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Keywords: inverse relationship, agriculture, Tanzania

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Abstract

The debate on the existence of an inverse relationship between farm size and productivity is probably one of the oldest debates in the development economics literature. While publication of more detailed agricultural data has pushed for an empirical revival of the topic, the concept of size is still problematic in these studies, as well as the limited attention given to existing varieties of farming practices. Using agricultural data on Tanzania, we introduce a crop/plot level of analysis which allows us to enquire whether an inverse relationship exists for crops grown on a given plots. In a context where intercropping is widespread, this level of analysis looks more appealing than the more traditional plot or farm levels. We control for the existing hypotheses in the literature that could explain the existence of the relationship. Further, we propose to control for a new set of hypotheses which have not received enough attention in the existing literature. Our results show that the inverse relationship is strikingly robust at this new level of analysis: yields are on average higher on smaller cultivated areas in all specifications and for all crops.

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1 Introduction

Since the seminal work on Russian peasantries in the early 20th century by agricultural economist and statistician Chayanov, economists have debated the existence of an inverse relationship between size and productivity in agriculture. This debate has had an important influence on land redistribution policies in several countries across Africa, such as Ethiopia or Zimbabwe. Despite being contested for about a hundred years, no consensus has been reached regarding this matter, and the inverse relationship still constitutes an important research area both at the theoretical and empirical levels, as well as at the policy level. At the theoretical level, it is at odds with the textbook which argues the inverse relationship should trigger a reallocation of land *across* households from the least productive to the most productive ones in the absence of market failures. Factor reallocation should also occur *within* households so as to equate productivity across plots farmed (Barrett, Bellemare and Hou, 2010). At the empirical level, the nature of agricultural data makes analysis subject to many biases, many of which remain to be acknowledged. Finally, at the policy level, the theoretical case for land redistribution policies as a means for eradicating poverty has been heavily challenged and called into question.

Using Tanzanian agriculture as a case study, this paper argues that a fruitful way to look at this old question is to consider a different level of analysis than the usual plot or farm size levels. Indeed, we argue that the concept of size is problematic when following such analysis. This is especially the case in sub-Saharan African countries where intercropping is heavily practiced, which implies there can be an important difference between a plot size and the area on that plot on which a crop is grown. This further enhances the complexities linked to crop-composition effects (Kimhi, 2006).

This study proposes to take the analysis to a new level, the crop/plot level, to help bypass some of the issues arising when studying the existence of the inverse relationship, especially regarding the problem of size, as argued above. By looking at the determinants of yields for a given crop on a particular plot, our focus makes the estimates of cultivated area more precise than is usually the case, and also allows us to exploit the specificities of each crop on each plot (for instance, whether the crop is intercropped). This paper thus contributes to redifining the concept of 'size' in the context of Tanzanian agriculture, which is a problematic issue in the applied agricultural literature.

With this approach, we contribute to the literature in two important ways. First, we test whether the existing theoretical hypotheses in the literature, following the typology established in Barrett, Bellamare and Hou (2010), can explain the relationship at our new level of analysis. These hypotheses posit that the inverse relationship may be the result of market failures, omitted variable bias or statistical fallacy (or any combination of them). Second, we propose two new hypotheses which, to the best of our knowledge, have not been formally tested in the literature: at a crop/plot level, the inverse relationship could be driven by omitting to account for whether the crop is intercropped or monocropped, or by not accounting for the fact that some crops are primary crops on a plot and hence may reflect a different type of farming. Results show that the inverse relationship is strikingly robust to the crop/plot level of analysis for the hypotheses established in the literature. Further, the inverse relationship is also robust to the new set of hypotheses we test.

Section 2 establishes a typology of the different theories proposed to explain the inverse relationship, and recent developments in the empirical literature. Section 3 presents the data and key summary statistics. Section 4 sets out the methodology to control for the existing hypotheses in the literature and reports empirical results. Section 5 is dedicated to testing new hypotheses that could explain the inverse relationship, together with associated empirical results. Section 6 concludes.

2 A brief history and typology of the inverse relationship

Chayanov (1926) is often credited with being the first to notice the possibility of an inverse relationship (henceforth IR) in Russian peasantry in the early 20^{th} century (Assunção and Braido (2007), Barrett, Bellemare and Hou (2010)).[1] In the early 1960s, Sen also reported on an observed inverse relationship in Indian agriculture: *'By and large, productivity per acre decreases with the size of holding. This trend with gross output per acre is observed, more or less strongly, in practically all the regions studied'* (1962:243), which he would then theorize into the idea that different modes of production may be underlying this relationship. This is the origin of one important orthodox explanation for the inverse relationship, namely that smaller farms relying on family labour escape the capitalist logic, under which less labour would be used, and use more unit of labour per acre of land.

The literature on the inverse relationship is so vast that it cannot be entirely covered here, for it would deserve a study of its own. Instead, we propose to establish a typology of existing theories, and classify them into one of four categories. The first category is made of studies based on orthodox economic theory. It encompasses both a large theoretical and empirical literature. While Sen can

[1] However, the idea of an IR can be found in earlier work, notably that of Marx and early marxists like Klautsky, who refer to the possibility of an IR, albeit arising out of different reasons that the ones usually posited in the literature: 'As Marx had suggested, peasants on small-sized farms which were so small in scale would be pushed by subsistence to work harder in order to survive while remaining mired in poverty' (Akram-Lodhi and Kay, 2010).

be considered a pioneer in this strand, the most prominent contemporary economist in this tradition is Barrett, who wrote extensively on the inverse relationship (see for example Barrett (1996) and Barrett, Bellemare and Hou (2010)). This tradition tends to emphasize theoretical arguments based on imperfect markets and a higher efficiency of family labour, as opposed to hired labour considered harder to monitor and supervise. On the empirical side, it tends to emphasize the possibility of large omitted variable biases in econometric applications, as well as issues related to the quality of data available, which could drive an artificial relationship. Recently, several studies have stressed the need to move to more disaggregated levels to assess whether the relationship can still be observed. This literature can be seen as going hand in hand with the publication of more and more detailed national agricultural surveys (especially by the World Bank), and a growing awareness of problematic aspects of agricultural data, especially when it comes to measurement issues (Gourlay, Kilic and Lobell, 2017).

The second category is sometimes referred to as 'neo-classical populism' (particularly criticized by the third tradition). In this category, the seminal contribution is undoubtedly Griffin, Khan and Ickowitz (2002), who argue that small holders tend to economise more on capital and farm the land more intensively. Large scale farmers, on the other hand, have higher capital-labour ratios and farm the land more extensively. This is considered to be the key mechanism by which an inverse relationship arises. While the term 'neo-classical' is used to explain that this tradition relies on the orthodox framework of differential factor prices and imperfect markets (developed in the first category), the term 'populist' comes from the fact that it largely emphasizes the usual policy implication in favour of land redistribution. In fact, it supports a radical program of land redistribution from large to small holders as a means to eradicate widespread rural poverty.

The third category is made of studies based on heterodox economic theories and the political economy of development. This approach is critical towards the two previous approaches on the ground that orthodox theory does not offer a framework dynamic enough to explain peasant transformations and modes of farming. This tradition is based on a criticism of the assumptions underlying theoretical frameworks in other categories as well as those underpinning support for land redistribution policies. For example, Sender and Johnston (2004) argue that the theoretical narrative on imperfect markets is an example of circular reasoning: while inequalities in size distributions are conceptualised as the result of market failures, the very same argument is used to explain any absence of evidence on an inverse relationship. Taking the example of land redistribution policies in Zimbabwe and South Africa, they question the policy implications drawn in previous research, namely that land redistribution in favour of smallholders would trigger reductions in poverty. In both countries, redistribution was highly problematic: in South Africa, less than 4% of poor households actually benefited from the program, while in Zimbabwe, women were largely excluded from any benefits following redistribution.[2] In the same tradition, Dyer (2004) explains that existing studies tend to conflate the macro and micro dimension of the topic. While it is true that an inverse relationship at the macro level exists (due to historical population shifts and patterns of settlements in best endowed regions), the same cannot be said for the micro level, for which there is in fact very little evidence (at the village or district level for instance).

Finally, a fourth category can be identified, which relies more on rural sociology and anthropology than economics. A leading contemporary scholar in this tradition is van der Ploeg. This agrarian tradition is critical of the economic traditions because it argues they are inherently static and fail to account for the continuously shifting nature of peasant farming, as well as the fact that a farming strategy has to be understood in its totality for it to make sense. It argues that the inverse relationship cannot hold in the long run, for when diminishing returns are observed, farming practices change, shifting the production function on a new path, thereby offsetting diminishing returns. Its strong anthropological focus also makes this literature critical of neo-classical populism, because it argues that agrarian reform can never simply boil down to a land redistribution reform (van der Ploeg, 2013). Finally, this tradition argues that economic analysis often assumes that both peasants and capitalist farmers share the aim of profit maximisation. While it is true that capitalist farming seeks to maximise profit (total production minus inputs *and* wages), peasant farming would instead maximise net gross output (total production minus inputs).[3]

All of these traditions reveal interesting insights, from the necessity to address statistical concerns in orthodox theory to that of understanding farming endeavours in agrarian studies. Finally, it is important to note that these categories are not completely isolated from each other. Rather, each of them tends to insist more on particular aspects of the debate, and the extent to which two categories share some features varies with the existing state of research. For example, Sen (1962), while operating within the orthodox tradition, seemed to share in the 1960s some common grounds with contemporary agrarian studies.

Within the orthodox tradition, the possibility of an inverse relationship is in principle at odds with the

[2] This does not constitute a rejection of the existence of an inverse relationship as such, but it is a good example of the debate on the effectiveness of development policies based on the idea that an inverse relationship prevails in agriculture.

[3] This tradition of thought is very Chayanovian in its conception of a farming household, where 'household equilibrium' depends on a set of internal balances such as the one between effort and drudgery.

standard textbook approach. Neoclassical theory suggests that if smaller farms (or plots) are more productive, then production factors would adjust towards the most productive land/farms. Several categories of explanations for explaining the inverse relationship have been given in this literature. Barrett, Bellamare and Hou (2010) classify them into the following categories:

• **Imperfect markets**: The idea behind the imperfect market story is that small-scale farmers are more productive than their larger counterparts due to market failures. In particular, it emphasizes that small farmers may over-supply labour on their farm while larger farmers may under-supply labour in the presence of land market failures. The underlying idea is that the shadow prices of production differ across households and that this correlates with farm size. This will be referred to as **Proposition 1 (P1)** in our study.

• **Omitted variable bias**: This explanation is based on the fact that many features of soil quality, such as potassium content, are unobservable to researchers. If such features are positively correlated with production but negatively correlated with cultivated area, then omitting these unobservable factors may generate a spurious inverse relationship between productivity and size. This will be referred to as **Proposition 2 (P2)** in our study.

• **Statistical fallacy**: The idea of statistical fallacy relies on the fact that if size is measured with error and this error is negatively correlated with size (i.e., if the size of smaller farms is systematically over-estimated), then coefficients on land can be artifically biased downwards, and any observed inverse relationship is simply driven by 'bad data'. This will be referred to as **Proposition 3 (P3)** in our study.

Barrett, Bellamare and Hou (2010) use data on Madagascar collected in 2002, with the special feature that it includes precise soil measurements at the *plot level* like nitrogen and potassium content. Their results suggest that the imperfect market idea can only explain up to one third of the observed relationship, while no support for the omitted variable bias proposition is found. Assunção and Braido (2007) use Indian data from the ICRISAT project and show that explanations based on peasants' 'mode of production' or on excessive supervision costs in large farms (i.e., explanations following the imperfect market proposition) are not supported by their analysis either.

The statistical fallacy proposition sheds light on the possibility that the observed inverse relationship is simply an artefact of the data due to behavioural response biases. This is a serious point to consider, for if it is valid, it casts doubt on decades of research on the inverse relationship. Traditionally, survey data report plot or farm areas as reported by the farmer, which is the most straightforward and economical way to report areas. However, GPS measurement is becoming cheaper as a technology and many surveys now report both farmers' self-reported areas and GPS measurements. Our data does report both measures, which allows to directly test for this possibility.[4] Carletto *et al.* (2015) compare measures of areas for several datasets for which both measures are available, including the dataset used for this study. They find large discrepancies in measurements and show that area for small plots is often over-reported while that for large ones is usually under-reported. These findings emphasize the need to enquire whether an inverse relationship can be observed using GPS measurements in order to test whether any observed relationship is a statistical artefact coming from report bias or not. Very recent research suggests that measurement error in production may also be problematic. Gourlay, Kilic and Lobell (2017) is the first study we are aware of looking at possible biases in farmers' self-reported output measures for maize in Uganda. These can be due, for example, to a natural tendency of rounding off, or to recall bias which distort the measurement of production. Their results show that farmers' over-estimation of output may be the driving force behind the existence of the inverse relationship, the over-estimation being particularly strong for small plots in their Ugandan dataset.

Recently, empirical research has also taken into account the important difference between plot size and farm size when discussing a possible inverse relationship (Sheahan and Barrett, 2016). Traditionally, studies have focused on farm size, but as more precise agricultural data becomes available, it is clear that farm size is a problematic measure. Furthermore, the choice of crop on a particular plot may be endogenous: farmers may devote particular crops to particular plots. In that sense, looking at the possibility of an inverse relationship at the plot level looks more appropriate. Kimhi (2006) stresses the possibility of having *crop composition effects*: small-scale farmers may produce different crops than their large-scale counterparts, which may drive an artificial inverse relationship if not taken into account. However, even the plot level is not satisfying in a context of widespread intercropping, as the plot aggregate output only has limited economic and agronomic meaning when several crops are grown together on a single piece of land. In this study, we overcome these difficulties by looking at whether an inverse relationship holds at the crop/plot level for a set of important crops in Tanzanian agriculture: maize, rice, beans and groundnut.

[4] Although in the first wave of data, only 25% of plots were randomly assigned for GPS measurement.

3 Data and summary statistics

The data used in this study is the World Bank LSMS data for Tanzania, as explained in detail in chapter 1. We use the first three waves, covering the years 2008/09, 2010/11 and 2013/14. Variables used for the analysis come from the household and agricultural modules. Table 1 presents summary statistics for the main variables in the analysis by pooling the three waves of data available. Most farms and plots are observed two or three times. In total we have 6669 observations in our sample.

Table 1: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.
Area variables				
Plot size SR (acres)	2.79	5.82	0.05	130
Plot size GPS (acres)	3.15	6.39	0.01	155.83
Discrepancy (GPS-SR)	0.36	3.76	-86.19	59.25
Cultivated area on plot SR (acres)	1.62	2.14	0.01	50
Cultivated area on plot GPS (acres)	1.8	2.77	0.01	68.2
Output/input variables				
Yield pooled SR (kg/acre)	273.43	306.35	6.67	2340
Yield pooled GPS (kg/acre)	308.19	352.35	6.45	2353
Family labour (days/plot)	78.61	78.45	0	1170
Hired labour (days/plot)	6.17	15.9	0	161
Organic fertiliser (kg/plot)	77.54	278.84	0	2000
Inorganic fertiliser (kg/plot)	13.74	51.09	0	950
Plot characteristics				
Elevation (meters)	1055.58	512.28	3	2184
Irrigation facility on plot (0/1)	0.02	1=112	0	1
Soil quality	2.41	0.61	1	3
Farm and household variables				
Farm size (acres)	5.99	11.21	0.05	274
Number of crops on farm	5.4	3.14	1	20
Female-head (0/1)	0.23	1=1518	0	1
Age of head	50.09	15.93	19	108

Note: Full details are available in Table A1 in the Appendix

Summary variables in the **area variables** category report average plot size and average cultivated area for a crop on a plot using both self-reported (SR) and GPS measurements. The sample is restricted to plots being GPS measured so that comparisons between measures can be directly made. We compute a measure of discrepancy defined as the difference between the GPS measurement and the self-reported measurement.[5] On average, plots are bigger when measured by GPS, with a higher

[5] We thus make the assumption here that the GPS measure is the 'true' measure of area. This is of course problematic, but as explained later in the section, GPS measures are seen as superior in quality to self-reported ones. We follow Carletto *et al.* (2013) in the computation of the discrepancy measure, who find a much lower average discrepancy for Uganda at 0.11 acres.

standard deviation. The average discrepancy between GPS and SR measure is quite large, at 0.36 acre, suggesting that controlling for land measurement may impact the study of the IR.[6] Note however, that the discrepancy measure can be very large both in underestimating and overestimating plot size as revealed by the minimum and maximum values. Although we do observe a general tendency for larger plots to be underestimated, these statistics show they can also sometimes be largely overestimated. Average cultivated area for a crop on a plot is much smaller than average plot area, reflecting widespread intercropping and mixed-cropping strategies: on average, a crop in our sample is planted on 58% of the plot surface when using self-reported measures. These statistics confirm that looking at plot level aggregates in the context of Tanzania is misguided, hence justifying our more disaggregated level of analysis.

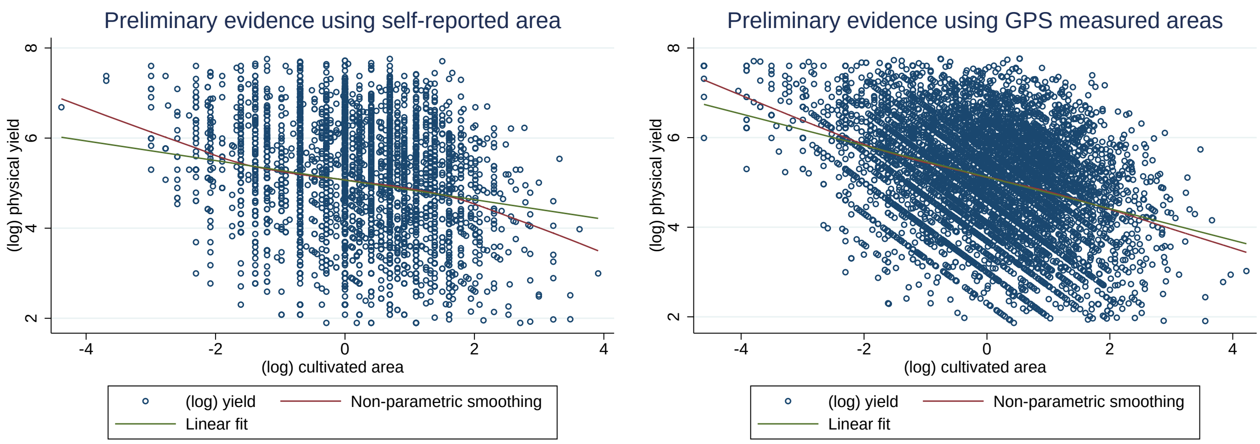
The **output/input variables** category reports information on average yields using both self-reported and GPS measurements. The average yield in our sample using farmers' self-reported data is 273 kg/acre. Using GPS data instead gives an average yield of about 308 kg/acre, with a higher standard deviation. Given that the average self-reported cultivated area is smaller than its GPS counterpart, one would expect the average self-reported yield to exceed the average GPS-measured yield. However, this does not necessarily have to be the case. When small plots are on average under-reported and large ones over-reported, it is possible for the average GPS yield to exceed the average self-reported one. In terms of **inputs**, family labour is very prevalent, with an average use of about 79 days per plot over the previous long season. Hired labour is much lower with just above 6 days, although this takes into account all farmers (i.e., it includes non-hirers). Restricting to hirers only, average hired labour increases to 21 days per plot. Similarly, we observe a large difference between use of organic and inorganic fertiliser. Most farmers cannot afford inorganic fertiliser, either because of its prohibitive price or because of access constraints (Minot, 2009). By restricting the sample to users only, average use of inorganic fertiliser increases to 81 kg per plot.

Regarding **plot characteristics**, the average elevation is rather uninformative given the vast geographical heterogeneity in Tanzania. This is reflected by the large standard deviation. Farming can take place at high altitudes, especially in the northern regions of the country, where climatic and soil conditions are very different from central or southern regions. Virtually all plots in our sample are heavily rainfall dependent: only 2% of them are irrigated. The soil quality variable is a categorical

[6]Figure 6 in the Appendix plots discrepancy against plot area. Consistent with De Groote and Traoré (2005), the discrepancy tends to be negative for very small plots and positive for larger ones, suggesting small-scale farmers overestimate their plot size, while large farmers underestimate it.

variable taking value 1 if the farmer judges the soil to be bad, 2 if average and 3 if good. Most plots are thus deemed to have relatively good soil according to farmers.[7] Finally, in terms of **farm/household** features, the average farm is 6 acres, with about 5 crops grown on the farm. Almost a quarter of households are female headed in our sample.

One way to motivate a study on a possible inverse relationship is to estimate a non-parametric regression of the log of yield on the log of area cultivated (Barrett, Bellemare and Hou (2010), Assunção and Braido (2007)). Figure 1 plots both a parametric and non-parametric regression of the log of yield on the log of cultivated area for all data (time and crops pooled), using both farmers' self-reported areas, and GPS measured areas. Results a priori confirm the existence of an inverse relationship and motivates our research question. Comparison of the linear and non-linear fit also suggests that parametric regression analysis is well suited for our purpose.



(a) Self-reported measures

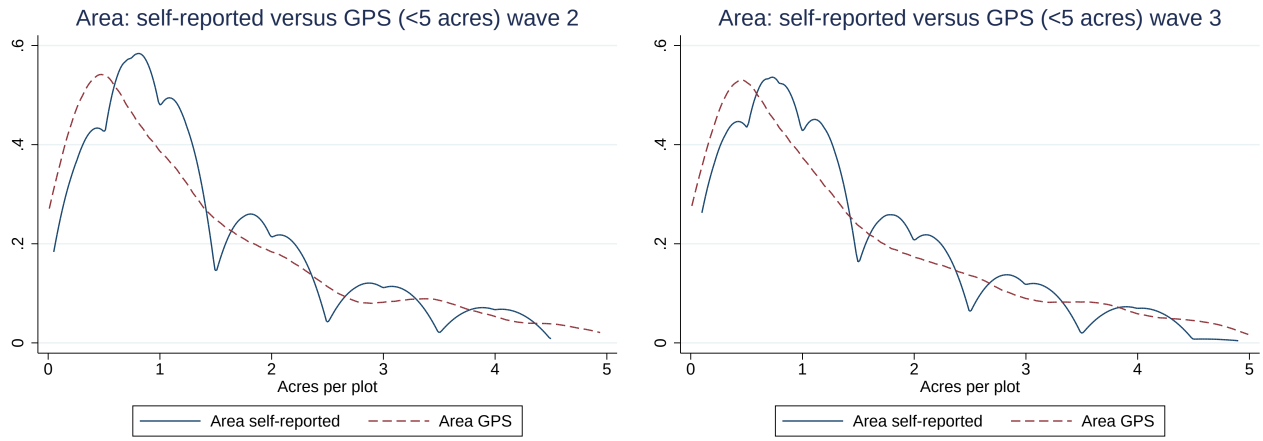
(b) GPS measures

Figure 1: Preliminary evidence using both self-reported and GPS measures

Although Figure 1 indicates that an inverse relationship a priori holds for both SR and GPS data, this does not imply that self-reported areas are not biased, as shown in Figure 2.

Figure 2 reports the kernel densities of self-reported areas and GPS measured areas for the second and third waves of the data (the proportion of GPS measured plots in wave 1 is too small to be reported), and shows that a bias is at work in the distribution of self-reported areas. The rationale for the statistical fallacy idea (proposition 3) is that measurement error may wrongly induce an inverse

[7]Although such measure is admittedly imperfect and most likely comes with a bias.



(a) Wave 2 (b) Wave 3

Figure 2: Kernel densities of cultivated area for SR and GPS measures

relationship *if* the bias takes the form of an underestimation of the size of small plots (i.e., if the error is negatively correlated with size).[8] Figures 2a and 2b reveal there is indeed a bias, but of a different kind. Rather than a systematic under reporting of small plot (which is only observed on *very* small plots, up to just above 0.5 acre), it seems that independently of plot size, the bias materialises in the form of bunching around integer values. After each integer value, the densities dramatically drop, resulting in a wave shaped distribution of self-reported areas, with peaks at integer values. On the other hand, the GPS distributions are, as expected, much smoother (Holden and Fisher (2013) observe a very similar pattern in their study of the IR in Malawi). However, while the bias is different from that described in proposition 3, the latter can still be empirically valid. Because many plots are very small (less than 1 acre), it may still be the case that small plots are under-reported on average. This is a point also made by Carletto *et al.* (2013) using Ugandan data: farmers are largely rounding off their estimates, which is directly related to the statistical fallacy idea since rounding off proportionally affects smaller plots more than larger ones.

Regarding GPS measures, a word of caution is useful. These measures are not devoid of bias either and should not be viewed as reflecting perfectly accurate measurements (Carletto *et al.*, 2015). Possible biases with GPS measurements include: bad weather conditions, inadequate walking speed, cutting corners and steepness of the land. Further, evidence from Monte Carlo simulations shows that GPS measurement accuracy increases with plot size (Bogaert *et al.*, 2005). When looking at small-scale agriculture as is the case in Tanzania, there is also a risk of measurement error with GPS data. However, it is generally accepted that when comparing self-reported and GPS data, the latter

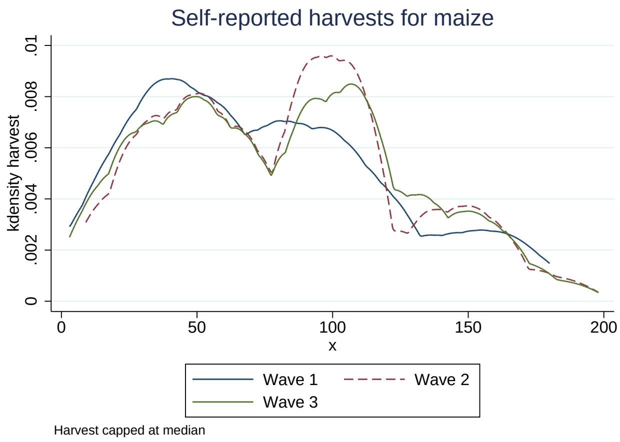
[8]'For the IR to be partially or fully explained by errors in land measurements, smaller farmers would have to systematically underreport land area with respect to larger farmers, thus resulting in artificially inflated yields in the bottom part of the distribution.' (Carletto *et al.*, 2013:255)

should be considered superior, with biases of smaller magnitude and less random that in self-reported data.

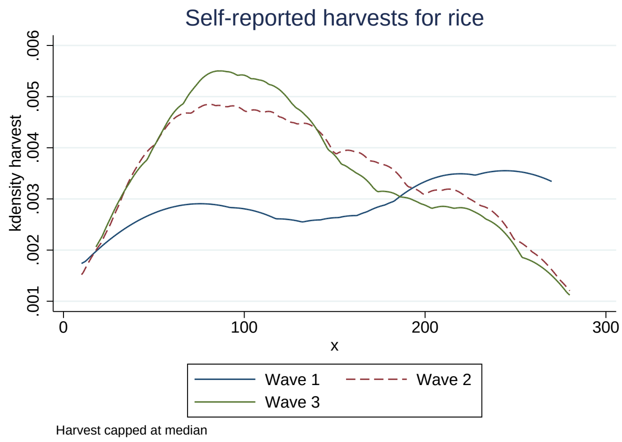
Finally, one potential concern is that while we possess more 'objective' measurement than self-reported areas with GPS measurements, we only have self-reported harvests. Recent frontier research has started exploring possible biases in *production* figures (i.e., in reported harvests and hence computed yields), and argues this may be of importance for the existence of an IR. Gourlay, Kilic and Lobell (2017) collected objective data in Uganda for production measures (using remotely-sensed estimates and precise cross cuttings) alongside self-reported measures. Possible measurement errors can arise because of a tendency of rounding off, but also because of recall problems or intentional biases (for example, a farmer may over-report his production if it is believed this could trigger participation in a public program). They find that self-reported yields tend to be higher, on average, than those calculated from more objective measures. The type of data they use is highly novel and is not available for existing LSMS datasets, including the one we use. Hence, we cannot replicate here their method. However, by plotting the densities of harvest for each crop, we can check whether any systematic bias in reported output seems to take place (for example, whether bunching around 'key' amounts, such as 50 or 100 Kg occur). Figure 3 plots densities of self-reported harvests capped at the median.[9]

Figure 3a shows that for maize, the main crop in our analysis, no clear bias is discernible, except perhaps for possible bunching around 100 kilograms in wave two. For rice there is no clear-cut evidence of widespread rounding off apart from a possible effect at 100kg in the third wave. For beans and groundnut, the concern for a possible report bias in harvest seems more justified in waves two and three. However, this is not a systematic under or overstimation bias, and hence is unlikely to affect the inverse relationship. In fact, the bunching around multiples of 20 may reflect relatively accurate measurements. Farmers typically evaluate their beans and nuts harvests using 20 litres plastic bags as units of measurement, which is often translated into 20 kilograms when reporting harvest. Hence, Figure 3 shows there is no a priori reason to suspect that a systematic under or over-estimation of harvests may affect our estimation of the IR.

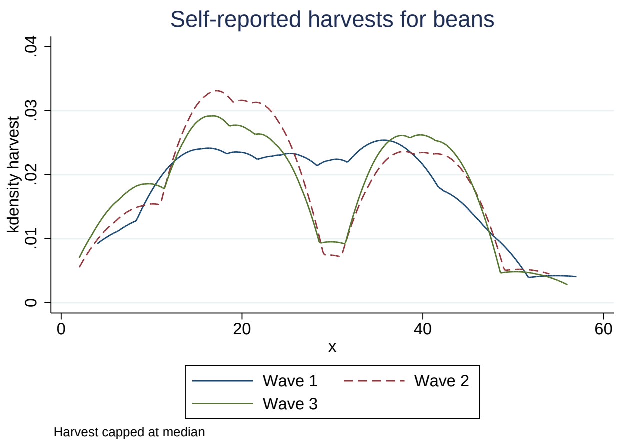
[9] The reason for capping at the median is twofold: the first is that it makes it easy to identify bunching over a smaller distribution, and the second is that we are mostly interested in small-scale farmers given that we are trying to evaluate whether yields are higher on smaller cultivated areas (there is growing consensus in the literature that self-reported bias are higher among small-scale farmers than their larger counterparts).



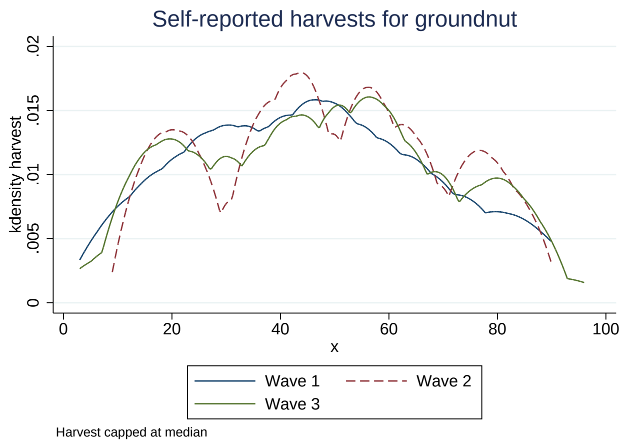
(a) Maize



(b) Rice



(c) Beans



(d) Groundnut

Figure 3: Kernel densities of self-reported harvest

4 Estimation strategy & results: Testing for conventional propositions

4.1 Estimation strategy

Our estimation strategy first consists in testing: the imperfect market proposition (*P1*), the omitted variable bias proposition (*P2*), and the statistical fallacy idea (*P3*). To do so, we exploit both the rich agricultural details from the questionnaires and the structure of the data (cross section and panel). As is common in the empirical literature, we estimate production functions from the most naive to the least naive specification, and we study whether the relationship still holds as one moves from more to less naive versions. The dependent variable is output per unit of land (kg/acre), so we will refer to our specifications as *yield functions* rather than production functions to avoid confusion. Table 2 summarises our estimation strategy, which builds and expands upon Barrett, Bellamare and Hou (2010).

Table 2: Estimation strategy: specifications

Hypothesis	Implications	Specification	Model
-	Benchmark model (OLS)	$log(yield_{cpi}) = \alpha_1 + \beta_1 log(area_{cpi}) + \boldsymbol{\gamma_1' x_{cpi}} + \epsilon_{cpi}$	(1)
1	Control for household heterogeneity (OLS)	$log(yield_{cpi}) = \alpha_2 + \beta_2 log(area_{cpi}) + \boldsymbol{\gamma_2' x_{cpi}} + \boldsymbol{\theta_2' HH_i} + \eta_{cpi}$	(2)
2	Control for plot characteristics (OLS)	$log(yield_{cpi}) = \alpha_3 + \beta_3 log(area_{cpi}) + \boldsymbol{\gamma_3' x_{cpi}} + \boldsymbol{\tau_3' plot_{pi}} + \rho_{cpi}$	(3)
1+2	Control for both (OLS)	$log(yield_{cpi}) = \alpha_4 + \beta_4 log(area_{cpi}) + \boldsymbol{\gamma_4' x_{cpi}} + \boldsymbol{\theta_4' HH_i} + \boldsymbol{\tau_4' plot_{pi}} + \nu_{cpi}$	(4)
1+2+3	Control for both using GPS measures (OLS)	$log(yield_{cpi}^{gps}) = \alpha_5 + \beta_5 log(area_{cpi}^{gps}) + \boldsymbol{\gamma_5' x_{cpi}^{gps}} + \boldsymbol{\theta_5' HH_i} + \boldsymbol{\tau_5' plot_{pi}} + \kappa_{cpi}$	(5)
1'+2'	Panel FE deals with unobserved HH and plot heterogeneity	$log(yield_{cpi}) = \alpha_6 + \beta_6 log(area_{cpi}) + \boldsymbol{\gamma_6' x_{cpi}} + \boldsymbol{\theta_6' HH_i} + \zeta_{cpi}$	(6)
1'+2'+3	Panel FE with land size corrected with GPS measures	$log(yield_{cpi}^{gps}) = \alpha_7 + \beta_7 log(area_{cpi}^{gps}) + \boldsymbol{\gamma_7' x_{cpi}^{gps}} + \boldsymbol{\theta_7' HH_i} + \boldsymbol{\tau_7' plot_{pi}} + \varepsilon_{cpi}$	(7)

Notes:

- The vector $\boldsymbol{x_{cpi}}$ includes controls for input usage at the plot/crop level: organic fertiliser and family labour (fixed) and inorganic fertiliser and hired labour (variable)
- In specifications using GPS measurement, land, yield and input usage have all been rescaled according to GPS measures instead of farmers' self-reported areas
- In model 6 and 7, propositions 1 and 2 are renamed 1' and 2' to differentiate the panel models from their OLS counterparts
- OLS specifications include regional and year fixed effects. Panel specifications include year dummies

We first start with OLS specifications. Model 1 is a benchmark model, where we simply regress the log of yield on the log of area cultivated, regional and year fixed effects and a set of controls including inputs usage. Fixed inputs include days of family labour and organic fertiliser, and variable inputs days of hired labour and inorganic fertiliser. The data provides information on these variables at the plot level, so that we have normalised relevant quantities by acre (days of work in the case of labour, and kilograms in the case of fertiliser). For example, if 40 days of household labour were spent on a plot of two acres, family labour per acre of land on that particular plot will be 20 days. However, the proportion of farmers not using inputs can be large (particularly for inorganic fertiliser), thus generating missing observations when taking logs. While imputing an arbitrarily chosen positive small number to the zeros is often used as a solution, we implement instead the inverse hyperbolic sine transformation (IHS), which is considered less arbitrary. Implementing the IHS has several benefits, such as adjusting for skewness in the data, retaining zero and negative observations, and not disproportionately misrepresenting zeros (Friedline *et al.*, 2015). For a given value x, the IHS transformation is given by:

$$ihs(x) = ln(\sqrt{x^2 + 1} + x)$$

While the IHS is usually used for dependent variables, it can also be applied to independent variables (Friedline *et al.*, 2015, Layton, 2001).[10] Once the IHS transformation is implemented, we are able to retain all observations for which no input use was reported.

Model 2 tests the imperfect market argument (*P1*). The conventional way to test for this in the literature is to include household fixed effects in order to control for within-household unobserved heterogeneity (Heltberg (1998), Barrett *et al.* (2010), Assunção and Braido (2007)). Inclusion of fixed effects is made possible by the levels of analysis usually followed in the literature: farm or plot level. In sub-Saharan Africa, farmers typically have several plots and several crops on the farm, so that any estimation strategy using a crop level or a plot level analysis will feature several observations *per household*. However, we study the IR at a more disaggregated level: the crop/plot level, where the level of observation is a crop on a given plot. As such, our samples do not have enough within variation to justify the use of household fixed effects. The proportions of households growing a given crop on one plot only is very large in our sample, particularly so for rice and groundnut. For example, the percentage of households only growing rice on one plot is 89% in wave three, that of households only growing groundnut on one plot is 92% in both waves two and three. Hence, using household fixed effects would dramatically reduce the number of degrees of freedom in our analysis and undermine the

[10] For examples of studies in the field of agricultural economics using the IHS, see Mihalopoulos and Demoussis (2001),

interpretation of results.[11]

Therefore, we test for the imperfect market proposition by controlling for household level observable characteristics instead. These include a dummy to control for female headed households, its interaction with the area variable (to capture the possibility of different IRs for male and female-headed households), a dummy for whether anyone in the household is member of a saving group, the education level and log of age of the head of household, a dummy capturing whether the household owns a means of transport, and the log of farm size. We also control for the total number of crops grown on the farm and that grown on a plot, as well as for a dummy taking value one if a household plants any crop on more than one plot and zero otherwise. We also include village-level variables which may also affect household-specific market failures.[12] These are dummy variables capturing whether there is a cooperative in the village, and whether improved seeds are available in the village.

Model 3 tests for possibility of an omitted variable bias in soil characteristics (*P2*) by including a vector of observable plot characteristics. The data are quite rich in this respect and provide information regarding several aspects of each plot. The underlying assumption here is thus that we have sufficient information on plot characteristics to remove this possible bias. The vector includes: soil quality (categorical variable reported by farmer), steepness of the land, log of elevation, whether the plot has an irrigation facility, whether it has an erosion facility, and dummies for soil type (loam, clay, sandy or other). We also include dummies capturing whether the crop is intercropped and whether it is the main crop on the plot. Although these are not physical features of plots as such, they may influence soil productivity and quality. For example, pulses can replenish the soils in nitrogen content. Model 4 combines the previous two propositions together (*P1 and P2*).

Model 5, our last specification using OLS estimation, is similar to model 4 but it additionally controls for the statistical fallacy possibility (*P1, P2 and P3*). As such, it is analogous to model 4 except that yields, area cultivated and input usage have all been rescaled according to GPS measurements instead of farmers' self-reported measurements.

We then move to panel fixed effect estimation. The rationale is that although we are controlling

or Yen and Jones (1997). For a thorough study of the merits and uses of the IHS, see Pence (2006).

[11] However, we are able to control for time invariant household/plot characteristic when moving to panel estimation, as explained below.

[12] In levels of analysis that allow for household fixed effects, their inclusion also controls, by definition, for village factors that affect the degree of market failures.

for a set of observed plot characteristics, there may still be large unobserved heterogeneity. This is an important step in the development of the literature on the IR. Studies relying on a plot level focus usually have to rely on OLS, because their level of analysis makes the use panel techniques complicated as plot size is largely time invariant. Among studies using panel techniques are Lamb (2003) who uses ICRISAT data, and Kagin *et al.* (2016) who use Mexican data to study the relationship between land cultivated and productivity and efficiency. However, their focus is at the farm level only, and hence is subject to issues of crop composition effects and general lack of precision regarding what is actually measured, as argued in Section 2. A recurrent criticism of existing studies is that any 'observed' IR may be driven by unobserved plot heterogeneity. Obvious missing variables are soil composition variables which truly measure land quality (such as nitrogen and potassium contents). Bringing a new focus at the crop/plot level of analysis allows us to bypass this issue, by looking into the determinants of productivity for a given crop on a given plot. Hence, even if plot size is time invariant, the crop mix on a plot is *not*. As a simple example, consider the following hypothetical situation: a plot of one acre is used to grow maize (monocropped). One year later, the same plot is covered with monocropped maize on half the plot only (0.5 acre) while the other half has beans and sorghum intercropped. Even though plot size is time invariant, the area planted with maize on that plot is not.[13] Because crop mixes are not time invariant, we have an unbalanced panel (not all farmers grow the same crops on the same plots across time).

The data thus allows us to study whether we can still observe an inverse relationship in panel analysis, and doing so means we can also confirm or refute the claim that any negative relationship found through OLS estimation is driven by unobserved heterogeneity at the plot level. Because the study looks at productivity determinants at the crop/plot level, the panel *id* level declared is a combination of household and plot. The unique panel identifier thus refers to a particular plot within a given household. These *id*s account for splitting households across time. Hence, when using panel specifications we are controlling for all household/crop/plot time invariant features. One such unobservable is crop specific farming knowledge, which is an important determinant of productivity.

We estimate two panel models, which are the equivalent to the two most complete OLS specifications: model 6 controls for the imperfect market and omitted variable bias propositions (*P1 and P2*), and model 7 further controls for the statistical fallacy possibility by using GPS measurements (*P1,*

[13] In some instances, even plot size can change. This can be because patches of land can be cleared and added to an existing plot, or because the structure of plots changes after a household splits (giving out some of the land to a son or daughter leaving the household for example). The cultivated area of a plot can also be altered over time.

P2 and P3).

All variables used in this analysis are described in table A1 in the Appendix.

4.2 Empirical results: testing propositions 1 to 3

Tables 3 to 6 below present key results for maize, rice, beans and groundnut. In all specifications, both the dependent variable and continuous variables are in logs so that coefficients can be interpreted as elasticities, with inputs transformed using the inverse hyperbolic sine transformation. Output tables in the main text have been simplified as much as possible with full output presented in the appendix. For the sake of simplicity, we do not report in the main text outputs for the model testing only for the imperfect market hypothesis (*P1*) or only for the omitted variable bias (*P2*). We only present here the more complete models that control for several propositions at the same time. The full output tables for all crops are reported in Tables A2 to A5 in the Appendix.

In each table, the first column reports results for the benchmark model ('naive specification') which only includes area cultivated and inputs as independent variables. The second column reports results for the model controlling for both the imperfect market and omitted variable bias propositions (*P1 and P2*). The third column further controls for the possibility of statistical fallacy (*P1, P2 and P3*). The last two columns are the panel equivalents to columns 2 and 3. Column 4 controls for the imperfect market and omitted variable bias propositions (*P1 and P2*), and column 5 further controls for the statistical fallacy possibility (*P1, P2 and P3*). The 'Estimation' line at the bottom of each table gives a reminder of whether OLS or panel fixed effects model is used, while the 'Area' line specifies whether self-reported (SR) or GPS measures are used.

Table 3: Yield functions for maize (main coefficients only)

	(1)	(2)	(3)	(4)	(5)
	Benchmark	P1+P2	P1+P2+P3	P1+P2	P1+P2+P3
Area	-0.221***	-0.259***	-0.358***	-0.637***	-0.654***
	(0.021)	(0.026)	(0.020)	(0.050)	(0.050)
Area*female		-0.144***	-0.109***	-0.074	-0.079
		(0.040)	(0.030)	(0.084)	(0.081)
Hired labour	0.123***	0.124***	0.115***	0.027	0.031
	(0.016)	(0.015)	(0.015)	(0.022)	(0.021)
Inorganic fert	0.140***	0.127***	0.116***	0.049**	0.050**
	(0.012)	(0.011)	(0.010)	(0.020)	(0.020)
Soil quality		0.133***	0.137***	0.072*	0.079**
		(0.026)	(0.024)	(0.038)	(0.038)

Female head		-0.064	-0.058	0.200	0.239
		(0.049)	(0.049)	(0.320)	(0.310)
Intercrop		-0.084**	-0.088**	-0.103*	-0.087*
		(0.036)	(0.034)	(0.053)	(0.052)
Maincrop		0.303***	0.328***	0.208**	0.234**
		(0.047)	(0.045)	(0.093)	(0.095)
N	3407	3407	3407	3407	3407
R^2	0.25	0.31	0.40	0.28	0.32
Regions	Yes	Yes	Yes	-	-
Year	Yes	Yes	Yes	Yes	Yes
Estimation	Pooled OLS	Pooled OLS	Pooled OLS	Panel FE	Panel FE
Area	SR	SR	GPS	SR	GPS

Standard errors clustered at HH level for models 1-5, and at HH/plot level for models 6-7
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table and all subsequent output tables reported in the main text only present the main coefficients of interest. Variables entering the analysis but not reported in the main text include **fixed inputs** (family labour, organic fertiliser and rainfall), as well as controls for the **imperfect markets** proposition (education level and age of head of household, membership of a saving group, ownership of a means of transport farm size, presence of village cooperative, availability of improved seeds, number of crops grown on the farm and number of plots with a given crop) and controls for the **omitted variable** bias possibility (soil type, steepness and elevation of the land, irrigation and erosion facility, number of trees per plot). For full output tables the reader can refer to the Appendix.

Table 4: Yield functions for rice (main coefficients only)

	(1)	(2)	(3)	(4)	(5)
	Benchmark	P1+P2	P1+P2+P3	P1+P2	P1+P2+P3
Area	-0.242***	-0.374***	-0.431***	-0.813***	-0.775***
	(0.050)	(0.064)	(0.053)	(0.147)	(0.098)
Area*female		-0.038	-0.056	-0.293	-0.206
		(0.090)	(0.072)	(0.220)	(0.204)
Hired labour	0.184***	0.163***	0.155***	0.116**	0.127**
	(0.022)	(0.021)	(0.019)	(0.052)	(0.057)
Inorganic fert	0.111***	0.096***	0.084***	-0.016	-0.034
	(0.033)	(0.028)	(0.026)	(0.056)	(0.058)
Soil quality		0.102*	0.115**	-0.054	-0.070
		(0.055)	(0.053)	(0.123)	(0.119)
Female head		0.089	0.038	1.307***	1.458***
		(0.094)	(0.093)	(0.452)	(0.403)
Intercrop		-0.419***	-0.479***	-0.218	-0.214
		(0.105)	(0.108)	(0.184)	(0.177)
Maincrop		0.092	0.108	0.219	0.175
		(0.097)	(0.095)	(0.221)	(0.218)
N	630	630	630	630	630
R^2	0.41	0.48	0.57	0.54	0.54
Regions	Yes	Yes	Yes	-	-
Year	Yes	Yes	Yes	Yes	Yes

Estimation	Pooled OLS	Pooled OLS	Pooled OLS	Panel FE	Panel FE
Area	SR	SR	GPS	SR	GPS

Standard errors clustered at HH level for models 1-5, and at HH/plot level for models 6-7

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: the full output includes the same controls as those listed under table 3

Table 5: Yield functions for beans (main coefficients only)

	(1)	(2)	(3)	(4)	(5)
	Benchmark	P1+P2	P1+P2+P3	P1+P2	P1+P2+P3
Area	-0.357***	-0.464***	-0.515***	-0.569***	-0.610***
	(0.041)	(0.051)	(0.040)	(0.092)	(0.090)
Area*female		-0.176**	-0.105	-0.048	-0.320
		(0.082)	(0.065)	(0.127)	(0.209)
Hired labour	0.074***	0.086***	0.064***	0.093**	0.077**
	(0.026)	(0.023)	(0.024)	(0.037)	(0.036)
Inorganic fert	0.005	0.011	0.014	-0.010	0.003
	(0.021)	(0.021)	(0.021)	(0.035)	(0.033)
Soil quality		0.089*	0.097**	0.067	0.057
		(0.049)	(0.048)	(0.082)	(0.080)
Female head		-0.089	-0.064	-0.038	-0.185
		(0.092)	(0.089)	(0.319)	(0.333)
Intercrop		-0.241**	-0.248***	0.026	-0.040
		(0.101)	(0.095)	(0.152)	(0.148)
Maincrop		0.391***	0.417***	0.234*	0.239
		(0.092)	(0.088)	(0.135)	(0.146)
N	936	936	936	936	936
R^2	0.24	0.33	0.44	0.50	0.50
Regions	Yes	Yes	Yes	-	-
Year	Yes	Yes	Yes	Yes	Yes
Estimation	Pooled OLS	Pooled OLS	Pooled OLS	Panel FE	Panel FE
Area	SR	SR	GPS	SR	GPS

Standard errors clustered at HH level for models 1-5, and at HH/plot level for models 6-7

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: the full output includes the same controls as those listed under table 3

Table 6: Yield functions for groundnut (main coefficients only)

	(1)	(2)	(3)	(4)	(5)
	Benchmark	P1+P2	P1+P2+P3	P1+P2	P1+P2+P3
Area	-0.358***	-0.431***	-0.473***	-0.988***	-0.925***
	(0.058)	(0.078)	(0.062)	(0.190)	(0.191)
Area*female		-0.043	-0.073	0.008	-0.220
		(0.091)	(0.078)	(0.302)	(0.207)
Hired labour	0.072*	0.067*	0.056	0.126	0.126

	(0.038)	(0.040)	(0.039)	(0.095)	(0.087)
Inorganic fert	0.006	0.009	0.004	-0.016	-0.045
	(0.037)	(0.038)	(0.039)	(0.093)	(0.085)
Soil quality		-0.111	-0.093	0.240	0.227
		(0.073)	(0.074)	(0.175)	(0.177)
Female head		-0.116	-0.056	-3.923***	-4.261***
		(0.113)	(0.111)	(0.801)	(0.689)
Intercrop		-0.036	0.018	0.204	0.192
		(0.110)	(0.107)	(0.303)	(0.296)
Maincrop		0.359***	0.363***	0.412	0.369
		(0.125)	(0.124)	(0.301)	(0.259)
N	460	460	460	460	460
R^2	0.25	0.33	0.40	0.66	0.66
Regions	Yes	Yes	Yes	-	-
Year	Yes	Yes	Yes	Yes	Yes
Estimation	Pooled OLS	Pooled OLS	Pooled OLS	Panel FE	Panel FE
Area	SR	SR	GPS	SR	GPS

Standard errors clustered at HH level for models 1-5, and at HH/plot level for models 6-7

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: the full output includes the same controls as those listed under table 3

The discussion of results is mainly focused on maize, which is the most important crop in our sample, and one of the most essential crops in Tanzania. We comment on results for rice, beans and groundnut whenever they clearly differ from those for maize.

Results for maize are presented in Table 3. The IR is robust to all specifications. In the benchmark model, a one percent increase in area cultivated is associated with a decrease in yield of 0.22% on average. Controlling for the imperfect market and omitted variable bias propositions (column 2) does not remove the IR. In fact, it slightly increases its magnitude: a one percent increase in area cultivated is now triggering a decrease in yields of around 0.26% on average. Controlling for the possibility of a statistical fallacy due to self-reported data unambiguously points towards an increase in the magnitude of the IR: a one percent increase in area cultivated is associated with a 0.36% decrease in yields. This result clearly goes against the proposition that the IR could be artificially driven by self-reported data. This is consistent with results in Carletto *et al.* (2015) who also find an increase the strength of the relationship when moving from self-reported to GPS measured data.[14]

When moving to panel models, the IR effect roughly doubles: a one percent increase in area cul-

[14]It is also consistent with preliminary evidence reported on Figures 1a and 1b in the summary statistics section. The fitted line for the GPS data cloud is steeper than the fitted line for the self-reported data.

tivated is associated with a 0.64% decrease in yields in the model with self-reported areas or 0.65% decrease in that with GPS measures. Controlling for unobserved time-invariant household/plot heterogeneity therefore triggers an increase in the magnitude of the IR, which goes against the criticism often made that negative area coefficients in OLS regressions are simply driven by this heterogeneity.

Also note that the IR is stronger for female headed-households in the OLS models: the interaction terms between area cultivated and a dummy taking value 1 if the household is female-headed are strongly negative and significant in columns two and three. However, the interaction loses significance in the panel models, which may be due to too little within variation in the dummy for female-headed households.

As expected, variable inputs have a strong positive effect on yields. Although the effect of inorganic fertiliser on yields weakens when moving from OLS to panel estimation, statistical significance is preserved. The dummy variable capturing whether the crop is intercropped is consistently negative across specifications, although it becomes weakly significant in the panel models. This suggests that maize intercropping characterises a low productivity environment. The dummy variable capturing whether the crop is the main crop on the plot is significant in all models at least at the 5% level. The effect is stable across specifications, at around 0.3 for OLS models, and 0.2 for panel ones. Hence, the physical productivity of maize is higher when the crop is treated as a priority crop by the farmer (this may involve higher effort, or better quality seeds for example).

To summarise, we find no evidence that controlling for propositions one to three is able to remove the IR: area coefficients are consistently negative and significant. In fact, using more precise GPS measurements as well as panel estimation increase the magnitude of the relationship.

Results for rice, beans and groundnut also show a consistently negative and significant area coefficient in all specifications. Hence, the IR is robust for all crops in all models. We also observe for these crops an increase in the strength of the relationship when moving from self-reported to GPS measured area, ass well as a strong increase when moving from OLS to panel estimation. This is particularly the case for groundnut, for which the magnitude of the IR in panel models is approaching unity.

There are, however, some important differences with respect to other variables. One is the interaction term between cultivated area and the female dummy. It is not significant in any models for rice and groundnut, suggesting that the IR is not significantly different in female headed households.[15] For beans, the interaction term is significant in the first OLS specification, but it is not robust to GPS measurements or panel estimation. As expected, the effects of variable inputs on yields also differ across crops. For example, we find no effect of inorganic fertiliser on yields for beans and groundnut, perhaps because pulses and nuts fix nitrogen in the soil, and hence do not require as much fertiliser as other crops unable to do so, such as maize. The effects on yields of intercropping or being a priority crop also differ across crops. For rice, the intercropping dummy is strongly negative and significant in the OLS models, with a much larger effect than for maize. On the other hand, being a priority crop has no effect on yields. The opposite happens for groundnut: the intercrop dummy is not significant in any model, but the main crop one is strongly significant in the OLS specifications. This crop is often considered a cash crop in the Tanzanian context. As such, treating is as a main crop rather than a residual one may characterise a commercial endeavour. Farmers may concentrate a greater (unobservable) effort on groundnut when treating it as a priority crop.

4.2.1 Summary of Results

Our results show unambiguous support for the existence of an IR between cultivated area and physical productivity measured in yields. For each crop we run a baseline benchmark regression, progressively augmented to control for existing hypotheses in the literature. Beyond crop-specific differences (notably in terms of the magnitude of the relationship, or the effect of variable inputs on productivity), three key findings characterise results:

> ***Finding 1***: *The use of GPS data does not remove the IR. Hence, the claim that biases in farmers' self-reported areas may be driving the relationship (proposition 3) is not verified. In fact, the IR is even stronger when using GPS data, which is consistent with recent empirical evidence comparing self-reported and GPS data.*

> ***Finding 2***: *The IR does not vanish when using panel fixed-effects models, suggesting that the criticism of OLS regressions based on the claim that the IR may be driven by unobserved plot heterogeneity is misguided. Once controlling for unobserved household/plot heterogeneity, we find a dramatic increase in the magnitude of the IR. This holds for all crops in our analysis.*

> ***Finding 3***: *Results show that whether a crop is intercropped and/or is the primary crop on a*

[15] This does not imply that female headed households are less productive in general, but only that the magnitude of

plot can have a strong effect on physical productivity. This result partly comes from our level of analysis at the crop/plot level, and hence, has been largely ignored in the existing literature on the IR.

Having tested for the conventional explanations for the IR, we now build on previous specifications to control for two new hypotheses following *Finding 3*. The effect of the intercropping and main crop dummies on yields suggests they may reflect different farming endeavours. As such, they could influence the presence of the IR if their prevalence correlates negatively with size. We thus take the analysis further in the next section by controlling for their possible effect on the IR.

the IR is not stronger than for male headed ones.

5 Controlling for two new hypotheses

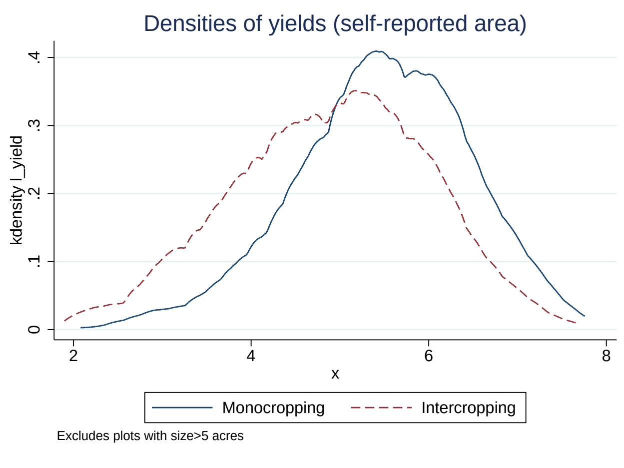
5.1 The 'intercropping' and 'main crop' propositions

Our results so far imply that whatever specification is followed, we observe a negative relationship between cultivated area and physical productivity. We have tested for the three propositions identified in the literature, and found that while they may influence the magnitude of the coefficient on cultivated land, the relationship still holds.

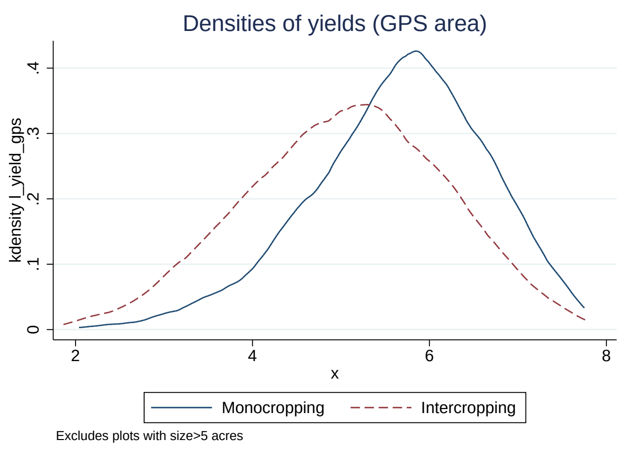
However, results from section 4 reveal two interesting features. The first of these is that the dummy variable for whether a crop is intercropped is strongly negative and significant in OLS models for maize, rice and beans, suggesting a higher productivity on plots (or parts of plots) which are monocropped. The effect is also weakly significant in the panel models for maize. This may be a preliminary indicator that intercropping may characterise a low productivity environment, and as such may directly influence the existence -or at least magnitude- of the inverse relationship. The second is that whether a crop is the main crop grown on a plot or not has an important impact on the yields of maize, beans and groundnut. This may characterise a particular farming endeavour which can also affect the relationship between size and productivity. We explain in more details the rationale for these propositions in the next subsections.

5.1.1 The intercropping proposition (*P4*)

Figure 4 plots graphs of the kernel densities of yields for crops which are intercropped (dashed line) and monocropped (plain line) for both measures of area.



(a) Self-reported measures



(b) GPS measures

Figure 4: Kernel densities of yields for intercropped and monocropped crops

At low levels of yields, there is a higher density of intercropped crops and vice versa. The mean is higher for monocropping with also a lower variance. This holds for both self-reported and GPS measures. Figures 4a and 4b are thus consistent with results in tables 3 to 6 which report strongly negative and significant coefficients for the intercropping dummy. Results indicate that yields decline both when area cultivated increases and when a crop is intercropped. If intercropping negatively correlates with area cultivated (i.e., if it is more prevalent on smaller plots), then the IR could be driven by a missing interaction between area and intercropping. We thus propose to formally control for this, which has not been done in the literature to the best of our knowledge.

Proposition 4: The inverse relationship may be driven by a missing interaction between area and a dummy for intercropping. More formally, the OLS regression controlling for propositions 1 to 3 (model 5) becomes:

$$log(yield^{gps}_{cpi}) = \alpha_5 + \beta_5 log(area^{gps}_{cpi}) + \underbrace{\delta_5 log(area^{gps}_{cpi}) * intercrop}_{\text{new interaction}} + \boldsymbol{\gamma_5' x^{gps}_{cpi}} + \boldsymbol{\theta_5' HH_i} + \boldsymbol{\tau_5' plot_{pi}} + \varrho_{cpi} \quad (1)$$

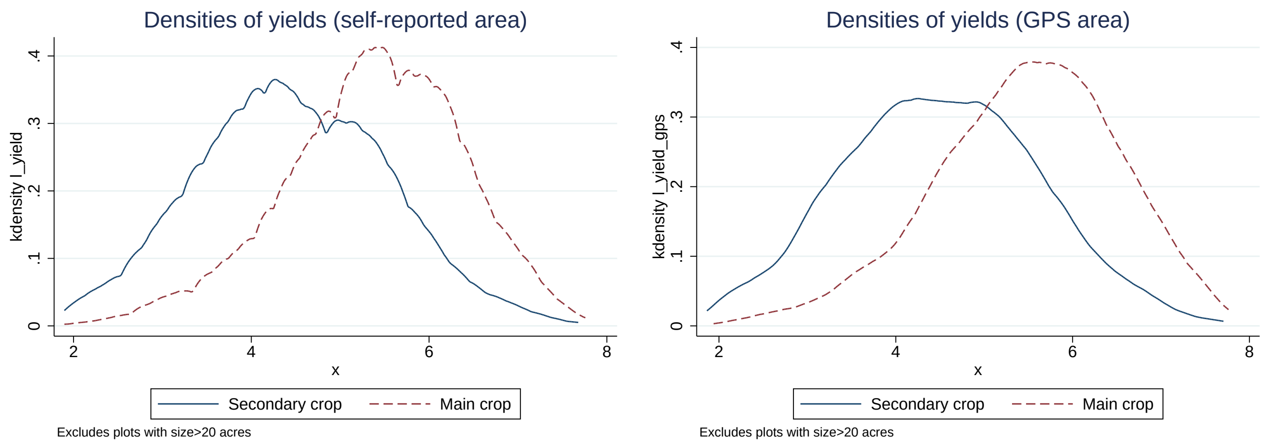
If this is our true model, then omitting to include this interaction term will make the OLS estimator biased downwards. If this interaction term explains the IR, we should fail to reject the null hypothesis $H_0 : \beta_5 = 0$. Accounting for intercropping is important for several reasons. One of them is that the rationale for intercropping may be different from what is usually thought. While it may be considered as a fertility enhancing strategy, the vast majority of farmers in Tanzania use intercroping as a risk mitigation strategy instead, where one crop can be used as a substitute for another in case of failure. This sort of risk reduction mechanism reflects a low productivity environment, as suggested by Figure 4. For farmers answering the questionnaire, intercropping may simply refer to a situation where several crops are grown on a plot, without necessarily implying that crops are densely planted together on a given area, as is usually conceived. This implies that there may be 'empty space' in intercropped areas which can mechanically generate an inverse relationship if such empty space is related to plot size. The pictures on Figure 7 in the Appendix may help conceptualise this issue.

5.1.2 The main crop proposition (*P5*)

The second proposition we wish to test is whether an IR still holds for crops which are the main crop on a plot. For each plot, farmers are asked to provide the relevant crop mix, and state which crop from

[16] A priority crop can be either a cash crop that is a key determinant of income, or a important subsistence crop for

that mix is the most important one.[16] The dummy variable for being main crop is highly significant and positive in OLS models for beans and groundnut and in both OLS and panel models for maize. Hence, a crop has on average a higher physical productivity if it is treated as a priority crop by the farmer.



(a) Self-reported measures

(b) GPS measures

Figure 5: Kernel densities of yields for primary and secondary crops

Maize and rice are typically the main crop on plots on which they are grown (82% for maize, 87% for rice), while for beans and groundnut the proportion is much smaller (23% for beans, 28% for groundnut). To the extent that farmers treat main crops and secondary crops differently, their productivity determinants can differ (for example, the input mix, effort applied or farming knowledge can be different). Figure 5 shows the densities of yield for primary and secondary crops. Both with self-reported and GPS data, secondary crops prevail in the lower tail of the distribution while primary crops prevail in the upper tail. As such, the existence and magnitude of the inverse relationship may be affected by this ranking of crops made by farmers if crop status correlates with cultivated area. We thus propose to control for this.

Proposition 5: The existence of an inverse relationship can be driven by omitting to account for whether a crop is the main crop on a plot or a secondary crop only. More formally, the OLS regression controlling for propositions 1 to 3 (model 5) becomes:

$$log(yield_{cpi}^{gps}) = \alpha_5 + \beta_5 log(area_{cpi}^{gps}) + \underbrace{\delta_5 log(area_{cpi}^{gps}) * maincrop}_{\text{new interaction}} + \boldsymbol{\gamma_5' x_{cpi}^{gps}} + \boldsymbol{\theta_5' HH_i} + \boldsymbol{\tau_5' plot_{pi}} + \xi_{cpi} \quad (2)$$

example.

If the IR is driven by conflating secondary and primary crops, then including the interaction term should remove the relationship for main crops.

5.2 Results: testing propositions 4 and 5

We test propositions 4 and 5 by building on specifications 4 and 5 using OLS, and 6 and 7 using panel fixed effects, which are the most complete specifications.[17] We only present key results for maize in the main text. Full output results for all crops are reported in the Appendix. As in the previous section, we briefly comment results on rice, beans or groundnut only if they clearly differ from those for maize. Table 7 presents key results of models testing for proposition 4, including an interaction term between area cultivated and whether the crop is intercroped. Table 8 presents results of models testing for proposition 5, including an interaction term between area cultivated an whether the crop is the main crop on the plot. Table Table 9 reports results for models controlling for both propositions 4 and 5.

[17]Hence, we omit in this part of the analysis the most naive specifications: the benchmark model, the model only controlling for the imperfect market proposition (P1), and that only controlling for the omitted variable possibility (P2).

5.2.1 Controlling for the intercropping proposition

Table 7: Testing P4 for maize (land coefficients only)

	(1)	(2)	(3)	(4)
	P1+P2	P1+P2+P3	P1+P2	P1+P2+P3
Area	-0.180***	-0.302***	-0.571***	-0.622***
	(0.036)	(0.025)	(0.059)	(0.056)
Intercrop	-0.082**	-0.094***	-0.103*	-0.091*
	(0.036)	(0.034)	(0.054)	(0.052)
Area*Intercrop	-0.118***	-0.088***	-0.100**	-0.049
	(0.035)	(0.025)	(0.050)	(0.042)
N	3407	3407	3407	3407
R^2	0.31	0.40	0.29	0.32
Estimation	Pooled OLS	Pooled OLS	Panel FE	Panel FE
Area	SR	GPS	SR	GPS

Clustered standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Results in Tables 7 show that controlling for proposition 4 does not remove the IR for maize, although it weakens its magnitude. For example, in the OLS specification that jointly controls for propositions one and two, the IR is weakened by about 31% (the area coefficient is reduced in magnitude from -0.259 to -0.180). As expected, the interaction term is negative across all models (although it loses significance in the last panel specification). The stand alone dummy is still negative and significant. This suggests that productivity is generally lower when maize is intercropped *and* that the IR more pronounced. We still observe an increase in the magnitude of the IR when moving from self-reported measures to GPS ones, and from OLS to panel estimation.

The IR is also robust to the inclusion of the interaction term for rice, beans and groundnut. Results for rice are similar to maize in the sense that adding the interaction term reduces the mitigates the IR but does not remove it. For beans, although the interaction term is only significant in one model, its inclusion in the regressions weakens the coefficient on area in all specifications. In the case of groundnut, none of the intercation coefficients is significant, which is expected, since we did not find the dummy for intercropping to be significant in the original set of results

To summarise, while accounting for the inter cropping proposition is able to remove a sizeable part of the observed negative relationship in the case of maize and rice, we still observe negative and significant coefficients on area cultivated.

5.2.2 Controlling for the main crop proposition

We now consider the effect of including an interaction term between the area variable and the main crop dummy (proposition 5).

Table 8: Testing P5 for maize (land coefficients only)

	(1)	(2)	(3)	(4)
	P1+P2	P1+P2+P3	P1+P2	P1+P2+P3
Area	-0.421***	-0.479***	-0.851***	-0.868***
	(0.042)	(0.037)	(0.089)	(0.081)
Maincrop	0.297***	0.328***	0.227**	0.245***
	(0.047)	(0.045)	(0.092)	(0.093)
Area*Maincrop	0.196***	0.141***	0.253***	0.244***
	(0.041)	(0.037)	(0.087)	(0.077)
N	3407	3407	3407	3407
R^2	0.32	0.40	0.29	0.33
Estimation	Pooled OLS	Pooled OLS	Panel FE	Panel FE
Area	SR	GPS	SR	GPS

Clustered standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

For proposition 5, we expect the interaction term to be *positive* in sign, as opposed to proposition 4: yields of priority crops tend to be higher than those of secondary crops, on average. Hence, the interaction between area cultivated and the dummy for whether the crop is a main crop should pick up this positive effect of being a 'priority crop' (possibly reflected in higher effort level). The baseline coefficients on area should increase in absolute value (i.e., become more negative), reflecting a stronger relationship for secondary crops. To compute the IR for main crops, one must now add the baseline term and the interaction term.

Results confirm that the baseline coefficients are stronger in magnitude, while the interaction term is positive whenever significant. All interaction terms are significant for maize at the one percent level. For the most complete OLS model for maize (jointly controlling for propositions one to three), the magnitude of the IR for a main crop is: -0.479+0.141=-0.338, which is close to the original coefficient of -0.358 in Table 3. The IR is much stronger for maize when it is treated as a secondary crop: a one percent increase in area cultivated is associated with a 0.48% decrease in yields. Similarly, while the IR in panel models is of similar magnitude for a main crop as in Table 3, it largely increases for secondary crops: a one percent increase in area cultivated results in a decrease in yields of about 0.86% in both panel specifications.

For rice, the interaction term is only significant in the OLS models. For beans, interaction terms are significant in both OLS models and suggests that the inverse relationship is largely overestimated for main crops when not accounting for their priority status. Finally, none of the interaction terms is significant for groundnut, for which the baseline area coefficients remain very close to those in Table 6. Given that the maincrop dummy is positive and significant in Table 6 in the OLS models, this implies that groundnut has a higher productivity when treated as a main crop, but that the IR itself is unaffected by whether it is a primary or secondary crop.

To sum up, results for maize suggest that the inverse relationship is underestimated whenever it is grown as a secondary crop, and overestimated whenever it is treated as priority crop. However, accounting for the priority of some crops over others does not remove the IR.

5.2.3 Jointly controlling for the intercropping and main crop propositions

Finally, we control for both interaction terms in the regressions: we allow the inverse relationship to be affected both by intercropping and the priority status of a crop.

Table 9: Testing P4 and P5 for maize (land coefficients only)

	(1)	(2)	(3)	(4)
	P1+P2	P1+P2+P3	P1+P2	P1+P2+P3
Area	-0.343***	-0.419***	-0.785***	-0.842***
	(0.053)	(0.043)	(0.103)	(0.091)
Intercrop	-0.080**	-0.093***	-0.100*	-0.081
	(0.035)	(0.034)	(0.053)	(0.052)
Area*Intercrop	-0.091***	-0.069***	-0.075	-0.031
	(0.035)	(0.026)	(0.051)	(0.043)
Maincrop	0.294***	0.325***	0.227**	0.243***
	(0.047)	(0.045)	(0.092)	(0.093)
Area*Maincrop	0.175***	0.121***	0.234***	0.237***
	(0.041)	(0.037)	(0.090)	(0.078)
N	3407	3407	3407	3407
R^2	0.32	0.40	0.29	0.33
Estimation	Pooled OLS	Pooled OLS	Panel FE	Panel FE
Area	SR	GPS	SR	GPS

Clustered standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Again, results unambiguously point towards the persistence of the IR: area coefficients are negative and highly significant in all models for all crops. However, the magnitude of the IR is substantially reduced when maize is both monocropped and treated as a priority crop. In the OLS model testing for propositions one and two, the original coefficient in Table 3 is -0.259. When accounting for both interaction terms, the relevant IR coefficient is now: -0.343+0.175=-0.168. Hence, we are explaining about 35% of the IR for monocropped maize when it is a priority crop. Similarly, we explain about 17% of the relationship in the OLS model using GPS measurements.

To summarise our results, we find that neither of the two new hypotheses we control for is able to remove the strong IR observed for all crops. Similar to our baseline results presented in section 4, we also find evidence of a greater magnitude of the IR when using GPS measured variables rather than self-reported, and that the magnitude of the relationship largely increases when moving from OLS to panel estimation.

6 Discussion and conclusions

The aim of this study is threefold. First, we propose to introduce a new level of analysis in the literature on the IR. By focusing on a crop/plot level, we are able to enquire in greater details about the issue of cultivated area, which represents an improvement over the plot level focus. Indeed, the latter omits from crop composition effects whenever more than one crop is grown and fails to account for the effect of inter-cropping on cultivated size and on yields. Hence, from a methodological perspective, this study tries to open the 'black-box' of size and show why and how this matters for the debate on the IR. Second, we control for the existing theoretical hypotheses that could explain the IR in this novel setup. Third, we control for two new hypotheses that could explain the IR. These can be tested only via a crop/plot focus, and hence have not formally been assessed yet in the literature (to the best of our knowledge).

Results show unambiguous support for the existence of an IR. We find that the existing propositions are not able to remove the observed IR. We further show the existence of several effects that are robust across crops: *(i)* the magnitude of the IR tends to increase when using GPS measurements rather than self-reported measures, *(ii)* the IR is robust -in fact, even stronger- when using panel fixed effects estimation, and *(iii)* the IR persists even when accounting for whether a crop is intercropped and/or is the main crop on a plot.

These results, however, are to be interpreted with caution when assessing whether an IR exists or not: they point towards the possibility of an IR within the specific context of Tanzanian agriculture, i.e., within a relatively narrow size distribution and in a situation of rain-fed small scale agricultural activities. However, the inherent limitations of agricultural data (limited information on soil quality and measurement errors in size in particular) warrant caution. Perhaps the best message to take from this analysis is one of *constistency* in the IR, by which we mean that the coefficient on area is significantly negative whatever the crop, specification and estimation procedure one looks at.

This new focus at the crop/plot level pushes the research frontier towards new directions. In particular, it is clear that more research on inter-cropping needs to be done to clearly understand farming practices in Tanzania. This study hints at in important effect of inter-cropping on yields but data limitations do not allow us to go further. What this does tell us, however, is that embracing a more holistic perspective on farming may be beneficial for the debate on the IR. In agrarian studies, farming is understood as a 'total concept' where one crop or plot cannot be understood in isolation from the operating principles of the farm itself. From an empirical viewpoint, this opens a whole new set of possibilities for studying the IR. In particular, one possible research pathway lies in exploring more flexible ways to estimate production or yield functions. This in turn requires deeper knowledge of the agrarian and agronomic literatures to understand how different modes of farming can influence the presence (or absence) of an IR.

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7 Appendix

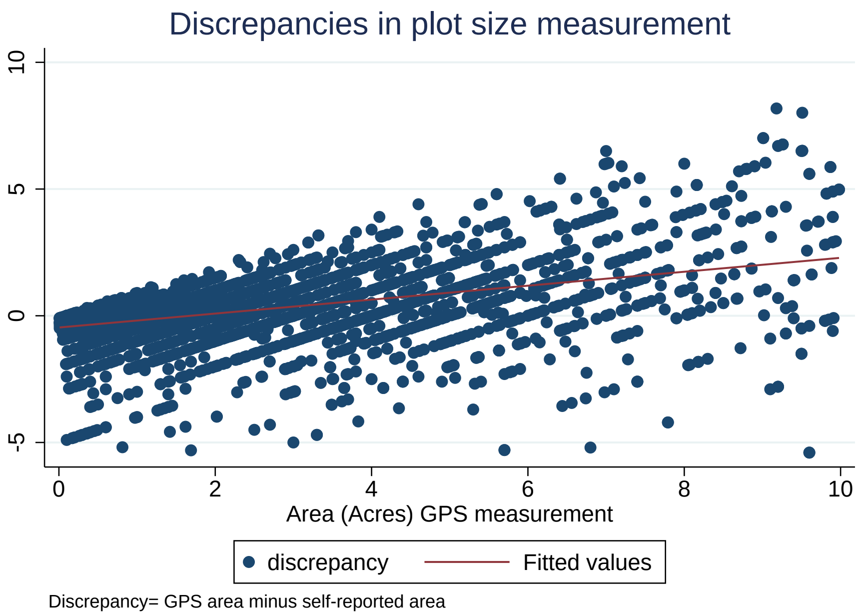

Figure 6: Discrepancies in plot sizes

Note: Discrepancy is calculated as the difference between GPS measures and self-reported measures. Hence, a negative value of the discrepancy variable implies the farmer is overestimating size, while a positive value implies the farmer is underestimating it. This graph omits the largest plots and largest discrepancy values for scale purposes.

Table A1: Definitions of variables used in analysis

Variable	**Definition**
Cultivated area	Refers to the area on a given plot planted with a given crop, which is obtain exploiting the information provided by farmers regarding the approximate surface on a plot on which the crop is grown (25, 50, 75 or 100%). When the crop is intercropped we use the area on which it is intercropped.
Family labour	Total number of days of household labour spent by acre on a given plot. E.g. if a plot is 2 acres and required 40 days of work, the number days worked per acre is 20.
Hired labour	Similar to the family labour variable but using days of hired labour instead
Organic fertiliser	Total amount of organic fertiliser,applied per acre of land on a given plot. E.g. if a plot is 2 acres and required 40 kg of organic fertiliser, the amount applied per acre is 20 kg
Inorganic fertiliser	Similar to the organic fertiliser variable but using inorganic fertiliser instead
Rainfall	Total rainfall in wettest quarter (mm) in the past 12 months at the district level
Maincrop	Dummy variable taking value 1 if the crop is the main crop on the plot, 0 otherwise
Soil quality	Categorical variable reported by farmers, takes value 1,2 or 3 for 'bad', 'average' and 'good' respectively
Steepness	Categorical variable reported by farmers, takes value 1,2, 3 or 4 for 'flat bottom', 'flat top', 'slightly sloped' and 'very steep' respectively
Elevation	Plot elevation in metres
Erosion	Dummy variable taking value 1 if the plot has an erosion facility, 0 otherwise
Irrigation	Dummy variable taking value 1 if the plot has an irrigation facility, 0 otherwise
Intercrop	Dummy variable taking value 1 if the crop is intercropped on that plot, 0 otherwise
Trees per plot	Number of trees planted on the plot
Crops per plot	Number of crops planted on the plot
Female head	Dummy variable taking value 1 if the household is headed by a woman, 0 otherwise
Saving group	Dummy variable taking value 1 if a household member is member of a saving group, 0 otherwise
Head education	Level of education of head of household, takes value 1,2, 3 or 4 for 'less than primary', 'primary', 'secondary' and 'university' respectively
Age	Age of the head of household
Transport	Dummy variable taking value 1 if the household owns a means of transport (bicycle/motorbike/car), 0 otherwise
Farm size	Farm size for each household measured in acres
Cooperative	Dummy variable taking value 1 if there is an agricultural cooperative in the village, 0 otherwise
Improved seeds	Dummy variable taking value 1 if improved seeds are available for sales in the village, 0 otherwise
Plots with crop	Number of plot on which a given crop is grown by the household
Crops on farm	Total number of crops grown on the farm by the household

(a) Large monocropped plot

(b) Small intercropped plot

Author's pictures (Morogoro region)

Figure 7: Motivating proposition 4

The picture in Figure 7a shows a large and densely planted mono cropped field of sisal, while that in Figure 7b shows a small intercropped plot (with cassava and bananas, among others). The latter is an example of intercopping where several crops are planted on a given area, which is different from inter cropping understood as a process where two crops are densely planted in alternative rows. It also makes it clear that to the extent that we are measuring output per unit of land on which a crop is cultivated, intercropping mechanically pulls this measure of productivity down. This therefore justifies the need to interact area cultivated with a dummy capturing whether the crop is intercropped (proposition 4).

7.1 Controlling for P1-P3: full output tables

Table A2: Yield functions for maize (full output)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Benchmark	P1	P2	P1+P2	P1+P2+P3	P1+P2	P1+P2+P3
Area	-0.221***	-0.254***	-0.224***	-0.259***	-0.358***	-0.637***	-0.654***
	(0.021)	(0.026)	(0.021)	(0.026)	(0.020)	(0.050)	(0.050)
Area*female		-0.130***		-0.144***	-0.109***	-0.074	-0.079
		(0.041)		(0.040)	(0.030)	(0.084)	(0.081)
Family labour	0.134***	0.159***	0.136***	0.160***	0.145***	0.128***	0.124***
	(0.023)	(0.023)	(0.023)	(0.023)	(0.021)	(0.031)	(0.030)
Hired labour	0.123***	0.126***	0.122***	0.124***	0.115***	0.027	0.031
	(0.016)	(0.016)	(0.016)	(0.015)	(0.015)	(0.022)	(0.021)
Organic fert	0.021***	0.020***	0.021***	0.018**	0.017**	0.003	0.003
	(0.008)	(0.008)	(0.008)	(0.007)	(0.007)	(0.013)	(0.013)

Inorganic fert	0.140***	0.133***	0.134***	0.127***	0.116***	0.049**	0.050**
	(0.012)	(0.011)	(0.011)	(0.011)	(0.010)	(0.020)	(0.020)
Rainfall	-0.022	0.008	-0.065	-0.042	0.007	-0.115	-0.090
	(0.077)	(0.075)	(0.079)	(0.077)	(0.074)	(0.100)	(0.101)
Female head		-0.067		-0.064	-0.058	0.200	0.239
		(0.051)		(0.049)	(0.049)	(0.320)	(0.310)
Farm size		0.123***		0.125***	0.182***	0.068	0.154***
		(0.028)		(0.028)	(0.023)	(0.053)	(0.045)
Saving group		0.061		0.084	0.092	0.092	0.094
		(0.077)		(0.074)	(0.074)	(0.107)	(0.112)
Head educ		0.015		0.007	0.012	0.056	0.052
		(0.033)		(0.032)	(0.031)	(0.053)	(0.053)
Age of head		-0.312***		-0.298***	-0.312***	-0.038	-0.074
		(0.065)		(0.063)	(0.060)	(0.490)	(0.476)
Transport		0.143***		0.147***	0.135***	0.097	0.087
		(0.039)		(0.038)	(0.036)	(0.074)	(0.074)
Plots with crop		-0.019		-0.073	-0.060	-0.165**	-0.201**
		(0.044)		(0.044)	(0.041)	(0.084)	(0.082)
Crops on farm		-0.023***		-0.017**	-0.026***	0.014	0.006
		(0.008)		(0.008)	(0.007)	(0.016)	(0.016)
Cooperative		0.072*		0.073**	0.090***	0.116**	0.114**
		(0.037)		(0.036)	(0.035)	(0.051)	(0.052)
Improved seeds		-0.063*		-0.061*	-0.055	0.031	0.033
		(0.036)		(0.035)	(0.034)	(0.049)	(0.049)
Erosion			-0.005	0.007	-0.010	0.138	0.140
			(0.052)	(0.052)	(0.052)	(0.086)	(0.088)
Irrigation			0.077	0.041	0.014	0.184	0.189
			(0.135)	(0.131)	(0.125)	(0.186)	(0.177)
Steepness			0.039**	0.034*	0.030*		
			(0.020)	(0.019)	(0.018)		
Elevation			0.057	0.079**	0.063*		
			(0.037)	(0.038)	(0.035)		
Intercrop			-0.121***	-0.084**	-0.088**	-0.103*	-0.087*
			(0.036)	(0.036)	(0.034)	(0.053)	(0.052)
Maincrop			0.296***	0.303***	0.328***	0.208**	0.234**
			(0.049)	(0.047)	(0.045)	(0.093)	(0.095)
Trees per plot			-0.000	-0.000	0.000	0.000	0.000

			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Soil quality			0.130***	0.133***	0.137***	0.072*	0.079**
			(0.027)	(0.026)	(0.024)	(0.038)	(0.038)
soil_type==SANDY			-0.206***	-0.218***	-0.188***		
			(0.044)	(0.043)	(0.043)		
soil_type==CLAY			0.025	0.015	0.037		
			(0.045)	(0.045)	(0.043)		
soil_type==OTHER			0.132	0.094	0.126		
			(0.099)	(0.097)	(0.090)		
time=2	0.054	0.064	0.058	0.070	0.068	0.092	0.110
	(0.063)	(0.062)	(0.078)	(0.077)	(0.076)	(0.112)	(0.111)
time=3	-0.042	-0.027	-0.059	-0.044	0.000	0.037	0.057
	(0.064)	(0.064)	(0.064)	(0.064)	(0.062)	(0.087)	(0.086)
Constant	4.512***	5.313***	3.848***	4.463***	4.344***	4.791**	4.693**
	(0.470)	(0.502)	(0.533)	(0.572)	(0.545)	(1.992)	(1.940)
Observations	3407	3407	3407	3407	3407	3407	3407
R^2	0.25	0.28	0.28	0.31	0.40	0.28	0.32
Regions	Yes	Yes	Yes	Yes	Yes	-	-
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Estimation	Pooled OLS	Pooled OLS	Pooled OLS	Pooled OLS	Pooled OLS	Panel FE	Panel FE
Area	SR	SR	SR	SR	GPS	SR	GPS

Standard errors clustered at household level for models 1-5, and at household/plot level for models 6-7

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3: Yield functions for rice (full output)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Benchmark	P1	P2	P1+P2	P1+P2+P3	P1+P2	P1+P2+P3
Area	-0.242***	-0.368***	-0.271***	-0.374***	-0.431***	-0.813***	-0.775***
	(0.050)	(0.065)	(0.049)	(0.064)	(0.053)	(0.147)	(0.098)
Area*female		-0.023		-0.038	-0.056	-0.293	-0.206
		(0.089)		(0.090)	(0.072)	(0.220)	(0.204)
Family labour	0.205***	0.217***	0.170***	0.175***	0.171***	0.108*	0.097
	(0.038)	(0.045)	(0.039)	(0.045)	(0.042)	(0.063)	(0.068)
Hired labour	0.184***	0.185***	0.161***	0.163***	0.155***	0.116**	0.127**
	(0.022)	(0.021)	(0.022)	(0.021)	(0.019)	(0.052)	(0.057)
Organic fert	0.046*	0.048**	0.058**	0.058**	0.054**	-0.012	-0.018
	(0.026)	(0.024)	(0.026)	(0.025)	(0.025)	(0.042)	(0.045)
Inorganic fert	0.111***	0.095***	0.114***	0.096***	0.084***	-0.016	-0.034

	(0.033)	(0.030)	(0.031)	(0.028)	(0.026)	(0.056)	(0.058)
Rainfall	0.137	0.169	0.075	0.093	0.112	-0.317	-0.333
	(0.114)	(0.116)	(0.107)	(0.110)	(0.105)	(0.218)	(0.223)
Female head		0.093		0.089	0.038	1.307***	1.458***
		(0.094)		(0.094)	(0.093)	(0.452)	(0.403)
Farm size		0.225***		0.171***	0.238***	0.215*	0.199
		(0.065)		(0.063)	(0.054)	(0.126)	(0.126)
Saving group		0.038		0.037	0.126	-0.387	-0.387
		(0.115)		(0.119)	(0.117)	(0.272)	(0.280)
Head educ		0.015		0.017	0.023	-0.119	-0.133
		(0.053)		(0.052)	(0.050)	(0.124)	(0.124)
Age of head		-0.376***		-0.325***	-0.411***	0.464	0.554
		(0.124)		(0.119)	(0.117)	(0.614)	(0.586)
Transport		0.107		0.160**	0.081	0.310	0.317
		(0.087)		(0.081)	(0.078)	(0.297)	(0.295)
Plots with crop		-0.072		-0.083	-0.107	-0.110	-0.077
		(0.099)		(0.097)	(0.094)	(0.241)	(0.236)
Crops on farm		-0.025		-0.006	-0.013	-0.063*	-0.067*
		(0.016)		(0.018)	(0.017)	(0.038)	(0.037)
Cooperative		0.139*		0.102	0.085	0.201	0.169
		(0.073)		(0.073)	(0.072)	(0.144)	(0.141)
Improved seeds		-0.015		0.010	0.014	-0.272*	-0.250
		(0.078)		(0.077)	(0.078)	(0.161)	(0.161)
Erosion			-0.108	-0.072	-0.024	0.356**	0.362**
			(0.102)	(0.102)	(0.098)	(0.177)	(0.177)
Irrigation			-0.009	-0.019	-0.046	-0.415	-0.376
			(0.224)	(0.210)	(0.197)	(0.334)	(0.319)
Steepness			-0.064	-0.064	-0.063		
			(0.041)	(0.040)	(0.039)		
Elevation			0.091*	0.087	0.072		
			(0.051)	(0.054)	(0.052)		
Intercrop			-0.451***	-0.419***	-0.479***	-0.218	-0.214
			(0.107)	(0.105)	(0.108)	(0.184)	(0.177)
Maincrop			0.074	0.092	0.108	0.219	0.175
			(0.101)	(0.097)	(0.095)	(0.221)	(0.218)
Trees per plot			0.000	0.000	0.000**	-0.000	-0.000

			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Soil quality			0.090	0.102*	0.115**	-0.054	-0.070
			(0.057)	(0.055)	(0.053)	(0.123)	(0.119)
soil_type==SANDY			-0.153	-0.140	-0.117		
			(0.096)	(0.098)	(0.097)		
soil_type==CLAY			0.013	0.030	0.083		
			(0.074)	(0.072)	(0.069)		
soil_type==OTHER			0.237	0.145	0.033		
			(0.266)	(0.284)	(0.268)		
time=2	-0.118	-0.126	-0.190	-0.251	-0.236	0.517*	0.474
	(0.142)	(0.144)	(0.167)	(0.168)	(0.162)	(0.282)	(0.288)
time=3	-0.224	-0.234	-0.271*	-0.274*	-0.201	0.081	0.067
	(0.143)	(0.144)	(0.147)	(0.149)	(0.145)	(0.242)	(0.234)
Constant	4.450***	5.304***	4.195***	4.904***	5.185***	4.848*	4.761*
	(0.750)	(0.884)	(0.851)	(0.988)	(0.964)	(2.643)	(2.786)
Observations	630	630	630	630	630	630	630
R^2	0.41	0.44	0.45	0.48	0.57	0.54	0.54
Regions	Yes	Yes	Yes	Yes	Yes	-	-
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Estimation	Pooled OLS	Pooled OLS	Pooled OLS	Pooled OLS	Pooled OLS	Panel FE	Panel FE
Area	SR	SR	SR	SR	GPS	SR	GPS

Standard errors clustered at household level for models 1-5, and at household/plot level for models 6-7

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A4: Yield functions for beans (full output)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Benchmark	P1	P2	P1+P2	P1+P2+P3	P1+P2	P1+P2+P3
Area	-0.357***	-0.468***	-0.370***	-0.464***	-0.515***	-0.569***	-0.610***
	(0.041)	(0.052)	(0.039)	(0.051)	(0.040)	(0.092)	(0.090)
Area*female		-0.188**		-0.176**	-0.105	-0.048	-0.320
		(0.086)		(0.082)	(0.065)	(0.127)	(0.209)
Family labour	0.061	0.108***	0.081**	0.117***	0.088***	0.080	0.132**
	(0.038)	(0.037)	(0.037)	(0.035)	(0.032)	(0.054)	(0.055)
Hired labour	0.074***	0.083***	0.078***	0.086***	0.064***	0.093**	0.077**
	(0.026)	(0.024)	(0.024)	(0.023)	(0.024)	(0.037)	(0.036)
Organic fert	0.003	0.005	0.015	0.015	0.014	0.032	0.029
	(0.013)	(0.013)	(0.014)	(0.013)	(0.013)	(0.029)	(0.028)
Inorganic fert	0.005	-0.005	0.020	0.011	0.014	-0.010	0.003

	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.035)	(0.033)
Rainfall	-0.232	-0.212	-0.182	-0.174	-0.121	0.669**	0.716***
	(0.157)	(0.160)	(0.148)	(0.150)	(0.141)	(0.267)	(0.277)
Female head		-0.098		-0.089	-0.064	-0.038	-0.185
		(0.095)		(0.092)	(0.089)	(0.319)	(0.333)
Farm size		0.254***		0.224***	0.259***	-0.118	0.027
		(0.053)		(0.053)	(0.044)	(0.107)	(0.092)
Saving group		0.044		0.008	-0.001	0.074	-0.068
		(0.121)		(0.122)	(0.120)	(0.306)	(0.393)
Head educ		-0.102*		-0.099*	-0.085	-0.223**	-0.196*
		(0.060)		(0.059)	(0.058)	(0.098)	(0.101)
Age of head		-0.119		-0.078	-0.076	0.799	0.147
		(0.117)		(0.111)	(0.105)	(1.831)	(1.838)
Transport		0.159**		0.145**	0.130*	0.206	0.233
		(0.073)		(0.072)	(0.070)	(0.152)	(0.153)
Plots with crop		-0.145*		-0.159*	-0.103	0.192	0.211
		(0.083)		(0.083)	(0.083)	(0.136)	(0.139)
Crops on farm		-0.029**		-0.016	-0.025*	0.016	-0.009
		(0.014)		(0.014)	(0.014)	(0.027)	(0.026)
Cooperative		0.004		0.024	0.065	0.216*	0.179
		(0.072)		(0.071)	(0.067)	(0.116)	(0.115)
Improved seeds		0.044		0.028	0.014	-0.012	0.006
		(0.073)		(0.070)	(0.068)	(0.115)	(0.118)
Erosion			-0.221**	-0.213**	-0.197**	-0.151	-0.123
			(0.087)	(0.084)	(0.084)	(0.134)	(0.134)
Irrigation			-0.124	-0.045	-0.032	-0.548	-0.359
			(0.311)	(0.338)	(0.322)	(0.464)	(0.521)
Steepness			0.061*	0.053*	0.037		
			(0.032)	(0.031)	(0.029)		
Elevation			-0.404**	-0.279	-0.168		
			(0.192)	(0.179)	(0.174)		
Intercrop			-0.297***	-0.241**	-0.248***	0.026	-0.040
			(0.103)	(0.101)	(0.095)	(0.152)	(0.148)
Maincrop			0.380***	0.391***	0.417***	0.234*	0.239
			(0.089)	(0.092)	(0.088)	(0.135)	(0.146)
Trees per plot			-0.000	-0.000	-0.000	0.000	0.000

			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Soil quality			0.098*	0.089*	0.097**	0.067	0.057
			(0.050)	(0.049)	(0.048)	(0.082)	(0.080)
soil_type==SANDY			0.046	0.072	0.054		
			(0.105)	(0.106)	(0.105)		
soil_type==CLAY			0.036	0.031	0.025		
			(0.077)	(0.075)	(0.072)		
soil_type==OTHER			-0.002	-0.045	0.107		
			(0.189)	(0.193)	(0.166)		
time=2	0.034	0.041	0.062	0.067	0.054	-0.102	-0.076
	(0.096)	(0.094)	(0.138)	(0.137)	(0.130)	(0.201)	(0.212)
time=3	0.035	-0.001	-0.043	-0.069	-0.050	-0.271	-0.225
	(0.096)	(0.097)	(0.097)	(0.099)	(0.098)	(0.210)	(0.210)
Constant	6.164***	5.668***	8.046***	6.651***	5.719***	-3.875	-1.830
	(0.931)	(1.037)	(1.524)	(1.563)	(1.542)	(6.888)	(6.887)
Observations	936	936	936	936	936	936	936
R^2	0.24	0.28	0.30	0.33	0.44	0.50	0.50
Regions	Yes	Yes	Yes	Yes	Yes	-	-
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Estimation	Pooled OLS	Pooled OLS	Pooled OLS	Pooled OLS	Pooled OLS	Panel FE	Panel FE
Area	SR	SR	SR	SR	GPS	SR	GPS

Standard errors clustered at household level for models 1-5, and at household/plot level for models 6-7

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A5: Yield functions for groundnut (full output)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Benchmark	P1	P2	P1+P2	P1+P2+P3	P1+P2	P1+P2+P3
Area	-0.358***	-0.449***	-0.354***	-0.431***	-0.473***	-0.988***	-0.925***
	(0.058)	(0.076)	(0.058)	(0.078)	(0.062)	(0.190)	(0.191)
Area*female		-0.041		-0.043	-0.073	0.008	-0.220
		(0.090)		(0.091)	(0.078)	(0.302)	(0.207)
Family labour	0.138**	0.189***	0.119*	0.159***	0.185***	0.148	0.107
	(0.061)	(0.059)	(0.061)	(0.058)	(0.055)	(0.156)	(0.147)
Hired labour	0.072*	0.078*	0.058	0.067*	0.056	0.126	0.126
	(0.038)	(0.040)	(0.039)	(0.040)	(0.039)	(0.095)	(0.087)
Organic fert	0.015	0.023	0.022	0.031	0.025	0.026	0.019
	(0.019)	(0.018)	(0.020)	(0.020)	(0.020)	(0.044)	(0.043)
Inorganic fert	0.006	-0.005	0.018	0.009	0.004	-0.016	-0.045

	(0.037)	(0.038)	(0.037)	(0.038)	(0.039)	(0.093)	(0.085)
Rainfall	-0.247	-0.145	-0.164	-0.049	-0.036	0.357	0.223
	(0.248)	(0.258)	(0.253)	(0.265)	(0.270)	(0.469)	(0.466)
Female head		-0.119		-0.116	-0.056	-3.923***	-4.261***
		(0.114)		(0.113)	(0.111)	(0.801)	(0.689)
Farm size		0.160**		0.139*	0.206***	-0.153	-0.237
		(0.081)		(0.081)	(0.064)	(0.203)	(0.183)
Saving group		0.128		0.060	0.177	-1.051**	-1.070**
		(0.168)		(0.167)	(0.173)	(0.509)	(0.516)
Head educ		0.048		0.035	0.061	0.071	0.075
		(0.094)		(0.092)	(0.092)	(0.288)	(0.270)
Age of head		-0.137		-0.094	-0.093	-3.751	-3.805
		(0.161)		(0.158)	(0.161)	(4.901)	(4.941)
Transport		0.163		0.153	0.183*	0.269	0.195
		(0.106)		(0.106)	(0.105)	(0.341)	(0.358)
Plots with crop		-0.206		-0.283*	-0.266*	-0.770**	-0.735**
		(0.153)		(0.153)	(0.160)	(0.321)	(0.356)
Crops on farm		-0.044**		-0.044**	-0.053***	-0.057	-0.052
		(0.022)		(0.022)	(0.021)	(0.069)	(0.068)
Cooperative		-0.137		-0.133	-0.154	0.059	0.068
		(0.094)		(0.096)	(0.095)	(0.172)	(0.166)
Improved seeds		-0.164		-0.127	-0.139	-0.252	-0.264
		(0.102)		(0.105)	(0.105)	(0.265)	(0.266)
Erosion			0.012	-0.009	-0.024	-0.164	-0.195
			(0.178)	(0.174)	(0.172)	(0.391)	(0.384)
Irrigation			0.548***	0.254	0.273	1.965***	1.973***
			(0.204)	(0.226)	(0.226)	(0.436)	(0.420)
Steepness			0.027	0.019	0.018		
			(0.056)	(0.055)	(0.054)		
Elevation			0.152	0.166	0.169		
			(0.112)	(0.110)	(0.106)		
Intercrop			-0.095	-0.036	0.018	0.204	0.192
			(0.112)	(0.110)	(0.107)	(0.303)	(0.296)
Maincrop			0.364***	0.359***	0.363***	0.412	0.369
			(0.119)	(0.125)	(0.124)	(0.301)	(0.259)
Trees per plot			-0.000	-0.000	-0.000	-0.000*	-0.000**

			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Soil quality			-0.092	-0.111	-0.093	0.240	0.227
			(0.073)	(0.073)	(0.074)	(0.175)	(0.177)
soil_type==SANDY			-0.232**	-0.207*	-0.194*		
			(0.110)	(0.109)	(0.108)		
soil_type==CLAY			0.054	-0.036	-0.061		
			(0.180)	(0.182)	(0.183)		
soil_type==OTHER			-0.139	-0.180	-0.215		
			(0.228)	(0.230)	(0.245)		
time=2	-0.098	-0.157	-0.061	-0.085	0.010	0.779*	0.781*
	(0.158)	(0.142)	(0.204)	(0.191)	(0.188)	(0.404)	(0.397)
time=3	-0.076	-0.130	-0.101	-0.155	-0.074	0.547	0.538
	(0.159)	(0.144)	(0.163)	(0.147)	(0.145)	(0.470)	(0.462)
Constant	5.625***	5.863***	4.368**	4.306**	3.976*	16.834	18.347
	(1.520)	(1.778)	(1.786)	(2.090)	(2.111)	(19.421)	(19.462)
Observations	460	460	460	460	460	460	460
R^2	0.25	0.29	0.29	0.33	0.40	0.66	0.66
Regions	Yes	Yes	Yes	Yes	Yes	-	-
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Estimation	Pooled OLS	Pooled OLS	Pooled OLS	Pooled OLS	Pooled OLS	Panel FE	Panel FE
Area	SR	SR	SR	SR	GPS	SR	GPS

Standard errors clustered at household level for models 1-5, and at household/plot level for models 6-7

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

7.2 Controlling for P4: full output tables

Table A6: Testing P4 for maize (full output)

	(1)	(2)	(3)	(4)
	P1+P2	P1+P2+P3	P1+P2	P1+P2+P3
Area	-0.180***	-0.302***	-0.571***	-0.622***
	(0.036)	(0.025)	(0.059)	(0.056)
Area*Intercrop	-0.118***	-0.088***	-0.100**	-0.049
	(0.035)	(0.025)	(0.050)	(0.042)
Area*female	-0.137***	-0.104***	-0.070	-0.073
	(0.040)	(0.030)	(0.084)	(0.081)
Family labour	0.160***	0.145***	0.125***	0.124***
	(0.023)	(0.021)	(0.031)	(0.030)
Hired labour	0.122***	0.115***	0.024	0.029
	(0.015)	(0.015)	(0.022)	(0.021)

Organic fert	0.018**	0.018**	0.001	0.003
	(0.007)	(0.007)	(0.013)	(0.013)
Inorganic fert	0.128***	0.116***	0.049**	0.050**
	(0.011)	(0.010)	(0.021)	(0.020)
Rainfall	-0.037	0.009	-0.108	-0.090
	(0.077)	(0.074)	(0.100)	(0.101)
Female head	-0.066	-0.061	0.221	0.245
	(0.050)	(0.049)	(0.322)	(0.311)
Farm size	0.126***	0.184***	0.070	0.155***
	(0.028)	(0.023)	(0.052)	(0.045)
Saving group	0.085	0.094	0.086	0.096
	(0.074)	(0.074)	(0.107)	(0.112)
Head educ	0.008	0.009	0.054	0.051
	(0.032)	(0.031)	(0.053)	(0.053)
Age of head	-0.298***	-0.313***	-0.079	-0.113
	(0.063)	(0.060)	(0.483)	(0.474)
Transport	0.146***	0.132***	0.094	0.083
	(0.038)	(0.036)	(0.074)	(0.074)
Plots with crop	-0.074*	-0.061	-0.172**	-0.203**
	(0.044)	(0.041)	(0.084)	(0.082)
Crops on farm	-0.017**	-0.027***	0.014	0.006
	(0.008)	(0.007)	(0.016)	(0.016)
Cooperative	0.071**	0.089**	0.113**	0.112**
	(0.036)	(0.035)	(0.050)	(0.051)
Improved seeds	-0.064*	-0.057*	0.031	0.036
	(0.035)	(0.034)	(0.049)	(0.049)
Erosion	0.009	-0.007	0.144*	0.143
	(0.051)	(0.052)	(0.086)	(0.088)
Irrigation	0.040	0.011	0.194	0.195
	(0.133)	(0.127)	(0.189)	(0.179)
Steepness	0.034*	0.031*		
	(0.019)	(0.018)		
Elevation	0.081**	0.065*		
	(0.038)	(0.035)		
Intercrop	-0.082**	-0.094***	-0.103*	-0.091*
	(0.036)	(0.034)	(0.054)	(0.052)
Maincrop	0.298***	0.323***	0.210**	0.232**

	(0.047)	(0.045)	(0.093)	(0.095)
Trees per plot	-0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Soil quality	0.134***	0.138***	0.073*	0.081**
	(0.026)	(0.024)	(0.038)	(0.038)
soil_type==SANDY	-0.216***	-0.188***		
	(0.043)	(0.042)		
soil_type==CLAY	0.016	0.036		
	(0.045)	(0.043)		
soil_type==OTHER	0.105	0.132		
	(0.098)	(0.090)		
time=2	0.073	0.067	0.107	0.117
	(0.077)	(0.076)	(0.112)	(0.111)
time=3	-0.045	-0.002	0.043	0.059
	(0.064)	(0.062)	(0.087)	(0.086)
Constant	4.426***	4.324***	4.913**	4.841**
	(0.572)	(0.545)	(1.967)	(1.933)
Observations	3407	3407	3407	3407
R^2	0.31	0.40	0.29	0.32
Regions	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Estimation	Pooled OLS	Pooled OLS	Panel FE	Panel FE
Area	SR	GPS	SR	GPS

Standard errors clustered at household level for models 1-5, and at household/plot level for models 6-7
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A7: Testing P4 for rice (full output)

	(1)	(2)	(3)	(4)
	P1+P2	P1+P2+P3	P1+P2	P1+P2+P3
Area	-0.287***	-0.374***	-0.643***	-0.699***
	(0.067)	(0.053)	(0.172)	(0.102)
Area*Intercrop	-0.301***	-0.226***	-0.430**	-0.326**
	(0.109)	(0.078)	(0.186)	(0.152)
Area*female	0.011	-0.055	-0.165	-0.184
	(0.088)	(0.069)	(0.218)	(0.175)
Family labour	0.174***	0.168***	0.148**	0.118*
	(0.041)	(0.040)	(0.059)	(0.064)
Hired labour	0.163***	0.157***	0.114**	0.109*

	(0.021)	(0.019)	(0.051)	(0.057)
Organic fert	0.056**	0.058**	-0.005	-0.009
	(0.025)	(0.025)	(0.034)	(0.039)
Inorganic fert	0.090***	0.076***	-0.031	-0.048
	(0.028)	(0.025)	(0.053)	(0.057)
Rainfall	0.085	0.096	-0.418*	-0.421*
	(0.110)	(0.103)	(0.235)	(0.223)
Female head	0.095	0.032	1.594***	1.715***
	(0.093)	(0.093)	(0.450)	(0.410)
Farm size	0.156**	0.233***	0.228**	0.222*
	(0.062)	(0.054)	(0.107)	(0.122)
Saving group	0.021	0.109	-0.381	-0.339
	(0.119)	(0.114)	(0.306)	(0.296)
Head educ	0.021	0.022	-0.083	-0.102
	(0.052)	(0.050)	(0.122)	(0.122)
Age of head	-0.344***	-0.440***	0.751	0.729
	(0.118)	(0.116)	(0.541)	(0.584)
Transport	0.154*	0.077	0.333	0.334
	(0.081)	(0.077)	(0.291)	(0.293)
Plots with crop	-0.078	-0.104	-0.165	-0.132
	(0.096)	(0.092)	(0.248)	(0.239)
Crops on farm	-0.001	-0.009	-0.073**	-0.081**
	(0.018)	(0.017)	(0.036)	(0.036)
Cooperative	0.099	0.080	0.234*	0.202
	(0.071)	(0.070)	(0.139)	(0.142)
Improved seeds	0.007	0.020	-0.297*	-0.230
	(0.075)	(0.077)	(0.161)	(0.160)
Erosion	-0.073	-0.028	0.335**	0.327**
	(0.100)	(0.098)	(0.155)	(0.158)
Irrigation	-0.040	-0.064	-0.407	-0.403
	(0.214)	(0.200)	(0.369)	(0.362)
Steepness	-0.053	-0.051		
	(0.040)	(0.040)		
Elevation	0.079	0.069		
	(0.054)	(0.052)		
Intercrop	-0.429***	-0.462***	-0.226	-0.214

	(0.104)	(0.108)	(0.183)	(0.183)
Maincrop	0.080	0.117	0.229	0.192
	(0.096)	(0.095)	(0.216)	(0.215)
Trees per plot	0.000	0.000**	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Soil quality	0.103*	0.122**	-0.052	-0.036
	(0.054)	(0.052)	(0.124)	(0.118)
soil_type==SANDY	-0.137	-0.119		
	(0.097)	(0.097)		
soil_type==CLAY	0.009	0.072		
	(0.071)	(0.068)		
soil_type==OTHER	0.143	0.009		
	(0.289)	(0.282)		
time=2	-0.204	-0.231	0.555*	0.448
	(0.162)	(0.158)	(0.284)	(0.290)
time=3	-0.236	-0.183	0.127	0.095
	(0.144)	(0.142)	(0.245)	(0.241)
Constant	5.059***	5.369***	4.064*	4.328
	(0.989)	(0.955)	(2.254)	(2.793)
Observations	630	630	630	630
R^2	0.49	0.57	0.57	0.56
Regions	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Estimation	Pooled OLS	Pooled OLS	Panel FE	Panel FE
Area	SR	GPS	SR	GPS

Standard errors clustered at household level for models 1-5, and at household/plot level for models 6-7
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A8: Testing P4 for beans (full output)

	(1)	(2)	(3)	(4)
	P1+P2	P1+P2+P3	P1+P2	P1+P2+P3
Area	-0.361***	-0.447***	-0.369***	-0.539***
	(0.096)	(0.065)	(0.129)	(0.107)
Area*Intercrop	-0.120	-0.083	-0.221**	-0.085
	(0.092)	(0.062)	(0.102)	(0.087)
Area*female	-0.189**	-0.104	-0.099	-0.329
	(0.082)	(0.066)	(0.128)	(0.205)
Family labour	0.117***	0.090***	0.078	0.136**

	(0.035)	(0.032)	(0.054)	(0.055)
Hired labour	0.086***	0.064***	0.088**	0.080**
	(0.023)	(0.024)	(0.037)	(0.036)
Organic fert	0.015	0.012	0.030	0.028
	(0.013)	(0.013)	(0.029)	(0.028)
Inorganic fert	0.012	0.013	-0.009	0.001
	(0.021)	(0.021)	(0.034)	(0.033)
Rainfall	-0.173	-0.121	0.640**	0.718***
	(0.149)	(0.141)	(0.263)	(0.273)
Female head	-0.094	-0.063	-0.090	-0.219
	(0.092)	(0.088)	(0.317)	(0.334)
Farm size	0.226***	0.263***	-0.120	0.039
	(0.053)	(0.044)	(0.106)	(0.095)
Saving group	-0.001	0.000	0.042	-0.061
	(0.124)	(0.120)	(0.310)	(0.387)
Head educ	-0.101*	-0.086	-0.239**	-0.207**
	(0.059)	(0.058)	(0.098)	(0.103)
Age of head	-0.070	-0.072	0.486	-0.136
	(0.111)	(0.105)	(1.740)	(1.824)
Transport	0.143**	0.127*	0.220	0.235
	(0.072)	(0.069)	(0.151)	(0.153)
Plots with crop	-0.157*	-0.101	0.149	0.198
	(0.083)	(0.083)	(0.138)	(0.139)
Crops on farm	-0.017	-0.025*	0.022	-0.009
	(0.015)	(0.014)	(0.026)	(0.026)
Cooperative	0.018	0.063	0.208*	0.173
	(0.071)	(0.067)	(0.114)	(0.114)
Improved seeds	0.027	0.013	-0.012	0.003
	(0.070)	(0.068)	(0.114)	(0.118)
Erosion	-0.202**	-0.186**	-0.131	-0.108
	(0.084)	(0.084)	(0.131)	(0.134)
Irrigation	-0.029	-0.031	-0.512	-0.350
	(0.339)	(0.323)	(0.464)	(0.517)
Steepness	0.052*	0.038		
	(0.031)	(0.029)		
Elevation	-0.277	-0.173		

	(0.179)	(0.174)		
Intercrop	-0.272***	-0.276***	0.014	-0.058
	(0.102)	(0.098)	(0.147)	(0.149)
Maincrop	0.394***	0.425***	0.240*	0.251*
	(0.093)	(0.089)	(0.133)	(0.146)
Trees per plot	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Soil quality	0.087*	0.096**	0.069	0.056
	(0.049)	(0.048)	(0.083)	(0.081)
soil_type==SANDY	0.070	0.050		
	(0.105)	(0.104)		
soil_type==CLAY	0.038	0.030		
	(0.076)	(0.072)		
soil_type==OTHER	-0.029	0.113		
	(0.193)	(0.165)		
time=2	0.069	0.045	-0.031	-0.050
	(0.137)	(0.129)	(0.206)	(0.212)
time=3	-0.067	-0.052	-0.250	-0.209
	(0.100)	(0.098)	(0.205)	(0.208)
Constant	6.625***	5.782***	-2.482	-0.751
	(1.561)	(1.540)	(6.559)	(6.860)
Observations	936	936	936	936
R^2	0.33	0.44	0.50	0.50
Regions	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Estimation	Pooled OLS	Pooled OLS	Panel FE	Panel FE
Area	SR	GPS	SR	GPS

Standard errors clustered at household level for models 1-5, and at household/plot level for models 6-7
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A9: Testing P4 for groundnut (full output)

	(1)	(2)	(3)	(4)
	P1+P2	P1+P2+P3	P1+P2	P1+P2+P3
Area	-0.332***	-0.420***	-1.179***	-0.985***
	(0.114)	(0.081)	(0.254)	(0.259)
Area*Intercrop	-0.132	-0.073	0.285	0.097
	(0.106)	(0.081)	(0.283)	(0.239)
Area*female	-0.033	-0.068	-0.053	-0.252

	(0.089)	(0.078)	(0.302)	(0.210)
Family labour	0.162***	0.187***	0.162	0.112
	(0.058)	(0.055)	(0.157)	(0.147)
Hired labour	0.069*	0.057	0.098	0.120
	(0.040)	(0.039)	(0.096)	(0.089)
Organic fert	0.032	0.025	0.021	0.018
	(0.020)	(0.020)	(0.043)	(0.043)
Inorganic fert	0.012	0.005	-0.004	-0.037
	(0.038)	(0.039)	(0.091)	(0.088)
Rainfall	-0.043	-0.033	0.345	0.230
	(0.266)	(0.272)	(0.455)	(0.455)
Female head	-0.119	-0.059	-3.996***	-4.267***
	(0.113)	(0.111)	(0.780)	(0.689)
Farm size	0.144*	0.210***	-0.204	-0.251
	(0.081)	(0.064)	(0.192)	(0.185)
Saving group	0.045	0.162	-0.885*	-0.978*
	(0.169)	(0.175)	(0.528)	(0.550)
Head educ	0.041	0.064	0.028	0.057
	(0.091)	(0.092)	(0.314)	(0.284)
Age of head	-0.099	-0.093	-4.787	-4.176
	(0.158)	(0.161)	(5.137)	(5.068)
Transport	0.144	0.175*	0.135	0.199
	(0.106)	(0.105)	(0.339)	(0.361)
Plots with crop	-0.282*	-0.267*	-0.770**	-0.737**
	(0.153)	(0.161)	(0.308)	(0.354)
Crops on farm	-0.044**	-0.054***	-0.048	-0.053
	(0.022)	(0.021)	(0.068)	(0.068)
Cooperative	-0.140	-0.157	0.048	0.069
	(0.097)	(0.096)	(0.161)	(0.165)
Improved seeds	-0.122	-0.136	-0.251	-0.296
	(0.105)	(0.105)	(0.269)	(0.289)
Erosion	-0.012	-0.020	-0.129	-0.190
	(0.173)	(0.171)	(0.406)	(0.386)
Irrigation	0.254	0.267	2.094***	2.015***
	(0.230)	(0.230)	(0.425)	(0.417)
Steepness	0.021	0.020		

	(0.055)	(0.055)		
Elevation	0.156	0.160		
	(0.110)	(0.107)		
Intercrop	-0.033	0.027	0.043	0.129
	(0.109)	(0.107)	(0.370)	(0.364)
Maincrop	0.367***	0.371***	0.380	0.350
	(0.124)	(0.124)	(0.300)	(0.267)
Trees per plot	-0.000	-0.000	-0.000*	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
Soil quality	-0.112	-0.092	0.225	0.225
	(0.073)	(0.074)	(0.163)	(0.172)
soil_type==SANDY	-0.202*	-0.193*		
	(0.110)	(0.108)		
soil_type==CLAY	-0.037	-0.057		
	(0.182)	(0.183)		
soil_type==OTHER	-0.155	-0.201		
	(0.233)	(0.246)		
time=2	-0.083	0.012	0.788**	0.747*
	(0.191)	(0.188)	(0.394)	(0.415)
time=3	-0.148	-0.074	0.656	0.557
	(0.147)	(0.145)	(0.482)	(0.462)
Constant	4.358**	4.000*	21.139	19.846
	(2.098)	(2.119)	(20.591)	(20.093)
Observations	460	460	460	460
R^2	0.33	0.40	0.66	0.66
Regions	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Estimation	Pooled OLS	Pooled OLS	Panel FE	Panel FE
Area	SR	GPS	SR	GPS

Standard errors clustered at household level for models 1-5, and at household/plot level for models 6-7
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

7.3 Controlling for P5: full output tables

Table A10: Testing P5 for maize (full output)

	(1)	(2)	(3)	(4)
	P1+P2	P1+P2+P3	P1+P2	P1+P2+P3
Area	-0.421***	-0.479***	-0.851***	-0.868***
	(0.042)	(0.037)	(0.089)	(0.081)

Area*Maincrop	0.196***	0.141***	0.253***	0.244***
	(0.041)	(0.037)	(0.087)	(0.077)
Area*female	-0.145***	-0.113***	-0.083	-0.074
	(0.039)	(0.030)	(0.084)	(0.081)
Family labour	0.160***	0.146***	0.127***	0.122***
	(0.023)	(0.021)	(0.030)	(0.030)
Hired labour	0.124***	0.116***	0.029	0.029
	(0.015)	(0.015)	(0.022)	(0.021)
Organic fert	0.017**	0.017**	0.004	0.004
	(0.007)	(0.007)	(0.013)	(0.013)
Inorganic fert	0.127***	0.116***	0.050**	0.050**
	(0.011)	(0.010)	(0.020)	(0.020)
Rainfall	-0.043	0.003	-0.104	-0.084
	(0.077)	(0.074)	(0.099)	(0.099)
Female head	-0.064	-0.058	0.209	0.240
	(0.049)	(0.048)	(0.316)	(0.305)
Farm size	0.127***	0.186***	0.067	0.152***
	(0.028)	(0.023)	(0.052)	(0.045)
Saving group	0.083	0.088	0.098	0.114
	(0.074)	(0.074)	(0.107)	(0.111)
Head educ	0.009	0.012	0.062	0.057
	(0.032)	(0.031)	(0.053)	(0.053)
Age of head	-0.301***	-0.314***	0.019	0.002
	(0.063)	(0.060)	(0.496)	(0.472)
Transport	0.143***	0.135***	0.091	0.087
	(0.038)	(0.036)	(0.074)	(0.073)
Plots with crop	-0.070	-0.062	-0.161*	-0.192**
	(0.044)	(0.041)	(0.084)	(0.082)
Crops on farm	-0.017**	-0.026***	0.015	0.005
	(0.008)	(0.007)	(0.016)	(0.016)
Cooperative	0.070*	0.087**	0.116**	0.121**
	(0.036)	(0.035)	(0.050)	(0.051)
Improved seeds	-0.057	-0.054	0.034	0.041
	(0.035)	(0.034)	(0.049)	(0.048)
Erosion	0.006	-0.008	0.127	0.133
	(0.051)	(0.052)	(0.085)	(0.087)
Irrigation	0.034	0.006	0.175	0.182

	(0.133)	(0.127)	(0.191)	(0.183)
Steepness	0.033*	0.030		
	(0.019)	(0.018)		
Elevation	0.075**	0.060*		
	(0.038)	(0.035)		
Intercrop	-0.082**	-0.087**	-0.100*	-0.079
	(0.036)	(0.034)	(0.053)	(0.052)
Maincrop	0.297***	0.328***	0.227**	0.245***
	(0.047)	(0.045)	(0.092)	(0.093)
Trees per plot	-0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Soil quality	0.135***	0.139***	0.075**	0.083**
	(0.026)	(0.024)	(0.038)	(0.037)
soil_type==SANDY	-0.210***	-0.186***		
	(0.043)	(0.043)		
soil_type==CLAY	0.017	0.037		
	(0.045)	(0.043)		
soil_type==OTHER	0.110	0.133		
	(0.099)	(0.092)		
time=2	0.072	0.068	0.097	0.122
	(0.076)	(0.075)	(0.111)	(0.110)
time=3	-0.045	-0.005	0.045	0.062
	(0.063)	(0.062)	(0.087)	(0.084)
Constant	4.495***	4.378***	4.457**	4.317**
	(0.570)	(0.543)	(2.014)	(1.925)
Observations	3407	3407	3407	3407
R^2	0.32	0.40	0.29	0.33
Regions	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Estimation	Pooled OLS	Pooled OLS	Panel FE	Panel FE
Area	SR	GPS	SR	GPS

Standard errors clustered at household level for models 1-5, and at household/plot level for models 6-7
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A11: Testing P5 for rice (full output)

	(1)	(2)	(3)	(4)
	P1+P2	P1+P2+P3	P1+P2	P1+P2+P3
Area	-0.504***	-0.587***	-0.480**	-0.681***

	(0.097)	(0.079)	(0.230)	(0.149)
Area*Maincrop	0.155*	0.182**	-0.385	-0.116
	(0.091)	(0.072)	(0.245)	(0.164)
Area*female	-0.032	-0.066	-0.330	-0.191
	(0.091)	(0.074)	(0.208)	(0.207)
Family labour	0.171***	0.166***	0.091	0.093
	(0.044)	(0.041)	(0.064)	(0.069)
Hired labour	0.161***	0.155***	0.117**	0.126**
	(0.021)	(0.019)	(0.053)	(0.058)
Organic fert	0.057**	0.054**	-0.012	-0.017
	(0.025)	(0.025)	(0.042)	(0.045)
Inorganic fert	0.098***	0.086***	-0.021	-0.040
	(0.028)	(0.025)	(0.055)	(0.059)
Rainfall	0.084	0.108	-0.331	-0.352
	(0.110)	(0.105)	(0.217)	(0.229)
Female head	0.091	0.040	1.253***	1.467***
	(0.094)	(0.093)	(0.479)	(0.411)
Farm size	0.171***	0.246***	0.231*	0.195
	(0.063)	(0.054)	(0.128)	(0.127)
Saving group	0.047	0.145	-0.457	-0.438
	(0.120)	(0.117)	(0.282)	(0.313)
Head educ	0.018	0.027	-0.117	-0.132
	(0.052)	(0.050)	(0.123)	(0.124)
Age of head	-0.326***	-0.416***	0.407	0.540
	(0.118)	(0.117)	(0.664)	(0.608)
Transport	0.157*	0.071	0.307	0.324
	(0.081)	(0.078)	(0.293)	(0.299)
Plots with crop	-0.076	-0.095	-0.130	-0.098
	(0.097)	(0.093)	(0.231)	(0.242)
Crops on farm	-0.005	-0.013	-0.061	-0.066*
	(0.018)	(0.017)	(0.037)	(0.037)
Cooperative	0.093	0.071	0.198	0.174
	(0.073)	(0.071)	(0.143)	(0.140)
Improved seeds	0.016	0.022	-0.276*	-0.255
	(0.076)	(0.077)	(0.158)	(0.159)
Erosion	-0.074	-0.033	0.379**	0.374**

	(0.102)	(0.098)	(0.178)	(0.180)
Irrigation	-0.047	-0.079	-0.359	-0.353
	(0.210)	(0.195)	(0.320)	(0.315)
Steepness	-0.063	-0.066*		
	(0.040)	(0.039)		
Elevation	0.089*	0.074		
	(0.054)	(0.052)		
Intercrop	-0.422***	-0.484***	-0.195	-0.225
	(0.105)	(0.108)	(0.182)	(0.179)
Maincrop	0.080	0.072	0.117	0.138
	(0.097)	(0.096)	(0.249)	(0.242)
Trees per plot	0.000	0.000**	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Soil quality	0.103*	0.111**	-0.054	-0.070
	(0.055)	(0.053)	(0.121)	(0.119)
soil_type==SANDY	-0.136	-0.120		
	(0.099)	(0.097)		
soil_type==CLAY	0.023	0.075		
	(0.071)	(0.068)		
soil_type==OTHER	0.131	0.026		
	(0.288)	(0.275)		
time=2	-0.253	-0.247	0.532*	0.483*
	(0.167)	(0.160)	(0.288)	(0.290)
time=3	-0.268*	-0.190	0.065	0.063
	(0.148)	(0.144)	(0.247)	(0.236)
Constant	4.972***	5.276***	5.317*	4.981*
	(0.992)	(0.972)	(2.868)	(2.925)
Observations	630	630	630	630
R^2	0.48	0.57	0.55	0.54
Regions	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Estimation	Pooled OLS	Pooled OLS	Panel FE	Panel FE
Area	SR	GPS	SR	GPS

Standard errors clustered at household level for models 1-5, and at household/plot level for models 6-7
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A12: Testing P5 for beans (full output)

	(1)	(2)	(3)	(4)

	P1+P2	P1+P2+P3	P1+P2	P1+P2+P3
Area	-0.504***	-0.558***	-0.567***	-0.615***
	(0.052)	(0.042)	(0.093)	(0.092)
Area*Maincrop	0.231***	0.204***	-0.009	0.028
	(0.081)	(0.063)	(0.130)	(0.101)
Area*female	-0.184**	-0.092	-0.047	-0.324
	(0.080)	(0.065)	(0.128)	(0.208)
Family labour	0.108***	0.086***	0.080	0.132**
	(0.035)	(0.032)	(0.054)	(0.056)
Hired labour	0.083***	0.061***	0.093**	0.078**
	(0.023)	(0.023)	(0.037)	(0.036)
Organic fert	0.016	0.014	0.032	0.029
	(0.013)	(0.013)	(0.029)	(0.028)
Inorganic fert	0.011	0.012	-0.010	0.002
	(0.021)	(0.022)	(0.035)	(0.034)
Rainfall	-0.163	-0.127	0.671**	0.718***
	(0.148)	(0.138)	(0.272)	(0.277)
Female head	-0.096	-0.066	-0.033	-0.202
	(0.092)	(0.088)	(0.321)	(0.345)
Farm size	0.223***	0.266***	-0.118	0.029
	(0.052)	(0.043)	(0.107)	(0.092)
Saving group	0.003	0.003	0.075	-0.067
	(0.122)	(0.120)	(0.307)	(0.391)
Head educ	-0.104*	-0.090	-0.222**	-0.198*
	(0.059)	(0.058)	(0.100)	(0.103)
Age of head	-0.078	-0.076	0.837	0.007
	(0.111)	(0.105)	(1.830)	(1.857)
Transport	0.138*	0.119*	0.206	0.234
	(0.072)	(0.069)	(0.152)	(0.153)
Plots with crop	-0.151*	-0.095	0.192	0.211
	(0.083)	(0.083)	(0.136)	(0.138)
Crops on farm	-0.016	-0.026*	0.017	-0.010
	(0.014)	(0.014)	(0.026)	(0.027)
Cooperative	0.018	0.064	0.217*	0.175
	(0.071)	(0.067)	(0.116)	(0.115)
Improved seeds	0.023	0.006	-0.012	0.004
	(0.070)	(0.067)	(0.115)	(0.119)

Erosion	-0.194**	-0.178**	-0.152	-0.120
	(0.083)	(0.083)	(0.133)	(0.132)
Irrigation	0.004	0.004	-0.548	-0.361
	(0.345)	(0.331)	(0.465)	(0.520)
Steepness	0.046	0.030		
	(0.031)	(0.029)		
Elevation	-0.292	-0.171		
	(0.179)	(0.173)		
Intercrop	-0.237**	-0.257***	0.025	-0.040
	(0.101)	(0.094)	(0.152)	(0.148)
Maincrop	0.469***	0.514***	0.232	0.248*
	(0.095)	(0.091)	(0.141)	(0.150)
Trees per plot	-0.000	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Soil quality	0.092*	0.102**	0.067	0.055
	(0.049)	(0.047)	(0.082)	(0.081)
soil_type==SANDY	0.080	0.059		
	(0.106)	(0.105)		
soil_type==CLAY	0.029	0.020		
	(0.076)	(0.072)		
soil_type==OTHER	-0.028	0.104		
	(0.196)	(0.169)		
time=2	0.070	0.028	-0.105	-0.070
	(0.136)	(0.127)	(0.210)	(0.212)
time=3	-0.061	-0.051	-0.274	-0.218
	(0.099)	(0.097)	(0.210)	(0.208)
Constant	6.693***	5.849***	-4.034	-1.285
	(1.550)	(1.535)	(7.017)	(6.949)
Observations	936	936	936	936
R^2	0.34	0.44	0.50	0.50
Regions	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Estimation	Pooled OLS	Pooled OLS	Panel FE	Panel FE
Area	SR	GPS	SR	GPS

Standard errors clustered at household level for models 1-5, and at household/plot level for models 6-7

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A13: Testing P5 for groundnut (full output)

	(1)	(2)	(3)	(4)
	P1+P2	P1+P2+P3	P1+P2	P1+P2+P3
Area	-0.456***	-0.482***	-1.023***	-1.006***
	(0.082)	(0.067)	(0.208)	(0.214)
Area*Maincrop	0.137	0.047	0.187	0.228
	(0.113)	(0.092)	(0.301)	(0.263)
Area*female	-0.043	-0.071	-0.050	-0.180
	(0.090)	(0.078)	(0.304)	(0.206)
Family labour	0.162***	0.186***	0.142	0.100
	(0.057)	(0.055)	(0.158)	(0.148)
Hired labour	0.069*	0.055	0.134	0.125
	(0.041)	(0.040)	(0.095)	(0.086)
Organic fert	0.032*	0.025	0.024	0.016
	(0.020)	(0.020)	(0.043)	(0.040)
Inorganic fert	0.011	0.005	-0.021	-0.054
	(0.038)	(0.039)	(0.093)	(0.084)
Rainfall	-0.062	-0.040	0.324	0.167
	(0.268)	(0.272)	(0.471)	(0.481)
Female head	-0.122	-0.060	-4.171***	-4.359***
	(0.113)	(0.111)	(0.914)	(0.712)
Farm size	0.143*	0.209***	-0.152	-0.205
	(0.081)	(0.064)	(0.201)	(0.183)
Saving group	0.071	0.181	-1.035**	-1.145**
	(0.168)	(0.175)	(0.525)	(0.531)
Head educ	0.040	0.062	0.036	0.062
	(0.092)	(0.093)	(0.313)	(0.274)
Age of head	-0.098	-0.093	-4.777	-4.668
	(0.158)	(0.161)	(5.406)	(5.268)
Transport	0.146	0.179*	0.280	0.136
	(0.106)	(0.105)	(0.335)	(0.371)
Plots with crop	-0.274*	-0.262	-0.731**	-0.701*
	(0.152)	(0.161)	(0.330)	(0.358)
Crops on farm	-0.044**	-0.054***	-0.063	-0.053
	(0.022)	(0.021)	(0.070)	(0.068)
Cooperative	-0.135	-0.156	0.040	0.032
	(0.096)	(0.095)	(0.174)	(0.167)

Improved seeds	-0.123	-0.139	-0.289	-0.235
	(0.105)	(0.105)	(0.266)	(0.280)
Erosion	-0.022	-0.029	-0.180	-0.206
	(0.174)	(0.172)	(0.388)	(0.386)
Irrigation	0.237	0.263	1.972***	1.947***
	(0.225)	(0.227)	(0.445)	(0.429)
Steepness	0.021	0.018		
	(0.055)	(0.055)		
Elevation	0.164	0.168		
	(0.111)	(0.106)		
Intercrop	-0.044	0.016	0.206	0.205
	(0.111)	(0.108)	(0.296)	(0.288)
Maincrop	0.363***	0.364***	0.371	0.307
	(0.124)	(0.124)	(0.308)	(0.255)
Trees per plot	-0.000	-0.000	-0.000*	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
Soil quality	-0.108	-0.092	0.245	0.239
	(0.073)	(0.074)	(0.176)	(0.173)
soil_type==SANDY	-0.218**	-0.200*		
	(0.110)	(0.110)		
soil_type==CLAY	-0.023	-0.062		
	(0.183)	(0.183)		
soil_type==OTHER	-0.156	-0.211		
	(0.230)	(0.246)		
time=2	-0.102	0.005	0.754*	0.816**
	(0.191)	(0.187)	(0.411)	(0.412)
time=3	-0.153	-0.074	0.585	0.631
	(0.147)	(0.145)	(0.486)	(0.502)
Constant	4.397**	4.011*	21.242	22.059
	(2.114)	(2.124)	(21.560)	(20.726)
Observations	460	460	460	460
R^2	0.33	0.40	0.66	0.66
Regions	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Estimation	Pooled OLS	Pooled OLS	Panel FE	Panel FE
Area	SR	GPS	SR	GPS

Standard errors clustered at household level for models 1-5, and at household/plot level for models 6-7

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

7.4 Jointly controlling for P4 and P5: full output tables

Table A14: Testing P4 and P5 for maize (full output)

	(1)	(2)	(3)	(4)
	P1+P2	P1+P2+P3	P1+P2	P1+P2+P3
Area	-0.343***	-0.419***	-0.785***	-0.842***
	(0.053)	(0.043)	(0.103)	(0.091)
Area*Intercrop	-0.091***	-0.069***	-0.075	-0.031
	(0.035)	(0.026)	(0.051)	(0.043)
Area*Maincrop	0.175***	0.121***	0.234***	0.237***
	(0.041)	(0.037)	(0.090)	(0.078)
Area*female	-0.139***	-0.108***	-0.079	-0.071
	(0.039)	(0.030)	(0.084)	(0.081)
Family labour	0.160***	0.146***	0.126***	0.122***
	(0.023)	(0.021)	(0.030)	(0.030)
Hired labour	0.123***	0.116***	0.027	0.028
	(0.015)	(0.015)	(0.022)	(0.021)
Organic fert	0.017**	0.017**	0.002	0.003
	(0.007)	(0.007)	(0.013)	(0.013)
Inorganic fert	0.128***	0.116***	0.050**	0.050**
	(0.011)	(0.010)	(0.020)	(0.020)
Rainfall	-0.039	0.005	-0.099	-0.084
	(0.077)	(0.074)	(0.099)	(0.099)
Female head	-0.065	-0.060	0.224	0.243
	(0.049)	(0.049)	(0.317)	(0.305)
Farm size	0.128***	0.187***	0.069	0.152***
	(0.028)	(0.023)	(0.052)	(0.045)
Saving group	0.084	0.090	0.093	0.116
	(0.074)	(0.074)	(0.106)	(0.111)
Head educ	0.010	0.010	0.060	0.056
	(0.032)	(0.031)	(0.052)	(0.053)
Age of head	-0.300***	-0.314***	-0.017	-0.024
	(0.063)	(0.060)	(0.490)	(0.472)
Transport	0.143***	0.133***	0.089	0.084
	(0.038)	(0.036)	(0.074)	(0.073)
Plots with crop	-0.072	-0.062	-0.167**	-0.193**
	(0.044)	(0.041)	(0.084)	(0.082)
Crops on farm	-0.017**	-0.027***	0.015	0.005

	(0.008)	(0.007)	(0.016)	(0.016)
Cooperative	0.069*	0.087**	0.114**	0.119**
	(0.036)	(0.035)	(0.050)	(0.051)
Improved seeds	-0.060*	-0.056*	0.034	0.042
	(0.035)	(0.034)	(0.049)	(0.049)
Erosion	0.008	-0.006	0.132	0.135
	(0.051)	(0.052)	(0.086)	(0.087)
Irrigation	0.034	0.004	0.184	0.186
	(0.134)	(0.128)	(0.192)	(0.184)
Steepness	0.033*	0.031*		
	(0.019)	(0.018)		
Elevation	0.077**	0.063*		
	(0.038)	(0.035)		
Intercrop	-0.080**	-0.093***	-0.100*	-0.081
	(0.035)	(0.034)	(0.053)	(0.052)
Maincrop	0.294***	0.325***	0.227**	0.243***
	(0.047)	(0.045)	(0.092)	(0.093)
Trees per plot	-0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Soil quality	0.136***	0.140***	0.076**	0.084**
	(0.026)	(0.024)	(0.038)	(0.037)
soil_type==SANDY	-0.210***	-0.186***		
	(0.043)	(0.042)		
soil_type==CLAY	0.017	0.036		
	(0.045)	(0.043)		
soil_type==OTHER	0.117	0.137		
	(0.099)	(0.092)		
time=2	0.073	0.068	0.109	0.127
	(0.076)	(0.075)	(0.111)	(0.109)
time=3	-0.046	-0.006	0.048	0.064
	(0.063)	(0.062)	(0.087)	(0.084)
Constant	4.462***	4.357***	4.574**	4.423**
	(0.571)	(0.543)	(1.993)	(1.926)
Observations	3407	3407	3407	3407
R^2	0.32	0.40	0.29	0.33
Regions	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Estimation	Pooled OLS	Pooled OLS	Panel FE	Panel FE

Area	SR	GPS	SR	GPS

Standard errors clustered at household level for models 1-5, and at household/plot level for models 6-7
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A15: TestingP4 and P5 for rice (full output)

	(1)	(2)	(3)	(4)
	P1+P2	P1+P2+P3	P1+P2	P1+P2+P3
Area	-0.349***	-0.488***	-0.226	-0.563***
	(0.107)	(0.087)	(0.253)	(0.180)
Area*Intercrop	-0.283**	-0.193**	-0.462**	-0.339**
	(0.117)	(0.084)	(0.186)	(0.150)
Area*Maincrop	0.067	0.123*	-0.467**	-0.164
	(0.093)	(0.074)	(0.235)	(0.189)
Area*female	0.011	-0.062	-0.200	-0.162
	(0.089)	(0.070)	(0.205)	(0.176)
Family labour	0.172***	0.165***	0.130**	0.114*
	(0.041)	(0.039)	(0.059)	(0.064)
Hired labour	0.162***	0.157***	0.115**	0.106*
	(0.021)	(0.019)	(0.052)	(0.057)
Organic fert	0.056**	0.057**	-0.004	-0.008
	(0.025)	(0.025)	(0.034)	(0.039)
Inorganic fert	0.091***	0.079***	-0.038	-0.057
	(0.028)	(0.025)	(0.053)	(0.056)
Rainfall	0.081	0.095	-0.443*	-0.451*
	(0.110)	(0.103)	(0.233)	(0.230)
Female head	0.095	0.034	1.550***	1.737***
	(0.093)	(0.093)	(0.472)	(0.420)
Farm size	0.157**	0.240***	0.248**	0.218*
	(0.062)	(0.054)	(0.110)	(0.122)
Saving group	0.026	0.125	-0.465	-0.408
	(0.121)	(0.116)	(0.306)	(0.327)
Head educ	0.021	0.025	-0.078	-0.099
	(0.052)	(0.050)	(0.120)	(0.122)
Age of head	-0.343***	-0.439***	0.704	0.716
	(0.118)	(0.117)	(0.592)	(0.619)
Transport	0.153*	0.071	0.331	0.345
	(0.081)	(0.077)	(0.281)	(0.296)

Plots with crop	-0.076	-0.096	-0.193	-0.164
	(0.095)	(0.092)	(0.239)	(0.242)
Crops on farm	-0.001	-0.009	-0.071**	-0.080**
	(0.018)	(0.017)	(0.035)	(0.036)
Cooperative	0.095	0.071	0.232*	0.210
	(0.072)	(0.070)	(0.137)	(0.141)
Improved seeds	0.009	0.025	-0.303*	-0.238
	(0.075)	(0.076)	(0.156)	(0.157)
Erosion	-0.074	-0.033	0.362**	0.343**
	(0.100)	(0.098)	(0.153)	(0.161)
Irrigation	-0.051	-0.083	-0.338	-0.371
	(0.215)	(0.198)	(0.345)	(0.348)
Steepness	-0.053	-0.055		
	(0.040)	(0.040)		
Elevation	0.081	0.071		
	(0.054)	(0.052)		
Intercrop	-0.430***	-0.468***	-0.198	-0.231
	(0.104)	(0.108)	(0.182)	(0.184)
Maincrop	0.076	0.091	0.107	0.140
	(0.096)	(0.096)	(0.239)	(0.234)
Trees per plot	0.000	0.000**	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Soil quality	0.104*	0.118**	-0.053	-0.033
	(0.054)	(0.053)	(0.122)	(0.118)
soil_type==SANDY	-0.135	-0.121		
	(0.097)	(0.097)		
soil_type==CLAY	0.008	0.068		
	(0.070)	(0.068)		
soil_type==OTHER	0.137	0.007		
	(0.292)	(0.285)		
time=2	-0.208	-0.239	0.576**	0.461
	(0.162)	(0.158)	(0.290)	(0.292)
time=3	-0.236	-0.178	0.110	0.091
	(0.144)	(0.142)	(0.251)	(0.244)
Constant	5.080***	5.404***	4.573*	4.621
	(0.989)	(0.963)	(2.474)	(2.980)
Observations	630	630	630	630

R^2	0.49	0.57	0.58	0.56
Regions	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Estimation	Pooled OLS	Pooled OLS	Panel FE	Panel FE
Area	SR	GPS	SR	GPS

Standard errors clustered at household level for models 1-5, and at household/plot level for models 6-7
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A16: TestingP4 and P5 for beans (full output)

	(1)	(2)	(3)	(4)
	P1+P2	P1+P2+P3	P1+P2	P1+P2+P3
Area	-0.492***	-0.590***	-0.312**	-0.523***
	(0.109)	(0.083)	(0.145)	(0.135)
Area*Intercrop	-0.013	0.034	-0.260**	-0.099
	(0.100)	(0.075)	(0.113)	(0.111)
Area*Maincrop	0.226**	0.221***	-0.107	-0.030
	(0.094)	(0.081)	(0.138)	(0.131)
Area*female	-0.186**	-0.092	-0.094	-0.327
	(0.080)	(0.065)	(0.126)	(0.206)
Family labour	0.109***	0.085***	0.081	0.136**
	(0.035)	(0.032)	(0.053)	(0.055)
Hired labour	0.083***	0.061***	0.089**	0.081**
	(0.023)	(0.023)	(0.037)	(0.036)
Organic fert	0.016	0.014	0.029	0.028
	(0.013)	(0.013)	(0.029)	(0.028)
Inorganic fert	0.011	0.012	-0.009	0.001
	(0.021)	(0.022)	(0.034)	(0.033)
Rainfall	-0.163	-0.127	0.652**	0.717***
	(0.148)	(0.139)	(0.267)	(0.274)
Female head	-0.097	-0.067	-0.044	-0.205
	(0.092)	(0.088)	(0.318)	(0.346)
Farm size	0.223***	0.265***	-0.117	0.039
	(0.052)	(0.044)	(0.107)	(0.095)
Saving group	0.002	0.003	0.042	-0.061
	(0.122)	(0.120)	(0.313)	(0.388)
Head educ	-0.104*	-0.090	-0.236**	-0.206**
	(0.059)	(0.058)	(0.098)	(0.104)
Age of head	-0.077	-0.078	0.879	-0.027

	(0.112)	(0.105)	(1.792)	(1.892)
Transport	0.138*	0.119*	0.220	0.235
	(0.072)	(0.069)	(0.150)	(0.152)
Plots with crop	-0.151*	-0.095	0.141	0.196
	(0.083)	(0.083)	(0.139)	(0.140)
Crops on farm	-0.016	-0.026*	0.027	-0.007
	(0.015)	(0.014)	(0.026)	(0.027)
Cooperative	0.017	0.065	0.219*	0.176
	(0.071)	(0.067)	(0.115)	(0.114)
Improved seeds	0.023	0.005	-0.011	0.005
	(0.070)	(0.067)	(0.114)	(0.119)
Erosion	-0.194**	-0.181**	-0.133	-0.109
	(0.083)	(0.082)	(0.131)	(0.134)
Irrigation	0.004	0.006	-0.500	-0.347
	(0.345)	(0.331)	(0.467)	(0.518)
Steepness	0.046	0.029		
	(0.031)	(0.029)		
Elevation	-0.292	-0.169		
	(0.179)	(0.173)		
Intercrop	-0.240**	-0.247***	0.002	-0.061
	(0.100)	(0.095)	(0.147)	(0.150)
Maincrop	0.467***	0.519***	0.217	0.242
	(0.093)	(0.091)	(0.142)	(0.151)
Trees per plot	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Soil quality	0.092*	0.102**	0.072	0.058
	(0.049)	(0.047)	(0.083)	(0.082)
soil_type==SANDY	0.079	0.061		
	(0.106)	(0.106)		
soil_type==CLAY	0.030	0.018		
	(0.076)	(0.072)		
soil_type==OTHER	-0.026	0.102		
	(0.196)	(0.169)		
time=2	0.070	0.030	-0.058	-0.052
	(0.136)	(0.127)	(0.213)	(0.212)
time=3	-0.061	-0.050	-0.284	-0.214

	(0.099)	(0.097)	(0.207)	(0.209)
Constant	6.689***	5.834***	-4.117	-1.181
	(1.550)	(1.533)	(6.903)	(7.120)
Observations	936	936	936	936
R^2	0.34	0.44	0.51	0.50
Regions	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Estimation	Pooled OLS	Pooled OLS	Panel FE	Panel FE
Area	SR	GPS	SR	GPS

Standard errors clustered at household level for models 1-5, and at household/plot level for models 6-7
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A17: TestingP4 and P5 for groundnut (full output)

	(1)	(2)	(3)	(4)
	P1+P2	P1+P2+P3	P1+P2	P1+P2+P3
Area	-0.367***	-0.429***	-1.248***	-1.131***
	(0.125)	(0.098)	(0.270)	(0.293)
Area*Intercrop	-0.112	-0.067	0.318	0.166
	(0.110)	(0.091)	(0.291)	(0.258)
Area*Maincrop	0.109	0.021	0.253	0.289
	(0.117)	(0.105)	(0.295)	(0.271)
Area*female	-0.035	-0.067	-0.138	-0.223
	(0.089)	(0.078)	(0.298)	(0.207)
Family labour	0.163***	0.187***	0.155	0.107
	(0.058)	(0.055)	(0.158)	(0.147)
Hired labour	0.071*	0.057	0.105	0.114
	(0.041)	(0.040)	(0.094)	(0.086)
Organic fert	0.033*	0.025	0.018	0.013
	(0.020)	(0.020)	(0.042)	(0.041)
Inorganic fert	0.013	0.006	-0.010	-0.042
	(0.038)	(0.039)	(0.091)	(0.086)
Rainfall	-0.055	-0.034	0.298	0.165
	(0.269)	(0.273)	(0.465)	(0.474)
Female head	-0.124	-0.060	-4.339***	-4.395***
	(0.113)	(0.111)	(0.907)	(0.714)
Farm size	0.146*	0.211***	-0.208	-0.220
	(0.081)	(0.065)	(0.189)	(0.181)
Saving group	0.056	0.165	-0.845	-1.008*

	(0.170)	(0.179)	(0.545)	(0.554)
Head educ	0.044	0.064	-0.023	0.028
	(0.092)	(0.093)	(0.353)	(0.297)
Age of head	-0.102	-0.093	-6.297	-5.535
	(0.158)	(0.161)	(5.724)	(5.532)
Transport	0.140	0.174	0.133	0.127
	(0.107)	(0.106)	(0.329)	(0.367)
Plots with crop	-0.275*	-0.265	-0.718**	-0.697*
	(0.152)	(0.161)	(0.319)	(0.355)
Crops on farm	-0.044**	-0.054***	-0.055	-0.055
	(0.022)	(0.021)	(0.069)	(0.067)
Cooperative	-0.140	-0.158*	0.021	0.025
	(0.097)	(0.096)	(0.161)	(0.161)
Improved seeds	-0.120	-0.136	-0.301	-0.283
	(0.105)	(0.105)	(0.273)	(0.294)
Erosion	-0.023	-0.023	-0.146	-0.201
	(0.173)	(0.171)	(0.405)	(0.388)
Irrigation	0.241	0.263	2.118***	2.012***
	(0.229)	(0.230)	(0.439)	(0.423)
Steepness	0.022	0.020		
	(0.055)	(0.055)		
Elevation	0.156	0.160		
	(0.110)	(0.107)		
Intercrop	-0.040	0.025	0.027	0.100
	(0.109)	(0.108)	(0.361)	(0.353)
Maincrop	0.369***	0.371***	0.320	0.259
	(0.124)	(0.124)	(0.314)	(0.273)
Trees per plot	-0.000	-0.000	-0.000*	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
Soil quality	-0.110	-0.092	0.229	0.238
	(0.073)	(0.074)	(0.164)	(0.167)
soil_type==SANDY	-0.211*	-0.195*		
	(0.110)	(0.110)		
soil_type==CLAY	-0.027	-0.058		
	(0.183)	(0.183)		
soil_type==OTHER	-0.140	-0.200		

	(0.234)	(0.247)		
time=2	-0.097	0.010	0.755*	0.768*
	(0.191)	(0.188)	(0.397)	(0.419)
time=3	-0.147	-0.074	0.721	0.689
	(0.147)	(0.145)	(0.499)	(0.507)
Constant	4.423**	4.013*	27.611	25.622
	(2.116)	(2.129)	(23.147)	(21.980)
Observations	460	460	460	460
R^2	0.33	0.40	0.67	0.67
Regions	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Estimation	Pooled OLS	Pooled OLS	Panel FE	Panel FE
Area	SR	GPS	SR	GPS

Standard errors clustered at household level for models 1-5, and at household/plot level for models 6-7

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$