***NOT FOR PUBLICATION**

Online Appendix: "Land Misallocation and Productivity"

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Contents

A The Data: The Malawi Integrated Survey of Agriculture, 2010/2011

The Malawi 2010-2011 Integrated Survey of Agriculture (ISA) is part of a new generation of household surveys funded by the Bill & Melinda Gates Foundation (BMGF) and led by the Living Standards Measurement Study (LSMS) Team in the Development Research Group (DECRG) of the World Bank to improve the quality and policy relevance of household-level data on agriculture in Sub-Saharan Africa. This way, the Malawi ISA incorporates an extended and comprehensive 'Agricultural Questionnaire' on agricultural production and factor inputs, including land quality and rain.

An important aspect of the Malawi ISA for the evaluation of macroeconomic policies is that it is a nationally-representative survey. To ensure representativeness, the survey follows a stratified 2-stage sample design. First, 768 enumeration areas (EAs) are selected with probability proportional to size (PPS) within each district of the 27 districts of Malawi. The sampling frame is based on the 2008 Population and Housing Census (PHC) that includes three major regions of Malawi, namely North, Center and South; and is stratified into rural and urban strata. The urban strata include the four major urban areas: Lilongwe City (the current capital city), Blantyre City (capital of the South region), Mzuzu City (capital of the North Region), and the Municipality of Zomba (old colonial capital). Second, random systematic sampling is used to select 16 primary households and 5 replacement households from the household listing for each sample EA.

A.1 Agricultural Production, Intermediate Inputs, and Value Added

The most important aspect of the Malawi ISA is that it provides detailed information on physical quantities of all farm agricultural production and the full set of inputs used in that production. In this Appendix we discuss the construction of agricultural production, intermediate inputs, and value added at the household-farm level.

Each household agricultural production are reported separately for crop produced by season. We focus on the rainy season that captures about 93% of the entire agricultural production in Malawi. Denote by ψ_i the type of crop i.[1] Denote the total quantity of nonpermanent crop-ψ_i harvested by household z per season s by $y_{\psi_i,s,z}$ (AG:g13). The information on harvested crop is available per plot, that is, $y_{\psi_i,s,z} = \sum_d y_{\psi_i,d,s,z}$ where $y_{\psi_i,d,s,z}$ is the amount of crop-ψ_i harvested by household z in season s and plot d. We find that there are up to 5 types of crops that are potentially harvested per plot. These data are collected for each plot cultivated by the household-farm.[2] The quantity produced of a given crop is in most cases reported in Kilograms (more than 90 percent of observations). We follow a standard conversion procedure to Kgs for the small set of cases in which units are reported differently.[3] We then use a common at-the-gate price to estimate the value of production for both sold and unsold production.

In terms of intermediate inputs, each household z incurs in input costs per season and plot associated with fertilizers, herbicides, pesticides, and seeds. Fertilizers are the most important intermediate input in terms of monetary costs. The main types of inorganic fertilizer used in Malawi are 23:21:0+4S/Chitowe and Urea, that account for almost 57% of fertilizer use. Inorganic fertilizer is used in 61% of all plots and organic fertilizer is used in 10.7% of all plots.[4] To attribute a value for each type of fertilizer, we use the prices paid by those households that purchased fertilizer without coupons, i.e., without interference of the Malawi Farming Input Subsidy Program (FSIP). We use the median price for all households.[5] More than 96 percent of all fertilizer purchases are reported in Kg., while the rest are reported in liters, buckets, wheelbarrows, ox carts, or others. We again use a

[1]Information on all typical nonpermanent crops ϕ_i is available. These crops are: maize (local, composite/OPV, hybrid, hybrid recycled), tobacco (Burley, flue cured, NNDF, SDF, oriental, other), groundnut (chalimbana, CG7, mani-pintar, mawanga, JL24, other), rice (local, faya, pusa, TCG10, IET4094, kilombero, etc.), ground bean, sweet potato, Irish (Malawi) potato, wheat, finger millet (mawere), Sorghum, peral millet (mchewere), beans, soybeans, pigeonpea (nandolo) cotton, sunflower, sugar cane, cabbage, tanaposi, nkhwani, therere/OKRA, tomato, onion, pea paprika, other). For exposition simplicity, we use rainy season variables name codes (AG:b-i) in the Agricultural questionnaire. The procedure for the simba (dry) season name codes (AG:j-o) is analogous, replacing 'c' for 'j' and so on.

[2]A plot is defined as a continuous piece of land on which a unique crop (or mixture of crops) is grown under a uniform consistent crop management system. These questions are generally asked to the person that makes the economic decisions on the plot (see AG:d01-d02).

[3]We use a 'price conversion' unit procedure to convert all crop-units pairs into Kgs, see de Magalhaes and Santaeulàlia-Llopis (2015).

[4]Pesticides/herbicides are used in 2.2% of all plots.

[5]As we discuss below, we use common prices so that our measure of productivity does not inherit nominal variation from subsidies across households.

standard conversion procedure to deal with the small set of observations where the reporting unit is different from Kg. We then value intermediate units using a common median price per unit for each type of intermediate input.

Finally, we construct our measure of output as agricultural value added at the farm level. That is, to define output for each household-farm we subtract to the household's agricultural production valued at common at-the-gate prices the value of intermediate inputs, also valued at common prices.

A.2 Land Size and Land Quality

Our preferred measure of household land is the sum of the size (in acres) of each household's plot used for cultivation. We include rented-in land (6.9% of all plots) in household land size. For the vast majority of plots, 98%, the acres per plot are recorded using GPS with precision of 1% of an acre. In the remaining 2% of plots, size is self-reported with an estimate from the household. This leaves virtually no room for error in our measure of land input, see a detailed assessment in Carletto et al. (2013). The data also contain detailed information on the quality of land for each plot used in each household. We consider all 11 dimensions of land quality available: elevation, slope, erosion, soil quality, nutrient availability, nutrient retention capacity, rooting conditions, oxygen availability to roots, excess salts, topicality, and workability.[6] Our benchmark land quality index is defined per household as the predicted value of output (net of rain effects which we discuss in the next Section) generated by the joint behavior of all dimensions of land quality controlling for capital and land size, see the first column in Table A-1.[7] We also explore alternative definitions of the land quality index in Table A-1 that depend on the number of land quality dimensions that we incorporate and on the way we control for capital and land. A reassuring aspect of our land quality index, defined from physical measures (e.g., erosion, soil quality, etc.), is that it is positively related

[6] The slope (in %) and elevation (in meters) are continuous variables while the rest of land quality variables are categorical such as soil quality (1 good, 2 fair, 3 poor), erosion (1 none, 2 low, 3 moderate, 4 high), nutrient availability, nutrient retention, rooting conditions, oxygen to roots, excess of salts, toxicity and workability (1 constraint, 2 moderate constraint, 3 severe constraint and 4 very severe constraint).

[7] For households with more than one plot we take a weighted average of each of these 11 dimensions using the size of plot as weight.

to land prices, see Table A-2, in particular, for the plots that have been obtained through the market for which we obtain a correlation of .503. Finally, we perform a robustness analysis of our reallocation results with respect to our entire set of land quality indexes without substantial changes in our findings, see Table A-3.

Table A-1: Land Quality Index and Its Dimensions

	Land Quality Index					
	Bench.	Alternative Definitions:				
Dimensions:	q_0	q_1	q_2	q_3	q_4	q_5
Elevation	✓	✓	✓	✓	✓	✓
Slope	✓	✓	✓	✓	✓	✓
Erosion	✓	–	✓	–	✓	–
Nutritient Availability	✓	–	✓	–	✓	–
Nutritient Retention	✓	–	✓	–	✓	–
Rooting Conditions	✓	–	✓	–	✓	–
Oxygen to Roots	✓	–	✓	–	✓	–
Excess Salts	✓	–	✓	–	✓	–
Toxicity	✓	–	✓	–	✓	–
Workability	✓	–	✓	–	✓	–
Additional Controls:						
Capital	✓	✓	–	–	✓ (Const.)	✓ (Const.)
Land Size	✓	✓	–	–	✓ (Const.)	✓ (Const.)

A.3 Rain

We use the annual precipitation which is the total rainfall in millimetres (mm) in the last 12 months. Figure A-1 plots the effects of rain, grouped in percentiles, on output. We find a clear positive and concave relationship between rain and output, that is, the effects of rain on output become less strong as rain increases. Throughout, our benchmark measure of output (value added) is net of the rain effects. As rain might be more relevant in some months than others we also tried an alternative measure of rain, the wettest quarter within the last 12 months. We find that this alternative measure of rain effects does not alter our

Table A-2: Land Quality Index and Land Price, Malawi ISA 2010/11

	Land Quality Index					
	Bench.	Alternative Definitions:				
	q_0	q_1	q_2	q_3	q_4	q_5
Full Sample:						
Effects on Land Price	.128	.271	.089	.197	.123	.312
Non-Marketed Land:						
Effects on Land Price	.116	.265	.076	.182	.105	.301
Marketed Land Share >0%:						
Effects on Land Price	.188	.236	.142	.227	.228	.311
Marketed Land Share 100%:						
Effects on Land Price	.275	.308	.225	.292	.332	.372
Purchased Land, Untitled:						
Effects on Land Price	.191	.246	.158	.199	.223	.299
Purchased Land, Titled:						
Effects on Land Price	.503	.763	.296	.673	.536	.885

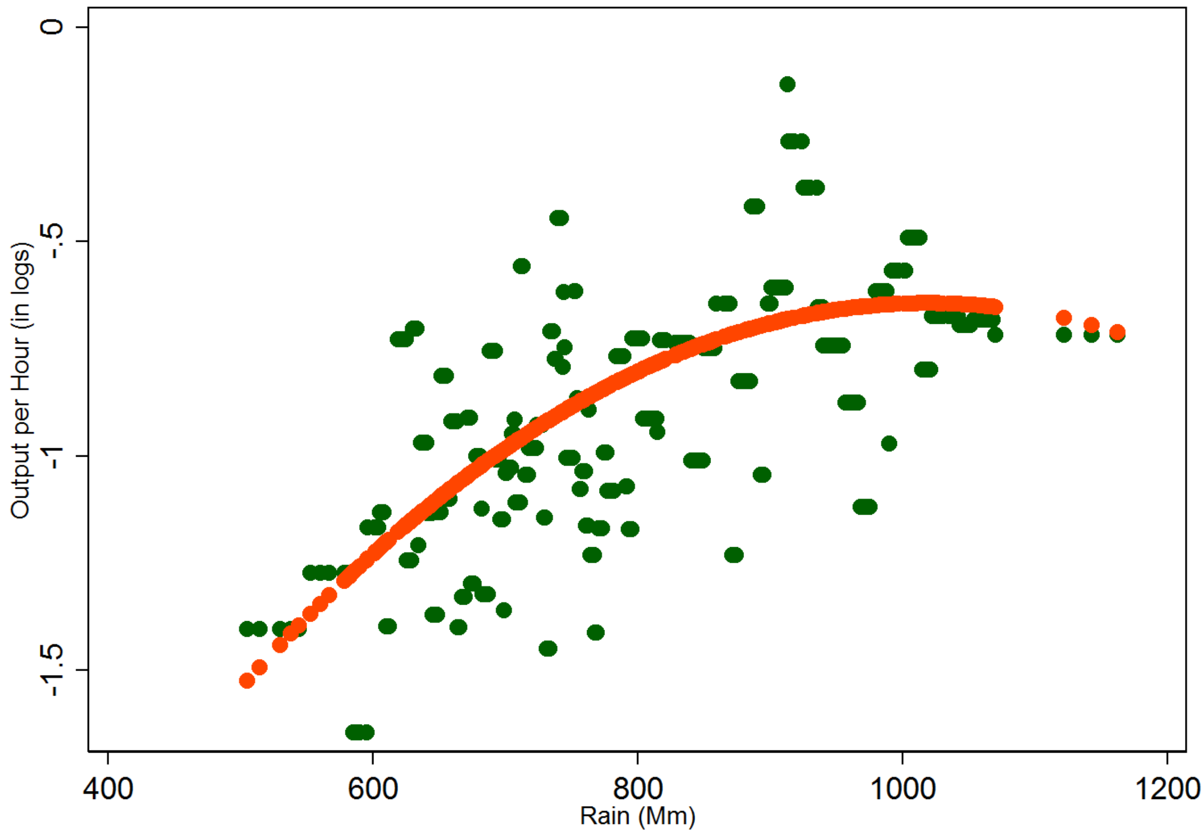
Notes: The table reports the OLS estimated coefficient β from the following specification: $\ln q_i = cons + \beta \ln p_i + \mathbf{1}_{region}$ where q_i is the land quality index, p_i is the price of land computed as the ratio between the self-reported estimated land value (under the hypothetical scenario in which the owner sells the land) and the quantity of land, and $\mathbf{1}_{region}$ is a set of regional dummies. We estimate this relationship using our benchmark measure of land quality and 5 alternative measures of land quality defined in Table A-1. In each case we consider alternative samples that include the full sample, farms with non-marketed land, farms with a positive marketed land share, farms with only marketed land, farms that have purchased untitled land and farms that have purchased titled land.

Table A-3: Output Gain, Robustness to Land Quality Index

	Bench.	Alternative Definitions of Land Quality				
	q_0	q_1	q_2	q_3	q_4	q_5
Output gain	3.59	3.42	3.90	3.53	3.44	3.42

results.

Figure A-1: The Effects of Rain on Output per Hour



Notes: Rain in percentiles and quadratic behavior.

A.4 Hours

In Malawi, not only the household head but also a large proportion of the households members, which average 4.57 per household, contribute to agricultural work. The household head is identified as the person who makes economic decisions in the household (e.g., use of production or transfers). We define household members as individuals that have lived in the household at least 9 months in the last 12 months. These household members potentially include family (e.g. children, spouses, siblings, and parents) and also non-relatives (e.g. lodgers and servants).[8] Individual information about each household member's (including children) extensive and intensive margins of labor supply is collected: (i) weeks worked, (ii) days per week, and (iii) hours per day. This information available in the 'Agriculture Questionnaire' is provided retrospectively by plot and by agricultural activity covering the entire agricultural production. Agricultural activities consist of land preparation/ planting, weeding/fertilizing, and harvesting.[9] The hired labor and free/exchange labor (e.g. exchange labourers or assistance for nothing in return) number of days worked by men, women and children are also collected by plot, activity and season. The detailed information on individual agricultural hours through the entire year avoids the seasonal component of labor supply; that is, we do not rely on data on labor supply related to 'last week/month' behavior. Our benchmark measure of household labor supply is aggregate hours of all individuals (household members and nonmembers) supplied in all plots cultivated by the household in the rainy season.[10]

A.5 Capital Equipment and Structures

Agricultural capital equipment includes implements (i.e., hand hoe, slasher, axe, sprayer, panga knife, sickle, treadle pump and watering can) and machinery (e.g. ox cart, ox plough, tractor, tractor plough, ridger, cultivator, generator, motorized pump, grain mill, and others). Agricultural capital structures includes chicken houses, livestock kraals, poultry kraals, storage houses, granaries, barns, pig sties, etc. To measure the capital stock per item we use the estimated current selling price of capital items ("If you wanted to sell one of this [ITEM] today, how much would you receive?") after conditioning on its use ("Did your household use the [ITEM] during the last 12 months?"). We construct the household agricultural capital stock by aggregating across all agricultural items. The use of the selling price (not available in previous LSMS data) avoids the cumbersome use of the age of capital

[8]Individual characteristics of each household member are collected. They include sex, age, language, religion, educational attainment, health behavior and status, marital status, societal system, geographical variables, migration characteristics, and so on.

[9]We conduct robustness to recall bias in agricultural production and hours in Appendix B.

[10]We have conducted robustness analysis under different specifications of hours that include using a different set of individuals (e.g., only head hours, and only members hours) or different units (e.g., weeks per year, or days per year). Further, to control for human capital, i.e., the fact that not all hours might contribute the same to agricultural production, we construct household efficiency units by weighting individual hours using the wages of hired labor by age and sex groups as weights. We find that our results are robust to these alternative specifications.

to impute current value from the value at the time of purchase which requires recalling and depreciation assumptions by asset's age. We discuss further issues on the measurement of capital, including alternative measures such as asset indexes, in Appendix B.

B Trimming Strategy and Measurement Error

We discuss our trimming strategy and measurement issues associated with agricultural output and factor inputs.

B.1 Trimming Strategy

There are very few missing observations in agricultural production, a blessing for a survey in a poor country. Our understanding from the World Bank field managers in charge of the data collection is that this is due to the fact that respondents took the Malawi ISA as "official". We focus on those households with nonnegative agricultural production, i.e, 9,538 household farms. Then, to retrieve household farm productivity (see Section **??**), we need data on all household farm inputs, i.e., hours, capital, land, all eleven dimensions of quality of land, and rain. These data are available for 92% of all observations. Further, our measure of output is value added, that is, agricultural production net of intermediate inputs (i.e., seeds, fertilizers, herbicides and pesticides). This leaves room for potential non-positive values of output that we drop. The resulting sample consists of 7,202 household farms.[11] Last, after visual inspection, we further trim from the distribution of household-farm productivity about 1% of the sample.

B.2 Dealing with Measurement Error

While the Malawi ISA survey response rate is high and there is little room for measurement error in our estimates of land size (as each plots' size is GPS measured, see Appendix A.2), there are other potential sources of measurement error associated with agricultural produc-

[11] Using lower than median prices to value intermediate inputs increases our sample size. Ultimately, the reduction of intermediate prices to zero implies our measure of output is simply agricultural production in which case all output observations are non-negative. In this case our reallocation exercise implies an aggregate output loss of .2562 which is larger than our benchmark output loss. That is, dropping non-positive value added observations biases slightly down our reallocation gains.

tion and other agricultural inputs that we discuss next.

B.2.1 Potential Recall Bias for Agricultural Production and Hours

In rural settings the underreporting of agricultural production is a recurrent issue for survey data.[12] There are two aspects of the Malawi ISA design that help mitigate and study this issue. First, the ISA applies an intense data collection strategy to capture agricultural production in which in many instances the survey provides internal consistency checks (e.g., households are asked total sales, and also sales by crop and by plot; the interviewer must check *in situ* that the two sums coincide or otherwise re-interview). Second, the ISA not only collects data on agricultural production but also close to "gold standard" data on consumption that includes food consumption (in physical units) from own production with 7 days recall.[13] This provides a unique opportunity to externally validate agricultural production using consumption data. In this context, a reassuring result is that in rural household-farms that do not sell their agricultural production and have little or no consumption purchases (i.e., about 50% of the entire rural sample), the reported agricultural production and the reported consumption net of transfers imply very similar quantities, which suggests a small scope for measurement error (from recall or elsewhere) in agricultural production, see de Magalhaes et al. (2015).

Not only agricultural production is collected retrospectively, but also hours. To further investigate the basis for potential recall bias in the collection of production and hours, we note that in Malawi there is only one main harvest associated with the only rainy season. The rainy season, which starts in late March/early April and goes through July, captures 93 percent of annual agricultural production.[14] Hence, given that ISAs data collection rolls over 12 months, when households are asked about their last collected harvest for the rainy season,

[12] A similar issue arises in the measurement of income for self-employed households in both rich and poor countries, see Deaton (1997).

[13] The 7 days recall consumption is found to be a good reliable compromise compared with more expensive and intense consumption data collection that can be set as benchmark or "gold standard", see the recent assessments in Beegle et al. (2010) and Gibson et al. (2015).

[14] The remaining production attained in the dry (Dimba) season and in terms of permanent crop. Further, the hours input is also more intensively used in the harvest season that in pre-harvest activities such as planting, weeding and fertilizing.

this might happen right after harvest or several months after it (e.g., some household farms asked in December might have collected their last harvest from the rainy season nine months before).[15] To assess the potential effects of recall on our reallocation results, we re-conduct our entire analysis for only the households farms that report agricultural production shortly after harvest. Our results are reported in Table B-1. We find that if we restrict our sample study to those households that report agricultural production within four months after their main harvest was collected, the output (productivity) gain is 3.7-fold which is slightly larger than the 3.6-fold output gain in our benchmark specification. This finding suggests that our results are robust to recall bias.

Table B-1: Robustness to Potential Output Recall Bias

	Benchmark	Post-Harvest Months
Output Gain	3.59	3.68

B.2.2 Proxying Agricultural Capital with an Asset Index

Our benchmark measure of agricultural capital (i.e., equipment and structures) uses the self-reported selling price of each of the agricultural assets in production during the year under study.[16] This implies that part of the variance in agricultural capital across households might be due to differences in the price of capital. If correctly measured, the selling price of capital should capture the relative price of investment associated with that particular asset and its depreciation since the year it was purchased.[17] But the use of the selling price might be limited if reported by households in areas where capital sales and purchases are infrequent or in which markets for those assets are not fully developed.

We assess how much variation there is in agricultural capital across households when, as opposed to our benchmark measure of agricultural capital, we use a physical asset index based

[15]For the case of Malawi ISAs 2010/11 there are actually 13 months, from March 2010 to March 2011.
[16]We proxy the value of agricultural capital services by the value of the agricultural capital stock.
[17]Under competitive markets the inverse of this price is productivity, i.e., the quality of capital.

solely on the "yes/no" answers (i.e., dummy variables) about the ownership of agricultural assets. The idea is that the use of simple "yes/no" answers reduces potential measurement error introduced by the households' self-reported inference on the price of capital. Precisely, we construct a standard asset index for agricultural capital following Filmer and Pritchett (2001) and McKenzie (2005) as:

$$\widetilde{k} = \sum_{k}^{n_k} \beta_k \left(\frac{x_k - \overline{x}_k}{\sigma_k} \right),$$

where $\beta'\beta = 1$ with $\beta = (\beta_1, ..., \beta_{n_k})'$, and $\overline{x}_k$ and σ_k are, respectively, the mean and standard deviation of the asset x_k. We include the full set of $n_k = 25$ agricultural assets collected in the Malawi ISA 2010 and specified in Appendix A.5. The agricultural capital index for a farm i, i.e., $\widetilde{k}_i = \sum_{k}^{n_k} \beta_k \left(\frac{x_{i,k} - \overline{x}_k}{\sigma_k} \right)$, is the principal component score for that farm.[18]

In terms agricultural capital dispersion, we find that the variance in logs of our benchmark measure of agricultural capital (i.e., through the self-reported selling price) is 1.82, while the variance associated with the asset index, $\widetilde{k}^1$, is 1.491. If instead of using only information on whether a farm owns (and uses) a given agricultural asset, we use further information on the quantity of assets of a given type used in production, we find that the variance associated with this alternative asset index, $\widetilde{k}^2$, is 1.181. This conforms to the notion that part of our benchmark agricultural capital measured through selling prices captures more than differences in the amount of physical capital some of which may be quality differences.

It is possible, however, that some variation in our benchmark measure of capital captures not only genuine variation in the quality of capital, but also some noise in the data collection or in the household's assessments of the price of their own capital. To investigate this, we re-conduct our reallocation exercise using the agricultural asset indexes described above as proxies for agricultural capital services. Due to the smaller variation of the capital indexes across households, the associated dispersion of farm productivity is larger under the indexes than under our benchmark measure of capital. Indeed, with $\widetilde{k}^1$ the household farm

[18] Note that $\left(\frac{x_{i,k} - \overline{x}_k}{\sigma_k} \right)$ has zero mean and variance λ, where λ is the largest eigenvalue of the correlation matrix of x.

productivity displays a variance (in logs) of 1.607, and of 1.551 with $\widetilde{k}^2$, while this dispersion is 1.435 in our benchmark. Further, while the correlation of our benchmark capital measure with its associated household farm productivity is -.015 (non-significant), the correlation of $\widetilde{k}^1$ and $\widetilde{k}^2$ with their associated household farm productivities are -.167 and -.089 (both significant). That is, the asset indexes drive the allocation of capital further away from the efficient allocation relative to our benchmark measure. This implies much larger output gains of 17.5-fold under $\widetilde{k}^1$ and of 16-fold under $\widetilde{k}^2$ (versus 3.6-fold in our benchmark), see Table B-2.

Table B-2: Robustness to Agricultural Capital Measured with an Asset Index

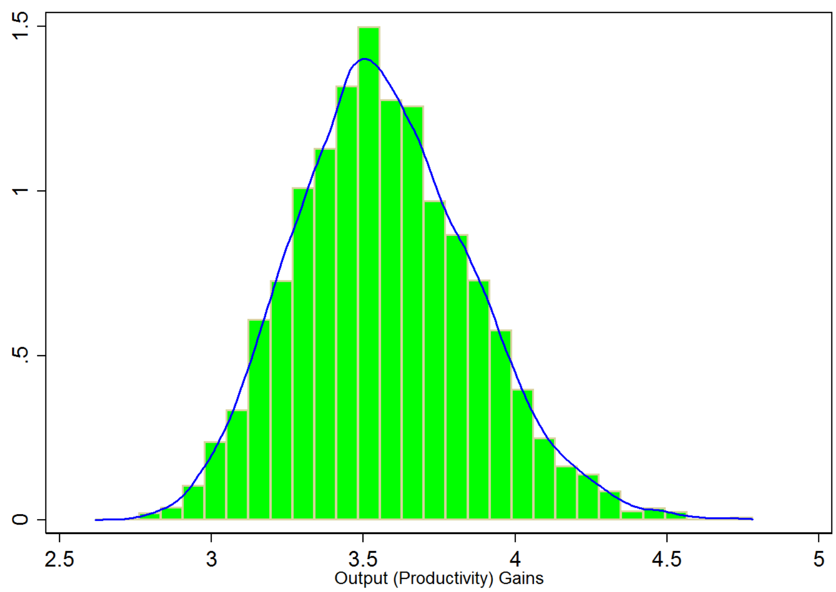
		Asset Indexes	
	Benchmark	$\widetilde{k}^1$	$\widetilde{k}^2$
Output Gain	3.59	17.54	16.00

Notes: The agricultural asset index $\widetilde{k}^1$ is constructed using "yes/no" information for 25 types of agricultural assets used in production. The agricultural asset index $\widetilde{k}^2$ further incorporates the quantity per agricultural asset used in production.

B.2.3 Further Accuracy Assessments: Bootstrapping Our Household-Farms

We show that our results are robust to potential inaccuracies associated with sample size. This is largely due to the fact that our sample size is relatively large. We find a nationwide output gain 3.58-fold, a bootstrap median gain of 3.55-fold, and 5th and 95th bootstrap percentiles of 4.07 and 3.11. These estimates are computed from 5,000 simulations obtained from random draws with 100 percent replacement, that is, each simulation consists of a sample of the same size as the original sample, and clustered at enumeration area—i.e., the smallest geographical area available in the Malawi ISA. Our bootstrap results imply that our reallocation findings are precise. We report in this Appendix the entire bootstrap distribution of output (productivity) gains in Figure B-1. The histogram reveals a distribution of output gains that are tight and close to normal with a slight skewness to the left. Precisely, with a median of 3.55 gains, the tails of the output gains basically die out well before reaching a factor of 2.5 gains from below while there is still some mass to the right of 4.5 gains from above.

Figure B-1: Histogram of Output Gains: Bootstrapped Simulations



Notes: Results from 5,000 simulations clustered at enumeration area.

C Further Insights on the Role of Land Markets

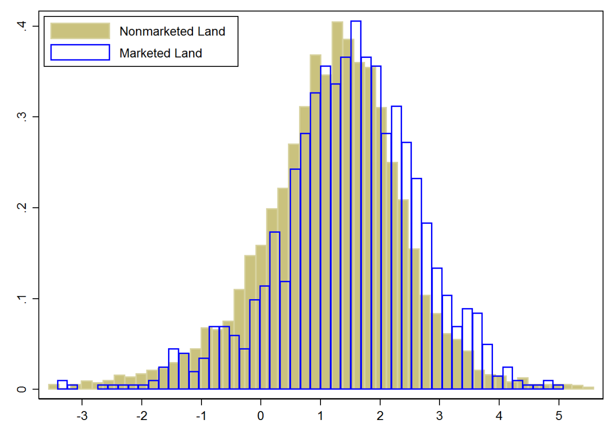
An interesting aspect of our results is that the gains from reallocation are more than twice as large for farms with no marketed land than for farms with some marketed land (purchased or rented in). This result highlights the importance of the role of land markets for aggregate output (and productivity). In this Appendix, we investigate further the differences between the farms that operate marketed land and the farms that do not.

C.1 Distribution of Farm TFP by Marketed Land

One potential concern with our characterization of the output gains across farms with and without marketed land is the possibility that access to marketed land is driven by farm productivity. However, our data indicates very small differences in productivity between farms with and without marketed land. These differences are too small compared to what it would be if access to marketed land was purely driven by frictionless selection in farm TFP.

Even though on average farms with some marketed land are 25 percent more productive than farms with no marketed land, the distribution of household-farm productivity is very similar between the group of household-farms with marketed land compared to the group of farms without marketed land, with respective variances of 1.19 and 1.17. Figure C-1 shows the close overlap of these distributions. Nevertheless, we assess the gains from reallocation holding constant farm-level TFP with fairly similar quantitative results.

Figure C-1: Density of Farm Productivity s_i (in logs) by Marketed Land, Malawi ISA 2010/11



Notes: Household-farm productivity s_i is measured using our benchmark production function, adjusting for rain ζ_i and land quality q_i , $y_i = s_i \zeta_i f(k_i, q_i l_i)$ with $f(k_i, q_i l_i) = k_i^{.36} (q_i l_i)^{.18}$, where y_i is farm output, k_i is capital, and l_i is land. All variables have been logged. The sample is divided between those that operate land acquired in the market and those that do not.

C.2 Demographics, Human Capital, Female Empowerment, and Welfare

In terms of demographics, we focus on the characteristics of the household head, see Table C-1. We find that 95.7% of farms with no marketed land are in rural areas, against 79.3% of those farms with some marketed land, and 71.3% of those farms operating only land obtained from the market. Household heads in farms with no marketed land tend to be slightly older, an average of 43.3 years of age, although the oldest group of farmers are those that purchased land, either untitled, 44.2 years, or titled, 44 years. The share of female heads in the household-farm population decreases with marketed land, 19% of females operating in farms with no marketed land whereas 16.4% in farms operating some marketed land. Further, the proportion of migrants heads increases with marketed land, 19% of migrants in farms operating no marketed land and 32.5% of migrants in farms operating marketed land.[19]

Land markets are also related to human capital. Years of schooling of household heads increase with marketed land, 4.9 years of schooling for in farms operating no marketed land, 7.1 years in farms operating some marketed land, and 7.7 years of schooling in farms that only operate marketed land.

In terms of production, marketed land is associated with higher production (valued at constant at-the-gate prices), higher agricultural value added, higher farm productivity s_i, higher land productivity (i.e., yield), and higher capital productivity (i.e., capital-to-output ratio). All these numbers are largely driven by farms with purchased land. For example, production is 223% higher for farms with purchased titled land than for farms with no marketed land, productivity is 47% higher, and capital productivity 12% higher. Interestingly, while land quality q_i also increases in farms with marketed land, on average by 42% compared with the land in farms with no marketed land, we find that for farms with land purchased with title, land quality decreases by 14% relative to the land quality of farms with no marketed land.

Female empowerment is also considered a measure of development. We find that access to land markets tends to enhance female empowerment in terms of female labor force participation and female wages. For households that operate only non-marketed land, female labor force participation is 26.9%, whereas this figure raises to 43.8% for household that operate some marketed land and 50.7% for households that only operate marketed land.[20] Female empowerment is also reflected in wages, as females that work in the market in households that operate some marketed land earn wages that are 168% higher than wages of females in household-farms that operate non-marketed land. Females wages in households that operate only marketed land are 234%. The largest female labor force participation and wages are observed in the household-farms that operate land purchased with a title, with a female labor force participation of 55.5% and female wages 339% higher than female wages in farms

[19]Most migration occurs from rural to rural areas, see de Magalhaes and Santaeulàlia-Llopis (2015).

[20]Labor force participation is defined as participation in nonagricultural marketed activities including own businesses, informal work, or working for a salary (including wages from other household farms).

with no marketed land.

Finally, land markets are also highly related to household welfare. We find that consumption in adult-equivalent units (nondurable consumption and food consumption) also increases with marketed land.[21] In terms of nondurable consumption, households that operate some marketed land consume 40% more per adult-equivalent than households with no marketed land, 51% more in households operating only marketed land, and 76% more in households operating land purchased with a title. In terms of food consumption the differences are minor, partly because the basket composition of those with marketed land has more weight towards non-food consumption. Consumption of maize per adult equivalent (in Kg.) is higher in farms operating non-marketed land than farms operating land purchased with a title.

To summarize, land markets are associated with other indicators of economic development such as human capital, female empowerment, migration, and welfare.

C.3 Land Markets and Access to Credit and Other Markets

We interpret the facts that farm productivity is unrelated to land holdings and that the capital to output ratio is roughly constant with farm productivity with the notion that restrictions to land markets affect the allocation of capital, as also argued in de Soto (2000).

The first panel in Table C-2 shows how access to land markets relates to access to credit markets. First, we find that there are not substantial differences in the self-reported need for a loan across households with different access to land. We find that 63.8% of households that do not operate any marketed land need a loan, and this number decreases slightly to 59.3% for households operating only marketed land, and to 57.7% for households operating purchased land. Second, conditional on needing a loan, we do observe substantial differences in loan applications rates with 27.7% of households with no marketed applying for a loan versus 41.1% of households with some marketed land applying for a loan, that is, almost a 50% higher rate of loan application for farms with marketed land than for farms with

[21] We use measures of annual deseasonlized consumption in de Magalhaes and Santaeulàlia-Llopis (2015) which crucially include own production valued using consumption prices adjusted by region and season.

no marketed land.[22] Third, there are also substantial differences across households with different access to land markets in terms of the success rates of being granted the loan. We find that 61.1% of households that apply for a loan and operate no marketed land succeed in obtaining a loan, whereas the success rate for farms that only operate marketed land is 69%. Note that since we observe which household-farms choose to apply for a loan and those that choose not to, the success rates that we compute control for self-selection. Putting together the application and success rates we find that the proportion of household farms who need a loan and get it unambiguously increases with access to land markets. This proportion is 16.9% for households that do not operate any marketed land, 26.2% for households that operate some marketed land, and 27.8% for households that operate only marketed land. That is, access to credit is associated with access to marketed land. Finally, this relationship between land markets and credit is also present in terms of the amount borrowed. Within households that succeed in getting a loan, household-farms that do not operate any marketed land borrow on average USD68, whereas this figure is USD154.8 for farms with some marketed land and USD194.6 for farms that operate only marketed land.

The second and third panel in Table C-2 display the relationship between land markets and labor and intermediate inputs markets. Unlike the case of credit markets, for labor we cannot control for self-selection (e.g., households are not asked about the willingness to hire labor and its success in doing so). Nevertheless, in terms of the proportion of hired labor in total farm hours we observe a clear positive relationship between access to land markets and labor markets. For farms that operate only non-marketed land, the amount of hired labor represents 4.6% of total farm hours while this figure increases to 15.9% for farms with some marketed land, and to 19.5% for farms that only operate marketed land. The intermediate inputs market on fertilizers and seeds portrays a similar picture. Household-farms that operate some marketed land use 51% more fertilizers and 21% more seeds than farms that operate only non-marketed land, and those with land purchased with a title use 156% more fertilizers and 54% more seeds than farms that operate only non-marketed land. Finally, in

[22] Households that need a loan but self-select into the group that does not apply for a loan justify this choice mostly by the fact that they do not know any lender and also because they believe their application would be turned down.

terms of technology adoption on fertilizers, we barely observe any differences in the use of organic fertilizer, i.e., low technology across groups with different access to land market, but we do observe substantial differences in the use of inorganic fertilizer, i.e., high technology, with household farms that operate some marketed land using 54% more inorganic fertilizer than farms with no marketed land. Similarly, in terms of technology adoption on seeds quality, access to land markets reduces the use of seeds from local maize, i.e, low technology, and increases the use of hybrid maize, i.e., high technology.

To summarize, our evidence suggests that the access to land markets is positively related with potentially more developed credit, labor and intermediate inputs markets. Further, in the context of intermediate inputs, access to land markets is also related to the adoption of better technologies such as inorganic fertilizer and hybrid maize seeds.

Table C-1: The Role of Land Markets: Household-Farm Demographics, Human Capital, Female Empowerment, and Welfare

	Marketed Land Share			Rented		Purchased	
Household-Farm Characteristics:	0%	$> 0\%$	100%	Untit.	Titled	Untit.	Titled
Demographics:							
▷ Rural (%)	95.7	79.3	71.3	70.6	81.5	87.3	77.3
▷ Age	43.3	40.7	41.7	41.9	39.3	44.2	44.0
▷ Females (%)	25.3	16.4	17.9	21.8	15.1	18.2	18.5
▷ Migrants (%)	19.0	32.5	37.1	37.6	27.3	46.4	30.4
Schooling Years	4.86	7.11	7.72	7.65	6.96	5.99	7.07
Production (Index):							
▷ Agricultural Production	100	137	117	75	128	209	223
▷ Agricultural Value Added	100	140	120	81	132	199	227
▷ Productivity, s_i	100	125	118	102	130	125	146
▷ Land Productivity: y_i/l_i	100	107	105	108	110	106	107
▷ Capital Productivity: y_i/k_i	100	107	103	78	118	106	113
▷ Land Quality, q_i	100	142	121	127	158	151	86
Female Empowerment:							
▷ Female Labor Force Part. (%)	26.9	43.8	50.7	51.0	41.7	21.7	55.5
▷ Female Wages (Index)	100	268	334	310	239	156	439
Welfare:							
▷ Nondurable Exp. (USD)	534	749	808	772	707	722	942
▷ Food Exp.(USD)	380	481	508	516	471	420	497
▷ Maize Consumption (kg)	269	291	323	233	335	249	218
Obs.	5,962	1,189	746	215	682	126	97

Notes: The share of marketed land is defined from the household-farm level information on how land was acquired, see Section **??**. Nondurable expenditures, food expenditures and maize consumption (in Kg) are transformed into an adult equivalent units using the equivalence scales in Krueger and Perri (2006). Expenditures are in USD using the exchange rate in 2010, i.e., we divide Kwachas by 152.

Table C-2: The Role of Land Markets: Household-Farm Access to Credit and Other Markets

	Marketed Land Share			Rented		Purchased	
Household-Farm Characteristics:	0%	> 0%	100%	Untit.	Titled	Untit.	Titled
Credit Market:							
▷ Need a Loan (%)	63.8	61.9	59.3	63.7	63.3	61.9	57.7
▷ Application Rate (%)	27.7	41.1	40.4	28.5	45.4	40.7	36.0
▷ Success Rates (%)	61.1	63.8	69.0	60.5	63.9	61.2	66.6
▷ Amount Borrowed (USD)	68.0	154.8	194.6	201.1	119.4	289.0	145.3
Labor Market:							
▷ Hired Labor (% of Farm Hours)	4.6	15.9	19.5	15.9	15.5	10.7	17.6
Intermediate Inputs Market/ Technoloty Adoption:							
▷ Fertilizer:							
Total Fertilizer (USD)	64.5	97.9	86.7	62.3	94.6	119.1	165.2
Low Tech: Organic Fert. (USD)	3.5	3.6	3.7	1.8	3.7	5.4	6.1
High Tech: Inorganic Fert. (USD)	60.8	94.2	84.8	60.4	90.7	113.7	158.9
▷ Seeds:							
Total Seeds (USD)	15.6	19.0	15.2	13.8	18.4	21.9	24.1
Low Tech: Local Maize (USD)	3.9	3.8	3.4	3.7	3.7	3.7	4.0
High Tech: Hybrid Maize (USD)	10.5	11.7	11.4	10.3	12.0	12.3	12.6
Number of Observations	5,962	1,189	746	215	682	126	97

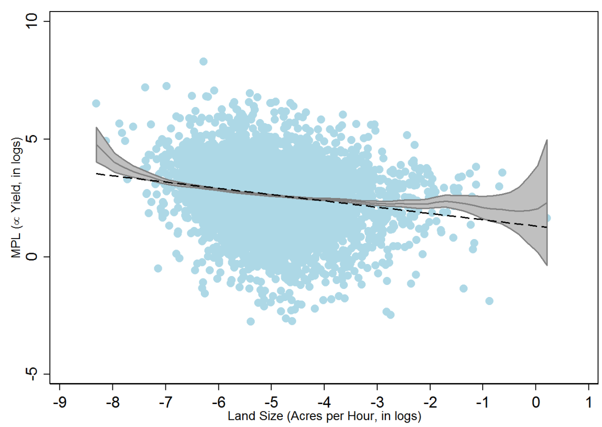
Notes: The share of marketed land is defined from the household-farm level information on how land was acquired, see Section **??**. Expenditures are in USD using exchange rate in 2010, i.e., we divide Kwachas by 152.

D Discussion on Farm Size and Robustness

D.1 Farm Size

Figure D-1 documents the relationship between land productivity (yield) by farm size in our data. Land productivity is slightly declining with farm size, which conforms with the finding in the inverse yield-to-size literature. For instance, the land productivity of the largest 10 percent of farms relative to the smallest 10 percent of farms is 0.34 (a 3-fold yield gap).

Figure D-1: Land Productivity by Farm Size, Malawi ISA 2010/11



Notes: Household-farm land size is the sum of all plots per household farm and marginal product of land (MPL) is constructed using our benchmark production function, i.e., MPL = .18 y_i/l_i. All variables have been logged.

D.2 Human Capital and Specific Skills

Table D-1 reports robustness results with respect to human capital and specific terrain skills. In each case, we perform the efficient reallocation exercise but within each education and skill type. With respect to schooling levels of the household head, the output gains are large at all schooling levels and roughly constant across the human capital spectrum. For no schooling farmers the output loss is 0.31 and between 0.26 to 0.28 for farmers with primary and more than primary schooling. Output losses may also be related to specific skills such as how to operate farms in different terrain roughness. Similarly to our findings for human capital, the output losses are large even within specific terrain roughness, 0.27 for high altitude plains

Table D-1: Robustness to Human Capital and Specific Skills

	Output Loss within Schooling Groups			
Schooling groups:	No Schooling	Dropouts	Primary	> Primary
Output gain	3.22	3.33	3.81	3.58
	Output Loss within Terrain-specific Skills			
Terrain-roughness Skills:	High Altitude Plains	Low Plateaus	Mid-Altitude Plateaus	Mid-Altitude Mountains
Output gain	3.69	3.71	3.03	2.74

Notes: The table reports robustness exercises within schooling groups and within types of terrain roughness for which specific skills might be required. The sample distribution across education groups defined as highest educational degree completed is: no schooling 25%, primary school dropouts 45%, primary school graduates 23%, and more than a primary school degree 7%.

and 0.36 for mid-altitude mountains.

D.3 Productivity Net of Transitory Health and Other Shocks

We compute the output losses associated with farm productivity measures that are net of health and other transitory shocks. To do so we regress our benchmark measure of productivity on a set of controls that capture potential sources of transitory shocks. Then, we use the residual from each of these regressions as the new measure of productivity. We find that the output gains with these alternative measures of productivity are fairly similar to our benchmark measure of farm TFP.

We describe in detail the variables that we use to adjust farm productivity for transitory shocks. We use six specifications that differ in the number of controls. The implications for the dispersion of farm productivity are reported in the first row of Table D-2. First, we include measures of health risk that include illness and injuries affecting the household head and present in the past two weeks.[23] These illnesses/injuries include, for example, malaria, diarrhea, stomach ache, respiratory problems, dental problems, eye problems, burns,

[23] These data are available at the individual level for each household member. While we focus our analysis on the household head, we find that the introduction of the health status of the rest of household members does not change our results.

fractures, wounds, and poisoning. Note that these illnesses/injuries potentially last more than the two weeks reference period and can affect annual productivity.[24] We also include hospitalizations over the past 12 months at both medical facilities (i.e., hospitals or health clinics) as well as at traditional healers dwellings. We also include health expenditures over the past 12 months either for prevention or treatment. Prevention predominantly includes regular checkups and doctor visits and treatment includes the costs of overnight stays at medical facilities or traditional healer dwellings, transportations costs, and food costs at those facilities. In terms of prevention, we also include the presence of bed nets and insecticide use to prevent malaria infection.[25] The result of netting health shocks from our farm productivity measure reduces the variance of productivity from our benchmark of 1.435 to 1.4226.

Second, the data records the deaths of any member of the household over the past two years. Information on the age of the deceased is available. We introduce death shocks as the deaths suffered by the household over the past 24 months for all individuals above 11 years old.[26] Controlling for death shocks, we find this further reduces the variance of farm productivity but not in any significant manner to 1.4225.

Third, the households also report whether in the last 12 months they have been faced with a situation in which they did not have enough food to feed the household. We find that this food insecurity episodes occur for 48.7% of all households. The main reason for food insecurity is no food stocks as a consequence of drought/poor rain (33.55%), lack of farm input (3.37%), and small land size (10.65%). Netting our measure of productivity from food security risks drops the variance of farm productivity further to 1.4137.

Finally, we also introduce additional controls that potentially affect productivity through the course of the year such as marital status and the performance of other income sources (i.e., labor market income, business income, capital income, and net transfers), or through

[24]We are not interested in including chronic diseases as we consider them part of the permanent component of farm productivity.

[25]We find that 19% of all households heads suffer some illness/injury present in the past 2 weeks in rural areas and 15% in rural areas, but only around 17% of households are treated for those illnesses/injuries. Also, 3% of household heads are hospitalized in the past 12 months in both rural and urban areas. However, health expenditures barely represent 1% of total consumption in both rural and urban areas.

[26]Most deaths are infant deaths of children below 1 year of age (17.81%), below 2 years of age 25.84%, and below 5 years of age 39.42.

their transitory nature previous to a reallocation policy such as the household distance to roads, population centers, input suppliers, auctions, markets, and border posts. We find that the sequential introduction of each of these additional controls further reduces, though not in substantial manner, the variance in farm productivity to a final variance of 1.4073. These small reductions in the variance of farm productivity do not affect substantially the magnitude of the output losses reported, in fact, the output losses are slightly higher than in the baseline measure of productivity that abstracts from these potential transitory effects on farm output and productivity.

Table D-2: Productivity Net of Health and Other Transitory Shocks

	Household-Farm Productivity: Specs. Net of Further Transitory Shocks					
	(1)	(2)	(3)	(4)	(5)	(6)
$var(s_i)$	1.4226	1.4225	1.4137	1.4119	1.4092	1.4073
Illness/Injury (last 2 wks)	✓	✓	✓	✓	✓	✓
Hospitalizations (last 12m.)						
▷ Formal:	✓	✓	✓	✓	✓	✓
▷ Traditional Healer:	✓	✓	✓	✓	✓	✓
Health Expend. (USD) (last 12m.)						
▷ Prevention	✓	✓	✓	✓	✓	✓
▷ Treatment	✓	✓	✓	✓	✓	✓
Malaria (last 12m.)						
▷ Nets	✓	✓	✓	✓	✓	✓
▷ Insecticide	✓	✓	✓	✓	✓	✓
Death (last 2 years)	–	✓	✓	✓	✓	✓
Food Security (last 12m.) :	–	–	✓	✓	✓	✓
Marital Status	–	–	–	✓	✓	✓
Distance to:						
Roads	–	–	–	–	✓	✓
Pop. Center	–	–	–	–	✓	✓
Input Supplier (Admarc)	–	–	–	–	✓	✓
Auction	–	–	–	–	✓	✓
Market (Boma)	–	–	–	–	✓	✓
Border Post	–	–	–	–	✓	✓
Other Income Sources:						
Labor	–	–	–	–	–	✓
Capital	–	–	–	–	–	✓
Business	–	–	–	–	–	✓
Livestock Produce	–	–	–	–	–	✓
Net Transfers	–	–	–	–	–	✓

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