE_1,

[33]Defined as percent change in average yield divided by the change in α - the land share of M

and ϵ. For small Δ's, the conclusion is consistent throughout all specifications: when household-time FE is used, the implied projections are very close to the actual.

Considerations for the education subsidy are similar. The difference with the cost subsidy is that the improved technology-specific education affects not only the choice of technology but also farmers' productivity, so Δf is likely to be larger. The main conclusion holds. The effect, which is identified by the household-time FE, is likely to prevail in case the government engages in cost or education subsidy. This happens because farmers who are affected by the subsidy are the ones, which are already (or close to) using the subsidized technology. These are the farmers, which are targeted by the household-time FE as well.

5 Estimation results

The main estimation results are summarized in Table 9. For all nine columns the variables specification is always as in (4). My main dependent variable is log energy yield (see Table 5). The technologies I compare are M (maize) and ML (maize-legume intecrop) - see Table 2 for the definition. I use five main estimation methods, which are described in Section 4.2. In columns (1), (3), (5), and (7) the rainfall and rainfall variance measures are taken from CMAP (see Table 6 for more information). The possibility of a large measurement error in weather indicators was discussed above. I deal with this problem using the instrumental variable approach. In columns (2), (4), (6), (8), and (9) CMAP measures of rainfall and rainfall variance are instrumented by the equivalent measures from RFE and MATH (see Table 6 for more information). The measurement error did prove to have a significant role in a number of specifications, especially for the household-time FE, so in what follows I stick to the results from IV estimations. As a robustness check, Table 15 in Appendix reports the results when variables are added one by one.

The magnitudes and significance of the coefficients differ by the specification, but the overall results seem to be in favor of the maize-legume intercrop: everything else equal, ML seems to be more productive, and it seems to absorb shocks better. The consistency of the results throughout the estimation methods and specifications is reassuring, as each method uses different sample of farmers and potentially insulates against (or vulnerable

Table 9: Estimation results: Energy yield

	pooled OLS		hhold-time FE		hhold-time & techn. FE		hhold FE		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	no IV	IV	no IV	IV	no IV	IV	no IV	IV	GMM
ML technology	0.18***	0.18***	0.31***	0.27***			0.15***	0.05	0.26***
(dummy or landshare)	(0.02)	(0.02)	(0.05)	(0.05)			(0.05)	(0.06)	(0.07)
rainfall, cm	0.36***	0.40**					0.82***	2.30***	2.07***
per day	(0.13)	(0.20)					(0.27)	(0.40)	(0.32)
ML X rainfall	-0.69***	-0.80***	-0.05	-1.25*	-1.95	-2.33	-1.11***	-2.42***	-2.04***
	(0.19)	(0.30)	(0.39)	(0.70)	(1.73)	(2.51)	(0.41)	(0.69)	(0.53)
rainfall	6.03***	5.87**					1.50	-30.60***	-4.58
variance, daily	(1.19)	(2.39)					(2.79)	(8.02)	(3.07)
ML X rainvar	9.45***	10.33***	0.47	8.69*	28.89**	20.57	20.58***	42.51***	14.69***
	(1.46)	(2.39)	(3.10)	(4.63)	(14.07)	(24.07)	(3.19)	(5.11)	(4.45)
temperature, C	2.35**	2.36**					11.10***	16.68***	23.55***
/100	(1.02)	(1.02)					(2.87)	(3.35)	(3.15)
temperature	1.46***	1.47***					0.75	-2.08*	3.86***
ˆ2 /100	(0.29)	(0.32)					(0.75)	(1.14)	(0.60)
temperature	-0.33***	-0.33***					-0.60***	-0.57***	-1.15***
ˆ3 /100	(0.07)	(0.07)					(0.18)	(0.19)	(0.17)
ML X temp	-1.97	-2.00	-5.59**	-7.41***	-24.99***	-23.25**	-9.77***	-14.55***	-16.63***
	(1.25)	(1.25)	(2.66)	(2.84)	(8.81)	(9.15)	(3.18)	(3.37)	(4.18)
ML X temp_sq	-0.68*	-0.66	-1.32**	-1.06	3.08	2.15	-1.66**	0.02	-3.80***
	(0.39)	(0.42)	(0.66)	(0.72)	(3.15)	(4.21)	(0.81)	(0.90)	(0.99)
ML X temp_cub	0.12	0.12	0.33**	0.31*	1.34**	1.19**	0.69***	0.53**	1.06***
	(0.09)	(0.09)	(0.15)	(0.17)	(0.58)	(0.59)	(0.20)	(0.21)	(0.23)
fertilizer,	3.37***	3.38***	2.93***	2.86***	0.28	0.32	3.00***	2.98***	2.80***
tonnes per ha	(0.14)	(0.14)	(0.44)	(0.45)	(0.63)	(0.63)	(0.28)	(0.29)	(0.37)
fertilizer	-2.50***	-2.50***	-1.34*	-1.22	0.47	0.41	-3.57***	-3.52***	-2.93***
ˆ2	(0.35)	(0.35)	(0.75)	(0.85)	(1.36)	(1.37)	(0.69)	(0.70)	(0.76)
ML X Txfert	1.06***	1.05***	-0.99**	-1.05**	-1.61	-0.99	0.91**	0.97**	0.29
	(0.19)	(0.19)	(0.47)	(0.49)	(1.80)	(1.97)	(0.39)	(0.41)	(0.57)
ML X Txfert_sq	-1.57***	-1.56***	2.90**	3.12*	3.62	1.58	-0.98	-1.01	0.35
	(0.48)	(0.48)	(1.41)	(1.67)	(7.14)	(7.72)	(1.12)	(1.15)	(1.56)
L.log_energy_yield									0.08**
									(0.03)
Constant	14.60***	14.60***	14.30***	14.30***	-0.02	-0.02	14.69***	14.81***	13.14***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.04)	(0.04)	(0.05)	(0.06)	(0.46)
Observations	13305	13305	1676	1676	196	196	5696	5696	3095
R-squared	0.17	0.17	0.17		0.16		0.18		
R-squared overall			0.13	0.13	0.03	0.03	0.16	0.10	

Note: Standard errors (clustered by household) in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Dependent variable in each regression - log_energy_yield. Technologies - M (maize) vs. ML (maize-legume intercrop). OLS, household FE, and GMM all include time fixed effects, which are also effectively controlled for in household-time FE. The results without time fixed effects are similar. GMM regression assumes all variables except time fixed effects potentially violate strict exogeneity assumption (so all variables are instrumented).

to) different kinds of biases. Importantly, household-time FE, which is the preferred method according to the reasoning and the model above, is consistent with the rest of the results. Household-time and technology FE, which is even more robust,[34] produces similar signs and magnitudes of the coefficients, but very few of them are significant. The effective sample for this method is very small, while the weight of a measurement error (in yield in particular) soars after "'double demeaning"'.[35]

The coefficient on ML - dummy in columns (1)-(6) and land share in columns (7)-(9) - is positive and statistically significant, except for the household FE.[36] This is, in particular, true for the househodel-time FE, which is the preferred estimation method. The estimates in IV regressions - columns (2), (4), and (9) - tell that calorie yields on plots with ML are around 15-30% higher than the yields of M.[37] Note that the coefficient on ML cannot be identified in household-time and technology FE, because the technology dummy does not change with time.

The results on the fertilizer use and its interaction with ML are also suggestive, but with a couple of caveats. Even though the coefficients on *fertilizer* and *fertilizer^2* are of the opposite signs, the overall response of the yield to the fertilizer is positive for both technologies in all specifications and for reasonable quantities of the fertilizer. [38] Even though the coefficient on *fertilizer* is positive, the response to the fertilizer seems to flatten out with more fertilizer applied, as can be seen from negative coefficients on *fertilizer^2*. The results of different estimation methods diverge on the interaction of ML and the fertilizer. Household-time FE says that ML is less responsive to the fertilizer - the coefficient on *ML X fert* is negative, while in OLS and GMM the coefficient is positive. In case of household-time FE the difference in the responsiveness is not large though - ML remains significantly more productive than M at any reasonable quantity of fertilizer applied, as shown in Figure 5.[39] The gap between the two technologies narrows down

[34]In particular, household-time and technology FE controls for time-constant technology-specific labor and seed inputs

[35]See Griliches and Hausman (1986) for details on measurement error in FE regressions

[36]It is also not statistically significant in some specifications of the GMM regression. See Table 27

[37]All other variables in the regressions are demeaned, so the coefficient on ML means the effect of using ML at sample average fertilizer use and weather

[38]500-600 kg per ha in most specifications, 200-300 kg per ha in case of ML in GMM specification

[39]In GMM specification the difference is also positive at reasonable quantity of fertilizer,

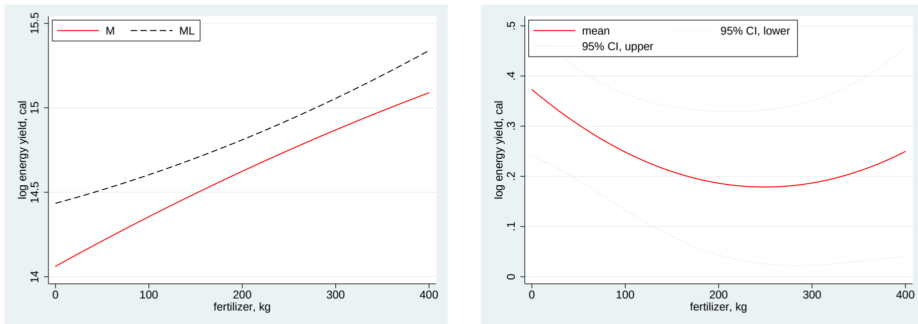


Figure 5: Estimated response to fertilizer in M vs. ML (left); Difference between ML and M with confidence interval (right)

Note: Based on the estimation in Table 1, column 4 - household-time FE. Figures 12 and 13 in Appendix use other estimates and yield measures. Standard errors for the confidence interval are bootstrapped.

to around 15% at 200 kg of fertilizer per hectare, but then starts to widen again. Starting from a sample average of around 80 kg per hectare, the gap between ML and M gets wider if fertilizer is used less, so according to the household-time FE ML would be more effective at absorbing adverse fertilizer use shocks for most of the farmers. The efficiency of the fertilizer for both technologies is around 13.7-14 thousand kCal per kg of nitrogen.[40] The flip side of being more resistant to the fertilizer use shocks, the efficiency of fertilizer for ML is generally lower than for M - 4% lower at the sample average of 80 kg per tonne.

Rainfall and rainfall variance, as expected, are important determinants of harvest in Malawi, and ML seems to be an effective absorbent of the weather shocks. Coefficient on rainfall is positive and significant in OLS and GMM (in household-time FE it is not identified). Controlling for the average rainfall, rainfall variance affects the yield negatively. The coefficients on ML interactions with rainfall and rainfall variance have the opposite signs, which means that ML likely smooths the weather's effect on yields.[41] Note that, as men-

but not always statistically significant. See Figure 12

[40] A calorie equivalent of around 3.8-3.9 kg of maize. Assuming 30% of nitrogen in a kg of fertilizer. The efficiency is calculated at the average fertilizer use among all farmers - 80 kg per hectare.

[41] For example, using the results from column 9, a decrease in rainfall of 0.1cm per day

tioned above, coefficients on rainfall and rainfall variance are not identified in household-time FE (my preferred specification), so the implicit assumption here is that their signs and magnitudes are similar to those in OLS or GMM; otherwise the interpretation of the coefficients on ML interactions can be different. [42] This result is consistent across all specifications, although the magnitudes of the coefficients differ, and in some specifications the result is not significant.[43] For the household-time FE it proved to be crucial to use IV for my rainfall measures. This result means that ML is less responsive to the weather shocks, droughts and sporadic rainfall in particular.

The relationship between the yield and the temperature is more complex. At the current range of observed temperatures in Malawi, the relationship is positive both for M and ML, but becomes negative after a threshold of around 26°C for M and 29°C for ML. This result should be taken with caution as the maximal average temperature observed in Malawi over the estimation period is 28.5°C, but it is consistent with Lobell et al. (2011). As with rainfall and rainfall variance, ML seems to be better than M at absorbing the temperature shocks, although it is harder to see just looking at the coefficients. Figure 6, which is based on the estimation in column (9), demonstrates this result. ML's response to the temperature follows a similar path to M: it first decreases, then starts to increase, and then decreases again. But ML's response curve is much smoother than M's curve.[44]

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would decrease average M yield by about 2.07*0.1=20%, but will reduce average ML yield by only (2.07-2.04)*0.1=0.3%. In some specifications the absolute value of the coefficient on ML interaction with the rainfall is actually larger than the coefficient on rainfall. Taken at a face value, this means that ML responds negatively to rainfall. This result is never statistically different from zero, and it is hardly plausible, but even if it is true, ML still smooths the weather effects, because the absolute value of the coefficient on ML interaction is never twice as high as the coefficient on rainfall

[42]OLS and (especially) household FE and GMM are frequently used in the literature to estimate the effect of random weather shocks on yield, which adds to plausibility of the assumption. See Section 6 for details. Important caveat here is that the coefficients are effectively estimated together with the technology use, which is endogenous

[43]Household-time and technology FE. Also some specifications of the GMM regression (see Table 27)

[44]Note that yield-depressing effect of extremely high temperature does not show up in OLS

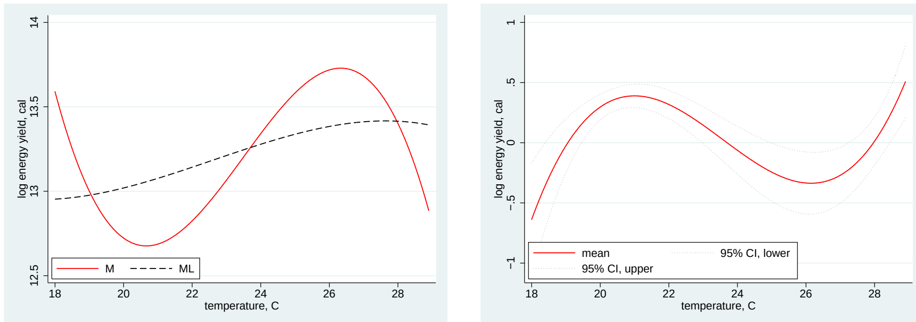


Figure 6: Estimated effect of temperature on yield: M vs. ML (left); Difference between ML and M with confidence interval (right)

Note: Based on the estimation in Table 1, column 9 - GMM. Using household-time FE estimates where possible yields similar results (see Figure 14 in Appendix). The maximal average temperature observed in Malawi over the estimation period is 28.5°C. For higher temperatures the predictions are out of sample. Standard errors for the confidence interval are bootstrapped.

6 Economic significance of results: Macroeconomic scenarios

The previous section discusses the economic rationale and statistical significance of the results, but how economically significant are they? Are plausible weather or fertilizer use shocks macroeconomically important for Malawi, and how effective is ML in smoothing them? I build a range of shock scenarios for Malawian agriculture to answer these questions. For each scenario I consider three stances of reform. The first stance is a baseline - the land used by M and ML remains as it is was in 2009. The second stance is a program - the government implements a subsidy or education program that increases land used for ML by 10 percentage points. The third stance is a hypothetical situation, when all land is used for ML. Note that the coefficients I identify in Table 9 are likely to be close to the true coefficients only in the case of the second stance (program), when changes in the land use are not that large. The results for the third stance are less robust and for demonstration only.

In each scenario I look at two main indicators. The first is the average change in yields as a result of the shock. The energy (or grain) loss of the yield can further be expressed in terms of GDP in case of a hypothetical situation that the government decides to compensate the loss by importing an equivalent amount of maize from abroad. As of 2013, 84% of Malawian households are rural, and of them around 86% grow either maize or maize-legume intercrop. So for example, at the 2013 Malawian kwacha to US dollar exchange rate, and the price of maize at 35 US cents per kg, a 5% average drop in yield translates into 1.15% of GDP of compensation cost.[45]

The second indicator that I look at is the change in the share of self-sufficient households, i.e. households that produce enough calories to cover their own energy needs throughout the year. At the FAO's recommended minimal dietary requirement of 1700 kCal per day,[46] an average self-sufficient Malawian household is supposed to harvest about 6.2 mln kCal per year. In 2009 only 17% of households reached self-sufficiency. Many households have alternative sources of revenue: growing other crops (e.g. tobacco), animal farming, or supplying labor ("'ganyu"') to richer households. However, changes in food self-sufficiency are likely to be correlated with the changes in food security.[47] The results on the self-sufficiency must be taken with caution, as the implicit assumption that I make here is that the impact of the shock is similar for all households, i.e. the shock does not affect the form of the distribution curve, it only shifts it.

I consider four medium-term and three long-term scenarios. Medium-term scenarios model the effect of four large but plausible adverse shocks, one shock per scenario: negative shocks to fertilizer use, rainfall, and temperature, positive shock to rainfall variance. The size of the fertilizer use shock is 10% decline from the current use. This shock can result from a corresponding increase in fertilizer price, which is not uncommon at all in the last two decades,[48] given that the overwhelming majority of Malawian farmers are credit-constraint.[49] The shock can also be the result of a change in the government fertilizer subsidy, which is subject to various fiscal risks (e.g. political instability and hence volatile foreign aid, relatively high level

[45] A cost which carves into already shaky external position of the country

[46] FAO (2008)

[47] Besides most of the alternative sources of revenue for Malawian households are likely to be pro-cyclical, i.e. move together with the staple crop yield. For example, adverse weather shock impacts not only the particular farmer, but the whole village, which likely reduces demand for ganyu labor.

[48] According to National Agricultural Statistics Service, USDA, the average absolute annual change in the price of Urea fertilizer in 1994-2013 is 24%

[49] In 2009 only 6% of them used loans to buy agricultural inputs

of external debt). The weather shocks are equal to half average standard deviation from the historical (2004-2009) mean, where average is taken over traditional authorities. This is roughly 30th percentile of the corresponding historical distribution.[50]

The long term scenarios involve only weather shocks, and are based on the long-term climate projections for Malawi summarized in IPCC (2007). I consider two standard scenarios: a "'mild"' optimistic B1, median of the nine climate models reported, and less optimistic A2, 10th percentile of the nine models (ensemble low). I also consider the same A2, supplemented by an assumption of severe positive temperature and negative rainfall shocks (which are, however, not that unrealistic in this scenario),[51] to test the effect of extreme weather conditions.

I first construct the baseline, i.e. when the technology use is the same as in 2009 (columns 1 and 4 of Table 11). To do this I estimate the effect of weather on yield in the baseline, by employing the framework used in Deschenes and Greenstone (2007), Deschenes and Greenstone (2011), Fisher et al. (forthcoming), and Burke et al. (2011). I simply fit the log of household yield to the weather indicators - rainfall, rainfall variance, and temperature. [52] As in my main estimation results, I instrument rainfall and rainfall variance by alternative measures to get rid of the measurement error. In Table 10 I report the results using OLS, FE, and GMM, but in my projections I rely on GMM. As argued by the papers above, OLS does not control for various long-term factors such as ability of farmers to adapt to slow changes in the weather, whereas FE supposedly provides the reaction of yield to a short-term weather shock. At the same time, and as discussed above, it is important in case of Malawi to take previous period's harvest into account, since many farmers are credit-constraint. GMM should take care of this. The results are as expected. They repeat the pattern of Table 9, and the magnitudes of the coefficients are mostly between those of M and ML users

[50]If the distribution is close to normal

[51]The exact shock (temperature or rainfall) is two standard deviations of the 90th percentile of TAs distributions. In other words, the shock has a 5% chance to materialize in at least 10% of TAs

[52]I am reluctant to use the GMM estimates from Table 9 because they are likely to be inconsistent. At the same time, the household-time FE, my preferred specification, does not identify the coefficients on weather for M users. Therefore, the most reliable option in this case is likely to estimate the regression of yield on weather variables without controlling for the technology choice

Table 10: Energy yield and weather shocks: Mixed technologies

	pooled OLS		hhold FE		
	(1)	(2)	(3)	(4)	(5)
	no IV	IV	no IV	IV	GMM
	b/se	b/se	b/se	b/se	b/se
rainfall, cm	0.55***	0.18	0.63***	1.77***	1.72***
per day	(0.10)	(0.16)	(0.22)	(0.32)	(0.31)
rainfall	0.32	-14.51***	-6.62***	-43.75***	-4.22*
variance, daily	(0.77)	(1.34)	(1.75)	(3.31)	(2.48)
temperature, C	2.67***	3.16***	6.67***	10.33***	16.06***
/100	(0.66)	(0.67)	(1.85)	(2.05)	(1.93)
temperature	-0.24	-1.37***	-2.08***	-7.13***	2.02***
^2 /100	(0.22)	(0.23)	(0.58)	(0.73)	(0.54)
temperature	-0.06	0.13***	0.02	-0.29**	-0.57***
^3 /100	(0.05)	(0.05)	(0.12)	(0.14)	(0.11)
fertilizer,	3.42***	3.51***	2.87***	3.77***	4.89***
tonnes per ha	(0.10)	(0.10)	(0.22)	(0.25)	(1.09)
fertilizer	-2.65***	-2.87***	-3.17***	-4.41***	-13.84**
^2	(0.26)	(0.25)	(0.58)	(0.63)	(6.50)
L.log_energy_yield					-0.04
					(0.06)
Constant	14.55***	14.59***	14.59***	15.08***	14.93***
	(0.01)	(0.01)	(0.04)	(0.06)	(0.89)
Observations	13305	13305	5696	5696	3095
R-squared	0.12	0.07	0.06		
R-squared overall			0.08	0.00	

Note: Standard errors (clustered by household) in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Dependent variable in each regression - log_energy_yield .

in Table 9.

The coefficients from Table 10, column 5 are then used to construct the baseline (columns 1 and 4 of Table 11), where shocks are departures from the historical averages or current 2009 use in case of fertilizer. The baseline for the fertilizer shock scenario is constructed using coefficients from Table 9, household-time FE, since this (preferred) specification allows estimation of coefficients on both fertilizer and its interaction with the technology dummy.

The program (columns 2,3,5,6 of Table 11) is then constructed in the following way:

$$\log y_{prog} = \log y_{bas} + 0.1 * (\beta_1 \Delta T_{ixt} + \beta_{21}(\Delta T_{ixt} * W_{it}) + \beta_{23}(\Delta T_{ixt} * F_{ixt})), \tag{24}$$

where β's are taken from Table 9, household-time FE. y_{bas} is the corresponding baseline value, ΔT_{ixt} is the change in the use of ML intercrop: $\Delta T_{ixt} = 0.1$ in the second stance of reform (columns 2 and 5 of Table 11), and $\Delta T_{ixt} = 0.52$ in the third stance of reform (columns 3 and 6 of Table 11).

The results are reported in Table 11. The first line compares the baseline and the program without shocks. A 10 percentage points increase in ML land share is likely to increase average energy yield by 2.4%, and increase the share of self-sufficient households by 0.66 percentage points (around 3.8% increase). ML smooths fertilizer shocks, although not so effectively as it does with the weather shocks. A 10% fertilizer use shock reduces yield by 2.17% in the program, and 2.18% in the baseline. Note that the program's yield with the fertilizer shock is higher than the baseline's yield without the shock. This means, for example, that a cut to the government fertilizer subsidy program, which causes a 10% drop in fertilizer use, would be yield-neutral if simultaneously a land share of ML increases by around nine percentage points. At the same time, the agricultural system would become more resistant to weather and fertilizer shocks.

Looking at the difference between the baseline and the program, ML is more effective at absorbing weather shocks rather than fertilizer shocks. The rainfall shock, which is particularly harmful,[53] reduces the baseline's average yield by 3.84%, which would cost 0.9% of GDP to compensate. Using more ML, as in program, does not eliminate the shock completely, but reduces its impact by 0.4 percentage points, which saves government around 0.1% of GDP.

The long-term climate projections are actually quite favorable for Malawi, though not in all aspects. The mild scenario B1 predicts a moderate increase in rainfall (8mm per month), substantial increase in temperature (+2.1°C), but also high rainfall variance. The less favorable scenario A2 foresees even bigger increase in temperature, which is still likely to be favorable for the yield, but lower rainfall and much higher rainfall variation. With these projections, yields are likely to go up both in the baseline and the program. However, the increase is larger in case of the program - a better ability to withstand adverse shocks in rainfall and increased rainfall variation allows better harnessing the potential of increased temperatures. Although the average predictions are favorable, and the median projected temperature increase is still within the range where the yield responds positively, there is now a non-zero probability of an extreme event (e.g. increase in temperature of 8°C from the current average level), which is likely to devastate the agricultural sector, as demonstrated in the last two lines of Table 11. As before, more use of ML helps to mitigate the catastrophe.[54]

[53] Note that the shocks are of the same magnitude if measured in standard deviations from the mean

[54] Note that this result relies on extrapolation of the temperature outside of historically observed data, so it shouls be taken with caution

Table 11: Effect of shocks on energy yield under different scenarios

Scenario	%Δ average yield			Δ self-sufficiency		
	Baseline	Δ ML +10p.p.	all use ML	Baseline	Δ ML +10p.p.	all use ML
No shocks	.	2.428	13.711	.	0.661	4.187
Medium term scenario						
Fertilizer use: -10%	-2.181	-2.172	-2.316	-0.331	-0.275	-0.165
Rainfall: -0.228 mm per day	-3.840	-3.480	-2.042	-1.212	-0.826	-0.331
Rainfall variance: + 0.314	-1.316	-0.958	0.464	-0.441	-0.496	0.661
Temperature: -0.307 degrees	-0.958	-0.873	-0.585	-0.220	-0.110	0.110
Long term scenario						
Scenario B1, median	14.205	14.232	14.366	4.959	5.289	4.077
Scenario A2, ensemble low	3.160	4.432	10.149	2.314	2.755	3.030
Scenario A2, ensemble low, ext. temperature	-23.924	-22.289	-14.603	-5.014	-4.738	-4.463
Scenario A2, ensemble low, ext. drought	-31.302	-28.362	-14.418	-7.934	-6.777	-3.140

Note: Three states of reform considered: *Baseline* - land shares of M and ML remain as they were in 2009; Δ *ML +10p.p.* - land share of ML increases by 10 p.p.; *all use ML* - land share of ML is 1. *No shocks* - computed are changes with respect to the baseline; in the rest of scenarios changes are with respect to the corresponding cell in the *No shocks* line. Seven shock scenarios considered. *Medium term scenarios*: negative shocks on fertilizer use, rainfall and temperature, positive shock on rainfall variance. The size of the latter three is equal to half standard deviation - mean by TAs over 2004-2009. *Long term scenarios* are described in IPCC (2000), data from the World Bank Climate Change Data Portal. *Scenario B1, median* - median of nine climate models used in IPCC (2007) - rainfall +8mm per month, temperature +2.1°C, rainfall variation +20% from current. *Scenario A2, ensemble low* - 10th percentile of the nine climate models - rainfall -16mm per month, temperature +2.9°C, rainfall variance +37% from current. *Scenario A2, ensemble low, ext. temperature* - rainfall and rainfall variation as in scenario above, extreme scenario for temperature +8.1°C. Temperature shock is formed as the sum of projected expected increase (+4.5°C) and two projected standard deviations (90th percentile over TAs) (3.6°C). *Scenario A2, ensemble low, ext. drought* - temperature and rainfall variation are as in scenario *A2, ensemble low*, extreme scenario for rainfall (-87mm per month) - formed as the sum of projected expected fall (-16mm per month) and two projected standard deviations (90th percentile over TAs) (-53mm per month).

7 Robustness checks

I provide several robustness checks of my main results. First, as mentioned in Section 5, I check the results using alternative measures of yield: cash yield, maize equivalent yield (Liu-Myers), grain or protein yield. The results are similar when it comes to the signs of coefficients, although the magnitudes differ for some specifications (Table 16).

Second, I check different definitions of technologies, and various modifications of the sample or specification. In particular, I check how hybrid maize performs against the maize-legume intercrop. I also repeat estimation in case maize and legumes are the only crops grown on a plot, in case they are recorded as one of three most important crops on a plot, and in case their harvest share is significant (50, 75, 95, or 100%). I also test other definitions of M and ML. See Tables 20 - 24. To reduce measurement error I then drop 1st and 99th percentiles of farmers' distribution by yield. I also check what happens if I use only plots with conventional units of measurement, i.e. whether errors in transformation rates affect my results. I also drop farms, which are larger than 2 ha, as they are less likely to belong to subsistence farmers. I check if the results are robust when I control for total seed input or land size, and when I add quadratic and cubic terms of rainfall and rainfall variance.[55] Qualitatively the results do not change: ML intercrop does seem to be more productive and more weather-resistant than monoculture maize, although in some specifications the results lose statistical significance. [56]

Another robustness check concerns the properties of the plots. It could be the case that farmers use the ML intercrop, which requires less fertilizer, at plots with a better soil quality and other properties, and then use fertilized maize at worse plots to make the most of them. This would bias the results on *ML technology* upwards. Note that the argument could go the other way around: farmers could use ML intercrop on the worse plots given the technology is productive anyway. In this case the bias would be downwards, which only reinforces my results.[57] My data on plot properties is very sparse, and therefore I cannot use it in my main specification. However, I can provide several arguments in the defense of my results. First, household-time FE effectively control for the soil quality at a region or district level, so what is uncontrolled for is the local variation, which is not likely to be high. Second, as Table 15 reports, even without controlling for fertilizer, ML performs better than M. In case of household-time FE, the coefficients on *ML technology* in columns (7) and (8) are identical, which leaves no room for the "plot properties bias" as implied by the argument above. Third, I use an auxilliary regression, where the dependent variable is the choice of technology (0 - M, 1 - ML) and independent variables are various plot properties, for which the data are available: distance from dwelling, slope, texture, number of weedings performed.[58] The results are reported in Table 17. They are inconclusive. If anything, I find that ML intercrop is used on plots with more adverse conditions - further away from a dwelling, and on plots with

[55]For the rainfall and rainfall variance I do find a non-linear pattern similar to the one of temperature - significant and large coefficients on the cubic terms, which makes extreme weather events especially harmfull for the yield. I also do find that, like with temperature, using the ML technology significantly reduces the impact of these extreme events. To conform with the existing literature, and to make the analysis more tractable, I decided to go with the linear specification for the rainfall and its variance in main specification. The non-linearity of the weather-yield relationship is left for further research

[56]Some of the results, including other robustness checks, are reported in Section A.6

[57]None of the strategies is consistent with the linear specification of the yield as in (4) - farmers should be indifferent on where to use ML intercrop

[58]The number of weedings can be considered both as a labor input and as a property of a plot - its propensity to produce weeds

larger slope. The results are often economically insignificant. For example, increasing the distance of a plot from dwelling by 1 km increases the change of using ML intercrop by only 1 to 6%.

7.1 What drives the performance of ML intercrop?

What drives the superior performance of the ML intercrop over M? Is it due to higher productivity of legumes, in which case the policy recommendation would be to encourage growing this crop regardless whether it is intercropped with maize, rotated or grown separately. Or are there also efficiency gains from growing maize and legume together, due to nitrogen sharing or denser planting (and despite competition depression)? I cannot answer these questions definitively because my data lacks critical inputs - seed input and area by crop.[59] The available evidence though suggests that the better performance of ML is both due to the productivity of legumes and the efficiency gains. The evidence is presented in Tables 12 and 13.

First, on average legumes do seem to have higher yield than maize, and hence productivity of ML intercrop could be driven by their presence in the mix of crops. Table 13, column 1 shows that in the cross-section of farmers (OLS), and controlling for weather and fertilizer use, legume yields are around 25% higher than those of maize. Table 12, columns 3 and 5 show that increased harvest share of legumes is associated with higher average yield.[60]

Second, as suggested by the indirect evidence, ML performance is also likely driven by the efficiency gains. Table 12, column 4 shows that ML is on average as productive as L, so the performance of ML cannot be only driven by the presence of legumes. Table 12, columns (1)-(3) demonstrate how ML performs compared to other technologies, which combine growing of maize and legume - M-L rotation and growing M and L separately (M+L). M-L

[59] The data on seed input per plot is available for waves 2 and 3 of the survey, however it is not clear whether farmers reported seeds only for maize or for all crops on plot. Total seed input is included as an explanatory variable in one of the robustness checks. The coefficient on it is positive, but the rest of the results are generally unchanged.

[60] Note that controlling for the harvest share of legumes in ML intercrops makes the coefficient on ML intercrop dummy insignificant. This is expected because the interpretation of the dummy is the average productivity differential when the harvest share of legumes approaches zero, at which point ML intercrop ceases to be intercrop (with an exception of intercrop plots, where legumes harvest completely failed, but the number of such plots is unlikely to be high)

Table 12: Estimation results: ML intercrop vs. other technologies

	(1) ML rotation b/se	(2) M+L b/se	(3) M+L, legume share b/se	(4) L b/se	(5) M, legume share b/se
ML X rainfall	-3.06**	-4.91**	-4.83**	-2.02**	-1.28*
	(1.39)	(2.11)	(2.06)	(0.92)	(0.68)
ML X rainvar	50.38***	40.21*	40.76*	7.34	5.57
	(16.43)	(22.25)	(21.70)	(11.41)	(4.52)
=1 if ML	-0.00	-0.28	-0.06	0.06	0.06
technology	(0.12)	(0.19)	(0.20)	(0.20)	(0.06)
ML X temp	5.99	9.60	8.17	2.28	-4.98*
	(8.41)	(11.95)	(11.71)	(6.04)	(2.80)
ML X temp_sq	3.11**	3.86**	3.78**	2.80**	-0.79
	(1.30)	(1.80)	(1.76)	(1.18)	(0.71)
ML X temp_cub	-0.96*	-0.95	-0.89	-0.43	0.24
	(0.55)	(0.76)	(0.74)	(0.38)	(0.16)
fertilizer,	-0.69	0.80	1.86	-8.45***	2.86***
tonnes per ha	(0.95)	(1.92)	(1.92)	(3.06)	(0.44)
fertilizer	4.21**	4.01	1.50	14.06**	-1.39*
^2	(2.14)	(6.51)	(6.42)	(5.97)	(0.83)
ML X fert	-1.12	-1.62	-2.03	9.29***	-0.70
	(1.13)	(1.78)	(1.74)	(3.10)	(0.48)
ML X fert_sq	8.01**	4.99	5.15	-8.98	2.58
	(3.55)	(7.25)	(7.08)	(6.35)	(1.64)
harvest share			0.79***		0.80***
of L			(0.30)		(0.13)
Constant	14.58***	14.72***	14.32***	14.53***	14.31***
	(0.06)	(0.07)	(0.17)	(0.19)	(0.02)
Observations	809	284	284	1599	1676
R-squared overall	0.01	0.05	0.03	0.04	0.10

Note Standard errors (clustered by household) in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Estimation method for all columns: household-time FE, IV used for *rainfall*. Dependent variable in all columns - log of energy yield. ML intercrop is compared with: column (1) - M-L rotation; (2) - M+L (growing M and L on separate plots); (3) - M+L, controlling for the harvest share of L; (4) - L (growing only L); (5) - M, controlling for the harvest share of L in ML.

Table 13: Estimation results: Maize and legume productivity for different technologies

	M vs. L		**M only** vs. M in M-L rotation	M yield, **ML** vs. M	L yield, **ML** vs. L
	(1)	(2)	(3)	(4)	(5)
	OLS	hhold-time FE	OLS	hhold-time FE	hhold-time FE
	b/se	b/se	b/se	b/se	b/se
rainfall, cm	1.07***		2.31***		
per day	(0.35)		(0.36)		
ML X rainfall	-0.04	0.86	-1.80***	-1.10	-0.80
	(0.39)	(0.57)	(0.42)	(0.70)	(1.12)
rainfall	0.51		-63.81***		
variance, daily	(4.59)		(5.15)		
ML X rainvar	-20.57***	-42.44***	51.49***	-0.18	80.23***
	(4.87)	(7.55)	(5.54)	(4.66)	(14.31)
=1 if	-0.25**	-0.08	-0.11**	-0.10**	-1.78***
technology in **bold**	(0.10)	(0.23)	(0.04)	(0.05)	(0.24)
temperature, C	-0.08		1.74		
/100	(2.27)		(2.16)		
temperature	-3.19***		-3.39***		
ˆ2 /100	(0.49)		(0.45)		
temperature	0.23		0.59***		
ˆ3 /100	(0.16)		(0.16)		
ML X temp	3.61	4.03	-1.81	-0.91	23.00***
	(2.44)	(3.61)	(2.46)	(2.85)	(7.62)
ML X temp_sq	2.10***	1.39*	2.47***	-0.57	9.41***
	(0.55)	(0.80)	(0.60)	(0.72)	(1.44)
ML X temp_cub	-0.13	-0.09	-0.44**	0.15	-1.90***
	(0.17)	(0.26)	(0.18)	(0.17)	(0.48)
fertilizer,	-7.09***	-10.25***	1.43***	3.06***	-13.12***
tonnes per ha	(1.40)	(3.03)	(0.28)	(0.45)	(3.71)
fertilizer	12.38***	27.90**	-0.78	-1.80**	18.20**
ˆ2	(2.74)	(11.76)	(0.60)	(0.85)	(7.29)
ML X fert	10.17***	12.38***	2.10***	-0.16	12.34***
	(1.41)	(3.04)	(0.33)	(0.49)	(3.77)
ML X fert_sq	-14.36***	-29.24**	-1.98***	1.44	-12.77*
	(2.77)	(11.76)	(0.75)	(1.67)	(7.74)
Constant	14.65***	14.29***	14.60***	14.25***	14.24***
	(0.10)	(0.23)	(0.04)	(0.02)	(0.23)
Observations	9533	3718	7058	1667	1558
R-squared	0.13		0.04		
R-squared overall		0.07		0.12	0.58

Note Standard errors (clustered by household) in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. In all columns, IV used for *rainfall*. Maize and legume productivity for different technologies (technology dummy is one for technologies in bold): columns (1) and (2) - M vs. L, log of energy yield, OLS and hhold-time FE; (3) - log of energy yield, maize only (no rotation or intercrop) vs. maize in M-L rotation; (4) - M only yield in M vs. ML; (5) - L only yield in L vs. ML.

rotation means that growing M is followed by growing L on the same plot next season, and so on. As I do not observe plots over time, and I do not observe farmers in consecutive years, I am not able to identify M-L rotators in the data. What I can do is to come up with a proxy. In particular, I define a farmer to be M-L rotator if she/he has a record of growing both M (and no L) and L (and no M) on separate plots in at least one of the three waves of the survey. M+L is then a special case of M-L rotation, when M and L are grown on separate plots within the same season (and then likely rotated). As the proxy for M-L rotation is likely to be very noisy, the results must be taken with caution. The results suggest, however, that ML intercrop is on average as productive as M-L rotation or M+L (after controlling for the legume share of harvest). At the same time, I am able to estimate the maize yield for farmers who rotate maize with legumes versus those who do not rotate, even though it is only possible in the cross-section of farmers, e.g. via OLS.[61] The results in Table 13, column 3 suggest that maize is significantly more productive when it is rotated with legumes. Likewise, Table 13, column 2 shows that maize is only slightly less productive than legumes when comparing among farmers who grow both (e.g. M+L - a subset of M-L rotators).[62] These results suggest that performance of M-L rotation is not only due to performance of legumes, maize becomes more productive too, and since ML intercrop is as productive as M-L rotation, there have to be efficiency gains there too.

It is not clear whether the efficiency gains stem from the nitrogen sharing, possibility of denser planting without too much of competition depression, or the combination of the two. To answer we need to know areas under maize and legumes, as well as the seed inputs by each crop. The answer probably also depends on the structure of the intercrop.[63] These data are not available. Table 13, columns 4 and 5 suggests though that it is probably the combination of the two. The columns report the yields of only maize and only legumes on plots with ML intercrop versus plots where these crops are grown separately. In both cases the yields at ML intercrop plots are lower - by about 10% for maize, and much more (about 73%) for legumes. This could be

[61] For M-L rotation, unlike ML intercrop, I directly observe areas under M and L, as they are grown on separate plots (possibly during different periods of time). However, by definition of my M-L rotation proxy, I cannot have farmers growing maize with and without rotation, i.e. no household-time fixed effect is possible

[62] This is what household-time FE imply

[63] F.e. one can grow M and L in separate rows or in the same row, etc.

the result of less denser planting when compared to monocropped plots (e.g. smaller area under each crop at ML intercrop plots), but it can also reflect the competition depression, e.g crops crowding out each other. Combining the two yields though gives the land equivalency ratio of more than one, which means that growing the same harvest, in the same proportions of M and L, would take more land if we use monocropped plots instead of ML intercrop.[64] This means that either the competition depression is not strong enough, and hence denser planting of maize and legumes is possible, or there is nitrogen sharing (or a combination of the two).

While on average ML intercrop is not the most productive technology (although still more productive than monocroped maize), it seems to perform best when it comes to weather-resistance. Table 12 shows that ML intercrop likely withstands rainfall shocks better than either M-L rotation or monocropped legumes, in addition to monocropped maize (as in my main specification). All coefficients on ML intercrop interaction with rainfall are negative and significant.[65] What drives this performance? Partly it might be due to the improved resilience of maize and/or legumes on the ML intercrop plots - Table 13, columns 3 and 4 show the negative coefficients on *ML x rainfall*, although they are both statistically insignificant.

Another possible part of the explanation is that growing the two crops together serves as an insurance - similar to the portfolio diversification in finance. A negative shock to one crop's yield is (partly) mitigated by the less affected yield of the other crop. This point is consistent with the evidence in Table 18. The left panel shows summary statistics of total, maize and legume grain yields on the ML intercrop plots. The mean total yield is higher than either maize or legume, but its standard deviation is the lowest. The right panel shows a simple regression of log maize yield on a ML intercrop plot on log legume yield. The two are positively correlated, which is expected, but as demonstrated by low R^2 in both specifications, the correlation is very low.

The portfolio diversification does not seem to explain the whole story

[64] Land equivalency ratio (LER) is defined as follows: $LER = \sum_{I=M,L} \frac{I\ yield\ on\ ML\ intercrop}{I\ yield\ on\ monocrop}$. From Table 13, columns 4 and 5, in our case LER=exp(-0.1)+exp(-1.78)=1.07. This is not necessarily different from 1 in a statistical sense, but LER is generally larger for other specifications (f.e. when M and L are the only crops grown on plot)

[65] Some coefficients seem implausibly large in absolute value, which is probably driven by smaller samples. All estimates are very imprecise, upper bounds of 95% confidence intervals almost reach zero in most specifications

though. If it did then ML intercrop were not more resilient than M+L, i.e. growing M and L separately within the same season. Table 12, columns 2 and 3 suggest that ML intercrop does perform better. The explanation could be that the insurance works more intensively at ML intercrop plots: one crop's failure due to an adverse weather shock means less inter-species competition for the other crop.

8 Conclusions

Using more biodiverse agricultural technologies is a viable way to improve food security in Sub-Saharan Africa. Using the evidence from Malawi I show that maize-legume intrecrop is both more productive and better at absorbing weather and fertilizer shocks. I do not identify the average population effect. The estimated coefficients are subject to technology-specific factors bias. However, I show that if the government implements a cost or education subsidy to induce the maize-legume intercrop usage the effect is likely to be the one I identify. This is because the complying farmers will be the group, which is very similar to my estimation sample.

According to my results, a reform that induces a nine percentage point increase in land used for the intercrop can be yield-neutral even if the fertilizer used drops by 10%. At the same time, a system like this is likely to be more resilient to weather and fertilizer use shocks.

This paper has its limitations, either due to data unavailability or due to a risk of turning into a book. First, I do not specify what kind of reforms would induce farmers to use more intercrop, and what their potential cost and effectiveness are. The space for reforms is clearly large though. Infrastructure for the legume markets and education are probably the most important reform directions, as demonstrated by few examples in Section 2.4.

The second limitation of the paper is that I do not take into account potential systematic differences between the labor and seed requirements of the two technologies, which may stall ML's take off despite higher yield. If the ML generally requires more labor or seed inputs then its net benefit may turn out to be lower than that of M. However, as mentioned in Section 2.4, field trials suggest that the labor requirements are not too different, so the potential ”‘excess”’ labor could stem purely from the lack of education. The scarce evidence on seed inputs in Section 7 suggests that the seed requirements are not likely to be the binding constraint either. In Section 4.3 I show that, even if we do not control for labor and seed inputs, for small policy changes household-time fixed effects regression still consistently estimates the effect of the policy on agricultural productivity. For larger policy changes this limitation has to be further investigated.

There are also factors, which I did not analyze in this paper, and which can add to the benefits of the intercrop. First, growing legumes can improve long-term quality of the soil, because of nitrogen fixation and legume biomass incorporation after the growing season. Second, consuming more biodiverse diet, e.g. maize vs. maize and legumes, improves nutrition, food security, and hence long-term health and productivity of the farmers (Kerr et al., 2011).

A Appendix

A.1 Summary of Malawian crops

Table 14: Malawian Crops: Cash, Energy, and Protein Value

crop	national price in 2007, MK/kg	energy, kCal/kg	proteins, gr/Kg	legume
Local maize	10.72	3560	95	0
Composite/OPV maize	12.5	3560	95	0
Hybrid maize	11.49	3560	95	0
Cassava	17.4	1090	9	0
Sweet potatoes	15.87	920	7	0
Irish potatoes	34.14	670	16	0
G/Nuts	15	5670	257	1
Ground bean/Nzama	16.16	3650	177	1
Rice	26.69	3570	75	0
Finger millet	34.65	3400	97	0
Sorghum	18.15	3430	101	0
Pearl millet	19.9	3400	97	0
Beans	54.01	3410	221	1
Soyabean	20.49	3350	380	1
Pigeonpea (Nandolo)	24.7	3430	209	1
Burley tobacco	156	0	0	0
Tobacco-other	n/a	0	0	0
Cotton	n/a	0	0	0
Sugar cane	n/a	300	20	0
Cabbage	n/a	190	10	0
Tanaposi - Chinese cabbage	n/a	190	10	0
Nkhwani - pumpkin leaves	n/a	0	0	0
Okra	n/a	310	16	0
Tomato	n/a	170	8	0
Onion	n/a	310	11	0
Peas - Nsawawa	n/a	3460	225	1
Other	n/a	0	0	0
Sunflower	n/a	3080	123	0
Pepper - piri piri	n/a	2760	107	0
Coffee	n/a	560	80	0
Rape - mpiri wotuwa	n/a	4940	196	0
Paprika	n/a	220	14	0
Cowpeas - Khobwe - Nseula	n/a	3420	234	1
Mucuna (Kalongonda) - legume	n/a	3430	234	1
Bonongwe - leafy greens	n/a	0	0	0
Watermelon	n/a	170	3	0
Mpoza - fruit	n/a	450	50	0
Pumpkin	n/a	190	9	0
Buffalo bean (Mucuna variety) - legume	n/a	3430	234	1
Cucumber	n/a	130	5	0
Kabaifa - nut	n/a	2620	70	0
Hyacinth Bean - Nkhungudzu	n/a	3430	234	1

Note Datasource: *national price* - community surveys in all three waves, median in the country's distribution of crop's prices; *energy, proteins* - Food Composition Tables, FAO. *legume* indicates whether the crop is nitrogen-fixing legume. MK - Malawian kwacha. Exchange rate as of September, 2011 - 165 MK for 1 USD.

A.2 Household-time-technology panel vs. household-time panel

By definition of geometric average, the total household yield at time t (y_{it}) is:

$$y_{it} = y_{i0t}^{1-\theta_{it}} y_{i1t}^{\theta_{it}} \Rightarrow \log y_{it} = \log y_{i0t} + \theta_{it}(\log y_{i1t} - \log y_{i0t}), \qquad (25)$$

where θ_{it} is the land share of ML (technology 1). Expand (25) using (4) and the fact that $T_{i0} = 0$ and $T_{i1} = 1$:

$$\begin{aligned} \log y_{it} = \beta_0 + \beta_{31} * W_{it} + \beta_{22} * F_{i0t} + \\ + \theta_{it} \left(\beta_1 + \beta_{21} * W_{it} + \beta_{22} * (F_{i1t} - F_{i0t}) + \beta_{23} * F_{i1t}\right) = \\ = \beta_0 + \beta_1 \theta_{it} + \beta_{31} * W_{it} + \beta_{21}(\theta_{it} * W_{it}) + \\ + \beta_{22} * F_{it} + \beta_{23}(\theta_{it} * F_{i1t}), \end{aligned} \qquad (26)$$

where $F_{it} = F_{i0t} + \theta_{it}(F_{i1t} - F_{i0t})$ - an arithmetic average of fertilizer use indicators over both technologies.

Therefore, the coefficient on θ_{it} in (5) is equal to the coefficient on T_{ix} in (4) in the probability limit, in case both are consistent. Similarly equal are the coefficients on the other variables and their interactions.

A.3 Auxilliary proofs for the model

A.3.1 OLS estimator of γ

Let K be the number of observations in our OLS regression: $K = (N - k_1) + (N - k_2)$. Then the OLS estimator of γ is:

$$\hat{\gamma} = \frac{\sum_{i=1}^{K} T_i f_i - K \bar{f} \bar{T}}{\sum_{i=1}^{K} T_i - K \bar{T}^2}, \tag{27}$$

where $\bar{f}$ and $\bar{T}$ are the corresponding sample averages. Now, since $T = 1$ if technology 2 is used, and zero otherwise:

$$\sum_{i=1}^{K} T_i = 0 * (N - k_2) + 1 * (N - k_1) = N - k_1; \tag{28}$$

$$\sum_{i=1}^{K} T_i f_i = (N - k_1)\bar{f}_2; \tag{29}$$

$$\bar{f} = 1/K \left((N - k_2)\bar{f}_1 + (N - k_1)\bar{f}_2\right); \tag{30}$$

$$\bar{T} = 1/K \sum_{i=1}^{K} T_i = 1/K(N - k_1). \tag{31}$$

Inserting these in (27) we get:

$$\begin{aligned}\hat{\gamma} = \frac{(N - k_1)\bar{f}_2 - 1/K\left((N - k_2)\bar{f}_1 + (N - k_1)\bar{f}_2\right) * (N - k_1)}{N - k_1 - 1/K(N - k_1)^2} &= \\ = \frac{K\bar{f}_2 - (N - k_2)\bar{f}_1 - (N - k_1)\bar{f}_2}{K - (N - k_1)} &= \\ &= \bar{f}_2 - \bar{f}_1.\end{aligned} \tag{32}$$

A.3.2 Proof of Proposition 4.1

Proposition. Let $TSE_1 \sim N(\mu_1, \sigma_1)$ and $TSE_2 \sim N(\mu_2, \sigma_2)$. Then

$$|E(TSE_2 - TSE_1)|_{pooled\ OLS} > |E(TSE_2 - TSE_1)|_{hhold-time\ FE} \tag{33}$$

Proof. Combine the technology selection criteria (8) with the data generating process (13) for f. Then for each household:

$$\forall\ i = 1, .., k_1\ (\alpha_i = 1) \text{ if } \lambda_2(TSE_{2i} - TSE_{1i}) < -\gamma - \epsilon + (c_{2i} - c_{1i}) \tag{34}$$
$$\forall\ i = k_2 + 1, .., N\ (\alpha_i = 0) \text{ if } \lambda_2(TSE_{2i} - TSE_{1i}) > -\gamma + (c_{2i} - c_{1i}) \tag{35}$$
$$\forall\ i = k_1 + 1, .., k_2\ (0 < \alpha_i < 1) \text{ if otherwise.} \tag{36}$$
$$\tag{37}$$

The TSE bias in pooled OLS is λ_2 times the difference between the expected TSE_2, taken over farmers $k_1 + 1$ to N - all those who use technology 2, and the expected TSE_1, taken over farmers 1 to k_2 - all those who use technology 1. The TSE bias in household-time FE is the same expected difference $TSE_2 - TSE_1$, but taken only over farmers $k_1 + 1$ to k_2 - those who use both technologies.

Denote $s_1 = 1/\lambda_2 * (-\gamma - \epsilon + (c_2 - c_1)$ and $s_2 = 1/\lambda_2 * (-\gamma + (c_2 - c_1))$, also denote $\mu = \mu_2 - \mu_1$ and $\sigma = \sigma_1 + \sigma_2$.

Expected TSE_2, taken over those who use the second technology (farmers $k_1 + 1$ to N):

$$\begin{aligned}
&\mathrm{E}\left(TSE_2 | \alpha < 1\right) = \\
&\qquad = \mathrm{E}\left(TSE_2 | TSE_2 - TSE_1 > s_1\right) = \\
&\qquad\qquad = \mathrm{E}\left(\mathrm{E}\left(TSE_2 | TSE_2 - TSE_1 > s_1, c_1, c_2\right)\right)
\end{aligned} \tag{38}$$

The last line follows from the law of iterated expectations. Now:

$$\begin{aligned}
&\mathrm{E}\left(TSE_2 | TSE_2 - TSE_1 > s_1, c_1, c_2\right) = \\
&\quad = \mathrm{E}\left(TSE_2 - TSE_1 | TSE_2 - TSE_1 > s_1, c_1, c_2\right) + \mathrm{E}(TSE_1) = \\
&\qquad = \mu_1 + \frac{\sigma\phi(\frac{s_1 - \mu}{\sigma})}{1 - \Phi(\frac{s_1 - \mu}{\sigma})},
\end{aligned} \tag{39}$$

where ϕ is a p.d.f. of the standard normal distribution, and Φ is a c.d.f. of the standard normal distribution. The last line follows from the fact that the difference of two normally distributed variables is also normally distributed, and hence the standard result about the expectation of truncated normal distribution.

Similarly, conditional expectaion of TSE_1, subject to using the first technology:

$$\mathrm{E}\left(TSE_1|TSE_2 - TSE_1 < s_2, c_1, c_2\right) =$$

$$= \mu_1 + \frac{\sigma\phi(\frac{s_2-\mu}{\sigma})}{\Phi(\frac{s_2-\mu}{\sigma})} \quad (40)$$

And expectation of $TSE_2 - TSE_1$, given both technologies are used:

$$\mathrm{E}\left(TSE_2 - TSE_1|s_1 < TSE_2 - TSE_1 < s_2, c_1, c_2\right) =$$

$$= \mu_2 - \mu_1 + \sigma\frac{\phi(\phi(\frac{s_1-\mu}{\sigma}) - \frac{s_2-\mu}{\sigma})}{\Phi(\frac{s_2-\mu}{\sigma}) - \Phi(\frac{s_1-\mu}{\sigma})} \quad (41)$$

Given c_1 and c_2, the difference between $|E(TSE_2 - TSE_1)|_{pooled\ OLS}$ and $|E(TSE_2 - TSE_1)|_{hhold-time\ FE}$ is:

$$\left|\frac{\phi(\frac{s_1-\mu}{\sigma})}{1-\Phi(\frac{s_1-\mu}{\sigma})} - \frac{\phi(\frac{s_2-\mu}{\sigma})}{\Phi(\frac{s_2-\mu}{\sigma})}\right| - \left|\frac{\phi(\frac{s_1-\mu}{\sigma}) - \phi(\frac{s_2-\mu}{\sigma})}{\Phi(\frac{s_2-\mu}{\sigma}) - \Phi(\frac{s_1-\mu}{\sigma})}\right| \quad (42)$$

To prove the proposition it is left to show that difference (42) is larger than zero. Since $s_1 < s_2$, we have $\Phi(\frac{s_1-\mu}{\sigma}) < \Phi(\frac{s_2-\mu}{\sigma})$. Now consider two cases: (1) - $\left|\frac{s_1-\mu}{\sigma}\right| > \left|\frac{s_2-\mu}{\sigma}\right|$, and (2) - $\left|\frac{s_1-\mu}{\sigma}\right| < \left|\frac{s_2-\mu}{\sigma}\right|$.

Consider case (1):

$$\left|\frac{s_1-\mu}{\sigma}\right| > \left|\frac{s_2-\mu}{\sigma}\right| \Rightarrow \frac{\phi(\frac{s_1-\mu}{\sigma})}{1-\Phi(\frac{s_1-\mu}{\sigma})} = \frac{\phi(-\frac{s_1-\mu}{\sigma})}{\Phi(-\frac{s_1-\mu}{\sigma})} > \frac{\phi(\frac{s_2-\mu}{\sigma})}{\Phi(\frac{s_2-\mu}{\sigma})} \quad (43)$$

This follows from the fact that the Inverse Mill's Ratio of the standard normal distribution is monotonically increasing, and that the case (1) implies that $-\frac{s_1-\mu}{\sigma} > \frac{s_2-\mu}{\sigma}$.

Given (43):

$$\left|\frac{\phi(\frac{s_1-\mu}{\sigma})}{1-\Phi(\frac{s_1-\mu}{\sigma})} - \frac{\phi(\frac{s_2-\mu}{\sigma})}{\Phi(\frac{s_2-\mu}{\sigma})}\right| - \left|\frac{\phi(\frac{s_1-\mu}{\sigma}) - \phi(\frac{s_2-\mu}{\sigma})}{\Phi(\frac{s_2-\mu}{\sigma}) - \Phi(\frac{s_1-\mu}{\sigma})}\right| =$$

$$= \frac{\phi(\frac{s_1-\mu}{\sigma})}{1-\Phi(\frac{s_2-\mu}{\sigma})} - \frac{\phi(\frac{s_2-\mu}{\sigma})}{\Phi(\frac{s_2-\mu}{\sigma})} - \frac{\phi(\frac{s_2-\mu}{\sigma}) - \phi(\frac{s_1-\mu}{\sigma})}{\Phi(\frac{s_2-\mu}{\sigma}) - \Phi(\frac{s_1-\mu}{\sigma})} =$$

$$= \frac{\phi(\frac{s_1-\mu}{\sigma})}{1-\Phi(\frac{s_1-\mu}{\sigma})}\frac{\Phi(\frac{s_2-\mu}{\sigma}) + 1 - 2\Phi(\frac{s_1-\mu}{\sigma})}{\Phi(\frac{s_2-\mu}{\sigma}) - \Phi(\frac{s_1-\mu}{\sigma})} - \frac{\phi(\frac{s_2-\mu}{\sigma})}{\Phi(\frac{s_2-\mu}{\sigma})}\frac{2\Phi(\frac{s_2-\mu}{\sigma}) - \Phi(\frac{s_1-\mu}{\sigma})}{\Phi(\frac{s_2-\mu}{\sigma}) - \Phi(\frac{s_1-\mu}{\sigma})} >$$

$$> \frac{\phi(\frac{s_2-\mu}{\sigma})}{\Phi(\frac{s_2-\mu}{\sigma})}\frac{1 - \Phi(\frac{s_1-\mu}{\sigma}) - \Phi(\frac{s_2-\mu}{\sigma})}{\Phi(\frac{s_2-\mu}{\sigma}) - \Phi(\frac{s_1-\mu}{\sigma})} > 0, \quad (44)$$

since $1 - \Phi(\frac{s_1-\mu}{\sigma}) = \Phi(-\frac{s_1-\mu}{\sigma}) > \Phi(\frac{s_2-\mu}{\sigma})$.

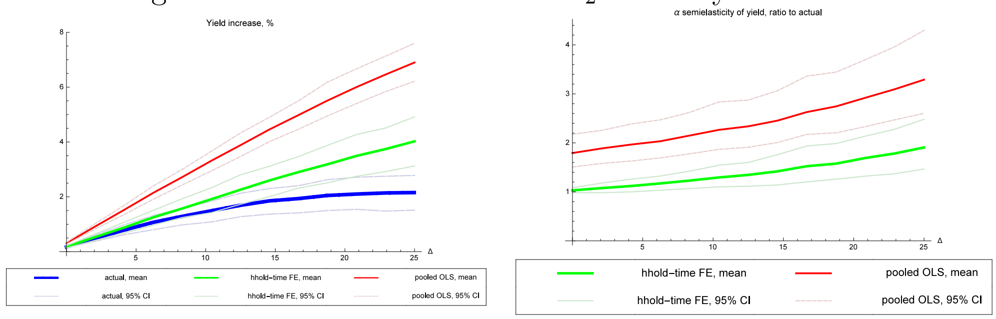
Now consider case (2). In this case, the inequality (43) reverses the order, and then the proof is analogous to the case (1):

$$\left|\frac{s_1-\mu}{\sigma}\right| < \left|\frac{s_2-\mu}{\sigma}\right| \Rightarrow \frac{\phi(\frac{s_1-\mu}{\sigma})}{1-\Phi(\frac{s_1-\mu}{\sigma})} = \frac{\phi(-\frac{s_1-\mu}{\sigma})}{\Phi(-\frac{s_1-\mu}{\sigma})} < \frac{\phi(\frac{s_2-\mu}{\sigma})}{\Phi(\frac{s_2-\mu}{\sigma})} \quad (45)$$

Therefore in both cases (1) and (2) $|E(TSE_2 - TSE_1)|_{pooled\ OLS} > |E(TSE_2 - TSE_1)|_{hhold-time\ FE}$. Since this result holds conditional on any c_1 and c_2, the unconditional expectation must hold too. Q.E.D.

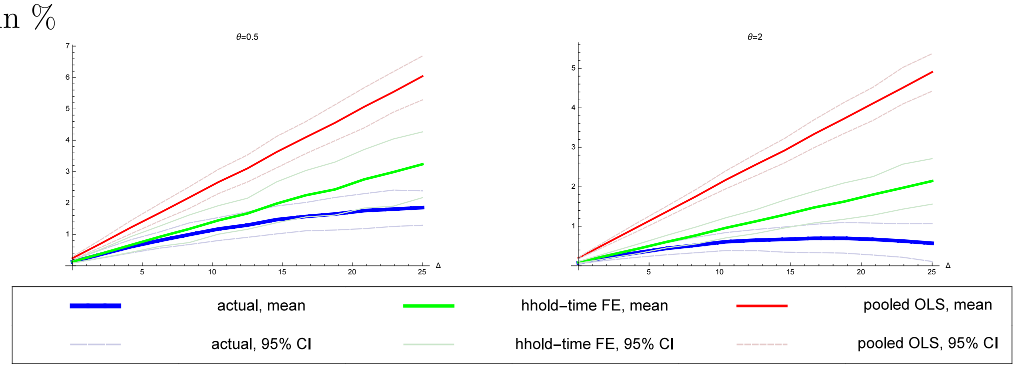
A.4 Model simulation: Robustness checks

Figure 7: Model simulation: TSE_2 normally distributed



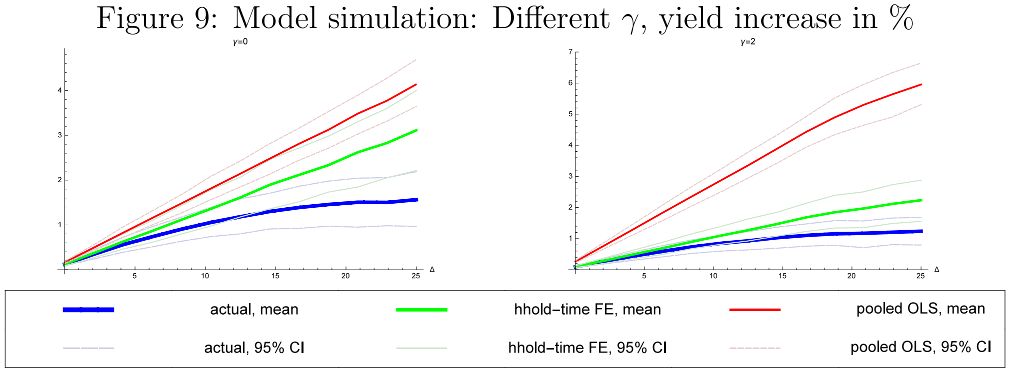
Sources: See notes for Figure 4 for the details on the model simulation. The only difference with the main calibration is that the TSE_2 is now normally distributed with mean 4.75 and standard deviation 0.875.

Figure 8: Model simulation: General CRRA utility function, yield increase in %



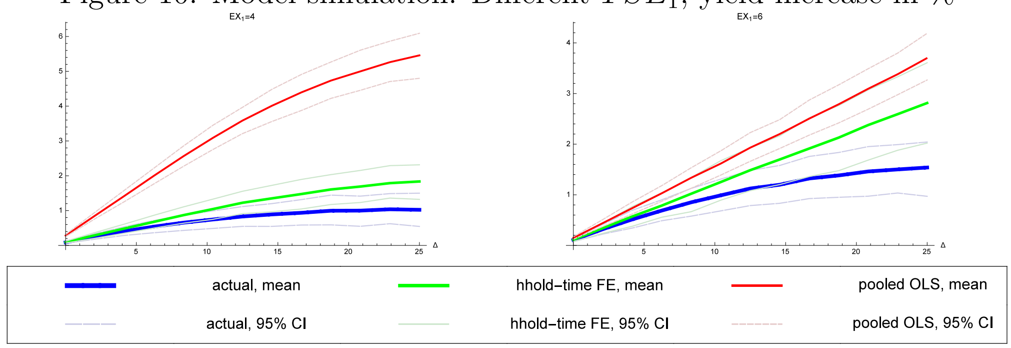
Sources: See notes for Figure 4 for the details on the model simulation. The only difference with the main calibration is that the farmers' utility is general constant relative risk aversion function (CRRA): $U(x) = \frac{1}{1-\theta}x^{1-\theta}$, where θ is the risk aversion coefficient. Note that the logarithmic function is the special case with $\theta = 1$.

Figure 9: Model simulation: Different γ, yield increase in %



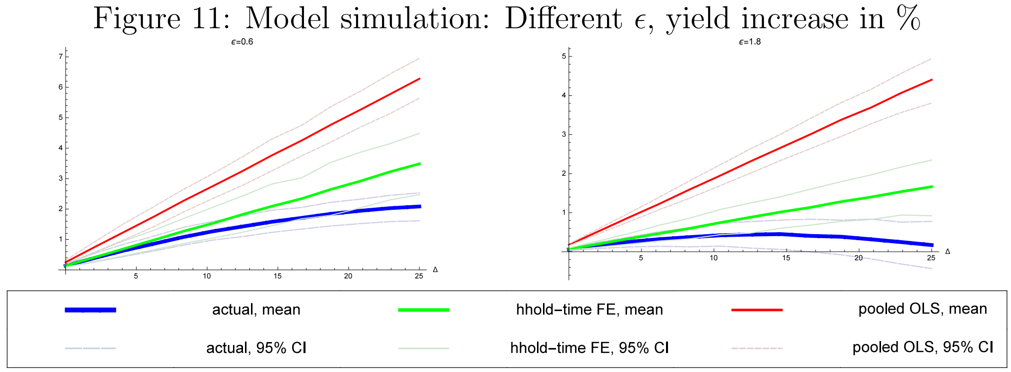
Sources: See notes for Figure 4 for the details on the model simulation. The only difference with the main calibration is γ - the coefficient on the ML dummy. Note that in the main calibration $\gamma = 1$.

Figure 10: Model simulation: Different TSE_1, yield increase in %



Sources: See notes for Figure 4 for the details on the model simulation. The only difference with the main calibration is TSE_1 - technology-specific education/experience for M (assumed constant for all farmers). Note that in the main calibration $TSE_1 = 5$.

Figure 11: Model simulation: Different ϵ, yield increase in %



Sources: See notes for Figure 4 for the details on the model simulation. The only difference with the main calibration is ϵ - the riskiness of M. Note that in the main calibration $\epsilon = 1.2$.

A.5 Additional estimation results

Table 15: Estimation results: Specific to general

	pooled OLS				hhold-time FE			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	no IV	IV	IV	IV	no IV	IV	IV	IV
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
ML technology	0.14***	0.19***	0.19***	0.25***	0.28***	0.25***	0.28***	0.27***
(dummy or landshare)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.05)	(0.05)
rainfall, cm		1.02***	0.99***	1.03***				
per day		(0.21)	(0.22)	(0.20)				
ML X rainfall		-1.26***	-1.61***	-1.36***		-0.68	-1.31*	-1.25*
		(0.32)	(0.32)	(0.30)		(0.69)	(0.73)	(0.70)
rainfall		-19.64***	-21.25***	-20.07***				
variance, daily		(1.96)	(2.14)	(2.00)				
ML X rainvar		13.18***	14.13***	7.70***		9.88**	12.55***	8.69*
		(2.42)	(2.65)	(2.48)		(4.06)	(4.83)	(4.63)
temperature, C			3.80***	3.53***				
/100			(1.14)	(1.03)				
temperature			-0.40	-1.09***				
^2 /100			(0.31)	(0.29)				
temperature			-0.07	0.09				
^3 /100			(0.08)	(0.07)				
ML X temp			-5.23***	-2.43*			-7.75***	-7.41***
			(1.40)	(1.28)			(2.97)	(2.84)
ML X temp_sq			-0.44	-0.74*			-1.36*	-1.06
			(0.45)	(0.42)			(0.75)	(0.72)
ML X temp_cub			0.20**	0.14			0.38**	0.31*
			(0.10)	(0.09)			(0.17)	(0.17)
fertilizer,				3.00***				2.86***
tonnes per ha				(0.15)				(0.45)
fertilizer				-1.98***				-1.22
^2				(0.36)				(0.85)
ML X Txfert				1.07***				-1.05**
				(0.20)				(0.49)
ML X Txfert_sq				-1.58***				3.12*
				(0.49)				(1.67)
Constant	14.42***	14.39***	14.43***	14.47***	14.35***	14.35***	14.35***	14.30***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Observations	13445	13305	13305	13305	1678	1676	1676	1676
R-squared	0.01	.	.	0.09	0.08			
R-squared overall					0.02	0.03	0.02	0.13

Note Standard errors (clustered by household) in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Dependent variable in each regression - log_energy_yield.

A.6 Additional estimation results and figures

Table 16: Estimation results: Alternative yield measures

	(1) energy b/se	(2) grain b/se	(3) cash b/se	(4) protein b/se	(5) maize equiv. b/se
ML X rainfall	-1.25*	-1.42**	-1.69**	-1.14	-3.13***
	(0.70)	(0.69)	(0.79)	(0.74)	(0.83)
ML X rainvar	8.69*	11.96***	14.08***	9.29*	32.98***
	(4.63)	(4.58)	(5.22)	(4.89)	(5.25)
ML technology	0.27***	0.19***	0.36***	0.53***	0.10*
(dummy or landshare)	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)
ML X temp	-7.41***	-6.86**	-8.07**	-9.01***	-15.21***
	(2.84)	(2.81)	(3.20)	(3.00)	(3.69)
ML X temp_sq	-1.06	-1.03	-0.73	-1.46*	-1.18
	(0.72)	(0.71)	(0.81)	(0.76)	(0.85)
ML X temp_cub	0.31*	0.24	0.16	0.38**	0.39*
	(0.17)	(0.17)	(0.19)	(0.18)	(0.22)
fertilizer,	2.86***	2.46***	2.44***	2.91***	2.64***
tonnes per ha	(0.45)	(0.44)	(0.50)	(0.47)	(0.54)
fertilizer	-1.22	-0.63	-0.30	-1.16	-1.08
^2	(0.85)	(0.84)	(0.95)	(0.89)	(0.99)
ML X fert	-1.05**	-0.65	-0.58	-1.25**	-0.45
	(0.49)	(0.48)	(0.55)	(0.51)	(0.58)
ML X fert_sq	3.12*	2.75*	2.88	3.30*	1.97
	(1.67)	(1.65)	(1.88)	(1.76)	(2.01)
Constant	14.30***	6.20***	8.68***	10.66***	2.20***
	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)
Observations	1676	1676	1676	1676	1480
R-squared overall	0.13	0.11	0.12	0.17	0.10

Note Standard errors (clustered by household) in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Estimation method for all columns: household-time FE, IV used for *rainfall*. Dependent variables: column (1) - log of energy yield (main measure, for comparison purposes); (2) - log of grain yield; (3) - log of cash yield; (4) - log of protein yield; (5) - log of maize equivalent yield (Liu-Myers).

Table 17: Choice of technology: Role of plot properties

	pooled OLS				hhold-time FE			
	(1) b/se	(2) b/se	(3) b/se	(4) b/se	(5) b/se	(6) b/se	(7) b/se	(8) b/se
Distance from	0.01**			0.02**	0.06**			0.06**
dwelling, km	(0.01)			(0.01)	(0.03)			(0.03)
Texture of soil		0.02*				-0.24**		
(1 - sand to 3 - clay)		(0.01)				(0.11)		
Slope (1 - flat		0.09***				0.19**		
to 4 - steep hilly)		(0.01)				(0.09)		
Number of			0.00	-0.01			0.11	0.01
weedings			(0.01)	(0.02)			(0.08)	(0.13)
Constant	0.49***	0.28***	0.50***	0.51***	0.44***	0.66**	0.31**	0.42*
	(0.01)	(0.02)	(0.02)	(0.03)	(0.02)	(0.29)	(0.15)	(0.24)
Observations	2200	8237	5188	2198	822	416	1261	821
R-squared	0.00	0.02	0.00	0.00	0.01	0.03	0.00	0.01
R-squared overall					0.00	0.00	0.00	0.00

Note Standard errors (clustered by household) in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Dependent variable in each regression - tM_ML (0 if M, 1 if ML).

Table 18: Maize and legume yields in intercrop: Summary statistics

	mean	sd
log total yield	6.41	0.87
log maize yield	6.00	1.06
log legume yield	4.79	1.22

	(1) pooled OLS b/se	(2) hhold FE b/se
log legume	0.13***	0.22***
yield	(0.01)	(0.02)
Constant	5.40***	4.95***
	(0.05)	(0.12)
Observations	6117	6117
R-squared	0.02	0.06
R-squared overall		0.02

Note Left panel: Summary statistics: total, maize, and legume yields in tonnes of grain per hectare. Only ML intercrop plots included. *Right panel:* Regressions of log maize yield on log legume yield. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Only ML intercrop plots are included.

Table 19: Estimation results: Disaggregate Household Fixed Effects

	(1) pooled OLS	(2) hhold-time FE	(3) hhold-time & techn. FE	(4) hhold FE, disaggregated	(5) hhold FE, aggregated	(6) hhold FE GMM
ML technology	0.25***	0.27***		0.09**	0.01	0.30**
(dummy or landshare)	(0.02)	(0.05)		(0.04)	(0.06)	(0.12)
rainfall, cm	1.03***			2.92***	3.48***	2.83***
per day	(0.20)			(0.36)	(0.39)	(0.38)
ML X rainfall	-1.36***	-1.25*	-1.60	-2.28***	-3.26***	-2.22***
	(0.30)	(0.70)	(2.47)	(0.55)	(0.77)	(0.68)
rainfall	-20.07***			-62.17***	-69.72***	-14.27***
variance, daily	(2.00)			(4.29)	(4.64)	(3.63)
ML X rainvar	7.70***	8.69*	12.52	36.58***	50.38***	15.74***
	(2.48)	(4.63)	(24.16)	(4.01)	(5.53)	(5.49)
temperature, C	3.53***			19.32***	23.09***	21.80***
/100	(1.03)			(2.56)	(3.31)	(3.39)
temperature	-1.09***			-6.14***	-6.16***	2.58***
ˆ2 /100	(0.29)			(0.77)	(0.83)	(0.69)
temperature	0.09			-0.51***	-0.64***	-0.90***
ˆ3 /100	(0.07)			(0.16)	(0.21)	(0.20)
ML X temp	-2.43*	-7.41***	-21.24**	-13.37***	-17.93***	-12.44***
	(1.28)	(2.84)	(8.88)	(2.39)	(3.66)	(4.72)
ML X temp_sq	-0.74*	-1.06	3.29	0.71	1.30	-1.53
	(0.42)	(0.72)	(4.04)	(0.63)	(0.98)	(1.15)
ML X temp_cub	0.14	0.31*	0.83	0.25*	0.39*	0.69***
	(0.09)	(0.17)	(0.60)	(0.14)	(0.23)	(0.26)
fertilizer,	3.00***	2.86***	2.82**	3.00***	2.88***	2.72*
tonnes per ha	(0.15)	(0.45)	(1.39)	(0.26)	(0.31)	(1.59)
fertilizer	-1.98***	-1.22	-1.00	-2.70***	-3.35***	-3.91
ˆ2	(0.36)	(0.85)	(2.38)	(0.51)	(0.77)	(4.36)
ML X Txfert	1.07***	-1.05**	-2.40	0.77**	1.29***	2.41
	(0.20)	(0.49)	(2.01)	(0.34)	(0.44)	(2.47)
ML X Txfert_sq	-1.58***	3.12*	4.40	-1.22	-1.36	-9.63
	(0.49)	(1.67)	(7.48)	(0.93)	(1.27)	(9.15)
L.log_energy_yield						-0.09
						(0.06)
Constant	14.47***	14.30***	-0.00	14.45***	14.95***	15.47***
	(0.02)	(0.02)	(0.03)	(0.01)	(0.06)	(0.89)
Observations	13305	1676	196	6818	5696	3095
R-squared	0.09			.		
R-squared overall		0.13	0.09		0.01	

Note Standard errors (clustered by household) in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Estimation method: column 1 - pooled OLS, column 2 - household-time FE, column 3 - household-time and technology FE, column 4 - household FE, disaggregated (e.g. no aggregation of harvest over household), column 5 - household FE, aggregated, column 6 - household FE GMM. For all columns, IV used for *rainfall.* Dependent variable for all columns - log of energy yield.

Table 20: Estimation results: Alternative Definitions of M and ML - Part 1

	ML		ML13		ML only	
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	hhold-time FE	OLS	hhold-time FE	OLS	hhold-time FE
=1 if ML	0.25***	0.27***	0.24***	0.26***	0.21***	0.26***
technology	(0.02)	(0.05)	(0.02)	(0.05)	(0.03)	(0.09)
rainfall, cm	1.03***		1.03***		0.93***	
per day	(0.20)		(0.20)		(0.24)	
ML X rainfall	-1.36***	-1.25*	-1.42***	-1.19*	-1.35***	-1.48
	(0.30)	(0.70)	(0.30)	(0.70)	(0.37)	(1.10)
rainfall	-20.07***		-20.07***		-21.33***	
variance, daily	(2.00)		(2.00)		(2.40)	
ML X rainvar	7.70***	8.69*	7.68***	9.87**	-0.11	7.72
	(2.48)	(4.63)	(2.52)	(4.73)	(3.55)	(8.98)
temperature, C	3.53***		3.53***		3.91***	
/100	(1.03)		(1.03)		(1.19)	
temperature	-1.09***		-1.09***		-0.91***	
ˆ2 /100	(0.29)		(0.29)		(0.33)	
temperature	0.09		0.09		0.10	
ˆ3 /100	(0.07)		(0.07)		(0.08)	
ML X temp	-2.43*	-7.41***	-2.11	-7.60***	-2.27	-14.47***
	(1.28)	(2.84)	(1.31)	(2.89)	(1.77)	(4.64)
ML X temp_sq	-0.74*	-1.06	-0.64	-1.02	-0.38	-2.48**
	(0.42)	(0.72)	(0.43)	(0.72)	(0.51)	(1.03)
ML X temp_cub	0.14	0.31*	0.12	0.31*	0.11	0.74***
	(0.09)	(0.17)	(0.09)	(0.17)	(0.12)	(0.26)
fertilizer,	3.00***	2.86***	2.99***	2.75***	2.88***	2.70***
tonnes per ha	(0.15)	(0.45)	(0.14)	(0.45)	(0.16)	(0.70)
fertilizer	-1.98***	-1.22	-1.98***	-1.07	-1.58***	-0.32
ˆ2	(0.36)	(0.85)	(0.36)	(0.85)	(0.38)	(1.28)
ML X fert	1.07***	-1.05**	0.95***	-0.97**	0.47**	-0.70
	(0.20)	(0.49)	(0.20)	(0.49)	(0.24)	(0.72)
ML X fert_sq	-1.58***	3.12*	-1.41***	3.11*	-0.96*	3.65
	(0.49)	(1.67)	(0.49)	(1.69)	(0.53)	(2.80)
Constant	14.47***	14.30***	14.47***	14.31***	14.48***	14.32***
	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.04)
Observations	13305	1676	12927	1636	8534	740
R-squared overall		0.13		0.12		0.12

Note Standard errors (clustered by household) in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. For all columns, IV used for *rainfall*. Dependent variable for all columns - log of energy yield. Definitions of M and ML intercrop: ML - M and L grown on the same plot vs. M grown without L (other crops permitted); ML13 - both M and L are listed among three most important crops grown on a plot; ML only - M and L are the only crops grown on a plot.

Table 21: Estimation results: Alternative Definitions of M and ML - Part 2

	ML share>50%		ML share>75%		ML share>95%		ML share=100%	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	hhold-time FE	OLS	hhold-time FE	OLS	hhold-time FE	OLS	hhold-time FE
=1 if ML	0.18***	0.27***	0.16***	0.27***	0.11***	0.23***	0.16***	0.05
technology	(0.03)	(0.07)	(0.03)	(0.07)	(0.03)	(0.08)	(0.05)	(0.16)
rainfall, cm	1.01***		1.00***		1.06***		1.08***	
per day	(0.21)		(0.21)		(0.22)		(0.22)	
ML X rainfall	-1.65***	-1.52*	-1.71***	-1.88**	-2.18***	-2.22**	-2.60***	-3.89*
	(0.35)	(0.87)	(0.35)	(0.94)	(0.38)	(1.11)	(0.59)	(2.09)
rainfall	-20.50***		-20.34***		-22.18***		-22.75***	
variance, daily	(2.04)		(2.09)		(2.23)		(2.26)	
ML X rainvar	13.12***	9.71	13.30***	10.93*	15.69***	12.72	18.32***	20.49
	(2.80)	(6.23)	(2.87)	(6.61)	(3.30)	(8.18)	(4.89)	(12.54)
temperature, C	3.61***		3.69***		3.43***		3.59***	
/100	(1.04)		(1.05)		(1.08)		(1.10)	
temperature	-1.17***		-1.17***		-1.22***		-1.17***	
ˆ2 /100	(0.30)		(0.30)		(0.31)		(0.31)	
temperature	0.11		0.11		0.14*		0.13*	
ˆ3 /100	(0.07)		(0.07)		(0.07)		(0.07)	
ML X temp	-0.45	-12.29***	-0.93	-13.19***	-0.74	-17.43***	-1.90	-18.50**
	(1.43)	(3.71)	(1.46)	(3.97)	(1.60)	(4.56)	(2.34)	(8.16)
ML X temp_sq	-0.42	-1.61*	-0.26	-1.58	0.58	-2.11*	0.38	-0.13
	(0.53)	(0.98)	(0.53)	(1.03)	(0.56)	(1.13)	(0.89)	(2.04)
ML X temp_cub	0.01	0.54**	0.03	0.57**	-0.09	0.80***	0.03	0.55
	(0.11)	(0.23)	(0.11)	(0.25)	(0.12)	(0.28)	(0.18)	(0.47)
fertilizer,	3.01***	2.85***	3.03***	3.08***	2.98***	2.70***	2.94***	3.15**
tonnes per ha	(0.15)	(0.62)	(0.15)	(0.65)	(0.15)	(0.72)	(0.15)	(1.37)
fertilizer	-2.01***	-0.42	-2.07***	-0.79	-1.98***	-0.64	-1.93***	-1.94
ˆ2	(0.36)	(1.56)	(0.36)	(1.62)	(0.36)	(1.75)	(0.37)	(2.85)
ML X fert	0.73***	-0.40	0.55**	-0.42	0.09	-0.27	0.26	-1.88
	(0.26)	(0.70)	(0.26)	(0.73)	(0.27)	(0.81)	(0.41)	(1.35)
ML X fert_sq	-2.37**	0.04	-1.76*	-0.28	-0.47	-0.44	0.28	4.61
	(1.02)	(2.81)	(1.02)	(2.99)	(1.06)	(3.26)	(1.55)	(6.11)
Constant	14.46***	14.22***	14.47***	14.23***	14.46***	14.20***	14.46***	14.31***
	(0.02)	(0.03)	(0.02)	(0.04)	(0.02)	(0.04)	(0.02)	(0.07)
Observations	10720	1032	10374	968	9319	798	7001	274
R-squared overall		0.08		0.08		0.08		0.12

Note Standard errors (clustered by household) in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. For all columns, IV used for *rainfall*. Dependent variable for all columns - log of energy yield. Definitions of M and ML intercrop: ML share¿X% - for ML, harvest shares of both M and L are larger than 10%, sum of the shares larger than X%; for M, its harvest share is larger than X%. X is either 50, 75, 95, or 100.

Table 22: Estimation results: Alternative Definitions of M and ML - Part 3

	(1) with M only & dummy	(2) with ML only & dummy	(3) 3 vs. 100-3 & rule	(4) 5 vs. 100-5 & rule
ML technology	0.30^{***}	0.26^{***}	0.28^{***}	0.29^{***}
(dummy or landshare)	(0.07)	(0.06)	(0.06)	(0.07)
ML X rainfall	-1.29^{*}	-1.26^{*}	-2.09^{**}	-2.29^{***}
	(0.70)	(0.70)	(0.84)	(0.86)
ML X rainvar	8.65^{*}	8.63^{*}	17.20^{***}	17.56^{***}
	(4.64)	(4.62)	(6.30)	(6.42)
ML X temp	-7.55^{***}	-7.35^{**}	-12.67^{***}	-13.55^{***}
	(2.85)	(2.86)	(3.53)	(3.58)
ML X temp_sq	-1.08	-1.07	-1.37	-1.61^{*}
	(0.72)	(0.72)	(0.87)	(0.90)
ML X temp_cub	0.31^{*}	0.31^{*}	0.53^{**}	0.58^{***}
	(0.17)	(0.17)	(0.21)	(0.22)
fertilizer,	2.84^{***}	2.86^{***}	3.14^{***}	2.95^{***}
tonnes per ha	(0.45)	(0.45)	(0.55)	(0.56)
fertilizer	-1.22	-1.22	-1.82^{*}	-1.54
ˆ2	(0.85)	(0.85)	(1.07)	(1.08)
ML X fert	-1.06^{**}	-1.05^{**}	-1.06^{*}	-0.88
	(0.49)	(0.49)	(0.62)	(0.64)
ML X fert_sq	3.21^{*}	3.14^{*}	2.94	2.45
	(1.68)	(1.67)	(2.33)	(2.44)
=1 if M only	0.05			
	(0.07)			
=1 if ML only		0.02		
		(0.07)		
Constant	14.27^{***}	14.30^{***}	14.26^{***}	14.23^{***}
	(0.05)	(0.02)	(0.03)	(0.03)
Observations	1676	1676	1200	1150
R-squared				
R-squared overall	0.13	0.13	0.13	0.12

Note Standard errors (clustered by household) in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. For all columns, IV used for *rainfall*. Dependent variable for all columns - log of energy yield. Definitions of M and ML intercrop: column (1) - as in the main specification, but regression includes "M only" dummy; (2) - as in the main specification, but regression includes "ML only" dummy; (3) - "3 vs. 100-3" rule: harvest share of M on M plots is at least 97%, harvest share of legumes on ML plots is at least 3%; (4) - "5 vs. 100-5" rule: harvest share of M on M plots is at least 95%, harvest share of legumes on ML plots is at least 5%.

Table 23: Alternative definition of ML intercrop (ML shares > 75%) vs. other technologies (Analog of Table 12)

	(1) ML rotation	(2) M+L	(3) M+L, legume share	(4) L	(5) M, legume share
=1 if ML technology	-0.04	-0.39	-0.15	-0.39**	-0.09
	(0.18)	(0.28)	(0.28)	(0.20)	(0.10)
rainfall, cm per day					
ML X rainfall	-4.75**	-4.37	-5.04*	-1.52	-1.65*
	(2.16)	(3.00)	(2.96)	(1.37)	(0.84)
rainfall variance, daily					
ML X rainvar	52.98**	38.89	52.99*	29.44*	7.17
	(21.26)	(30.13)	(28.86)	(16.68)	(6.05)
temperature, C /100					
temperature ˆ2 /100					
temperature ˆ3 /100					
ML X temp	7.85	14.84	13.19	18.15**	-10.50***
	(11.48)	(16.41)	(16.12)	(8.24)	(3.69)
ML X temp_sq	3.23*	4.23	4.67*	4.89***	-1.30
	(1.82)	(2.65)	(2.59)	(1.70)	(0.97)
ML X temp_cub	-0.95	-1.14	-1.18	-1.23**	0.49**
	(0.75)	(0.99)	(0.97)	(0.53)	(0.23)
fertilizer, tonnes per ha	-4.38***	1.87	3.49	-5.89	3.24***
	(1.57)	(2.96)	(2.96)	(3.93)	(0.61)
fertilizer ˆ2	18.04***	4.29	1.23	9.96	-1.23
	(6.98)	(11.01)	(10.85)	(6.82)	(1.54)
ML X fert	2.24	-1.89	-2.04	6.48	-0.16
	(1.89)	(2.93)	(2.86)	(3.98)	(0.69)
ML X fert_sq	-10.08	-1.44	-3.41	-5.23	-0.90
	(8.79)	(12.84)	(12.53)	(7.82)	(2.77)
harvest share of L			1.01**		1.00***
			(0.43)		(0.20)
Constant	14.36***	14.67***	14.11***	14.71***	14.23***
	(0.08)	(0.10)	(0.26)	(0.17)	(0.03)
Observations	426	164	164	726	1032
R-squared overall	0.04	0.08	0.07	0.12	0.07

Note Standard errors (clustered by household) in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Estimation method for all columns: household-time FE, IV used for *rainfall*. Dependent variable in all columns - log of energy yield. ML intercrop is defined as all plots with harvest shares of both M and L larger than 10%, sum of the shares larger than 75%. ML intercrop is compared with: column (1) - M-L rotation; (2) - M+L (growing M and L on separate plots); (3) - M+L, controlling for the harvest share of L; (4) - L (growing only L); (5) - M, controlling for the harvest share of L in ML.

Table 24: Maize and legume productivity for different technologies (with alternative definition of ML intercrop, ML shares >75%, analog of Table 13)

	M vs. L		**M only** vs. M in M-L rotation	M yield, **ML** vs. M	L yield, **ML** vs. L
	(1)	(2)	(3)	(4)	(5)
	OLS	hhold-time FE	OLS	hhold-time FE	hhold-time FE
=1 if	-0.23**	-0.32	-0.09**	-0.24***	-1.46***
technology in **bold**	(0.10)	(0.25)	(0.04)	(0.07)	(0.21)
rainfall, cm	1.07***		2.31***		
per day	(0.35)		(0.36)		
ML X rainfall	-0.07	0.90	-1.77***	-1.80**	-0.84
	(0.39)	(0.58)	(0.43)	(0.86)	(1.48)
rainfall	0.51		-63.81***		
variance, daily	(4.59)		(5.15)		
ML X rainvar	-20.85***	-44.75***	51.30***	5.31	39.90**
	(4.91)	(7.76)	(5.57)	(6.26)	(17.98)
temperature, C	-0.08		1.74		
/100	(2.27)		(2.16)		
temperature	-3.19***		-3.39***		
ˆ2 /100	(0.49)		(0.45)		
temperature	0.23		0.59***		
ˆ3 /100	(0.16)		(0.16)		
ML X temp	3.77	3.41	-1.45	-7.97**	19.57**
	(2.44)	(3.64)	(2.47)	(3.77)	(8.98)
ML X temp_sq	2.03***	1.37*	2.36***	-0.86	5.67***
	(0.55)	(0.80)	(0.61)	(0.99)	(1.82)
ML X temp_cub	-0.12	-0.05	-0.42**	0.39	-1.29**
	(0.17)	(0.26)	(0.18)	(0.24)	(0.59)
fertilizer,	-7.08***	-7.03**	1.43***	3.32***	-11.61***
tonnes per ha	(1.39)	(3.27)	(0.28)	(0.63)	(4.36)
fertilizer	12.38***	17.63	-0.78	-1.26	18.25**
ˆ2	(2.74)	(12.30)	(0.60)	(1.57)	(7.36)
ML X fert	10.18***	9.12***	2.12***	-0.17	11.71***
	(1.40)	(3.27)	(0.33)	(0.71)	(4.41)
ML X fert_sq	-14.45***	-19.08	-2.04***	-1.10	-13.68
	(2.77)	(12.30)	(0.75)	(2.84)	(8.41)
Constant	14.65***	14.52***	14.60***	14.17***	14.42***
	(0.10)	(0.25)	(0.04)	(0.03)	(0.19)
Observations	9229	3668	6804	1029	723
R-squared	0.13		0.04		
R-squared overall		0.07		0.08	0.48

Note Standard errors (clustered by household) in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. In all columns, IV used for *rainfall*, estimation method - household-time FE. Maize and legume productivity for different technologies (technology dummy is one for technologies in bold): columns (1) and (2) - M vs. L, log of energy yield, OLS and hhold-time FE; (3) - log of energy yield, maize only (no rotation or intercrop) vs. maize in M-L rotation; (4) - M only yield in M vs. ML; (5) - L only yield in L vs. ML. ML intercrop is defined as all plots with harvest shares of both M and L larger than 10%, sum of the shares larger than 75%.

Table 25: Alternative functional specifications for weather variables

	linear		square		cubic	
	(1)	(2)	(3)	(4)	(5)	(6)
	pooled OLS	hhold-time FE	pooled OLS	hhold-time FE	pooled OLS	hhold-time FE
ML technology	0.22***	0.24***	-0.00	0.35***	0.09**	0.28***
(dummy or landshare)	(0.02)	(0.04)	(0.04)	(0.08)	(0.03)	(0.09)
fertilizer,	2.97***	2.84***	2.96***	2.98***	3.15***	2.72***
tonnes per ha	(0.14)	(0.45)	(0.15)	(0.45)	(0.15)	(0.47)
fertilizer	-1.98***	-1.16	-1.92***	-1.24	-2.07***	-0.96
ˆ2	(0.37)	(0.85)	(0.38)	(0.85)	(0.36)	(0.88)
ML X fert	1.00***	-1.14**	0.90***	-1.03**	0.57***	-0.98*
	(0.19)	(0.49)	(0.20)	(0.49)	(0.21)	(0.51)
ML X fert_sq	-1.46***	3.50**	-1.29***	3.04*	-0.80	3.37**
	(0.50)	(1.67)	(0.50)	(1.67)	(0.50)	(1.71)
rainfall, cm	1.13***		0.66***		4.71***	
per day	(0.20)		(0.25)		(0.44)	
ML X rainfall	-1.38***	-1.51**	-0.72**	-1.51**	-2.29***	-5.08***
	(0.30)	(0.74)	(0.34)	(0.70)	(0.67)	(1.60)
rainfall	-19.15***		-15.51***		8.22*	
variance, daily	(1.95)		(2.56)		(4.34)	
ML X rainvar	8.77***	11.44**	7.12**	19.39***	2.99	18.46*
	(2.38)	(4.57)	(3.28)	(6.12)	(5.73)	(9.96)
temperature, C	2.34***		4.16***		8.31***	
/100	(0.51)		(0.83)		(1.36)	
ML X temp	-2.47***	-3.94***	-2.98***	-2.21	-4.73***	-3.21
	(0.63)	(1.39)	(1.05)	(1.97)	(1.76)	(3.43)
rainfall			-16.72***		5.72**	
ˆ2			(3.11)		(2.36)	
ML X			19.46***	2.33	5.35*	6.36
rainfall_sq			(4.02)	(5.22)	(2.90)	(5.11)
rainfall			1.09		6.50***	
variance ˆ2 x 100			(1.26)		(1.02)	
ML X rainvar_sq			1.44	-7.32***	11.08***	-10.13*
			(1.52)	(2.56)	(2.28)	(6.14)
temperature			-0.81***		-0.42	
ˆ2 /100			(0.21)		(0.34)	
ML X temp_sq			0.31	-0.24	-0.83	-0.05
			(0.26)	(0.45)	(0.52)	(0.81)
rainfall					-0.90***	
ˆ3 x 100					(0.11)	
ML X					0.51***	1.03***
rainfall_cube					(0.17)	(0.36)
rainfall					-44.68***	
variance ˆ3 x 1000					(6.79)	
ML X					-24.75**	19.05
rainvar_cube					(10.65)	(23.59)
temperature					-0.16*	
ˆ3 /100					(0.08)	
ML X temp_cub					0.26**	0.04
					(0.12)	(0.21)
Constant	14.42***	14.30***	14.61***	14.30***	14.38***	14.30***
	(0.01)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)
Observations	13305	1676	13305	1676	13305	1676
R-squared	0.09		0.08		0.05	
R-squared overall		0.13		0.12		0.10

Note Standard errors (clustered by household) in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. In all columns, IV used for *rainfall*, *rainfallˆ2*, and *rainfallˆ3*. Dependent variable in all specifications - log energy yield. Columns 1,2 - all weather variables (rainfall, rainfall variance, temperature) linear; column 3,4 - all weather variables linear and quadratic; column 5,6 - all weather variables linear, quadratic, and cubic.

Table 26: M vs. ML controlling for seed input and land size

	pooled OLS		hhold-time FE	
	(1)	(2)	(3)	(4)
	log_energy_yield	log_energy_yield	log_energy_yield	log_energy_yield
ML technology	0.21***	0.23***	0.33***	0.36***
(dummy or landshare)	(0.05)	(0.05)	(0.07)	(0.07)
rainfall, cm	2.67***	2.63***		
per day	(0.42)	(0.41)		
ML X rainfall	-3.94***	-3.89***	-1.55*	-1.66*
	(0.56)	(0.56)	(0.91)	(0.89)
rainfall	-8.91***	-9.18***		
variance, daily	(2.63)	(2.60)		
ML X rainvar	17.61***	17.96***	4.77	6.59
	(3.51)	(3.47)	(5.48)	(5.40)
temperature, C	19.65***	19.21***		
/100	(1.98)	(1.96)		
temperature	2.85***	2.65***		
ˆ2 /100	(0.39)	(0.39)		
temperature	-0.85***	-0.82***		
ˆ3 /100	(0.10)	(0.10)		
ML X temp	-14.50***	-14.49***	-8.52**	-8.75**
	(2.50)	(2.47)	(3.67)	(3.60)
ML X temp_sq	-1.63***	-1.61***	-1.63*	-1.48*
	(0.56)	(0.56)	(0.83)	(0.82)
ML X temp_cub	0.64***	0.64***	0.39**	0.36*
	(0.13)	(0.13)	(0.19)	(0.18)
fertilizer,	3.18***	3.06***	2.66***	2.51***
tonnes per ha	(0.22)	(0.22)	(0.49)	(0.48)
fertilizer	-2.47***	-2.44***	-1.23	-1.29
ˆ2	(0.47)	(0.46)	(0.89)	(0.87)
ML X fert	0.32	0.22	-1.38**	-1.34**
	(0.30)	(0.30)	(0.58)	(0.57)
ML X fert_sq	-0.66	-0.53	4.64**	4.21**
	(0.71)	(0.70)	(1.83)	(1.80)
log seed input,	0.10***	0.08***	0.06	0.04
kg per ha	(0.01)	(0.01)	(0.05)	(0.05)
plot area, ha		-0.17***		-0.29***
		(0.04)		(0.06)
Constant	13.89***	14.06***	14.07***	14.25***
	(0.05)	(0.06)	(0.13)	(0.14)
Observations	4954	4954	1215	1215
R-squared	0.20	0.21		
R-squared overall			0.11	0.15

Note Standard errors (clustered by household) in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. In all columns, IV used for *rainfall*. Dependent variable in all specifications - log energy yield. Seed data is available only for waves 2 and 3 of the survey (hence, GMM estimation is not possible).

Table 27: Estimation results: Various specification of GMM regression

	(1) main specification	(2) all var's except yield strictly exogenous	(3) weather var's only strictly exogenous	(4) T and fert. vars lagged	(5) no time f.e.	(6) orthogonal projections
ML technology	0.26***	0.27***	0.15*	0.17	0.28***	0.26***
(dummy or landshare)	(0.07)	(0.07)	(0.08)	(0.13)	(0.07)	(0.07)
rainfall, cm	2.07***	1.32***	2.54***	1.88***	2.18***	2.07***
per day	(0.32)	(0.31)	(0.34)	(0.50)	(0.32)	(0.32)
ML X rainfall	-2.04***	-1.63***	-2.09***	-0.67	-2.10***	-2.04***
	(0.53)	(0.53)	(0.57)	(0.83)	(0.54)	(0.53)
rainfall	-4.58	-1.47	-8.34**	-7.67*	-8.84***	-4.57
variance, daily	(3.08)	(3.00)	(3.44)	(4.36)	(3.03)	(3.07)
ML X rainvar	14.69***	12.29***	17.47***	14.17**	13.92***	14.75***
	(4.45)	(4.71)	(5.06)	(6.50)	(4.47)	(4.45)
temperature, C	23.55***	23.09***	25.24***	28.63***	21.01***	23.56***
/100	(3.16)	(3.10)	(3.17)	(4.06)	(3.13)	(3.15)
temperature	3.86***	3.40***	2.82***	4.01***	3.72***	3.86***
ˆ2 /100	(0.60)	(0.56)	(0.56)	(0.83)	(0.60)	(0.60)
temperature	-1.15***	-1.20***	-1.13***	-1.53***	-0.99***	-1.16***
ˆ3 /100	(0.17)	(0.17)	(0.17)	(0.25)	(0.17)	(0.17)
ML X temp	-16.63***	-15.80***	-17.44***	-21.40***	-13.82***	-16.67***
	(4.18)	(4.21)	(4.35)	(5.73)	(4.17)	(4.18)
ML X temp_sq	-3.80***	-3.20***	-2.42**	-4.69***	-2.70***	-3.80***
	(0.99)	(0.93)	(0.95)	(1.41)	(0.98)	(0.99)
ML X temp_cub	1.06***	1.09***	0.99***	1.54***	0.79***	1.07***
	(0.23)	(0.23)	(0.23)	(0.33)	(0.22)	(0.23)
fertilizer,	2.80***	2.88***	2.94***	-2.73	2.97***	2.80***
tonnes per ha	(0.37)	(0.31)	(0.39)	(2.04)	(0.37)	(0.37)
fertilizer	-2.93***	-2.44***	-3.19***	6.82	-3.25***	-2.93***
ˆ2	(0.76)	(0.64)	(0.74)	(5.97)	(0.78)	(0.76)
ML X Txfert	0.29	0.49	0.47	0.40	0.32	0.29
	(0.57)	(0.48)	(0.58)	(2.68)	(0.57)	(0.57)
ML X Txfert_sq	0.35	-0.47	-0.00	9.36	-0.09	0.34
	(1.56)	(1.32)	(1.59)	(9.98)	(1.61)	(1.56)
L.log_energy_yield	0.08**	0.12***	0.11***	0.17***	0.03	0.08**
	(0.03)	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)
(mean) wave=1	0.00	0.00	0.00	0.00		0.00
	(.)	(.)	(.)	(.)		(.)
(mean) wave=2	12.91***	12.31***	0.00	11.64***		12.89***
	(0.46)	(0.58)	(.)	(0.63)		(0.47)
(mean) wave=3	13.14***	12.54***	0.24***	12.04***		13.13***
	(0.46)	(0.57)	(0.04)	(0.61)		(0.46)
Constant	0.00	0.00	12.57***	0.00	13.72***	0.00
	(.)	(.)	(0.52)	(.)	(0.46)	(.)
Observations	3095	3095	3095	3095	3095	3095

Note Standard errors (clustered by household) in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. In all columns, IV used for *rainfall*, *rainfallˆ2*, and *rainfallˆ3*. Dependent variable in all specifications - log energy yield. Wave represents the wave of the survey (total of 3). Detailed description of the specifications: column 1 - the main specification from Table 9; column 2 - all variables except lagged log_energy_yield are assumed strictly exogenous; column 3 - only weather variables (rainfall rainfall variation and their interactions with T) are assumed strictly exogenous; column 4 - similar to column 3, but T and fertilizer variables are instrumented with second lags; column 5 - similar to column 1, but time fixed effects are not included; column 6 - similar to column 1, but orthogonal projections are used instead of differencing.

Table 28: Main estimation results with time fixed effects

	(1)	(2)	(3)	(4)
	pooled OLS	hhold-time FE	hhold-time & techn. FE	hhold FE GMM
ML technology	0.18***	0.27***		0.10
(dummy or landshare)	(0.02)	(0.05)		(0.13)
rainfall, cm	0.40**			1.85***
per day	(0.20)			(0.47)
ML X rainfall	-0.80***	-1.25*	-1.60	-0.83
	(0.30)	(0.70)	(2.47)	(0.80)
rainfall	5.87**			-8.09*
variance, daily	(2.39)			(4.25)
ML X rainvar	10.33***	8.69*	12.52	15.45**
	(2.39)	(4.63)	(24.16)	(6.41)
temperature, C	2.36**			28.33***
/100	(1.02)			(4.05)
temperature	1.47***			3.80***
ˆ2 /100	(0.32)			(0.81)
temperature	-0.33***			-1.50***
ˆ3 /100	(0.07)			(0.25)
ML X temp	-2.00	-7.41***	-21.24**	-21.82***
	(1.25)	(2.84)	(8.88)	(5.77)
ML X temp_sq	-0.66	-1.06	3.29	-4.39***
	(0.42)	(0.72)	(4.04)	(1.37)
ML X temp_cub	0.12	0.31*	0.83	1.51***
	(0.09)	(0.17)	(0.60)	(0.33)
fertilizer,	3.38***	2.86***	2.82**	-2.16
tonnes per ha	(0.14)	(0.45)	(1.39)	(2.01)
fertilizer	-2.50***	-1.22	-1.00	3.75
ˆ2	(0.35)	(0.85)	(2.38)	(5.30)
ML X Txfert	1.05***	-1.05**	-2.40	0.49
	(0.19)	(0.49)	(2.01)	(2.84)
ML X Txfert_sq	-1.56***	3.12*	4.40	11.26
	(0.48)	(1.67)	(7.48)	(9.77)
(mean) wave=1	0.00			0.00
	(.)			(.)
(mean) wave=2	-0.57***			12.43***
	(0.03)			(1.07)
(mean) wave=3	-0.34***			12.81***
	(0.02)			(1.05)
L.log_energy_yield				0.11
				(0.07)
Constant	14.60***	14.30***	-0.00	0.00
	(0.02)	(0.02)	(0.03)	(.)
Observations	13305	1676	196	3095
R-squared	0.17			
R-squared overall		0.13	0.09	

Note Standard errors (clustered by household) in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. In all columns, IV used for *rainfall*, *rainfallˆ2*, and *rainfallˆ3*. Dependent variable in all specifications - log energy yield. Wave represents the wave of the survey (total of 3).

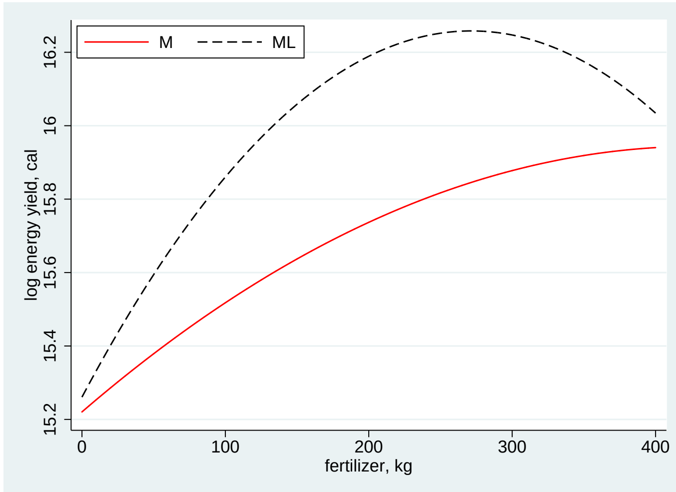


Figure 12: Estimated response to fertilizer: M vs. ML - GMM

Note: Based on the estimation in Table 1, column 9 - GMM.

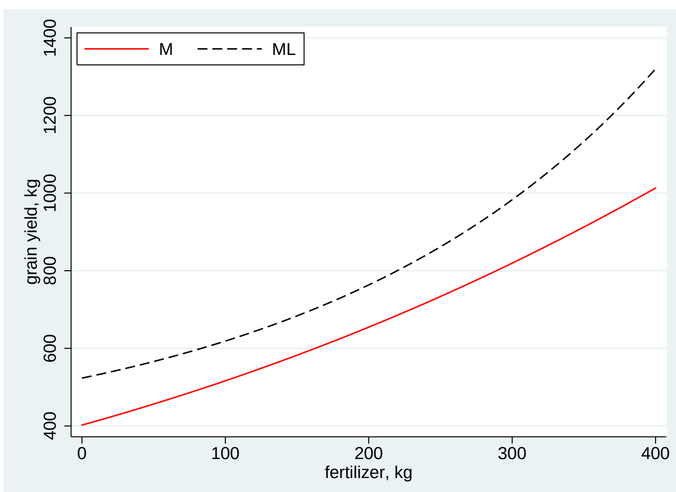


Figure 13: Estimated response to fertilizer: M vs. ML - Grain yield

Note: Based on the estimation in Table 1, column 4 - household-time FE. Yield measure - log grain yield.

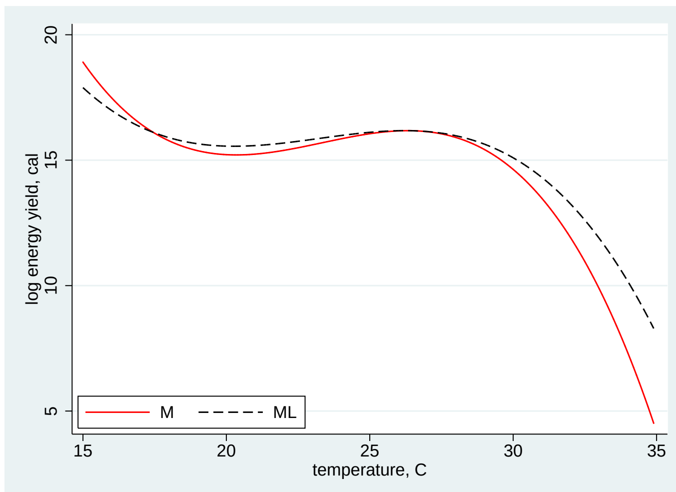


Figure 14: Estimated effect of temperature on yield: M vs. ML - Household-time FE

Note: Based on the estimation in Table 1, column 4 (household-time FE) for ML-specific coefficients, column 9 (GMM) for non ML-specific coefficients. The maximal average temperature observed in Malawi over the estimation period is 28.5°C. For higher temperatures the predictions are out of sample.

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