Land Misallocation and Productivity[†]

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Abstract

Using detailed household-farm level data from Malawi, we measure real farm total factor productivity (TFP) controlling for a wide array of factor inputs, land quality, and transitory shocks. The distribution of farm TFP has substantial dispersion but factor inputs are roughly evenly spread among farmers. The striking fact is that operated land size and capital are essentially unrelated to farm TFP implying a strong negative effect on agricultural productivity. A reallocation of factors to their efficient use among existing farmers would increase agricultural productivity by a factor of 3.6-fold. We relate factor misallocation to severely restricted land markets as the vast majority of land is without a title and a very small portion of operated land is rented in. The gains from reallocation are 2.6 times larger for farms with no marketed land than for farms that operate marketed land.

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1 Introduction

A fundamental question in the field of economic growth and development is why some countries are rich and others poor. The literature has offered many useful perspectives but in this paper we build on two. First, agriculture is important in accounting for productivity differences between rich and poor countries. This is because poor countries are much less productive in agriculture and allocate most of their labor to this sector than rich countries. Moreover, low productivity in agriculture together with a subsistence constraint for food explains the large fraction of employment in agriculture in poor countries. As a result, the key question is why agricultural labor productivity is so low in poor countries.[1] Second, (mis)allocation of factors of production across heterogeneous production units is important in explaining differences in measured productivity across countries.[2] In particular, Adamopoulos and Restuccia (2014a) emphasize that misallocation in the agricultural sector in poor countries, specifically policies and institutions that affect land allocations and farm size, may explain their low agricultural productivity. In this paper, we use detailed household-farm level data from Malawi to measure real farm total factor productivity (TFP) controlling for a wide array of factor inputs, land quality, and transitory shocks. We show that operated land size and capital are essentially unrelated to farm TFP which provides direct and comprehensive evidence of misallocation. Factor misallocation has a substantial negative effect on agricultural productivity. Importantly, we provide evidence that the bulk of productivity losses are associated with restricted land markets.

Malawi represents an interesting case to study for several reasons. First, Malawi is an extremely poor country in Africa. According to international comparable measures of output, Malawi GDP per capita in 1990 is around 1/35 that of the United States. Most of this difference is due to low labor productivity. Second, as with most poor countries, labor productivity in the agricultural sector in Malawi is much lower than in the aggregate. For instance, agricul-

[1] See, for instance, Restuccia et al. (2008).

[2] See Banerjee and Duflo (2005), Restuccia and Rogerson (2008), Hsieh and Klenow (2009), among others.

tural GDP per worker relative to that of the United States in 1990 is 1/104 whereas relative aggregate GDP per worker in the same year is 1/39.[3] The distinction between aggregate productivity and agricultural productivity is important since in Malawi most of the employment is in the agricultural sector. The share of employment in agriculture in Malawi in 1990 is 65% whereas this share is only 2.5% in the United States. Third, the land market in Malawi is largely underdeveloped. Most of the land in Malawi is customary and without a title. In our sample, more than 83% of household farms do not operate any marketed land (either purchased or rented-in). For these households land is typically granted by local leaders, transmitted by inheritance, or received as bride price. Finally, the land distribution in Malawi is fairly concentrated in extremely small operational scales, with more than 70 percent of all households operating less than 2 acres of land (less than 1 hectare). Following, Adamopoulos and Restuccia (2014a), we argue that a plausible explanation to low productivity in agriculture in Malawi is the misallocation of factors associated with frictions, policies and institutions that affect the distribution of operated land.

We assess the quantitative importance of factor misallocation using detailed household-farm micro data from Malawi. A key element of the analysis is the measure of real farm TFP which requires detailed information on outputs, inputs, and other factors. The data is the 2010/11 Integrated Survey of Agriculture (ISA) for Malawi collected by the World Bank and consists of a large nationally-representative sample of more than 12 thousand households. Using the detailed micro data we measure real farm productivity controlling for a wide array of factor inputs, land quality, and transitory shocks. Even though there is substantial dispersion in our measure of farm TFP, factors of production are roughly evenly spread among farmers. The striking fact is that operated land size and capital are essentially unrelated to farm productivity. These patterns imply that the marginal products of capital and land are strongly positively related with farm TFP which, under a standard framework of farm size constitutes evidence of factor misallocation.

[3] See, for instance, Restuccia et al. (2008) and Adamopoulos and Restuccia (2014a).

To assess the role of misallocation on agricultural productivity in Malawi, we consider as a benchmark the efficient allocation of factors across existing household-farms in the data, taking as given the total amounts of land and capital. We calculate the aggregate output loss as the ratio of actual to efficient output, where the efficient output is the aggregate agricultural output resulting from the efficient allocation of capital and land across farms. Since the total amounts of capital, land, and number of farmers are kept the same under the efficient allocation, the output loss is equivalent to a TFP loss. Our main finding is that the output loss is 0.28 in the full sample. That is, if capital and land are reallocated across farms in Malawi to their efficient uses, agricultural productivity would increase by a factor of 3.6-fold. This large productivity impact of misallocation would unravel a substantial process of structural change with broader implications for aggregate outcomes. For instance, in the context of a simple two-sector model, the increase in agricultural TFP would reduce the share of employment in agriculture from 65 percent to 4 percent, and it would increase agricultural labor productivity and average farm size by a factor of 16.2-fold. These effects would be even larger in a more sophisticated model that includes ability selection across sectors such as that in Lagakos and Waugh (2013), endogenous investment by farmers as in Goldstein and Udry (2008), endogenous human and physical capital accumulation, among other well-studied channels in the literature.

In order to put our evidence of factor misallocation in Malawi and its large negative impact on agricultural productivity in perspective relative to the existing literature, we note that our evidence is closely linked to the seminal work of Hsieh and Klenow (2009) for the the manufacturing sector in China and India. Our analysis contributes to this work by providing evidence of misallocation in agriculture in a very poor country that is less subject to concerns of measurement and specification errors that has casted doubt on the extent of misallocation in poor countries. The evidence of misallocation we provide is strong because: (a) it is easier to measure output and productivity in agriculture than in other sectors, essentially outputs and most inputs are easily measured in quantities, (b) the micro data provides precise measures of quantity and quality of inputs as well as transitory shocks, and there are very few missing observations, making the analysis less subject to measurement and specification errors, and (c) the large sample size and prevalence of maize production allow us to corroborate the extent of misallocation for farms that produce essentially the same crop within narrow geographic and other relevant characteristics. For these reasons we argue that, to the best of our knowledge, our analysis constitutes the most direct and comprehensive evidence of misallocation in a poor country.

A limitation of the empirical literature on factor misallocation is the weak link between misallocation and the policies and institutions that cause it. While this limitation has inspired a promising quantitative literature studying specific policies and institutions, the findings are yet elusive in explaining the bulk of TFP differences across countries.[4] In this context, another important contribution of our paper is to provide a strong empirical connection between factor misallocation and the limited market for land, showing large productivity losses associated with restricted land markets. The evidence comes from contrasting the output losses among farmers that have no marketed land to those that operate marketed land. We also contrast the difference in the output loss that arises from different forms of marketed land, such as land purchased with or without a title and land rented formally or informally. Our findings are striking. The output loss of farms that operate land that is not marketed is 0.24 (slightly larger than the 0.28 output loss in the full sample). But for farms that operate some marketed land, the output loss is cut by half to 0.51. The output loss for farms with all marketed land is 0.64. To put it differently, the gains from reallocation are 2.6 times larger for farms with no marketed land than for farms with only marketed land. Among farms with marketed land, we find that the lowest output losses are for farms that operate land purchased with a title, with an average output loss of 0.72. These results have important implications for the design of policies and institutions to promote a better allocation of factors.

We find that misallocation has important implications for income inequality. Even though the actual allocation of factors is evenly spread among heterogeneous farmers, we find that

[4]See for instance the surveys in Restuccia and Rogerson (2013) and Hopenhayn (2014).

factor equalization is ineffective at equalizing incomes in Malawi, in addition to its negative effect on agricultural productivity already discussed. Taking the actual allocation of factors as endowments and decentralizing the efficient allocation via perfectly competitive rental markets, we show that the income distribution associated with the efficient allocation features not only much lower overall income inequality, but also that the largest gains are accrued by the poorest farmers. For instance, whereas the ratio of actual income in the top to bottom quintile of the productivity distribution is a factor of 34-fold, it is reduced to a factor of 4-fold in the efficient allocation. Moreover, whereas the efficient to actual income ratio increases by a factor of 2-fold for the top quintile of the productivity distribution, the increase is a factor of 24-fold for the bottom quintile and 4-fold for the second quintile. Hence, the poorest farmers benefit the most from the reorganization of operational scales. A market arrangement where operational scales can deviate from land holdings substantially improves aggregate income, reduces poverty, and alleviates income inequality relative to operational scales that favor factor equalization across household farms.

Our paper relates to the broad literatures on misallocation and the role of agriculture in aggregate productivity discussed earlier. In addition, our paper is closely related to a set of papers emphasizing misallocation of land as an important factor, for instance Adamopoulos and Restuccia (2014a), Chen (2014), and Adamopoulos and Restuccia (2014b). Chen (2014) extends a standard model of farm size by allowing for untitled land and studying the aggregate impact of differences in the extent of untitled land across countries. Adamopoulos and Restuccia (2014b) study the misallocation and productivity impact of a specific land policy: land reforms. We differ from these papers in studying land misallocation in an economy with a severely restricted land market to assess the aggregate impact of factor misallocation. Our result on the aggregate impact of factor misallocation is several orders of magnitude larger than previously found, suggesting an important role of imperfections in land markets for the low productivity in poor countries. Our emphasis on the importance of land markets connects to the literature in development studying the role of land rights for investment in agriculture.[5] We complement this literature by emphasizing the importance of land markets for the allocation of factors across productive uses in the agricultural sector. Like Adamopoulos and Restuccia (2014b), our paper uses micro data to study macro development, an approach that relates to a growing literature in macroeconomics.[6]

The paper proceeds as follows. In the next section, we describe the important elements of the micro data for our analysis and in Section 3 we report the main facts from the data in Malawi. In section 4 we assess the productivity impact of misallocation by comparing aggregate agricultural output in the actual data to the hypothetical efficient allocation of factors. We discuss output losses across geographical areas, traditional authority, language, specific skills, as well as across the extent of access to marketed land. We also report some robustness exercises. Section 5 explores the income inequality implications of the reallocation of factors to the efficient allocation. In section 6 we discuss the broader implications of reallocation in the context of a two-sector model. We conclude in Section 7. An on-line appendix is available at: `https://www.dropbox.com/s/je5wv90trv2nmq3/RS_Online_Appendix.pdf?dl=0`.

2 Data

We use a new and unique household-level data set collected by the World Bank, the Malawi Integrated Survey on Agriculture (ISA) 2010/11. The survey is comprehensive in the collection of the entire agricultural production (i.e., physical amounts by crop and plot) and the full set of inputs used in all agricultural activities at the plot level, all collected by a new and enlarged agricultural module that distinguish ISA from previous Living Standards Measurement Study (LSMS) surveys. The data are nationally-representative with a sampling frame based on the

[5] See for instance Goldstein and Udry (2008) and the references therein.

[6] See for instance Hsieh and Klenow (2009); Buera et al. (2014); Gollin et al. (2014); and de Magalhaes and Santaeulàlia-Llopis (2014a), among others.

Census and an original sample that includes 12,271 households (and 56,397 individuals) of which 81% live in rural areas.[7]

The survey provides information on household-farm characteristics over the entire year and we focus our attention to agricultural activities related to the rainy season. The detail on household-farm agricultural production is excruciating. Information on agricultural production is provided by each and all crops produced by the household. This is an economy largely based on maize production that uses 80% of the total land. The total quantity of crop harvested per crop and by each household is available per plot. We then value agricultural production using median at-the-gate prices per region. In crop production, each household potentially uses different quantities of intermediate inputs such as fertilizers, herbicides, pesticides and seeds. This information is also provided by plot. We also apply common median prices to value these intermediate inputs. As a result, our benchmark measure of household-farm output is a common-price measure of value added constructed as the value of agricultural production (of all crops) minus the costs of the full set of intermediate inputs.[8]

We measure household land as the sum of the size of each cultivated household plot. This includes rented-in land, which consists of 12.5% of all cultivated land. On average, household farms cultivate 1.8 plots.[9] Plot size is recorded in acres using GPS (with precision of 1% of an acre) for 98% of plots (for the remaining 2% of plots, size is estimated). Further, the data contains very detailed information on the quality of land for each plot used in every household. There are 11 dimensions of land quality reported: elevation, slope, erosion, soil quality, nutrient availability, nutrient retention capacity, rooting conditions, oxygen availability

[7] The Malawi ISA is part of a new initiative 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. We provide further details on the Malawi ISA and the construction of agricultural output and its factor inputs in the Appendix A. See also de Magalhaes and Santaeulàlia-Llopis (2014b) for a broader analysis of cross-sectional facts of ISA data for different Sub-Saharan countries.

[8] We discuss in Section 4 the implications of subsidized input prices, i.e., purchases of fertilizers done by redeeming coupons provided by the Malawi Input Subsidy Program for our measure of productivity and our results on the productivity effects of misallocation.

[9] Land is the largest household asset representing 46% of household total wealth. House structure is 27%, livestock is 11%, agricultural equipment and structures (eg. tools and barns) is 3%, see de Magalhaes and Santaeulàlia-Llopis (2014b).

to roots, excess salts, topicality, and workability. This allows us to control for land quality to measure household-farm productivity.

In terms of agricultural capital, we have information on both equipment and structures. Capital equipment includes implements (hand hoe, slasher, axe, sprayer, panga knife, sickle, treadle pump, watering can, and so on) and machinery (e.g. ox cart, ox plough, tractor, tractor plough, ridger, cultivator, generator, motorized pump, grain mill, and so on), while capital structures includes chicken houses, livestock kraals, poultry kraals, storage houses, granaries, barns, pig sties, among others. To proxy for capital services after conditioning for its use in agricultural activities, we aggregate across the capital items evaluated at the estimated current selling price.[10]

In Malawi, a large proportion of the households members, beside the household head, contribute to agricultural work. Household size is 4.6 with extended families in which several generations live together in a single household. We use the survey definition of household members as individuals that have lived in the household at least 9 months in the last 12 months. In terms hours, data are collected at the plot level for each individual that participates in agriculture and by agricultural activity (i.e., land preparation/planting, weeding/fertilizing, and harvesting). Precisely, our data provides information of weeks, days per week, and hours per day employed per plot, activity and individual. To compute household-farm hours we aggregate the hours of all plots, activities and individuals. Further, the same information is provided for hired labor and labor received in exchange (for free), but most household-farm hours consist of family hours. We add hours by hired labor and free exchange of labor to our measure of total household hours.

Since our data comprises a single cross section of households for 2010-11, it is important to control for temporary output shocks that may explain variation in output and hence produc-

[10]This selling price for agricultural capital items, rarely available in previous LSMS data, helps capture potential differences in the quality and depreciation of capital across farms. We provide robustness of our results to alternative physical measures of agricultural capital such as asset indexes for agricultural equipment and structures in Appendix B.2.2. We find that using these alternative indexes to proxy for agricultural capital renders larger output losses and gains from reallocation relative to our baseline measure of capital.

tivity across households in the data. The single most important temporary shock for farmers is weather. We use the annual precipitation which is total rainfall in millimetres (mm) in the last 12 months. In further robustness exercises, we net household-productivity from additional transitory shocks in the form of health, deaths or food security risks suffered by the household in the last 12 months.

Geographic and institutional characteristics are also recorded for each household-farm. We use several partitions of these characteristics to conduct robustness exercises. In particular, we use geographical information on the region, districts, and enumeration area to which household-farms belong and institutional characteristics such as the traditional authority (TA) governing the household-farm or ethno-linguistic characteristics. TAs are relevant for our exercise as chiefs appointed by TAs perform a variety of functions that include resolving issues related to land and property.[11]

Finally, we note that the survey response is very high with little very few missing observations. Conditioning on households that produce agricultural output and for which all factor inputs, including the 11 dimensions on land quality, are available and further trimming about 1% of the household-farm productivity distribution, our sample consists of 7,157 households.[12]

To summarize, the data allows us to obtain precise measures of real household-farm productiv-

[11] Traditional Authorities are part of the administrative structure of Malawi. Any one district is only in one region, any one TA is only in one district. Traditional authorities (and their sub-ordinate chiefs) are 'town chiefs' formally recognized under the Chiefs Act (1967) and receive a monetary honorarium by the government. The Chiefs Act states that chieftaincies are hereditary and hierarchical, being the highest level in the TA or the Paramount Chief (PC) and TAs cover the entire country. There can be several TAs within each ethno-linguistic group. The sub-structure is such that below each TA there are Sub-TAs, Group Village Headmen (GVH), and Village Headmen (VH). All villages have a VH, and several villages will be grouped under one GVH. These chiefs perform a variety of functions: cultural affairs, administration and management of various sorts, oversight of issues related to land and property, resolving disputes, an involvement in politics, and promoting economic and social development. The TAs that we use in our reallocation exercise are the ones provided by Malawi ISA 2010/11 which are a subset of those used by the National Statistical Office to organize the data collection of the Malawi Census. There are about 380 populated TAs and wards in the country with an average population of just under 26,000 persons; TAs are found in rural areas, while urban-equivalent administrative wards are in the four urban centers of Blantyre, Lilongwe, Mzuzu, and Zomba. District and local government authorities may recognize additional TAs or sub-chiefs used in order to create reasonably sized administrative units within large TAs.

[12] See further details on the trimming strategy in Appendix B.1.

ity which is a key input in our assessment of factor misallocation in Malawi and its aggregate productivity impact. Overall, ISA represents a substantial improvement with respect to previous LSMS questionnaires. The detailed information on quantity inputs and outputs reduces substantially the possibility of measurement error and composition bias, making this dataset ideal for our purpose of measuring productivity at the farm level, assessing the quantitative extent of factor misallocation in the Malawian economy, and the extent to which productivity losses due to misallocation are related to imperfections or frictions in the land market.

3 Facts

We use the micro data from ISA 2010/11 described in the previous section to emphasize the following facts about the allocation of factors and productivity in the agricultural sector in Malawi.

Fact 1: Operational Scale. The operational scale of farms is extremely small. For each household, we compute the amount of land used for agricultural production regardless of the land status (whether land is owned, rented, etc.). Hence, we focus on the operational scale of the household-farm. We find that 78.3% of households operate less than 1 hectare (henceforth, Ha.), 96.1% of households operate less than 2 Ha., and only 0.3% of households operate more than 5 Ha., see the first column in Table 1. The average farm size is 0.83 Ha. To make a comparison of operational scales in Malawi with other countries, we also report the distribution of farm sizes from the World Census of Agriculture in Adamopoulos and Restuccia (2014a). These data include all land used for agricultural production and corresponds to the year 1990. Table 1 reports summary statistics. First, we note that despite the 20 years difference between ISA 2010/11 and the Census 1990 the distribution of land across the two sources is very similar. Second, comparatively with other countries, the operational scale of farms in Malawi is extremely small, ∼0.70-0.83 Ha., whereas average farm size is 187 Ha. in the United States and 16.1 Ha. in Belgium. Belgium is a good reference for a developed country since the land endowment (measured as land per capita) is similar to that of Malawi (land per capita is 0.56 Ha. in Malawi and 0.5 Ha. in Belgium, whereas land per capita is 1.51 Ha. in the United States).

Fact 2: Land Markets. The land market is largely underdeveloped in Malawi. We find that the proportion of household-farms that do not operate any marketed land is 83.4%. These are households that obtain their land granted by a village chief, inherited or as bride price. The remaining 16.6% of households operate some land obtained from the market, either rented or purchased, and the proportion of household-farms whose entire operated land was obtained in the market is 10.4%. Disaggregating the main types of marketed land, we find that 3.0% of household-farms rent-in land informally (e.g., land borrowed for free or moved in without permission), 9.5% rent-in land formally (e.g., leaseholds, short-term rentals or farming as a tenant), 1.8% purchase land without a title and 1.3% purchase land with a title.

Fact 3: Subsistence Consumption. We find that most farmers produce agricultural goods for their own consumption and very little agricultural output is sold in the market. We illustrate this finding using some standard proxies for subsistence consumption in Figure 1. Figure 1, panel (a), reports the density of the share of food on nondurable expenditures. There is a high degree of reliance on food in the household's consumption budget. On average 65% of household nondurables consist of food, with a median household consuming 72% of its nondurables expenditures in food.[13] Figure 1, panel (b), reports a set of subsistence consumption proxies against each percentile of the distribution of operated land. First, the food share of consumption is rather inelastic with respect to land. Second, food security risk, defined as a situation of not enough food to feed all household members in the last 12 months, is suffered by 48% of households and while this risk tends to decline with land, land is not able to fully

[13] We use deseasonalized and annualized consumption measures in de Magalhaes and Santaeulàlia-Llopis (2014a).

hedge against it; more than 32% percent of households in the top 10% of the land distribution still face some shortage of food. Third, the share of agricultural sales in total agricultural production is on average 11% and this only raises to 19% for the households at the top 10% of the land distribution. What the patterns in these figures show is that Malawi is essentially characterized as a subsistence economy.

Fact 4: Land Quality. There are important differences in the land characteristics of farms. For instance, Table 2 documents the heterogeneity in terrain roughness (elevation and slope). For the full sample, more than 34 percent of land is high-altitude plains while around 20 percent are low plateaus and 19 percent mid-altitude plateaus. These characteristics also differ by region where the center region is mostly high-altitude plains whereas the south region is mostly low plateaus. Figure 2, panel (a) and (b), further document these differences in elevation and slope across farms and within regions. As a result of the heterogeneity in land characteristics, it is important to control for land quality in our measure of productivity. To do so, we construct an index of land quality as follows. Our benchmark land quality index is q_i^0 is constructed by regressing log output in each farm on the full set of land quality dimensions described in Section 2.[14] Figure 3, panel (a), reports the distribution of the land quality index q across households in the full sample and across regions. There are substantial variations in q across households and across regions. In Table 3 we report the dispersion (variance of the log) of land quality indexes versus the dispersion in the quantity of land across households in our data. The main observation from Table 3 is that while there is variation in land quality across farmers, the variation is not substantial relative to the variation in the quantity of land and the variation in the amount of agricultural output. For instance, the variance of log quality relative to the variance of log quantity of land is only 4.7 percent. Land quality variation is also low within regions and within individual land characteristics. Our conclusion of a small quantitative role of land quality for output differences across household farms is robust to variations in the index

[14] We have also considered alternative land quality indexes for subsets of the land quality dimensions and with different forms of land size and capital controls in Appendix A.2.

and to more flexible functional forms. We discuss these variations in Appendix A.2.

Fact 5: Rain Shocks. In Malawi, weather shocks, in particular rain, is the single most important source of transitory shocks to agricultural production—we find that most cropland is rain-fed and 84% of household-farms do not have any alternative irrigation system. Figure 3, panel (b), reports the density of rain for the entire population of farmers and, separately, for farmers within regions. We note what appear substantial differences across household-farms and regions with median values for the Center and South region that fall below the range of of the distribution of rain in the North region. To quantify the actual dispersion in rain we report the variance of logs of rain in the bottom of Table 3 for our entire sample and regions. We find that the dispersion of rain is very small compared to the dispersion in land size and even smaller relative to output. In particular, the dispersion in annual precipitation is 5.2% that of land size and 2.1% that of agricultural output. The small role of rain variation further appears within regions, districts, and enumeration areas, as well as using alternative definitions of precipitation measures, with mean cross-sectional variances that decline with the size of the geographical area. In short, rain is not a substantial contributor to output variation across farm households in Malawi.

Fact 6: Household-Farm Productivity. Using the micro data, we measure farm productivity and find that factors of production are strongly misallocated across farmers in Malawi. For instance, we find that the amount of land and capital in farms is essentially uncorrelated with farm productivity which is inconsistent with the efficient allocation of factors in any standard model of farm size. The implications of these patterns is that land productivity, which is proportional to output per unit of land, and capital productivity, which is proportional to output per unit of capital, are strongly dispersed across farms and increasing in farm productivity, whereas in an efficient allocation these measures of factor productivity should be roughly equal across farmers. We measure farm productivity by exploiting the detailed micro data where not only we obtain real measures of output and value added but also control for land quality and transitory shocks such as rain as described previously. We measure farm-level total factor productivity (TFP) s_i as the residual from the following farm-level production function $y_i = s_i \zeta_i k^{\theta_k} (q_i l_i)^{\theta_l}$ where y_i, k_i, and l_i are output, capital, and land at the farm level in per hour terms, ζ_i is a rain shock, q_i is land quality, and $\theta_{k,l}$ are the input elasticities.[15] We choose $\theta_k = 0.36$ and $\theta_l = 0.18$ from the capital and land income shares in U.S. agriculture reported in Valentinyi and Herrendorf (2008). Figure 4 documents the distribution of farm productivity across all households in our sample. There are large differences in farm productivity across households that remain even within regions. The dispersion in farm productivity compares in magnitude to that of the variation in productivity (TFPQ) across plants in the manufacturing sector in the United States, China, and India reported in Hsieh and Klenow (2009), see the summary statistics reported in Table 4. Table 5 reports the variance decomposition of farm output per hour using the assumed production function above. We note that farm productivity s_i and to a lesser extent inputs of capital and land are the key determinants of output variation across farm households in Malawi, with rain and land quality playing a quantitatively minor role.

What is important to keep in mind in looking at farm-level observations is that in a standard model of farm size such as that in Adamopoulos and Restuccia (2014a), the efficient allocation of factors is such that more productive farmers would operate larger farms (operate more land), operate more capital, and produce more output. Essentially, an efficient allocation of factors across heterogeneous farmers is that factors are allocated to the most productive uses, until the marginal product of each factor is equalized across farmers. Figures 5 and 6 report several variables of interest across farms by farm-level TFP s_i. The patterns are striking. The data show that the actual allocations of land and capital in farms are unrelated to farm productivity. Figure 5, panel (a), shows the amount of land in each farm by farm productivity using our

[15] Our analysis uses measures of output, capital, and land per hour as our emphasis is on the allocation of land and capital across household farms. We note, however, that hours in farms are uncorrelated with farm TFP and, as a result, our characterization and analysis is unaffected by treating hours as an explicit input in the farm production function.

benchmark measure of productivity that adjusts for rain and quality as described previously. Land in farms is essentially uncorrelated to farm TFP, the correlation between land size and productivity is 0.05. Figure 5, panel (b), documents the relationship between the amount of capital in farms by farm productivity. Capital and productivity across farms are essentially unrelated, the correlation between the two variables is -0.01. Figure 5, panel (c), shows that the capital to land ratio is essentially unrelated to farm productivity, with a correlation between these variables of -0.03.

Whereas in an efficient allocation more productive farms should command more capital and land to the point of equalizing the marginal products of these factors, the lack of positive relationship between land and capital suggests that the marginal product of these factors are not equated across farms indicating misallocation. Figure 6, panels (a) and (b), show that the marginal product of land (proportional to the yield or output per unit of land) and capital (proportional to output per unit of capital) are strongly positively correlated with farm productivity. The correlation between these measures of factor productivity and farm TFP are .77 and .76 in each case.

To summarize, the actual allocation of land across farmers in Malawi is unrelated to farm productivity which is consistent with our characterization of the land market where the amount of land in farms is more closely related to inheritance norms and redistribution and access to land is severely restricted in rental and sale markets so more productive farmers cannot grow their size. Capital is also unrelated to farm productivity with the capital to land ratio being roughly constant across farm productivity. Our interpretation of this finding is that restrictions to land markets are also affecting capital allocations echoing de Soto (2000) findings that land market restrictions and insecure property rights of farmers limit the ability to raise capital for agricultural production.[16] These findings constitute strong evidence of land and capital misallocation across farmers in Malawi. We emphasize that since farm size and productivity

[16] We find further direct evidence of the relationship between land markets and access to credit in our micro data for Malawi, see Appendix C.2 for a discussion. See also the related discussion in Besley and Ghatak (2009).

are essentially unrelated in Malawi, it is misleading to characterize farm level observations and diagnose policy recommendations based on the more common measure of farm size. This echoes the work of Restuccia and Rogerson (2008) and Adamopoulos and Restuccia (2014a) in emphasizing the role of policies and institutions driving a wedge between size and productivity at the establishment level in developing countries.

4 Quantitative Analysis

How important is land and capital misallocation for aggregate productivity? We assess the quantitative impact of factor misallocation on agricultural productivity in Malawi. We do so without imposing any additional structure other than the farm-level production function assumed in the construction of our measure of household-farm productivity. As a benchmark for comparison, we solve for the efficient allocation of factors across farms given the total amounts of capital and land. We compare the implications of the efficient allocations versus the actual allocations on aggregate output and productivity in agriculture.

More specifically, we solve for the efficient allocation of capital and land across a fixed set of heterogeneous farmers s_i. A planner chooses the allocation of capital and land across a given set of farmers with productivity s_i to maximize agricultural output given fixed total amounts of capital K and land L. The planner solves the following problem:

$$Y^e = \max_{\{k_i, l_i\}} \sum_i s_i (k_i^{\alpha} l_i^{1-\alpha})^{\gamma},$$

subject to

$$K = \sum_i k_i, \qquad L = \sum_i l_i.$$

The efficient allocation equates marginal products of capital and land across farms and has a simple form. Letting $z_i \equiv s_i^{1/(1-\gamma)}$, the efficient allocations are given by simple shares of a measure of productivity ($z_i / \sum z_i$) of capital and land:

$$k_i^e = \frac{z_i}{\sum z_i} K, \qquad l_i^e = \frac{z_i}{\sum z_i} L.$$

We note for further reference, that substituting the efficient allocation of capital an land into the definition of aggregate agricultural output renders a simple constant returns to scale aggregate production function for agriculture on capital, land, and agricultural farmers given by

$$Y^e = Z N_a^{1-\gamma} [K^\alpha L^{1-\alpha}]^\gamma, \tag{1}$$

where $Z = (\sum z_i g(z_i))^{1-\gamma}$ is total factor productivity as the average productivity of farmers and N_a is the number of farms. We choose α and γ consistent with the production function used in our measure of farm-level productivity so that $\alpha\gamma = 0.36$ and $(1-\alpha)\gamma = 0.18$ as the capital and land income shares in the U.S. economy reported in Valentinyi and Herrendorf (2008). This implies $\gamma = 0.54$.[17] The total amount of capital K and land L are the total amounts of capital and land across the farmers in the data. Farm level productivity s_i's are given by our measure of farm TFP from data as described previously. Before we move on to document the aggregate impact of misallocation, we illustrate the extent of factor misallocation in Figure 7, where we contrast the actual allocation of land and capital and the associated factor productivity by farm TFP against the efficient allocation of factors and the associated factor productivities across farms. In the efficient allocation, operational scales of land and capital are strongly increasing in farm productivity so that factor productivity is constant across farms. The efficient allocation contrasts sharply with the actual allocation in Malawi.

[17] We use factor income shares from a developed economy as estimates of the elasticities in the production function since variation in the corresponding measures in a poor country are likely reflecting frictions or distortions in factor markets. We evaluate the robustness of our results using different capital and land shares in the Appendix F. Using the micro data we construct alternative capital and labor shares rendering similar aggregate results. The main difference is that the land share in Malawi would be larger and hence implies larger effects of land-only redistribution.

4.1 Results on the Output Loss

To summarize the impact of misallocation on productivity, in what follows we report the aggregate output loss defined as

$$\frac{Y^a}{Y^e} = \frac{\sum y_i^a}{Y^e},$$

where Y^a is actual agricultural output aggregated from farm-level output using $y_i = s_i \left(k_i^{\alpha} l_i^{1-\alpha}\right)^{\gamma}$, where k and l are actual allocations and; and Y^e is efficient aggregate agricultural output as defined previously. Because the efficient allocation takes as given the total amounts of capital, land, and the number of farmers observed in the data, the output loss is also a TFP loss.[18]

Table 6, panel (a), reports the main results. For the full sample in the entire Malawi, the output loss is 0.28, that is actual agricultural output is 28 percent of that of efficient agricultural output at the aggregate level. We can also express the results in terms of the gains from reallocation from the actual distribution of factors to the efficient, which is the inverse of the output loss. If capital and land were reallocated efficiently in Malawi to maximize agricultural output, output and hence productivity would increase by a 3.6-fold factor. This is a very large increase in productivity as a result of a reduction in misallocation, at least compared to the results in the misallocation literature when evaluating specific policies which has found increases on the order of 5 to 30 percent. Even when eliminating all wedges in manufacturing in China and India in Hsieh and Klenow (2009), the increases range between 100-160 percent. Given that the real productivity dispersion across farms in Malawi is not much larger than the productivity dispersion of manufacturing plants reported in Hsieh and Klenow (2009), what this result suggests is that the actual allocation of resources in Malawi is much more distorted than that of those other countries or to put it differently that factors are more severely misallocated in Malawi.[19] Because we have a large sample, our mean output loss is tightly estimated. In Table

[18] The computation of actual output at the farm level abstracts from rain and land quality as it is the case in the efficient allocation. We also emphasize that the empirical measure of farm productivity s_i is purged of rain and land quality effects as described in Appendix A.

[19] Note that a more direct comparison with the analysis of Hsieh and Klenow (2009) for the case of India and China would be to report dispersion in log revenue productivity (TFPR). However, unlike for the case of

6, panel (a), we also report the 5 and 95 percentiles of Bootstrap estimates, which provide a narrow interval between 0.25 and 0.32 for the aggregate output loss.[20]

We also report the output loss for narrower definitions of geographical areas and institutions such as language classifications. Table 6, panel (b), reports these results. In the fist column, we report the output loss for the average of regions (i.e., output loss of reallocating factors within a region for each region and then averaged across regions), for the average across districts (a narrower geographical definition than region), for the average across enumeration areas. Enumeration areas are a survey-specific geographical description and is the narrower definition available. Each enumeration area amounts to about 16 households in the data, which given the average land holdings amounts to about 30 acres of geographically connected land. The table reports results by Traditional Authority (TA) and language. Columns 2 to 4 report the Median, Min, and Max in each case.

What is striking about the numbers in Table 6, panel (b), is that the gains from reallocation are large in all cases, even within narrowly defined geographical areas, traditional authority and language. In particular, reallocating capital and land within a region generates output losses of the same magnitude as in the aggregate (mean output loss of 0.29).[21] Similarly, within districts, the average output loss is 0.34, but the output losses can be as large as 0.14 and the lowest 0.48. Even for the narrowest geographical definition, enumeration areas, just reallocating factors within 16 households, average output losses are 0.60 and can be as large as 0.09 in some areas. Considering reallocation within enumeration areas also serves as a further check on the relevance of land quality since within such a narrow geographical definition it is unlikely that

manufacturing firms, most of the production of farms in Malawi is not sold in markets and hence revenue of farms would have to be imputed. More importantly, the micro data allow us to directly measure real productivity across farms and hence assess the aggregate productivity implications without the need to characterize the associated market wedges.

[20] We also report the output loss when the dispersion in factor inputs is reduced across farm productivity types, see Appendix B.2.3. In the more conservative case where all the dispersion within productivity groups is eliminated, the output loss is still substantial .40 (versus .28 in the baseline) which implies a substantial reallocation gain of 2.5-fold.

[21] The idea is that narrower geographic definitions provide additional land quality control, see Larson et al. (2014) for a similar strategy.

land quality plays much if any role. We also report the distribution of output losses in each enumeration area in the survey in Figure 8. The output loss within traditional authorities is 0.32 in average, with the largest 0.18 and median 0.29. Within languages, the average output loss is 0.30, the largest 0.17 and median 0.26.

4.2 The Role of Land Markets

We have found strong evidence that capital and land are severely misallocated in the agricultural sector in Malawi. We connect this misallocation to the limited market for land in Malawi. Even though the amount of operated land that is rented in or purchased is relatively small in our data, we assess the output loss across farms that differ in the extent of marketed land in their operation as further evidence of the connection of misallocation to land markets.

Table 7 reports the aggregate output loss for farms that operate with no marketed land, with some marketed land as either rented in or purchased, and with only marketed land. The output loss is much higher for those farms with no marketed land than with some marketed land. For instance, the output loss for those farms with no marketed land, which comprises 83 percent of the sample of household farms, is 0.24, slightly larger than the 0.28 output loss for the entire sample. But for farms with some marketed land, which comprises the remaining 17 percent of the sample farms, the output loss is 0.51. The striking finding is that the output loss of factor misallocation is reduced by more than half when farms have access to some marketed land.

The output loss is even smaller among the set of farmers whose all their operated land is either rented in or purchased. These farmers comprise 10 percent of the sample and have an output loss of 0.64 versus 0.24 for farmers with no marketed land. That is, the gains from reallocation are 2.6 times larger for farms with no marketed land than for farms that operate only marketed land. Table 7 also decomposes the output losses among farmers by the type of operated marketed land: (a) rented-in informally, for example land borrowed for free or moved-in without permission; (b) rented-in formally such as leaseholds, short-term rentals or farming as tenant; (c) purchased as untitled; and (d) purchased as titled. The vast majority of farmers with some marketed land are formally renting-in, 9.5 percent of the sample out of the 17 percent with some marketed land. The output loss is fairly similar for farmers operating land rented-in formally or informally, an output loss of roughly 0.58 for both. The lowest output loss is recorded for farms with operated land that was purchased with a title, 0.72 versus 0.24 for farms with no marketed land. Interestingly, farmers with purchased land without a title record a fairly large output loss, 0.20, somewhat larger than the output loss for farmers without marketed land of 0.24. We note however that the sample of farms with purchased land is fairly limited, only 3.1 percent of the sample: 1.8 percent of farms with purchased untitled land and 1.3 percent of farms with purchased titled land.

It is interesting to note that farms with and without marketed land differ along many dimensions, which we report in detail in the Appendix C, further asserting the importance of land markets for farm operation. For instance, on average farms with some marketed land are more productive than farms with no marked land. But greater access to land markets means that farmers with marketed land command more inputs and produce more output but, as a result of greater input use, capital and land productivity does not rise as much from farmers with no marketed land. Further, we find that access to land markets is related with access to other markets (e.g., credit) and with other indicators of economic development. Farmers with marked land are substantially more educated than farmers with no marketed land, women in these farms are more empowered in terms of labor force participation and market wages, more of these farmers are migrants, a fewer proportion live in rural areas, and a larger proportion of these farmers invest in intermediate inputs and technology adoption.

4.3 Further Robustness Results

We conduct further robustness results to human capital and specific skills, transitory health and other shocks, specific type of crops, and distortions to intermediate input use.

Human Capital and Specific Skills Table 8 reports robustness results with respect to human capital and specific terrain skills. In each case, we perform the efficient reallocation exercise discussed earlier but within each education and skill type. With respect to schooling levels of the household head, the output losses 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 and 0.36 for mid-altitude mountains.

Other Transitory Output Variation Table 9 reports the output losses associated with a measure of farmer productivity that further adjusts for transitory health and other shocks. We regress our benchmark measure of farm productivity on a set of controls for transitory shocks which includes health and death shocks, food security risk, marital status, distance to markets and the availability of other income sources. In each case, we use the residual from each of these regressions as the new measure of farm productivity. Using these alternative measures of productivity, we perform the efficient reallocation exercise discussed earlier. Output losses are large in all cases, from 0.28 in the benchmark specification to 0.27 when using all controls.

Crop Type Production In our sample, close to 80% of land is devoted to maize production, see also FAO (2013).[22] Since optimal farm operational scale may differ across crop types, we

[22] Maize, cassava, and potatoes are the main crops produced in Malawi in terms of volume with roughly equal amount in tonnes, but it is maize that accumulates the vast majority of cropland. The importance of maize

investigate whether the output losses are different across farms producing different crops. Since most farms produce both maize and non-maize crops, we consider reallocation among farms that produce mostly maize and those farms that produce mostly non-maize. We report the results in Table 10 where the first column is the output losses in the nationwide benchmark, the next two columns are farms that produce mostly maize (whether the maize share is positive or above the median of all farms), and the last two columns for those farms that produce mostly non-maize (wether the non-maize share is positive or above the median). The output loss among farms that produce maize is somewhat smaller (0.37 for farms with maize production above the median versus 0.28 in the benchmark), which implies that the farms with non-maize production have output losses that are larger (0.24 for farms that produce non-maize above the median versus 0.28 in the benchmark). We conclude that crop composition and the dependence of maize production in Malawi are not driving our main output-loss results.

Distortions to Intermediate Inputs Our main results are derived with a measure of farm productivity that is constructed from value added output in each farm. As discussed earlier, this measure of valued added is constructed using common agricultural output prices and common intermediate input prices so as to obtain a real measure of farm productivity that is devoid of potential idiosyncratic price distortions in the economy. This is relevant in Malawi because intermediate inputs are subsidized via the "Malawi Input Subsidy Program" and the basic allocation of the subsidies is based on income of the farmer, with poorer farmers receiving higher subsidies. We assess the potential bias in our farm-productivity calculations if instead we construct farm productivity using actual expenditures on intermediate inputs by each farmer. If poorer farmers are less productive than richer farmers but receive more subsidies to intermediate inputs as it is the case in the data, using actual expenditures in intermediate inputs biases the dispersion in farm productivity down, making less productive farmers appear more productive than what they are. Figure 9, panel (a), documents that less productive farmers (which are also

further appears in terms of the household diet in Malawi where about 50% the average daily calorie intake is obtained from maize, 8.4% from potatoes, and 5.8% from cassava, see FAO (2013) and de Magalhaes and Santaeulàlia-Llopis (2014a).

poor farmers) receive a subsidy that is more than 60 percent their output while more productive farmers (richer farmers) receive a subsidy that is less than 10 percent their output. This implies that a measure of productivity that uses actual expenditures in intermediate inputs instead of the actual quantities of intermediate inputs substantially underestimates productivity dispersion across farms. This is illustrated in Figure 9, panel (b), where farm productivity and the marginal product of land are reported for our baseline measure of farm productivity (that uses a quantity measure of intermediate inputs) and a measure of productivity that uses expenditures. The variance of the log productivity falls from 1.44 in our baseline measure of productivity to 0.85 using actual expenditures in intermediate inputs (a reduction in productivity dispersion of more than 40 percent). The output loss associated with this biased measure of productivity is 0.33, although still substantial, is 17 percent smaller than the output loss of 0.28 associated with our baseline measure of farm productivity. This analysis also illustrates the importance of the implementation of policies which in this case even well-intended policies further contribute to distorting factor inputs.

5 Inequality Implications

Unlike the actual distribution of factors in the Malawian economy which is fairly flat across farmers with different productivity, the efficient allocation implies a substantial increase in the dispersion of operational scales, both in terms of the distribution of capital and land across farmers. This massive redistribution of factors across farmers may lead to concerns over distributional implications, specially since the actual allocation of factors reflects policy choices and institutional features in place partially to alleviate poverty and distributional concerns.

In this section, we study the distributional implications of redistributing operational scales towards the efficient allocation. Table 11 reports the actual and efficient distribution of factors across farmers by productivity and Table 12 reports actual and efficient output and income.

As discussed previously, whereas the actual distribution of land across farm TFP is fairly flat, with most farms operating less than 2 acres of land, the efficient distribution implies that the top quintile of farm TFP operates on average almost 6 acres and 97 percent of the land whereas the lowest quintile only operates less than a percent of the land. This implies a substantial redistribution of factors and operational scales to achieve the higher levels of aggregate productivity. But it is important to emphasize that despite relative equalization of factor inputs across farmers, the actual distribution of income is widely dispersed, in fact as dispersed as the distribution of productivity. For instance, taking agricultural output as a measure of farm income, the ratio of top to bottom quintile of income is a factor of 34-fold even though the ratio of capital and land factors is within a factor of 1 to 2-fold. To put it differently, equalizing access to land across households does not necessarily translate into income equalization as these farmers differ substantially in their productivity of working the farm.

To gauge the income effects of factor redistribution we pursue the following counterfactual. We consider the actual distribution of factors as endowments and allow the efficient allocation of factors to be achieved via perfectly competitive rental markets for capital and land, that is, with perfect markets a decentralized competitive allocation corresponds to the efficient allocation. Given the competitive rental rates of capital and land in this decentralized solution, we compute the income associated with the efficient allocation as:

$$\text{endowment income} = r_k(k^a - k^e) + r_l(l^a - l^e) + y^e,$$

where (k^a, l^a) are the actual allocation of capital and land which we take as endowment and (k^e, l^e) are the efficient allocations, r_k and r_l are the prices that support the efficient allocation as a competitive equilibrium, and y^e is efficient output. Table 12 reports the results for this measure of endowment income and compare the income inequality to that of the actual income, which we assume is approximated by actual output y^a.

Not only farmers in the lower end of the productivity (and income) distribution benefit the most from the increase in the average yield and aggregate agricultural output, but also overall inequality declines. For instance, the overall variance of the log income decreases from 1.8 with actual income to 1.2 to efficient income. More dramatic are the changes in income across the richest and poorest households. Whereas the ratio of income between farmers in the top and bottom quintiles is a factor of 34-fold in the actual allocation, this ratio is 3.4 in the efficient allocation, that is income inequality among these farmers falls by a factor of 10-fold. Moreover, the ratio of efficient to actual income increases for all household farms but this increase is much larger for the households at the bottom of the productivity distribution, 23.7-fold for the first quintile, 3.9-fold for the second quintile and only 2-fold for the top quintile.

Well-functioning rental markets for capital and land to achieve the efficient allocation of operational scales can lead to substantial increases in agricultural productivity as well as dramatic reductions in inequality levels and poverty.

6 Two-Sector Implications

We assess the broader implications of reallocation by considering the effects of increased productivity in agriculture on the movement of factors across sectors. We argue that a TFP increase of a 3.6-fold factor in the agricultural sector would produce a process of substantial structural change in the Malawian economy. This reallocation would produce broad impacts in the economy through well-known features such as the potential selection effects associated with the movement of labor from agriculture to non-agriculture and dynamic investment effects such as additional investments farmers would make to exploit increased farm size, capital and human capital accumulation, among many others.

To provide a simple characterization of these broader implications of reallocation, we consider an extension of the previous analysis to allow for a non-agricultural sector.[23] Recall that the aggregate production function for agriculture in the efficient allocation is given by equation (1). To simplify the analysis, without much loss of generality, we abstract from capital by assuming that $\alpha = 0$. Hence, the aggregate production function in agriculture is given by:

$$Y_a = ZL^{\gamma} N_a^{1-\gamma},$$

where N_a is the fraction of employment in agriculture and $\gamma = 0.54$. The non agricultural production function is given by $Y_n = A(1 - N_a)$. We assume that preferences are such that consumers not only have a minimum consumption of agricultural goods $\bar{a}$, but also this level is a satiation point so per capita consumption of agricultural goods is given by $\bar{a}$ and any income above the one required for this amount of agricultural consumption is spent on non-agricultural goods.[24] We continue to consider a benevolent social planner that chooses the allocation of labor across sectors to maximize consumer's welfare. Given our assumptions about preferences, the solution to this allocation problem has a simple form and is given by:

$$N_a = \left(\frac{\bar{a}}{ZL^{\gamma}}\right)^{\frac{1}{1-\gamma}}.$$

Note that the solution is such that an increase in productivity in the agricultural sector Z reduces the share of employment in agriculture. In particular, the change in employment in agriculture can be easily calculated using the above equation from the change in TFP in agriculture raised to the power $1/(1 - \gamma)$. We report the results in Table 13. With $\gamma = 0.54$, an increase in productivity of 3.6 implies a decrease in the employment share in agriculture of 16.2-fold. In other words, the share of employment in agriculture in Malawi would decrease from the actual 65 percent to only 4 percent which is close to the average for rich countries, see for instance Restuccia et al. (2008). This tremendous reallocation of labor from agriculture to non-agriculture implies that average farm size would increase by a factor of 16.2-fold (recall that

[23]For a more elaborate analysis of misallocation in agriculture in the context of a two-sector economy see Adamopoulos and Restuccia (2014a).

[24]See for instance Gollin et al. (2002) for a model with such preferences.

in our previous one-sector analysis of misallocation, by construction the gains in agricultural productivity of moving to the efficient allocation involved no change in average farm size). It is also easy to see that the increase in labor productivity in agriculture Y_a/N_a is given by a factor of 16.2-fold, whereas agricultural output per unit of land or yield Y_a/L remains the same. This is because for the preferences we consider, the increase in productivity is exactly offset by the decrease in agricultural labor so total agricultural output remains the same. Hence, for our quantitative experiment, the entire increase in agricultural labor productivity is reflected in an increase in average farm size and none in an increase in the yield. This implication is roughly consistent with the findings from micro data across countries in Gollin et al. (2014) where the large differences in agricultural labor productivity across countries is mostly reflected in differences in average farm size (land per worker in agriculture).

We emphasize that the effects just described abstract from other potential sources of amplification. For instance, the potential role of selection into the ability of farmers that stay in agriculture. This feature that has been found quantitatively important in amplifying the productivity increases in the agricultural sector. Lagakos and Waugh (2013) find that selection can further increase productivity in the agricultural sector by a factor of more than 2-fold. Also, complementary investments such as mechanization, improvements in land quality, or the adoption of modern technologies could further increase productivity in the agricultural sector. Overall, we find that the increase in agricultural productivity due to the more efficient allocation of factors can unravel a substantial process of structural change and productivity growth in agriculture that can dramatically change the face of the Malawian economy.

7 Conclusions

We assessed the importance of factor misallocation for productivity in agriculture using detailed household-level data from Malawi. The micro evidence indicated substantial misallocation of capital and land in Malawi as factor inputs are essentially unrelated to farm TFP. Our results provide direct and comprehensive evidence of misallocation in a poor country. The evidence is strong as the unique data set allows for precise estimates of productivity at the household-farm level.

To assess the aggregate productivity impact of misallocation, we considered as a benchmark the efficient allocation of factors across a given set of heterogeneous farmers with farm-level TFP measured in the data, holding the total amounts of capital and land. The main result is that a reallocation of capital and land to their most efficient uses would increase productivity by a factor of 3.6-fold. This large increase in agricultural productivity would unravel a substantial process of structural change with broader implications for aggregate outcomes. Our analysis also provided a strong empirical connection between factor misallocation and the limited market for land, showing large productivity losses associated with restricted land markets. We found that the gains from reallocation are 2.6 times larger for farms with no marketed land than for farms with only marketed land. Our results emphasize the importance of land markets for factor misallocation in agriculture that may explain the large productivity differences across countries.

Our analysis takes the distribution of farmlands across productive farmers as given and asked about the efficiency gains of reallocation. Understanding the institutional and policy elements leading to the misallocation of land is useful in connecting the results with the design and implementation of policy and development strategies. It may also be of interest to study the dynamic implications of misallocation for productivity whereby a reduction in misallocation encourages the more productive farmers to grow, utilize modern inputs (mechanization, chemical seeds, intermediate inputs), and invest in farm productivity, see for instance Restuccia and Rogerson (2013) and Restuccia (2013). We leave these interesting and important extensions of our analysis for future research.

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Table 1: Size Distribution of Farms (% of Farms by Size)

	ISA 2010/11	World Census of Agriculture 1990		
	Malawi	Malawi	Belgium	USA
Hectares (Ha):				
≤ 1 Ha	78.3	77.7	14.6	–
$1-2$ Ha	17.8	17.3	8.5	–
$2-5$ Ha	3.7	5.0	15.5	10.6
$5-10$ Ha	0.2	0.0	14.8	7.5
10+ Ha	0.0	0.0	46.6	81.9
Average Farm Size (Ha)	0.83	0.7	16.1	187.0

Notes: The first column reports the land size distribution (in hectares) for household farms from the Malawi 2010/11 Integrated Survey of Agriculture (ISA). The other columns report statistics from the World Census of Agriculture 1990 for Malawi, Belgium, and United States documented in Adamopoulos and Restuccia (2014a).

Table 2: Heterogeneity in Terrain Type, Malawi ISA 2010/11

	Full Sample			By Region, Terrain Type (%)		
Terrain Type:	Terrain (%)	Elevation (meters)	Slope (%)	North	Center	South
Lowlands	1.03	132	5.98	.00	.00	2.16
Rugged Lowlands	.11	106	16.23	.00	.00	.24
Plains	4.92	86	1.71	.00	.00	10.33
Mid-altitude Plains	8.31	474	1.76	8.85	8.73	7.81
High-altitude Plains	34.88	873	2.34	23.24	46.63	30.55
Platforms (very low plateaus)	2.11	401	6.19	1.40	.23	3.74
Low plateaus	20.57	727	6.46	14.62	7.56	32.28
Mid-altitude plateaus	19.25	1,218	6.55	34.65	32.09	4.19
Hills	.62	381	16.83	.29	.00	1.20
Low Mountains	3.38	769	15.98	3.90	.26	5.48
Mid-altitude Mountains	4.82	1,314	16.59	13.05	4.50	2.03
	100.00	834	5.29	100.00	100.00	100.00

Notes: Terrain type can be broadly classified as a combination of elevation (in meters) and slope (in percent). The first column reports the distribution of terrain type for our full sample and the second and third columns report the average elevation and slope within each terrain type. The last three columns report the distribution of terrain type (in percentage) by region.

Table 3: Dispersion of Output, Land Size, Land Quality, and Rain, Malawi ISA 2010/11

		Within Geographic Areas		
	Full Sample	Regions	Districts	Enum. Area
Output, y_i:	1.896	1.867	1.778	1.649
Land Size, l_i:	.749	.746	.719	.671
Land Quality:				
▷ Index, q_i	.852	.833	.568	.147
▷ Index Subitems:				
Elevation	.439	.349	.075	.001
Slope (%)	.657	.635	.453	.093
Erosion	.480	.496	.472	.427
Soil Quality	.608	.605	.514	.458
Nutrient Avail.	.387	.402	.248	.023
Nutrient Ret. Cap.	.329	.365	.180	.016
Rooting Conditions	.342	.372	.302	.029
Oxygen Avail. to Roots	.097	.094	.105	.010
Excess Salts	.037	.045	.048	.004
Toxicity	.027	.038	.033	.003
Workability	.475	.474	.335	.033
Quality-Adjusted Land Size, $q_i l_i$:	1.571	1.531	1.243	.808
Rain, ζ_i:				
▷ Annual Precip. (mm)	.039	.025	.014	.001
▷ Precip. of Wettest Qrter (mm)	.026	.013	.005	.000

Notes: Output y_i, land size (in acres) l_i, land quality index q_i, quality-adjusted land size $q_i l_i$, and rain ζ_i, are continuous variables for which we use the variance of logs as a measure of dispersion. Subitems of land quality, slope (in %) and elevation (in meters), are also continuous variables and we also report the variance of logs as dispersion measure. The other subitems of land quality are categorical variables such as soil quality (with categories 1 good, 2 fair, 3 poor), erosion (with categories 1 none, 2 low, 3 moderate, 4 high) and nutrient availability, nutrient retention, rooting conditions, oxygen to roots, excess of salts, toxicity and workability that take values from four categories (1 low constraint, 2 moderate constraint, 3 severe constraint and 4 very severe constraint). For all categorial variables we use the proportion of non-mode values in the sample as measure of dispersion. The construction of the land quality index q_i is discussed in Section 3. For the last three columns referring to within geographic areas, we report the averages across geographic area under consideration (e.g., the variance of output in the 'Regions' column is the average across regions of the variance of output by region).

Table 4: Dispersion of Productivity across Farms and Manufacturing Plants

	Farms		Manufacturing Plants		
	Malawi	USA	USA	China	India
Statistic	ISA 2010/11	1990	1977	1998	1987
SD	1.19	0.80	0.85	1.06	1.16
75-25	1.15(3.2)	1.97	1.22	1.41	1.55
90-10	2.38(10.8)	2.50	2.22	2.72	2.77
N	7,157	AR(2014)	164,971	95,980	31,602

Notes: The first column reports statistics for the household-farm productivity distribution from the micro data in Malawi. The second column reports statistics for farm productivity in the United Sates from the calibrated distribution in Adamopoulos and Restuccia (2014a) to U.S. farm-size data. The other columns report statistics for manufacturing plants in Hsieh and Klenow (2009). SD is the standard deviation of log productivity; 75-25 is the log difference between the 75 and 25 percentile and 90-10 the 90 to 10 percentile difference in productivity. N is the number of observations in each dataset.

Table 5: Variance Decomposition of Agricultural Output, Malawi ISA 2010/11

	Benchmark		$(\zeta_i = 1, q_i = 1)$	
	Level	%	Level	%
$var(y)$	1.896	100.0	1.896	100.0
$var(s)$	1.435	75.7	1.457	76.8
$var(\zeta)$	.039	2.1	–	–
$var(f(k, ql))$	.383	20.2	.343	18.1
$2cov(s, \zeta)$	-.044	-2.3	–	–
$2cov(s, f(k, ql))$	.034	1.8	.096	5.1
$2cov(\zeta, f(k, ql))$	.048	2.5	–	–

Notes: The variance decomposition uses our benchmark production function that adjusts for rain ζ_i and land quality q_i across household farms, $y_i = s_i \zeta_i f(k_i, q_i l_i)$ with $f(k_i, q_i l_i) = k_i^{.36}(q_i l_i)^{.18}$. All variables have been logged. The variables are output y_i, household-farm productivity s_i, rain ζ_i, structures and equipment capital k_i, and quality-adjusted land size, $q_i l_i$. The first two columns report results from our benchmark specification where rain and land quality are controlled for. The last two columns report the results abstracting from rain and land quality, i.e. we set $\zeta_i = 1$ and $q_i = 1$ $\forall i$. In each case, the column 'Level' reports the variance and the column '%' reports the contribution to total output in percentage points. The construction of the land quality index q_i and rain ζ_i and their effects on farm productivity are discussed in detail in Section 3.

Table 6: Results on the Output Loss (Y^a/Y^e)

(a) Main Results

		Bootstrap Simulations		
	Full Sample	Median	5th pct.	95th pct.
Nationwide	.2788	.2817	.2455	.3211

(b) By Geographical Areas and Institutions

	Average	Median	Min	Max
Geographic Areas:				
Regions	.2943	.2921	.2757	.3485
Districts	.3410	.3568	.1409	.4821
Enum. Areas	.6077	.6245	.0911	.9624
Institutions:				
Traditional Authority	.3213	.2872	.1791	.7220
Language	.2980	.2576	.1681	.8646

Notes: In panel (a), bootstrap median and confidence intervals are computed from 5,000 simulations obtained from random draws with 100 percent replacement, i.e., each simulation consists of a sample of the same size as the original sample. See further discussion in Appendix B. Panel (b) reports the ratio of actual to efficient output when the reallocation exercise is conducted within three narrower definitions of geographical areas (3 regions, 31 districts and 713 enumeration areas) and two measures of institutional settings/cultural identity (53 traditional authorities and 13 languages). We drop enumeration areas with less than 5 household-farm observations.

Table 7: Land Markets, Output Loss for Farms with Marketed vs. Non-marketed Land

	By Marketed Land Share			By Marketed Land Type			
	No	Yes	All	Rented		Purchased	
	(0%)	(> 0%)	(100%)	Informal	Formal	Untit.	Titled
Output (Productivity):							
Losses	.2411	.5081	.6378	.5809	.5782	.1951	.7192
Gains	4.146	1.968	1.567	1.721	1.729	5.125	1.390
Observations	5,962	1,189	746	215	682	126	97
Sample (%)	83.4	16.6	10.4	3.0	9.5	1.8	1.3

Notes: The output loss is calculated as in our benchmark full sample reallocation but aggregate output losses are computed separately for subsamples of farm households defined by the share of marketed land used and its type. This share of marketed land is defined from the household-farm level information on how land was acquired, see Section 2. Each column refers to a particular subsample. The first column reports the output losses (and its inverse, the gains) for the subsample of household farms that do not operate any marketed land. The household farms in this subsample operate land that was either granted by a chief, inherited or as bride price. The second column refers to the subsample of household farms operating a strictly positive amount of marketed land, either purchased or rented-in. The third column refers to the subsample of household farms for which all their operated land is marketed land. The last four columns disaggregate the results by the main types of marketed land: (1) rented informally, i.e. land borrowed for free or moved in without permission; (2) rented formally, i.e. leaseholds, short-term rentals or farming as a tenant; (3) purchased without a title; and (4) purchased with a title. There is 1% of households with marketed land whose type is missing in the Malawi ISA data.

Table 8: Robustness to Human Capital and Specific Skills

Output Loss within Schooling and Terrain-specific Groups

Schooling Groups:	No Schooling	Dropouts	Primary	> Primary
Output (Productivity):				
Losses	.3104	.3005	.2628	.2795
Gains	3.221	3.327	3.805	3.577
Terrain-roughness Skills:	High Altitude Plains	Low Plateaus	Mid-Altitude Plateaus	Mid-Altitude Mountains
Output (Productivity):				
Losses	.2712	.2697	.3297	.3655
Gains	3.687	3.707	3.033	2.735

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%. The sample distribution of terrain types is reported in Table 2.

Table 9: Robustness to Health and other Transitory Risks

Output Loss when Productivity is Net of Health and Other Transitory Risks

		Productivity Specification					
	Bench.	(1)	(2)	(3)	(4)	(5)	(6)
Further Transitory Risks Controls:							
Health Risk (last 12m)	–	✓	✓	✓	✓	✓	✓
Death Risk (last 2 years)	–	–	✓	✓	✓	✓	✓
Food Security Risk (last 12m)	–	–	–	✓	✓	✓	✓
Marital Status	–	–	–	–	✓	✓	✓
Distance to Markets	–	–	–	–	–	✓	✓
Other Income Sources	–	–	–	–	–	–	✓
Output (Productivity):							
Losses	.2788	.2763	.2764	.2679	.2678	.2685	.2674
Gains	3.586	3.619	3.617	3.731	3.734	3.723	3.738

Notes: This table reports measures of household-farm productivity that controls for transitory effects on output such as health and other individual shocks. Our measure of health risks includes illnesses/injuries in the last 2 weeks, hospitalizations in the last 12 months (formal and at traditional healer locations), health expenditures in the last 12 months (including prevention expenditures and treatment) and malaria conditions in the last 12 months (including the use of bed nets and insecticides). Death risk includes deaths in the family over the past two years depending on the age of the deceased. Food security states whether the household suffered an episode of not being able to feed family members in the last 12 months. In higher order specifications we also include marital status, distance to roads, markets and main suppliers, and variation in other sources of income. See further details in Appendix **??**.

Table 10: Reallocation Results by Crop Type

	Bench.	Maize Share >0%	Maize Share > Median	Non-Maize Share >0%	Non-Maize Share > Median
Output (Productivity):					
Losses	.2788	.3534	.3687	.2618	.2419
Gains	3.586	2.828	2.711	3.819	4.133

Notes: This table reports the efficient reallocation exercise within households producing the main crop in Malawi, maize, and within households producing non-maize crops. Because most households (74%) produce both maize and non-maize crops, the table also reports the reallocation results within household-farms whose production of maize is above median production. The median share of maize production within the group of household-farms that produce a strictly positive amount of maize is 83.1% and the median share of non-maize production within the group of household-farms that produce a strictly positive amount of non-maize crops is 66.2%.

Table 11: Actual and Efficient Distribution of Land, Capital, MPL and MPK

Malawi ISA 2010/11 Productivity Partition	Bottom(%)			Quintiles					Top(%)				
	0-1	1-5	5-10	1st	2nd	3rd	4th	5th	10-5	5-1	1	Total	$var(\ln x)$
Productivity s_i:	.07	.23	.41	.75	2.10	3.72	6.39	21.50	32.36	48.06	112.01	6.89	1.435
Land, l_i:													
Actual	1.35	.94	1.50	1.19	.87	1.01	1.03	1.99	2.36	2.86	2.78	1.22	.749
Efficient	.00	.00	.00	.00	.01	.04	.14	5.91	11.40	21.70	88.66	1.22	6.782
Capital, k_i:													
Actual	204.01	98.10	64.34	55.93	25.35	21.84	24.70	26.71	28.50	32.44	34.35	30.91	1.820
Efficient	.00	.00	.01	.04	.32	1.10	3.60	149.52	288.46	548.94	2,242.11	30.91	6.782
MPL ($\propto$ Yield):													
Actual	.23	.90	.96	.75	2.10	3.72	6.39	21.50	56.37	69.81	152.09	21.27	1.485
Efficient	76.30	76.30	76.30	76.30	76.30	76.30	76.30	76.30	76.30	76.30	76.30	76.30	.000
MPK:													
Actual	.00	.01	.04	.75	2.10	3.72	6.39	21.50	9.35	12.34	24.66	1.68	2.154
Efficient	6.03	6.03	6.03	6.03	6.03	6.03	6.03	6.03	6.03	6.03	6.03	6.03	.000

Notes: Households are ranked from bottom to top according to household-farm productivity s_i. Land (acres) and capital (USD) are expressed in per 100 hours terms. Regarding with the marginal product of land, MPL, and the marginal product of capital, MPK, we compute for each productivity bin, $\text{MPL} = .18 \frac{\sum_i y_i}{\sum_i l_i}$ and $\text{MPK} = .36 \frac{\sum_i y_i}{\sum_i k_i}$, and the variance is computed with respect to household-farm specific ratios $\text{MPL}_i = .18 \frac{y_i}{l_i}$ and $\text{MPK}_i = .36 \frac{y_i}{k_i}$.

Table 12: Actual and Efficient Distribution of Operational Scale vs. Income

Malawi ISA 2010/11 Productivity Partition	Bottom(%)			Quintiles					Top(%)				
	0-1	1-5	5-10	1st	2nd	3rd	4th	5th	10-5	5-1	1	Total	$var(\ln x)$
Output, y_i:													
▷ Level:													
Actual	.01	.04	.08	.14	.39	.69	1.20	4.78	7.41	11.12	23.53	1.44	1.824
Efficient	.00	.00	.00	.00	.05	.18	.60	25.06	48.35	92.01	375.83	5.18	6.782
▷ % of Total:													
Actual	.01	.16	.55	2.01	5.46	9.57	16.67	66.26	51.24	38.42	16.16	100.00	–
Efficient	.00	.00	.00	.02	.20	.71	2.33	96.71	93.22	88.57	71.95	100.00	–
Income:													
▷ Level:													
Actual	.01	.04	.08	.14	.39	.69	1.20	4.78	7.41	11.12	23.53	1.44	1.824
Efficient	13.34	6.64	5.02	4.28	2.22	2.17	2.56	14.65	25.76	46.47	177.08	5.18	1.228
Ratio: Actual/Eff.	155.78	58.03	39.73	23.70	3.88	2.27	1.58	1.97	2.58	3.71	9.86	6.68	–
▷ % of Total:													
Actual	.01	.16	.55	2.01	5.46	9.57	16.67	66.26	51.24	38.42	16.16	100.00	–
Efficient	2.59	6.41	9.71	16.55	8.58	8.41	9.88	56.56	49.68	44.73	33.90	100.00	–

Notes: Households are ranked from bottom to top according to household-farm productivity s_i. The definition of income refers to a scenario in which the ownership of household-farm endowments of land and capital does not change and there is reallocation entirely through rental markets, see Section 5.

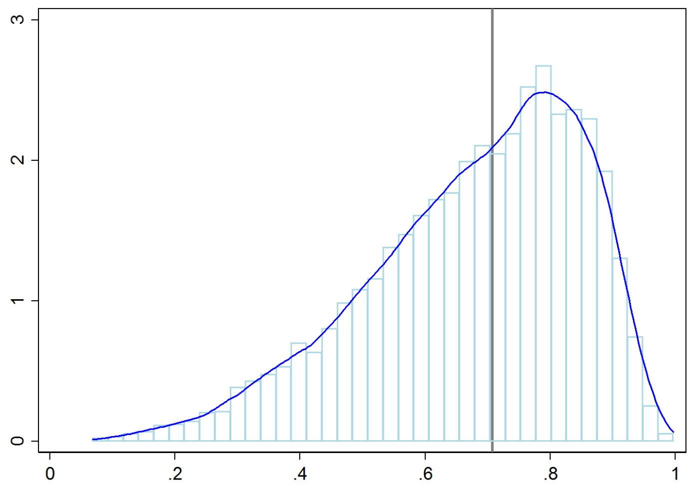
Table 13: Reallocation Results with Two Sectors

	Benchmark	Increased Productivity
Productivity in Agriculture (Z)	1.00	3.60
Yield (Y_a/L)	1.00	1.00
Share of Employment in Ag. (N_a)	0.65	0.04
Average Farm Size (L/N_a)	1.00	16.2
Labor Productivity in Ag. (Y_a/N_a)	1.00	16.2

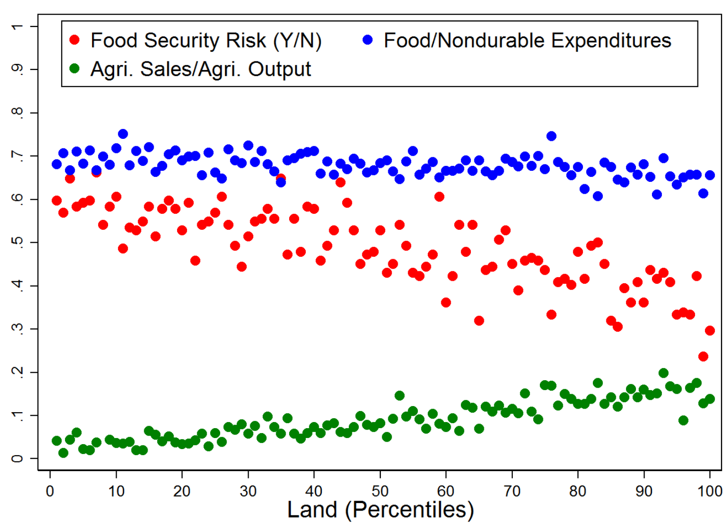
Notes: The "Benchmark" refers to the actual allocation in Malawi. The "Increased Productivity" refers to the efficient reallocation which in the full sample increases total factor productivity in agriculture by a factor of 3.6-fold. The table reports the effects of increased TFP in agriculture on output per unit of land in agriculture (yield), the share of employment in agriculture, average farm size, and aggregate labor productivity in agriculture when factors are allowed to be reallocated across agriculture and non-agriculture.

Figure 1: Subsistence Consumption, Malawi ISA 2010/11

(a) Density of Food Share in Nondurable Expenditures



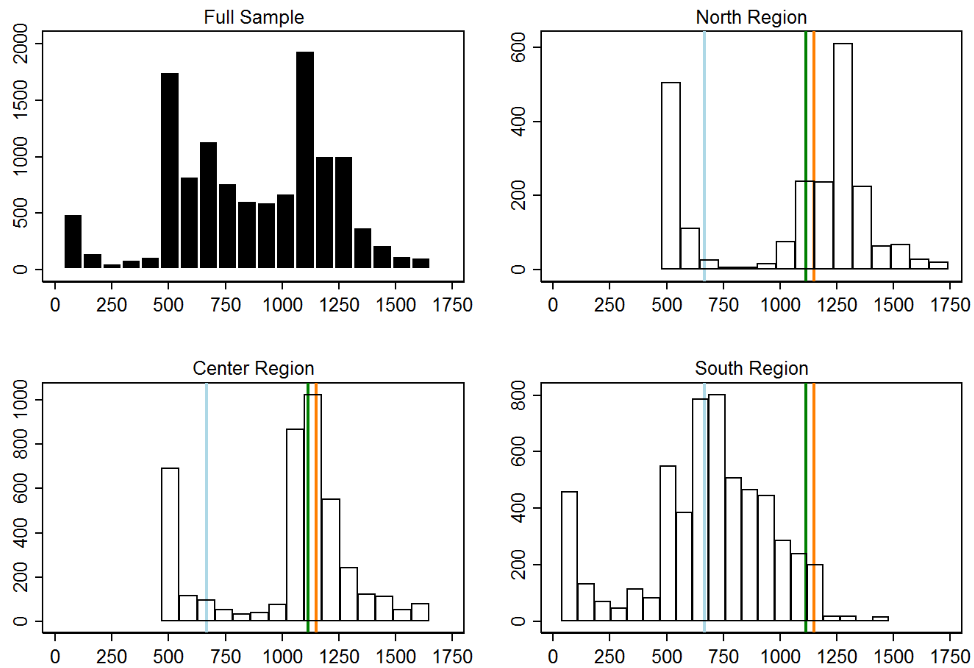
(b) Subsistence Consumption Proxies by Land Size



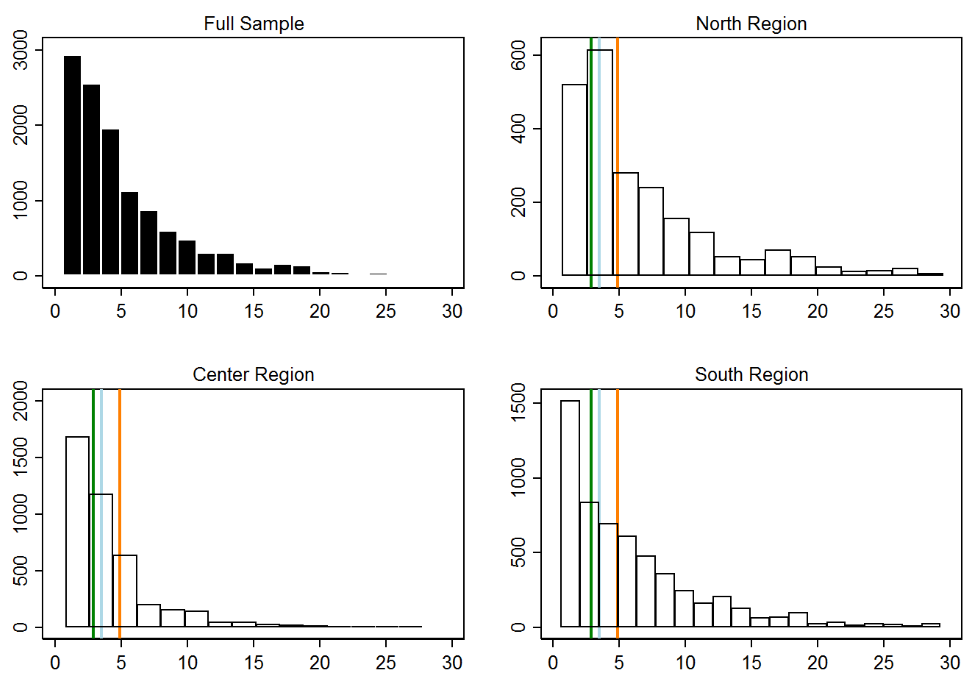
Notes: Food includes food purchases that are consumed, home produced food that is consumed valued at consumption market prices, and food gifts received that are consumed valued at consumption market prices. Nondurable expenditures include food, clothing, utilities, and other nondurable expenditures. All consumption subitems have been deseasonalized using the 12 months roll-over nature of the Malawi IHS 2004/05 and 2010/11 and then annualized; these consumption data are borrowed from de Magalhaes and Santaeulàlia-Llopis (2014a). Agricultural production and sales are in annual terms and described in Appendix A. Food security risk refers to whether the household faced a situation in which there was not enough food to feed all members in the last 12 months.

Figure 2: Land Quality Inputs: Histograms of Elevation and Slope, Malawi ISA 2010/11

(a) Elevation (meters)



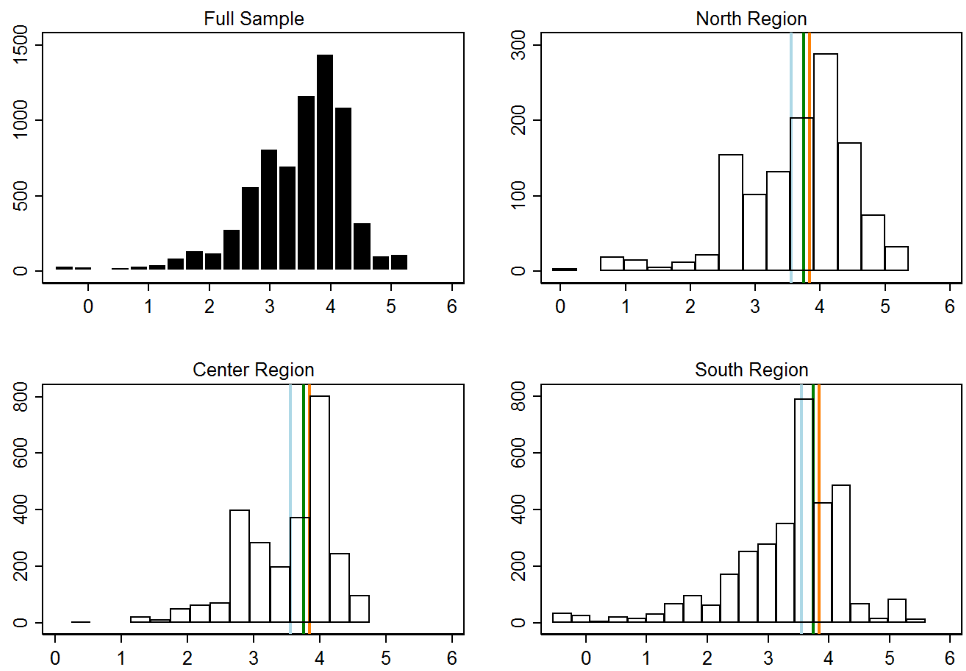
(b) Slope (%)



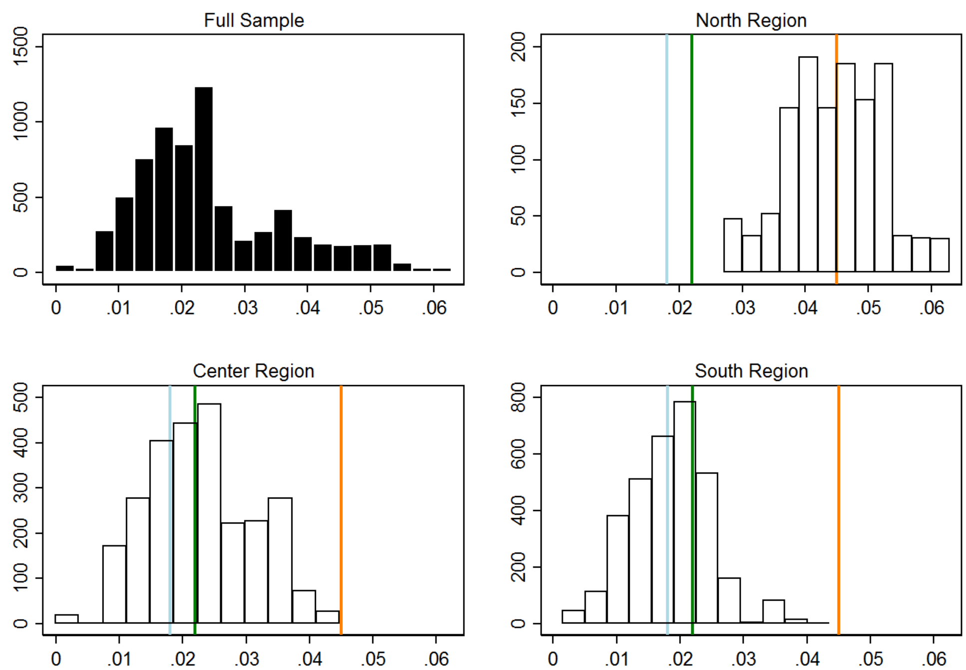
Notes: Elevation and slope are collected at the plot level. Household-farm values that we report here are averages across plots within households weighted by plot size. Median values by region are depicted with vertical lines: Orange (North), green (Center) and light blue (South).

Figure 3: Histograms of Land Quality Index and Rain, Malawi ISA 2010/11

(a) Land Quality Index, q_i (in logs)

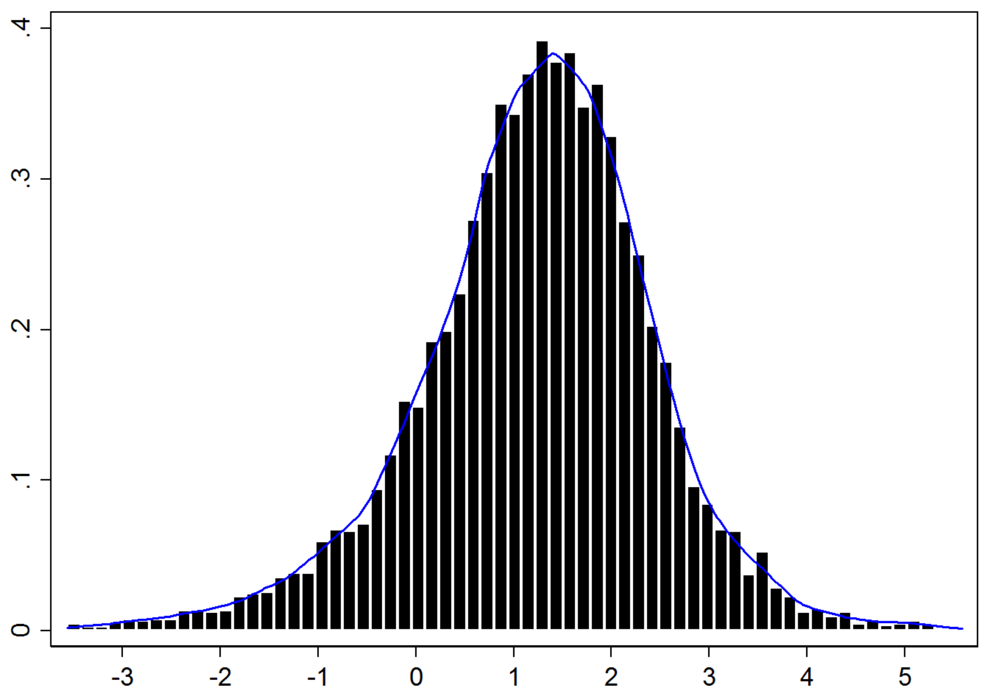


(b) Rain, ζ_i (in logs)



Notes: The land quality index is computed in Section 3. Median values by region are depicted with vertical lines: Orange (North), green (Center) and light blue (South).

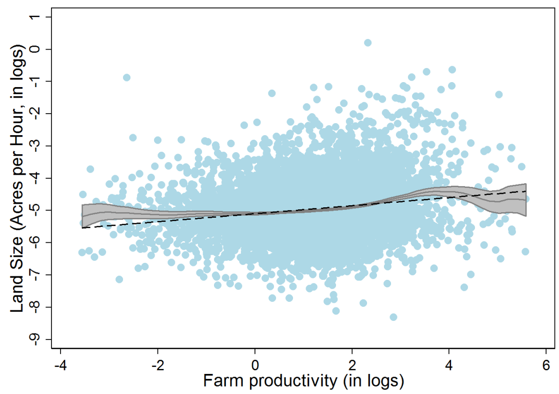
Figure 4: Density of Farm Productivity s_i (in logs), Malawi ISA 2010/11



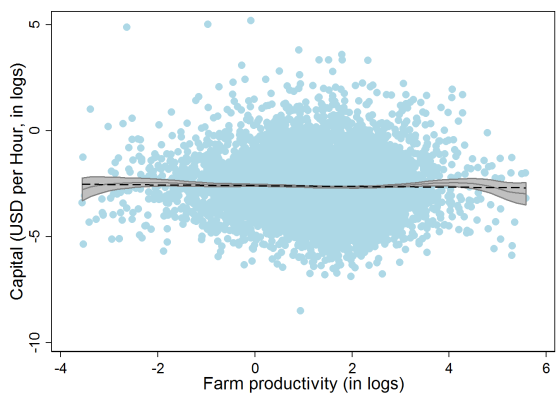
Notes: Household-farm productivity s_i is measured using our benchmark production function, adjusting for rain ζ_i and land quality q_i , $y_i = s_i \zeta_i f(k_i, q_i l_i)$ with $f(k_i, q_i l_i) = k_i^{.36}(q_i l_i)^{.18}$, where y_i is farm output, k_i is capital, and l_i is land. All variables have been logged.

Figure 5: Land and Capital by Farm Productivity, Malawi ISA 2010/11

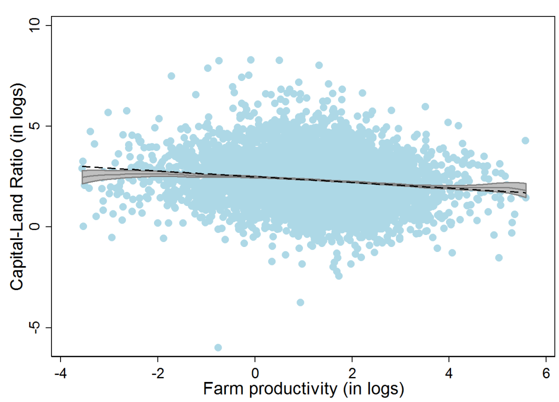
(a) Land Size by Farm Productivity



(b) Capital by Farm Productivity



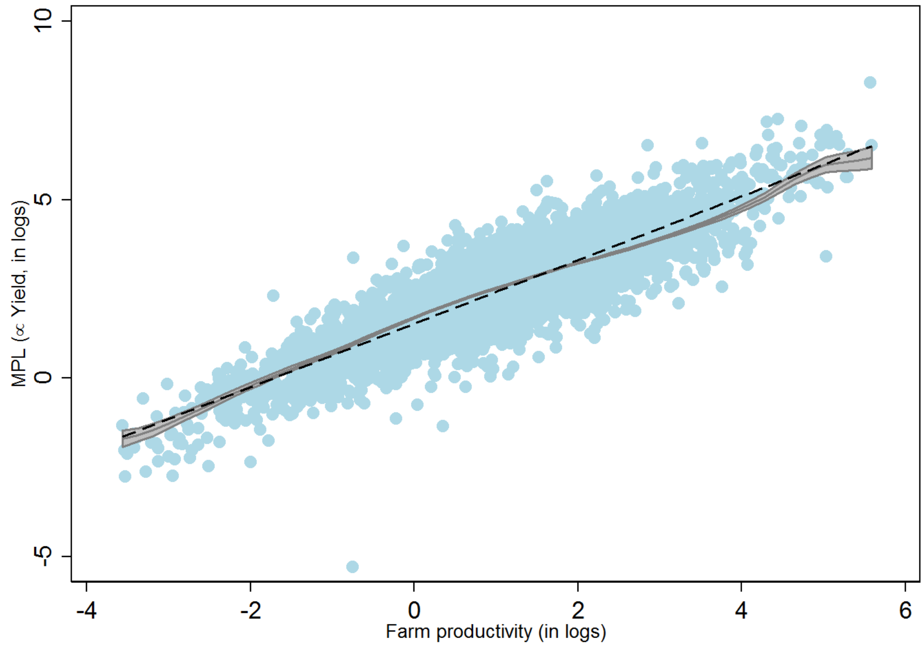
(c) Capital-Land Ratio by Farm Productivity



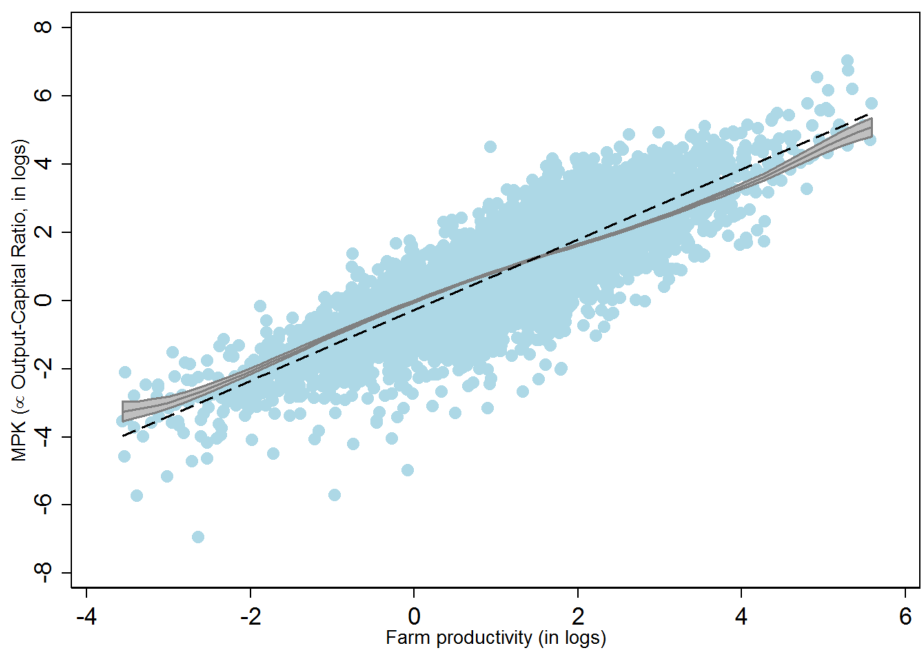
Notes: Panel (a) reports the relationship between operated farm land size (in acres per hour) l_i and farm productivity s_i. Panel (b) reports the relationship between farm capital (in USD per hour) k_i and farm productivity s_i. Panel (c) reports the relationship between the farm capital to land ratio k_i/l_i and farm productivity s_i. The computation of farm productivity, s_i, is discussed in Section 3. All variables have been logged.

Figure 6: Marginal Product of Land and Capital by Farm Productivity, Malawi ISA 2010/11

(a) MPL ($\propto$ Yield) vs. Farm Productivity



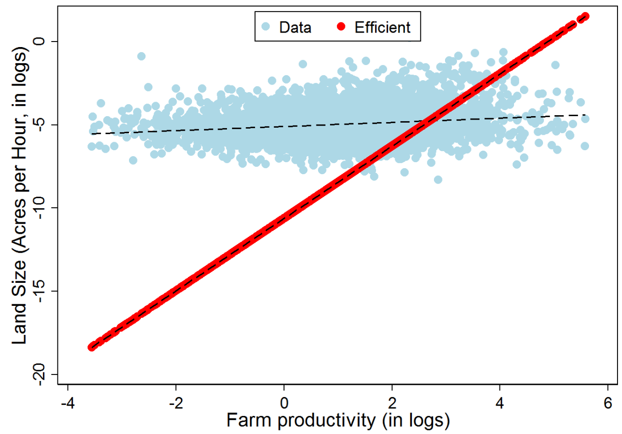
(b) MPK ($\propto$ Output-Capital Ratio) vs. Farm Productivity



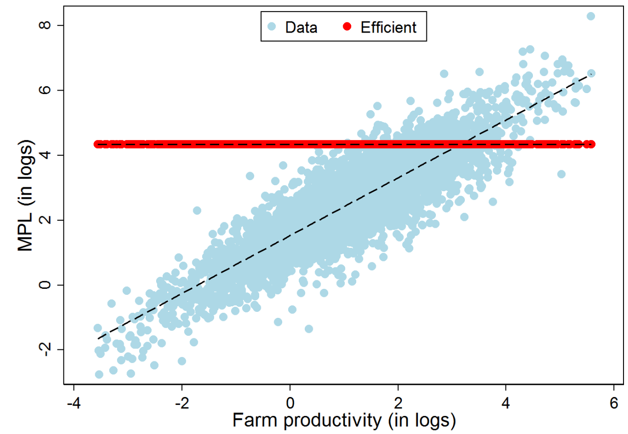
Notes: Panel (a) reports the relationship between the marginal product of land constructed using our benchmark production function, i.e., MPL $= .18\ y_i/l_i$ (which is proportional to the yield) and farm productivity s_i. Panel (b) reports the relationship between the marginal product of capital constructed using our benchmark production function, i.e., MPK$= .36\ y_i/k_i$ (which is proportional to the output-capital ratio) and farm productivity, s_i.. The computation of farm productivity s_i is discussed in Section 3. All variables have been logged.

Figure 7: Land Size, Capital, MPL and MPK: Actual and Efficient Allocations

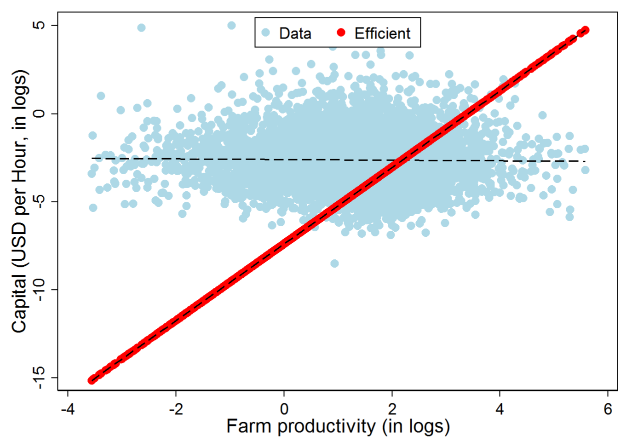
(a) Land Size vs. Farm Productivity



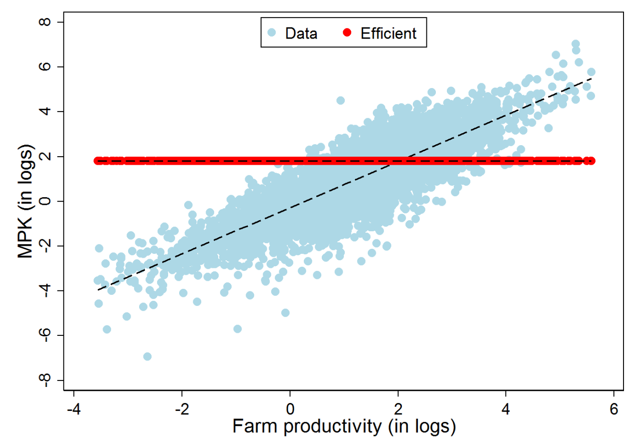
(b) MPL vs. Farm Productivity



(c) Capital vs. Farm Productivity

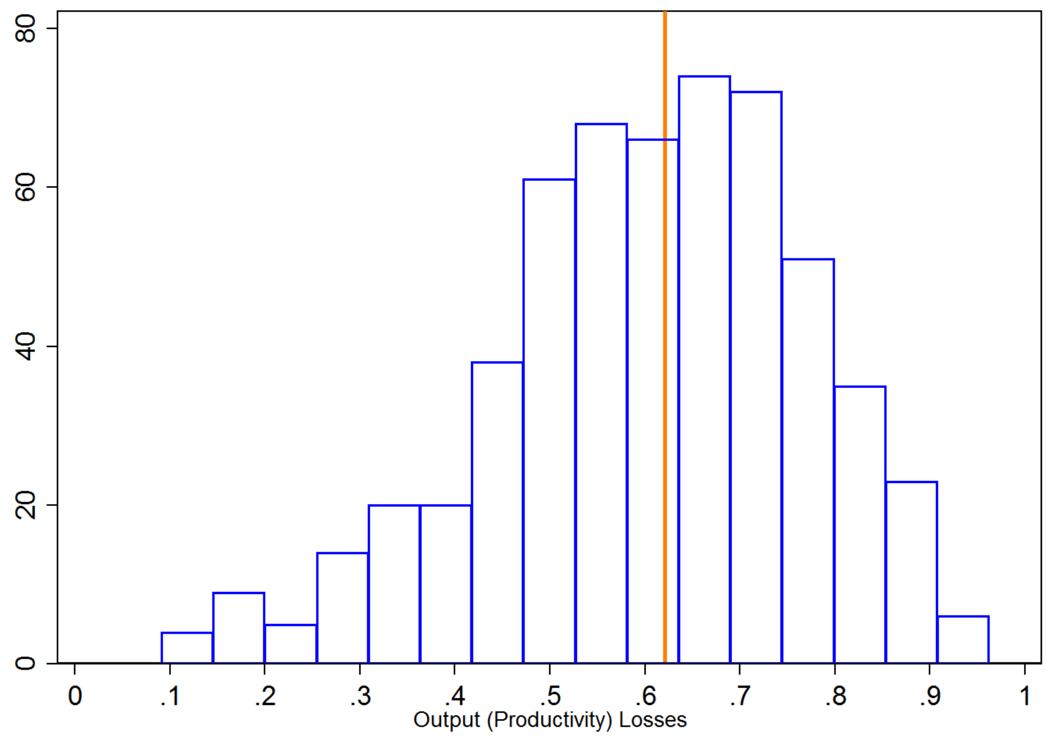


(d) MPK vs. Farm Productivity



Notes: Panel (a) scatters the actual and efficient relationship between land size, l_i, and farm productivity, s_i. Panel (b) scatters the actual and efficient relationship between the marginal product of land, MPL, and farm productivity, s_i. Panel (c) scatters the actual and efficient relationship between capital, k_i, and farm productivity, s_i. Panel (d) scatters the actual and efficient relationship between the marginal product of capital, MPK, and farm productivity, s_i. The computation of farm productivity, s_i, is discussed in Section 3. All variables have been logged.

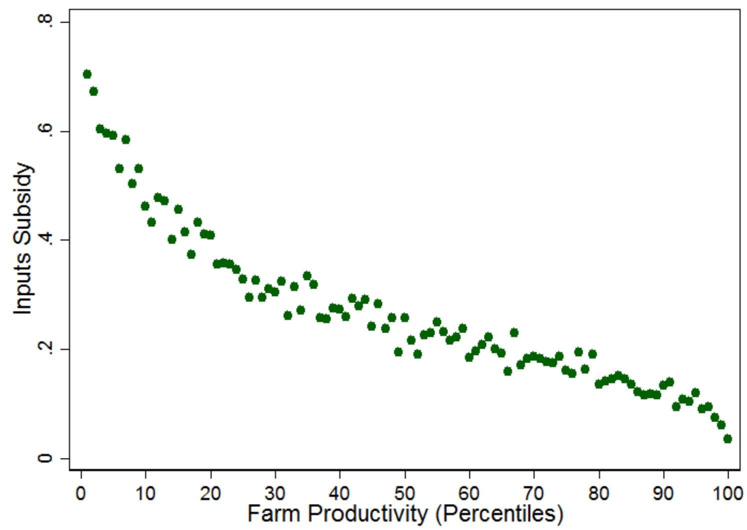
Figure 8: Histogram of Output (Productivity) Losses within Enumeration Areas



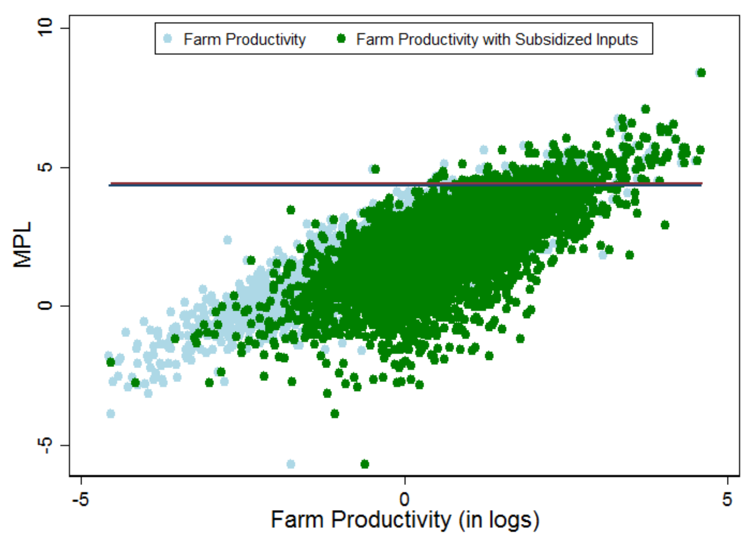
Notes: The figure reports the output loss (actual to efficient output) by enumeration area. Enumeration areas are a survey definition of groups of about 16 households each, the narrowest geographic area in the survey.

Figure 9: Subsidy to Intermediate Inputs and Farm Productivity

(a) Input Subsidy relative to Output



(b) Land Productivity vs. Farm Productivity



Notes: Panel (a) reports the subsidy to intermediate inputs as a fraction of output for each household farm by farm productivity. Panel (b) documents the relationship between land productivity and farm productivity for our benchmark measure of productivity that uses real intermediate inputs versus a measure of productivity that uses actual expenditures in intermediate inputs.