Land Misallocation and Productivity[†]

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January 2017

Abstract

Using detailed household-level data from Malawi on physical quantities of outputs and inputs in agricultural production, we measure total factor productivity (TFP) for farms controlling for land quality, rain, and other transitory shocks. We find that operated land size and capital are essentially unrelated to farm TFP implying substantial factor misallocation. The aggregate agricultural output gain from a reallocation of factors to their efficient use among existing farmers is a factor of 3.6-fold. We directly link factor misallocation to severely restricted land markets as the vast majority of land is allocated by village chiefs and not marketed. In particular, the output gain from reallocation are 2.6 times larger for farms with no marketed land than for farms that only operate marketed land.

Keywords: misallocation, land, productivity, agriculture, Malawi, micro data.
JEL codes: O1, O4.

[†]For helpful comments we thank Aslihan Arslan, Nadege Azebaze, Fancesco Caselli, Leandro M. de Magalhaes, Matthias Doepke, Pascaline Dupas, Chang-Tai Hsieh, Chad Jones, Joe Kaboski, Pete Klenow, Evelyn Korn, Per Krusell, Rody Manuelli, Virgiliu Midrigan, Andrew Newman, Chris Pissarides, Nancy Qian, Richard Rogerson, José-Víctor Ríos-Rull, Paul Romer, Nancy Stokey, Kjetil Storesletten, Kei-Mu Yi, and seminar participants at Edinburgh, ENSAI, SITE, SED, NBER Summer Institute, Toronto, IMF Workshop on Inequality, CIDE Mexico, Queen's, Marburg, Universitat d'Alacant, CEMFI, RIDGE, Wilfried Laurier University, HEC Montreal, Oxford CSAE, World Bank Land & Poverty Conference, ECAMA-IPFRI-IPA, Notre Dame conference on misallocation and development, UAB, FAO-Roma, Universitat de Barcelona, and LSE. All remaining errors are our own. Restuccia gratefully acknowledges the financial support from the Canadian Research Chairs program and the Social Sciences and Humanities Research Council of Canada. Santaeulàlia-Llopis gratefully thanks the Weidenbaum Center on the Economy, Government, and Public Policy for financial support.

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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 we build on two. First, agriculture is relevant because poor countries are substantially less productive in agriculture relative to non-agriculture compared to rich countries and allocate most of their labor to this sector.[1] Second, the misallocation of factors of production across heterogeneous production units is important in accounting for differences in measured productivity across countries.[2] We exploit a unique micro-level data from Malawi to measure total factor productivity (TFP) in farms controlling for land quality and transitory shocks. We find that operated land size and capital are essentially unrelated to farm TFP, providing strong evidence of misallocation. Quantitatively, factor misallocation has a substantial negative effect on agricultural productivity, implying a 3.6-fold gain from efficient reallocation. This gain is much larger than those reported for the manufacturing sector of China and India (e.g. Hsieh and Klenow, 2009). Importantly, we provide direct evidence linking the bulk of agricultural productivity losses from misallocation to restricted land markets.

Malawi represents an interesting case to study for several reasons. First, Malawi is an extremely poor country in Africa, featuring very low agricultural productivity, a large share of employment in agriculture, and extremely low farm operational scales. Second, the land market in Malawi is largely underdeveloped. Most of land in Malawi is customary and user rights are allocated locally by village chiefs. In our representative sample, more than 83 percent of household farms do not operate any marketed land (either purchased or rented-in).[3] Third, the detailed micro data for Malawi allow

[1] See, for instance, Gollin et al. (2002) and Restuccia et al. (2008).

[2] For instance Restuccia and Rogerson (2008) and Hsieh and Klenow (2009). See also Gancia and Zilibotti (2009) for an analysis connecting misallocation and technology.

[3] In Malawi, the vast majority of land is either directly or indirectly distributed by the village head (or superior chiefs that exercise power over a collection of villages). The Customary Land Act grants these local leaders the power of allowing/banning land transactions (e.g., inheritance) and resolve disputes across villagers related to land limits (Kishindo, 2011; Morris, 2016). This status quo has remained stable since colonial times (Pachai, 1973). While not yet in place, the Malawi Land Bill passed in 2016 aims at reducing these powers.

us to precisely connect land constraints at the household-farm level and factor misallocation in agriculture, providing an important departure from the existing macro development literature.

Our contribution is based on two elements that are essential for the assessment of the quantitative importance of factor misallocation and its sources. The first element is a measure of farm-level TFP which requires detailed information on outputs, inputs, and other factors such as land quality and transitory shocks that are relevant in our context. The second element is the direct identification from the data of which production units are operating land acquired from the market or not, which provides the basis to directly connecting misallocation and land markets. It is important to note that none of these two key elements, measurements of farm-level TFP and information on how operated land is acquired, is present in recent studies of misallocation in agriculture, such as Adamopoulos and Restuccia (2014). The data is the 2010/11 Integrated Survey of Agriculture (ISA) for Malawi collected by the World Bank. This is a large nationally-representative sample of more than 12 thousand households.[4] Whereas the dispersion in our measure of farm-level TFP is quantitatively similar to previous studies in other sectors and countries, our finding is that factors of production are roughly evenly spread among farmers. That is, operated land size and capital are essentially unrelated to farm productivity, generating substantially larger amounts of misallocation than found in other contexts. To assess the aggregate impact 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; and calculate the output (productivity) gain as the ratio of efficient to actual output. Our main finding is that the output gain is 3.6-fold in the full sample, that is, if capital and land were reallocated across farms in Malawi to their efficient uses, agricultural productivity would increase by 260 percent.

A limitation of the empirical literature on misallocation is the weak link with policies and institutions that cause it (e.g. Hsieh and Klenow, 2009), a caveat that also applies to previous studies of

[4]The ISA data are considered a *gold standard* for the study of poor countries; see a detailed analysis in de Magalhaes and Santaeulàlia-Llopis (2015). We provide further discussion in Section 2.

land allocations in the agricultural sector (e.g. Adamopoulos and Restuccia, 2014). This limitation has inspired a promising quantitative literature studying specific policies and institutions, but the findings are yet elusive in accounting for the bulk of TFP differences across countries (Restuccia and Rogerson, 2016). In this context, an important contribution of our analysis 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 gains among farmers that have no marketed land to those that operate marketed land. We find that reallocating factors among farms with no marketed land to reduce the dispersion in marginal products to the same extent to those farms with all marketed land increases agricultural output and productivity by a factor of 2.6-fold. This result provides an important first step in directly identifying (lack of) land markets as a relevant institution generating misallocation and productivity losses. Our results have important implications for the design of policies and institutions to promote better factor allocation.[5]

Our evidence of factor misallocation based on producer-level TFP measures is closely linked to the seminal work of Hsieh and Klenow (2009) for the manufacturing sector in China, India, and the United States. Our analysis contributes to this work by providing evidence of misallocation in the agricultural sector of a very poor country that is less subject to concerns of measurement and specification errors that cast doubt on the extent of misallocation in poor countries. The evidence of misallocation we provide is strong because of several reasons. First, it is easier to measure producer-level TFP in agriculture than in other sectors since output and most inputs are directly measured in physical quantities (Beegle et al., 2012; Carletto et al., 2013). Moreover, there is less product heterogeneity in the agricultural sector than in other sectors, and such heterogeneity can be controlled for in our data by focusing on individual crops. Indeed, the prevalence of maize production

[5]We recognize that even with detailed and excellent micro data from ISA Malawi, measuring precisely farm-level TFP is an enormous difficult task. However, we find it reassuring that the gains from factor reallocation are large even when comparing groups of farmers in the same country operating with and without marketed land, as the potential biases of mis-measurement, unobserved heterogeneity, and randomness are mitigated in the comparison.

in Malawi allows us to corroborate the extent of misallocation for farms that produce the same crop. There is also a high response rate in the dataset with very few missing observations, making the analysis less subject to measurement and specification errors. Second, the micro data provide precise measures of the quality of inputs (e.g., eleven dimensions of land quality) as well as transitory shocks such as rain and health shocks that we explicitly control for to measure farm-level TFP. Third, the large sample size allows us to assess the robustness of our results to within narrow geographic areas and other relevant characteristics. Fourth, the micro data provide information on land and capital rental payments that we use to compute land and capital income shares for the agricultural sector in Malawi that generate virtually identical results to our baseline calibration to U.S. shares. Fifth, while Hsieh and Klenow (2009) assess the reallocation gains in China and India relative to the gains in the United States, we are able assess the reallocation gains relative to a set of farmers in Malawi whose operated land is all marketed, providing a more direct benchmark comparison. Sixth, the link between the degree of misallocation in manufacturing China and India and its causes is weak in Hsieh and Klenow (2009). More recently, for the case of China, Song et al. (2011) show that credit market imperfections are important in explaining resource misallocation between private and state-owned enterprises. Analogously, we provide a direct link between misallocation and land markets in agriculture exploiting information on how each plot was acquired. For all these reasons, we argue that our analysis constitutes the most direct and comprehensive evidence of misallocation in a poor country.

We also explore the broader consequences of misallocation on structural transformation and inequality. The productivity increase from efficient reallocation in Malawi would unravel a substantial process of structural change, for instance, in the context of a standard two-sector model, a reduction in the share of employment in agriculture from 65 percent to 4 percent and an increase in average farm size by a factor of 16.2-fold, making these statistics closer to industrialized-country levels. These effects would be even larger in more elaborate models that include endogenous investments in productivity, ability selection across sectors, among other well-studied channels in the literature.[6] A potential argument that justifies the actual land allocation is the reduction of income inequality. That is, the distribution of land can operate as an ex-ante redistribution mechanism. Interestingly, even though the actual allocation of factors is evenly spread across farmers, we find that factor equalization is ineffective at equalizing incomes in Malawi. 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 much lower income inequality and poverty. The introduction of rental markets, where operational scales can deviate from land-use rights, substantially improves aggregate productivity reducing poverty and alleviating income inequality.

Our paper relates to a growing literature in macroeconomics using micro data to study macro development such as Gollin et al. (2014), Buera et al. (2014), Adamopoulos and Restuccia (2015), Bick et al. (2016), and Santaeulàlia-Llopis and Zheng (2016). More closely related to our work is the macroeconomic study of misallocation in the agricultural sector based on the size distribution of farms across countries (Adamopoulos and Restuccia, 2014).[7] Our first advantage over previous macroeconomic studies on agriculture is that we are able to recover TFP measures at the farm level and, hence, assess the quantitative impact of factor misallocation in the agricultural sector in a specific country, as in Hsieh and Klenow (2009) for manufacturing China and India. Importantly, our results imply larger productivity losses from factor misallocation in agriculture than in manufacturing in poor countries. Our second advantage is that our analysis is able to directly connect misallocation to restrictions in land markets, providing an important direct link to policy analysis that is missing in Hsieh and Klenow (2009) and Adamopoulos and Restuccia (2014). Within the micro development literature, Foster and Rosenzweig (2011) provide evidence of inefficient farm

[6] See for instance Goldstein and Udry (2008), Lagakos and Waugh (2013), and Adamopoulos et al. (2017).

[7] Recent work in this area include: Adamopoulos and Restuccia (2015) who study the impact of a specific policy—land reform—on productivity exploiting panel micro data from the Philippines, Chen (2016) who studies the impact of land titles on agricultural productivity across countries, and Gottlieb et al. (2015) who study the implications of communal land on misallocation and productivity in agriculture.

sizes in India that may be connected to the low incidence of tenancy and land sales limiting land reallocation to efficient farmers. Udry (1996) focuses on the intra household-farm reallocation of factors across wives and husbands for a relatively small sample of farms, obtaining a small role of misallocation in Burkina Faso. Our results indicate a large role for misallocation. There is a crucial difference between our work and that of Udry's. We focus on reallocations across farms instead of within farms. By exploiting large representative data to study nationwide factor reallocation across farms, our analysis delivers, arguably, a more accurate picture of the macroeconomic gains from reallocation.[8] Finally, Midrigan and Xu (2014) find that firms' internal capital accumulation substantially mitigates credit market imperfections after entry. It is important to emphasize that this channel, while potentially important for other factors, is limited for land which is not reproducible and accumulates only through transactions. This is consistent with recent empirical evidence showing that household land holdings barely grow over the lifecycle in Sub-Saharan Africa (de Magalhaes and Santaeulàlia-Llopis, 2015).

The paper proceeds as follows. In the next section and section 3, we describe important elements of the micro data and construct our measure of farm TFP in Malawi. Section 4 assesses the aggregate productivity impact of misallocation, linking it with the extent of access to marketed land. Sections 5 and 6 discuss the broader implications of misallocation on structural change and inequality. We conclude in Section 7. An on-line Appendix is available at: `https://www.dropbox.com/s/je5wv90trv2nmq3/RS_Online_Appendix.pdf?dl=0`.

[8] There is an important literature in micro development analyzing the role of tenancy and property rights for agricultural productivity such as Shaban (1987), Besley (1995), Banerjee et al. (2002), among others. Whereas this literature has focused on the impact of endogenous investments and effort incentives on farm productivity, our analysis focuses on the impact of resource allocation on aggregate agricultural productivity, taking as given farm-level TFP. Integrating the role of land-market institutions on both factor misallocation and endogenous farm-level productivity, is an important and promising area of study that we leave for future research.

2 Data

We use a new and unique household-level data set collected by the World Bank, the Malawi Integrated Survey of Agriculture (ISA) 2010/11, see de Magalhaes and Santaeulàlia-Llopis (2015). 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 Census and an original sample that includes 12,271 households (and 56,397 individuals) of which 81% live in rural areas.[9]

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 each crop harvested by each household is available per plot. We value agricultural production using median at-the-gate prices. 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 real value added constructed as the value of agricultural production (of all crops) minus the costs of the full set of intermediate inputs.[10]

[9]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. For further details on the Malawi ISA data and the construction of agricultural output and inputs see Appendix A.

[10]We use common prices of outputs and intermediate inputs to construct real value added in farms in the same spirit as the real measures of output across countries from the International Comparison Project and the Penn World Table.

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.[11] 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). 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.[12] 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 to roots, excess salts, topicality, and workability. This allows us to control for land quality to measure household-farm productivity.

Regarding land, we emphasize that the land market is largely underdeveloped in Malawi. The proportion of household-farms that do not operate any marketed land is 83.4%. These are households whose land was granted by a village chief, was inherited or was given as bride price. The remaining 16.6% of farm 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

[11]In rural Malawi, land is the largest household asset representing 44% of household total wealth. House structure is 30%, livestock is 13%, and agricultural equipment and structures (e.g. tools and barns) is 3%, see de Magalhaes and Santaeulàlia-Llopis (2015).

[12]To make a comparison of operational scales in Malawi with other countries, we report the distribution of farm sizes from the World Census of Agriculture in Adamopoulos and Restuccia (2014). These data include all land used for agricultural production and corresponds to the year 1990. 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. Comparatively with other countries, the operational scale of farms in Malawi is extremely small, $\sim$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 developed-country reference 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).

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 (2014).

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.

In terms of agricultural capital, we have information on both equipment and structures. Capital equipment includes implements (such as hand hoe, slasher, axe, sprayer, panga knife, sickle, treadle pump, and watering can) and machinery (such as ox cart, ox plough, tractor, tractor plough, ridger, cultivator, generator, motorized pump, and grain mill), 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.[13]

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

[13]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. Our results are robust to using these alternative indexes to proxy for agricultural capital.

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). The 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 productivity 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, and we also exploit the more recent 2013 round data where about 1/4 of the original households are interviewed to calculate a more permanent component of farm TFP as an estimated fixed effect in the panel.

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.[14]

Finally, we note that the survey response is very high with very few missing observations. Condi-

[14]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 of 1967 and receive a monetary honorarium by the government.

tioning 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.[15]

The data allows us to construct fairly precise measures of real household-farm productivity. The ISA data 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 the dataset ideal for our purpose of measuring productivity at the farm level, assessing the extent of factor misallocation in the Malawian economy, and assessing the extent to which productivity losses due to misallocation are related to imperfections or frictions in the land and other input markets.

3 Measuring Farm Productivity

We use the micro data from ISA 2010/11 described in the previous section to measure productivity at the farm level. Constructing a measure of farm total factor productivity (TFP) is essential in assessing the extent to which factors are misallocated in the agricultural sector. The detailed micro data for Malawi presents a unique opportunity to assess factor misallocation in agriculture and its aggregate productivity implications. Fewer assumptions are required to measure micro-level productivity in our context compared to many studies of misallocation focusing on the manufacturing sector since our data for agriculture comprises physical quantities of outputs and most inputs whereas additional assumptions are required to separate price and quantity from sales or revenue data of manufacturing plants.

We measure farm productivity by exploiting the detailed micro data where not only we obtain real

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

measures of output and value added in each farm but also control for land quality and a wide array of transitory shocks. We measure farm-level total factor productivity (TFP) s_i as the residual from the following farm-level production function,

$$y_i = s_i \zeta_i k_i^{\theta_k} (q_i l_i)^{\theta_l}, \quad \theta_k + \theta_l < 1, \tag{1}$$

where y_i is real value added, k_i is capital, l_i is the amount of land in operation, ζ_i is a rain shock, q_i is land quality, and $\theta_{k,l}$ are the input elasticities. In our analysis, we focus on the allocation of capital and land across farms, abstracting from differences in labor inputs. For this reason, we measure value added, capital, and land in the data in per total labor hour terms. This implies that our residual measure of TFP is not affected by actual differences in the labor input across farmers in the data.[16] In constructing our measure of farm TFP, 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). We later discuss the sensitivity of our results to these factor shares using our micro data for Malawi.

Our measure of output is real value added which takes into account the real amount of intermediate inputs used in production. This is relevant in Malawi because intermediate inputs are subsidized via the "Malawi Input Subsidy Program" and the subsidy allocation is based on farmer's income, with poorer farmers receiving higher subsidies. According to our preferred measure of productivity, less productive farmers, which are also poorer farmers, receive a subsidy that is more than 60 percent their output, whereas 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 actual quantities of intermediate inputs substantially underestimates productivity dispersion across farms. In our data, not accounting for distortions in intermediate input prices underestimates the dispersion in farm TFP by 23 percent.[17]

[16] We note, however, that labor hours are misallocated across farms since farm hours are uncorrelated with farm TFP. As a result, our characterization of misallocation is conservative in terms of the potential gains from efficient reallocation.

[17] Misallocation of intermediate inputs via the input subsidy program is distinct from the misallocation due to

We are interested in permanent measures of productivity at the farm level, associated with the productivity of the farm operator. As a result, two key elements for this measure are to distinguish between the productivity of the farmer and the productivity of the land under operation and to abstract from temporary variations in output due to whether shocks. We deal with each of these components in turn.

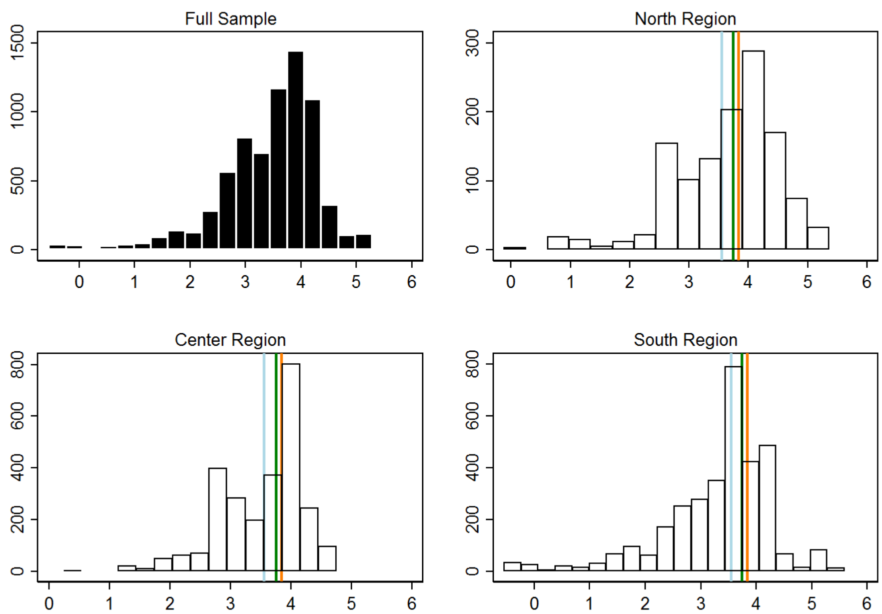
There are important differences in the land characteristics operated by farms in our sample. For the full sample, more than 34 percent of land is high-altitude plains while around 20 percent are low plateaus and 19 percent mid-altitude plateaus. These characteristics also differ by region where the Center region is mostly high-altitude plains whereas the South region is mostly low plateaus. We control for land quality in our measure of productivity by constructing an index as follows. Our benchmark land quality index q_i^0 is constructed by regressing log output in each farm on the full set of land quality dimensions described in Section 2. To the extent that farm inputs are positively related to land quality, our benchmark index attributes too much variation to land quality. We nevertheless use this index as our benchmark because it is conservative with respect to the productivity effects of misallocation.[18] There is substantial variation in land quality q across households and across regions, see for instance Figure 1, panel (a); but this variation is not quantitatively substantial relative to for example variation in TFP across farms. In Table 2 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. We find that the dispersion in land quality is large and slightly above that of land size nationwide, respectively .859 and .749 in terms of the variance of the log. Not surprisingly, the dispersion in land quality decreases with the size of geographic area: the average dispersion is .833 within regions, .568 within districts, and .147 within enumeration areas.

imperfect land markets we emphasize and as a result we focus on value added measures of output and abstract from intermediate-input distortions. Nevertheless, it is important to emphasize that intermediate input distortions are another source of productivity losses in the agricultural sector in Malawi.

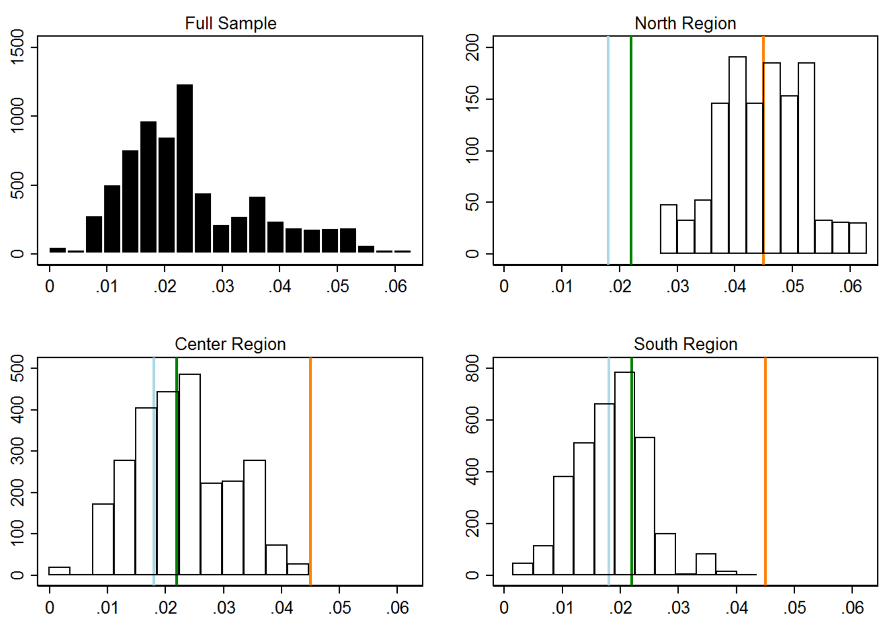
[18] We have considered many alternative land quality indexes with similar results including imposing exogenous functional forms, different subsets of land quality dimensions, and different forms of land size and capital controls, see Appendix A.

Figure 1: 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 constructed by regressing log output in each farm on the full set of land quality dimmensions. Median values by region are depicted with vertical lines: Orange (North), green (Center) and light blue (South).

Table 2: Dispersion of Output, Land Size, Land Quality, and Rain, Malawi ISA 2010/11

	Full Sample	Within Geographic Areas: Regions	Districts	Enumeration Areas
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 availability	.387	.402	.248	.023
Nutrient retention capability	.329	.365	.180	.016
Rooting conditions	.342	.372	.302	.029
Oxygen available 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 precipitation (mm)	.039	.025	.014	.001
Precipitation of wettest quarter (mm)	.026	.013	.005	.000

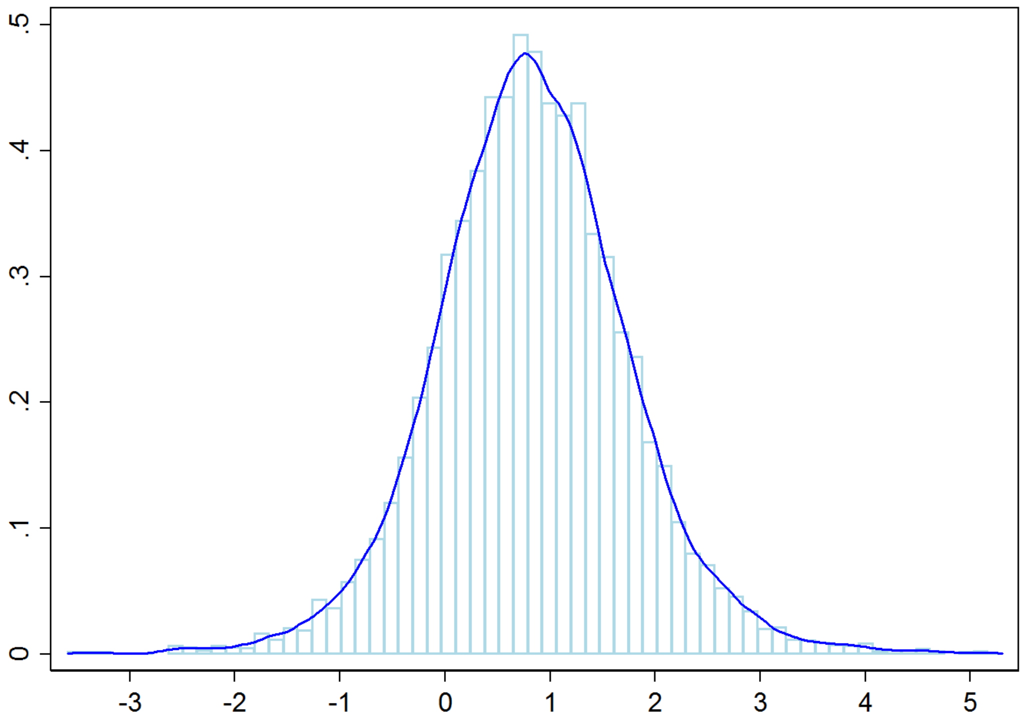
Notes: Output y_i, land size (in acres) l_i, land quality index q_i, quality-adjusted land size $q_i l_i$, and rain ζ_i, are continuous variables for which we use the variance of logs as a measure of dispersion. Subitems of land quality, slope (in %) and elevation (in meters), are also continuous variables 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).

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 1, 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 2 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.

Having constructed our measure of farm TFP, Figure 2 documents its distribution 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 physical productivity (TFPQ) across plants in the manufacturing sector in the United States, China, and India reported in Hsieh and Klenow (2009), see Table 3. Whereas the ratio of physical productivity between the 90 to 10 percentile is a factor of around 15-fold in China and India and around 9-fold in U.S. manufacturing, the 90-10 ratio across farms in our sample is 10.8-fold. Similarly, the 75-25 ratio is 3.2-fold in our sample of farms whereas it is around 4.5-fold across manufacturing plants in China and India.

Table 4 reports the variance decomposition of farm output per hour using our assumed production function. We note that farm productivity s_i and to a lesser extent the inputs of capital and land

Figure 2: 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.

are the key determinants of output variation across farm households in Malawi, with rain and land quality playing a quantitatively minor role. For instance, the variance of farm TFP accounts for 76 percent of the total variance of output and the variance of capital and quality adjusted land inputs for about 20 percent, whereas when rain and land quality are assumed constant across farms, the variances of these two factors and their contribution to the total variance are fairly similar. The small quantitative role of land quality for output differences across household farms is robust to variations in the index which we discuss in Appendix A.

Table 3: 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	1.97	1.22	1.41	1.55
90-10	2.38	2.50	2.22	2.72	2.77
N	7,157	–	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 (2014) 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 4: 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 variance contribution to the total in percentage.

4 Quantitative Analysis

We assess the extent of factor misallocation across farms in Malawi and its quantitative impact on agricultural productivity. 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. We then study the connection between factor misallocation and land markets.

4.1 Efficient and Actual Allocations

As a benchmark reference, we characterize the efficient allocation of capital and land across a fixed set of heterogeneous farmers that differ in productivity 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

$$Y^e = ZN_a^{1-\gamma}[K^\alpha L^{1-\alpha}]^\gamma, \tag{2}$$

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. For our benchmark, 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 $(1-\alpha)\gamma = 0.18$ are the capital and land income shares in the U.S. economy (Valentinyi and Herrendorf, 2008) — and we do sensitivity with factor shares directly computed from our Malawi micro data (see section 4.4.2). This implies $\gamma = 0.54$. 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.

We illustrate the extent of factor misallocation in Figure 3, where we contrast the actual allocation of land and capital and the associated factor productivities by farm TFP with the efficient allocation of factors and factor productivities across farms. In the figure, each dot represents a household farm in the data whereas the line represents the variable in the efficient allocation. In the efficient allocation, operational scales of land and capital are increasing in farm productivity so that factor productivities are constant across farms. The patterns that emerge in comparing the efficient allocation with actual allocations are striking as the efficient allocation contrasts sharply with the actual allocation of capital and land in Malawi. The data show that operational scales of land and capital in farms are unrelated to farm productivity. Figure 3, panel (a), shows the amount of land operated by each farm against farm productivity using our baseline measure of productivity that adjusts for rain and quality as described previously. Contrary to the efficient allocation where there is a tight mapping between land size and TFP, actual land in farms is essentially uncorrelated to farm TFP, the correlation between land size and productivity is .05. This pattern implies that the average (or marginal) product of land is not equalized across farms as it would be the case in the efficient allocation. Figure 3, panel (b) documents the marginal product of land (which in our framework is proportional to the output per unit of land or yield) across farms, which is strongly positively related to farm TFP with a correlation (in logs) of .77.

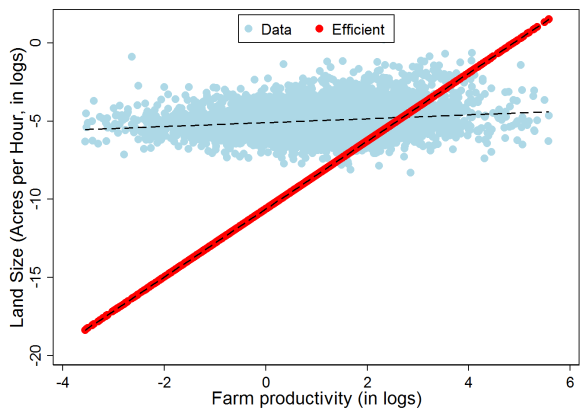
Figure 3, panel (c), documents the relationship between the amount of capital in farms by farm productivity. As with land, capital and productivity across farms are essentially unrelated, the correlation between the two variables is -.01. And this pattern implies an increasing marginal product of capital with farm TFP which we document in panel (d) with a correlation between these variables (in logs) of .76. Although not documented in the figure, the data indicates that the capital to land ratio is essentially unrelated to farm productivity, with a correlation between these variables of -.03. This finding suggests that larger farms use more capital but since larger farms are not more productive on average, the capital to land ratio remains roughly constant with respect to farm TFP.

That the actual allocation of land across farmers in Malawi is unrelated to farm productivity 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 fact 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.[19] Our findings constitute strong evidence of land and capital misallocation across farmers in Malawi.

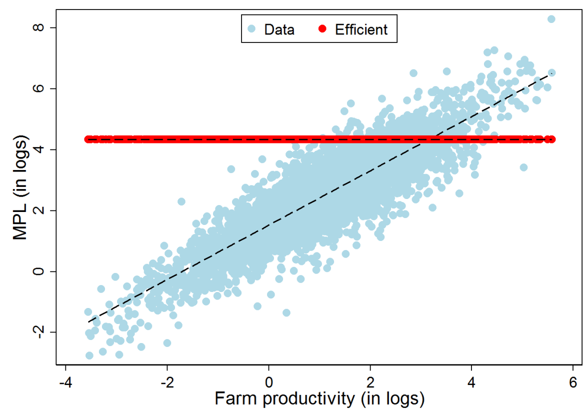
[19]See the related discussion in Besley and Ghatak (2010). We find further direct evidence of the relationship between land markets and access to credit in our micro data for Malawi, see Appendix C for a discussion.

Figure 3: Land Size, Capital, MPL and MPK: Actual and Efficient Allocations

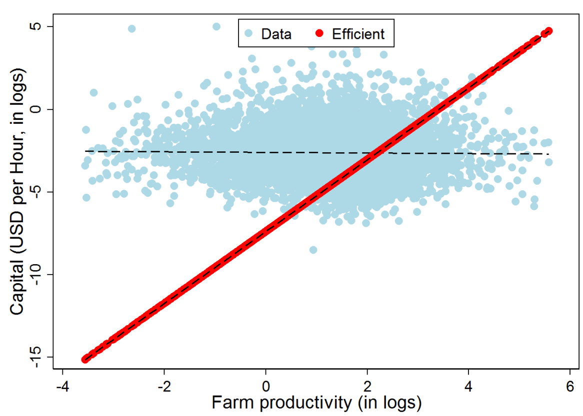
(a) Land Size vs. Farm Productivity



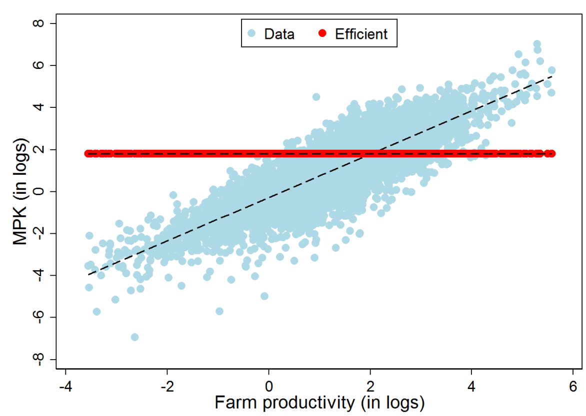
(b) MPL vs. Farm Productivity



(c) Capital vs. Farm Productivity



(d) MPK vs. Farm Productivity



Notes: Panel (a) reports actual and efficient land size in farms l_i with respect to farm productivity s_i. Panel (b) reports actual and efficient marginal product of land (MPL) with respect to farm productivity s_i. Panel (c) reports actual and efficient capital in farms k_i with respect to farm productivity s_i. Panel (d) reports actual and efficient marginal product of capital (MPK) with respect to farm productivity s_i. All variables have been logged.

4.2 Aggregate Output Gain

To assess the impact of misallocation on aggregate productivity, in what follows we report the aggregate output gain defined as the ratio of efficient to actual aggregate output,

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

where Y^e is efficient aggregate agricultural output as defined previously and Y^a is actual agricultural output aggregated from farm-level output y_i using the production function in equation (1) with our measure of farm productivity and the actual amounts of capital and land operated by each farm.[20] Because the efficient output takes as given the total amounts of capital, land, and the number of farmers observed in the data, the output gain is also a TFP gain.

Table 5, panel (a), reports the main results. For the full sample in the entire Malawi, the output gain is 3.6-fold, that is, if capital and land were reallocated efficiently in Malawi to maximize agricultural output, output and hence productivity would increase by 260 percent. This is a very large increase in productivity as a result of a reduction in misallocation compared to the results when evaluating specific policies which have found increases on the order of 5 to 30 percent or even when eliminating all wedges in manufacturing in China and India in Hsieh and Klenow (2009) with increases ranging between 100 to 160 percent. Given that the productivity dispersion across farms in Malawi is similar to that of manufacturing plants reported in Hsieh and Klenow (2009), a larger reallocation gain suggests that resources in Malawi are more misallocated than in those other countries. Indeed, the standard deviation of log revenue productivity in Malawi is 1.05 compared to 0.67-0.74 in the case of India and China in Hsieh and Klenow (2009). Because we have a large sample, our mean output gain is tightly estimated. In Table 5, panel (a), we also report the 5 and 95 percentiles of Bootstrap

[20] The computation of actual output at the farm level abstracts from rain and land quality and hence is comparable to the efficient output described in the previous subsection. Our measure of farm productivity s_i though is purged of rain and land quality effects.

estimates, which provide a narrow interval, between 3.1 and 4.2-fold output gain.

Table 5: Agricultural Output Gain (Y^e/Y^a)

(a) Main Results

		Bootstrap Simulations		
	Full Sample	Median	5th pct.	95th pct.
Nationwide	3.59	3.55	4.07	3.11

(b) Within Productivity-s_i Variation

	Benchmark	95%	90%	80%	0%
Output Gain	3.59	3.40	3.25	3.00	2.48

(c) By Geographical Areas and Institutions

	Average	Median	Max	Min
Geographic Areas:				
Regions	3.40	3.42	3.63	2.87
Districts	2.93	2.80	7.10	2.07
Enum. Areas	1.65	1.60	11.00	1.04
Institutions:				
Traditional Authority	3.11	3.48	5.58	1.39
Language	3.36	3.88	5.95	1.16

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), see text in Section 4 for details. Panel (c) reports the ratio of efficient to actual output when reallocation occurs 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.

Factor inputs are severely misallocated in Malawi, implying the large aggregate productivity gains just discussed. There are two features of factor misallocation in Figure 3, panels (a) and (c): factor inputs are dispersed among farmers with similar productivity (misallocation in factor inputs within s_i productivity types) and factor inputs are misallocated across farmers with different productivity (which lowers the correlation of factor inputs with farm productivity). We argue that factor input variation within a farm-productivity type is not due to measurement error as factor inputs such as land are measured with tight precision. Nevertheless, we can assess the magnitude of the aggregate output gain associated with lower dispersion in factor inputs within a productivity type. We remove within-s variation in factor inputs by regressing separately log land and capital on a constant and log farm productivity s and use the estimated relationship to construct measures of factor inputs that partially or fully remove residual variation. The results are in Table 5, panel (b). At the extreme, with no within-s variation of factor inputs, there is only gain from reallocation across productivity types. Even in this case, the output gain is still substantial a 2.5-fold (versus 3.6-fold in the baseline). This implies that 70 percent of the output gain is due to misallocation of factor inputs across farmers with different productivity.

We also report the output gain for narrower definitions of geographical areas and institutions such as language classifications. Table 5, panel (c), reports these results. In the first column, we report the output gain for the average of regions (i.e., output gain 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), and for the average across enumeration areas. Enumeration areas are a survey-specific geographical description and is the narrowest geographical 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 also 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 5, panel (c), 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 gains of the same magnitude as in the aggregate (mean output gain of 3.4-fold).[21] Similarly, within districts, the average output gain is 2.9-fold, but the output gain can be as large as 7.10-fold and as low as 2.1-fold. Even for the narrowest geographical definition, enumeration areas, just reallocating

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

factors within 16 households, average output gains are 1.7-fold and can be as large as 11-fold in some areas. The output gain within traditional authorities is 3.1-fold in average, with the largest 5.6-fold and median 3.5-fold. Within languages, the average output gain is 3.4-fold, the largest 6-fold and median 3.9-fold.

4.3 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 factor misallocation directly to the limited market for land in Malawi. To do so, we use plot-level information about how each plot was acquired and group household-farms by the share of marketed land that they operate. We find that 83.4 percent of all household farms operate only non-marketed land and the remaining 16.6 percent operate some marketed land, with 10.4 percent operating exclusively marketed land. Using this classification of household farms, we explicitly assess the output gain across farms that differ in the extent of marketed land in their operation.

Table 6 reports the aggregate output gain 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 gain is much higher for those farms with no marketed land than with some marketed land. For instance, the output gain for those farms with no marketed land, which comprises 83.4 percent of the sample of farms, is 4.2-fold, slightly larger than the 3.6-fold output gain for the entire sample. But for farms with some marketed land, which comprises the remaining 16.6 percent of the sample farms, the output gain is 2-fold. The output gain of factor misallocation is reduced by more than half when farms have access to some marketed land. The output gain is even smaller among the set of farmers whose entire operated land is either rented in or purchased. These farmers comprise 10.4 percent of the sample and have an output gain of 1.6-fold versus 4.2-fold for farms with no marketed land.

These results provide direct and solid evidence of the connection of misallocation to land markets.[22]

Table 6 also decomposes the output gains 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 16.6 percent with some marketed land. The output gain is fairly similar for farmers operating land rented-in formally or informally, an output gain of 1.72-1.73-fold. The lowest output gain is recorded for farms with operated land that was purchased with a title, 1.39-fold versus 4.15-fold for farms with no marketed land. Interestingly, farmers with purchased land without a title record a fairly large output gain, 5.13-fold, somewhat larger than the output gain for farmers without marketed land. We note however that the sample of farms with purchased land is fairly limited, only 3.1 percent of the sample with 1.8 percent of farms with purchased untitled land and 1.3 percent of farms with purchased titled land.

Even though we have showed a strong connection between land markets and the degree of output loss generated by misallocation, farms with marketed land are still far from operating at their efficient scale which suggests that land markets are still limited even for farms with access to marketed land. For instance, the correlation between land size and farm TFP is .14 for farms with no marketed land, .25 for farms with some marketed land, and .30 for farms that operate all marketed land. Having access to marketed land implies that farmers can command more inputs and produce more output. Also, operating marketed land is associated with greater access to other markets (e.g., credit) and with other indicators of economic development. Farmers with marketed 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

[22]The distribution of farm TFP, which we report in Figure C-1 in Appendix C, is slightly shifted to the right for farms with marketed land compared to farms with no marketed land, however, the output gain difference between the two groups remains large even when controlling for farm productivity.

Table 6: Land Markets—Output Gain 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 Gain	4.15	1.97	1.57	1.72	1.73	5.13	1.39
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 gain is calculated as the ratio of efficient to actual output separately for subsamples of farm households defined by the share of different types of marketed land used. The share of marketed land is defined from the household-farm level information on how land was obtained, see Section 2. Each column refers to a particular subsample. The first column reports the output gain for the subsample of household farms that do not operate any marketed land. 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 only 1% of households with marketed land whose type is missing in the Malawi ISA data.

are migrants, a fewer proportion live in rural areas, and a larger proportion of these farmers invest in intermediate inputs and technology adoption. We report these dimensions of farm differences by the type of operated land in Appendix C. One potential concern with our characterization is the possibility that access to marketed land is driven by farm productivity. We find however very small differences in productivity between farms with and without marketed land. These differences are too small compared to what it would be if access to marketed land was purely driven by frictionless selection in farm TFP. Even though on average farms with some marketed land are 25 percent more productive than farms with no marketed land, the distribution of household-farm productivity is very similar between the group of household-farms with marketed land compared to the group of farms without marketed land, with respective variances of 1.19 and 1.17. Nevertheless, we can assess the gains from reallocation holding constant farm-level TFP. To do so, we regress household-farm output gains from reallocation on household-farm productivity and a dummy variable that controls for whether the farm operates marketed land. Specifically, we estimate using OLS the following relationship: $\ln \frac{y_i^e}{y_i^a} = cons + \psi_1 \ln s_i + \psi_2 \mathbf{1}_{market}$, where ψ_2 is captures the effect of marketed land on the farm output gain controlling for farm productivity s_i. We use actual output as weights so as to reproduce the output gains of reallocation in our nationwide benchmark. We find that $\psi_2 = -.39$, that is, operating marketed land decreases the output gain by 39 percent holding productivity constant.

Finally, to gain further perspective of the productivity gains from reallocation, we note that Hsieh and Klenow (2009) report the gains from reallocation for the manufacturing sectors in China and India relative to those in the United States. The idea is that the U.S. data is not necessarily absent of frictions or measurement and specification errors, but that more misallocation in China and India than in the United States is indicative of more distortions in those countries. Our decomposition of the degree of misallocation across groups of households farms with or without marketed land provides a more direct reference for the gains of reallocation, that is, reallocation gains attained by household farms without marketed land relative to farms operating marketed land. Taking advantage of the fact that we can identify which household farms have marketed land, we restrict the gains of reallocation of household-farms that do not operate marketed land to be at most the gains attained by households farms that operate marketed land. The output gain of farms with no marketed land relative to the output gain of farms with only marketed land is 2.6-fold (4.2/1.6). This implies a reallocation gain that is three times the one obtained in Hsieh and Klenow (2009) for the manufacturing sector of China and India relative to the United States. Further, this gain may be a lower bound, as it is unlikely that there is no misallocation among farms operating only marketed land given the extent of land reallocation frictions in Malawi. Nevertheless, the fact that we use a group of household farms within Malawi as benchmark reference mitigates the effects of differential institutional features and frictions (beyond land markets access) that are more prevalent when using the United States or another country as reference in comparison with Malawi.

4.4 Discussion

4.4.1 Farm Size vs. Farm Productivity

A common theme in the development literature is the view that small farms are more efficient than large farms. This view stems from a well-documented inverse relationship between yields (output per unit of land) and farm size (e.g. Berry and Cline, 1979). A key concern is whether the yield by farm size is a good proxy for farm TFP. Our data for Malawi provide an opportunity to directly assess the relationship between the yield and farm TFP. Consistent with the literature, in the Malawi data, the yield is negatively related with farm size.[23] As documented earlier, yield and farm TFP are strongly positively correlated across farms but this is because the allocation of land is not related to productivity (misallocation) so many productive farmers are constrained by size. But in an efficient allocation in our framework, there would be no relationship between yields and farm TFP as the marginal product of land would be equalized across farmers.[24] To appreciate the distinction between farm TFP and farm size, note that land productivity of the largest 10 percent of farms relative to the smallest 10 percent of farms is 0.34 (a 3-fold yield gap). This characterization contrasts sharply with our earlier documentation that land productivity is strongly increasing with farm TFP, see Figure 3 panel (b): land productivity of the 10 percent most productive farms relative to the 10 percent least productive farms is a factor of 58-fold.

Whereas the pattern of land productivity by size suggests reallocation of land across farm sizes— from large to small farms— the pattern of land productivity by farm TFP suggests reallocation across farmers with different productivity—from less productive to more productive farmers. We

[23] See Appendix D, Figure D-1 which documents the relationship between land productivity (yield) and farm size in our data. Land productivity declines with farm size, which conforms with the finding in the inverse yield-to-size literature.

[24] The yield is a measure of farm productivity commonly used in studies of agricultural development, e.g., Binswanger et al. (1995). If the yield and farm TFP are uncorrelated in an efficient allocation, changes in policies and institutions that allow a better allocation of land would tend to, other things equal, reduce land productivity of the expanding farms and increase land productivity of the contracting farms, potentially masking the productivity benefits of the reforms.

find that the aggregate output and productivity gains of these two forms of reallocation are dramatically different. As discussed earlier, reallocating factors across farms with different productivity can increase agricultural output and TFP by a factor of 3.6-fold. In contrast, reallocating factors across farms by size, taking the yield-by-size as a measure of productivity, accrues a gain in output of only 26 percent. And this gain may be an upper bound as the implementation of reallocation by size may lead to further amounts of misallocation. For instance, land reforms are often pursued to implement reallocation of land from large to small holders that are also accompanied by further restrictions in land markets in order to bias redistribution to smallholders and landless individuals. This redistribution can lead to productivity losses instead of gains as it was the case in the comprehensive land reform in the Philippines (see, Adamopoulos and Restuccia, 2015).

4.4.2 Further Robustness

We conduct robustness checks to alternative factor shares and technology parameters, specific crop-type production, human capital and specific skills, and transitory health and other shocks.

Technology parameters We note that by restricting agricultural factor shares to those in the United States in our baseline measure of farm productivity we aim at limiting the impact of factor market distortions in Malawi on the calibrated shares. However, the U.S. agricultural sector is not necessarily absent of frictions which, in turn, might differ from those in Malawi. To address this issue, we use household-farm rented-in land and capital payments reported in our micro data to compute, respectively, the land and capital share of income for the agricultural sector in Malawi. We use these factor shares to redo our measurement of productivity and reallocation gains in Malawi. The results are reported in Table 7. Our benchmark results that use the U.S. values of the agricultural sector, are reproduced in the first column. The second and third columns provide two alternatives. In the second column, Full Sample, we measure factor shares of output using the average rental rates of land and capital. We compute these rates as the ratio of factor rental payments to the factor stocks from the sample of farms that rent-in all of their capital and land. Then we use these rental rates to impute the land and capital rental income for all farms in the entire sample. This implies an average capital share of income of 0.19 and an average land share of income of 0.39. With these factor shares, the output gain in the full sample is 3.57-fold, nearly identical to the 3.59-fold in our baseline calibration. In the third column, Renting Sample, we assume that the land and capital shares of output are the averages from the renting sample only, that we then apply to all farms in the sample. In this case, factor shares are lower which imply a smaller but still substantial output gain of 3-fold. We conclude that our results do not depend crucially on factor shares using Malawi data, even if we use factor income shares from households that have access to rental markets in Malawi.

Table 7: Reallocation Results with Factor Shares From Malawi Micro Data

	Baseline	Micro Malawi ISA Data	
	Calibration	Full Sample	Renting Sample
(θ_k, θ_l)=	(0.36,0.18)	(0.19,0.39)	(0.09,0.33)
Output gain	3.59	3.57	3.04

Notes: The baseline calibration selects factor shares based on U.S. data from Valentinyi and Herrendorf (2008). "Full Sample" measures land and capital shares using the average rental rates of land and capital computed as the ratio of factor rental payments to factor stocks from the sample of farms that rent in all of their capital and land. We use these rental rates to impute the land and capital rental income per farm in the entire sample by multiplying the rates by the respective farm-level stocks. "Renting Sample" measures factor shares using the average ratios of factor rental payments to value added using the renting sample only and then applying these averages to the entire sample. The sample of farm-households used is the same in all specifications.

Rather than factor shares of capital and land, the results are more sensitive to the implied income share of labor. This is because in our framework, the share of labor is determined by the extent of decreasing returns in the farm production function γ. In the misallocation literature, there is not a lot of guidance as to the exact value of this parameter. A large quantitative literature considers values between 0.8-0.85 (e.g. Restuccia and Rogerson, 2008), whereas monopolistic competition frameworks such as that in Hsieh and Klenow (2009) consider a preference curvature parameter that maps into decreasing returns of 0.67 (for an exposition of this mapping see Hopenhayn, 2014). The value for γ ranges from 0.54 in our baseline calibration to U.S. shares to 0.58 and 0.42 using Malawi data. Hence, our calibration and estimates are lower than the values typically considered in the literature. For each value of γ, we recompute farm productivity and the output gains from reallocation. While the output gains become small for small values of γ, in the range of plausible values, from 0.4 to 0.8, the output gains range from 3-fold to more than 10-fold. That is, using values of γ closer to those considered in the manufacturing (and other) sectors would increase our output gains from reallocation. We have also explored a constant elasticity of substitution (CES) production technology and find that our results remain fairly robust to more extreme elasticity of substitution between capital and land.

Crop type production In our data, most of the agricultural land is devoted to maize production (around 80 percent), see also FAO (2013).[25] Since optimal farm operational scale may differ across crop types, we investigate whether the output gains 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 8 where the first column reports the output gain in the nationwide benchmark, the next two columns report output gains for farms that produce mostly maize (whether the maize share is positive or above the median of all farms), and the last two columns report output gains for those farms that produce mostly non-maize (wether the non-maize share is positive or above the median). The output gain among farms that produce maize is somewhat smaller (2.7-fold for farms with maize production above the median versus 3.6-fold in the benchmark), which implies that the farms with non-maize production have output gains that are larger (4.1-fold for farms that

[25]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 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).

produce non-maize above the median). We conclude that crop composition and the dependence of maize production in Malawi are not critical in determining the large negative productivity impact of factor misallocation.

Table 8: Reallocation Results by Crop Type

	Benchmark	Maize Share >0%	Maize Share > Median	Non-Maize Share >0%	Non-Maize Share > Median
Output gain	3.59	2.83	2.71	3.82	4.13

Notes: The table reports output gains within households producing maize and non-maize. Because most household farms produce both maize and non-maize crops (around 74 percent), the table also reports output gains 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%.

Other robustness results In Appendix D we report further robustness results related to differences in human capital across farm operators and other specific skills, as well as adjusting our measure of farm TFP to other transitory shocks (other than rain) such as health and death shocks, food security risk, marital status, distance to markets and the availability of other income sources. Overall, we find that the output gain of factor reallocation to be large in all cases. More importantly, ISA conducted a second wave of interviews for roughly one-fourth of the original sample in 2013. That is, there is a panel for almost 3,000 household farms in Malawi for 2010 and 2013. This provides us with the opportunity to recover for each household an alternative measure of productivity defined as the estimated fixed effect of individual farm TFP across waves. We find that the fixed effects from the panel roughly capture 87 percent of the original cross-sectional TFP variation. Importantly, this new measure of TFP based on fixed effects is, again, essentially unrelated to land and capital. The output gain from efficient reallocation in 2010/11 using this alternative measure of farm TFP is 3.1-fold, fairly close to the 3.6-fold output gain with our benchmark measure of farm TFP. Hence, our results are fairly robust to alternative measures of productivity that isolate more permanent components of farm TFP.

5 Implications for Structural Change

Increased productivity from an efficient allocation of resources would trigger broader implications in the economy. We assess the implications of increased productivity in agriculture on structural transformation associated with the reallocation of labor across sectors. 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.[26] Recall that the aggregate production function for agriculture in the efficient allocation is given by equation (2). 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

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

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.[27] 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 9. 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 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.[28] 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.

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

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

[28]Note that agricultural output per unit of land or yield Y_a/L remains the same 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.

Table 9: Misallocation, Productivity, and Structural Transformation

	Benchmark	Increased Productivity
Productivity in Agriculture (Z)	1.00	3.60
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.

in the agricultural sector (e.g., Lagakos and Waugh 2013 and Adamopoulos et al. 2017). 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.

6 Implications for Economic Inequality

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, in terms of the distribution of operated capital and land across farmers. This massive redistribution of factors across farmers may lead to concerns over distributional implications, specially if the actual allocation of factors reflect policy and institutional choices in place to alleviate poverty and distributional concerns, see de Magalhaes and Santaeulàlia-Llopis (2015).[29]

[29] For example, de Magalhaes and Santaeulàlia-Llopis (2015) show that the bottom 20% and top 20% of the land distribution hold a similar share of aggregate consumption in rural Malawi, respectively 20% and 25%.

We study the distributional implications of the efficient operational scales. Table 10 reports the actual and efficient distribution of factors, output, and income across farmers by productivity. 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, representing 97 percent of the total land. This implies a substantial redistribution of factors to achieve higher levels of aggregate productivity. We note that despite relative equalization of factor inputs across farmers, the actual distribution of income is widely dispersed in Malawi, 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.

To gauge the distributional income effects of factor redistribution we pursue the following counterfactual. We consider the actual distribution of factors as endowments and allow the efficient allocation to be achieved via perfectly competitive rental markets. 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 10 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 agricultural output y^a.

Table 10: Actual and Efficient Distribution of Land, Capital, MPL and MPK

	Productivity Partition Quintiles					
	1st	2nd	3rd	4th	5th	$var(\ln x)$
Farm productivity (s_i)	.75	2.10	3.72	6.39	21.50	1.435
Land (l_i)						
Actual	1.19	.87	1.01	1.03	1.99	.749
Efficient	.00	.01	.04	.14	5.91	6.782
Capital (k_i)						
Actual	55.93	25.35	21.84	24.70	26.71	1.820
Efficient	.04	.32	1.10	3.60	149.52	6.782
MPL ($\propto$ Yield)						
Actual	4.21	11.00	17.82	29.10	82.04	1.485
Efficient	76.30	76.30	76.30	76.30	76.30	.000
MPK						
Actual	.73	2.19	3.94	7.25	24.54	2.154
Efficient	6.03	6.03	6.03	6.03	6.03	.000
Output (y_i)						
Level:						
Actual	.14	.39	.69	1.20	4.78	1.824
Efficient	.00	.05	.18	.60	25.06	6.782
Percentage of total:						
Actual	2.01	5.46	9.57	16.67	66.26	–
Efficient	.02	.20	.71	2.33	96.71	–
Agricultural income						
Level:						
Actual	.14	.39	.69	1.20	4.78	1.824
Efficient	4.28	2.22	2.17	2.56	14.65	1.228
Income gain	23.70	3.88	2.27	1.58	1.97	–
Percentage of total:						
Actual	2.01	5.46	9.57	16.67	66.26	–
Efficient	16.55	8.58	8.41	9.88	56.56	–

Notes: Households are ranked by farm productivity s_i. Land, capital, and output are in per hours terms. MPL is the marginal product of land and MPK the marginal product of capital computed for each bin as, MPL $= .18 \frac{\sum_i y_i}{\sum_i l_i}$ and MPK $= .36 \frac{\sum_i y_i}{\sum_i k_i}$, and the variance is computed with respect to household-farm specific ratios MPL$_i = .18 \frac{y_i}{l_i}$ and MPK$_i = .36 \frac{y_i}{k_i}$. Actual income is agricultural output whereas efficient income is computed assuming actual allocations are the endowments and the efficient allocation is achieved via perfectly competitive rental markets. Income gain is the efficient to actual income ratio.

Not only farmers in the lower end of the productivity (and income) distribution benefit the most from the increase in the return to factors, 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 larger for the poorest households: 23.7-fold increase 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.

7 Conclusions

Misallocation of land and other complementary factors in the agricultural sector is enormous in Africa. Using detailed nationally representative household-farm level data for Malawi, we show that a reallocation of land (and capital) to their efficient uses increases agricultural output and productivity by a factor of 3.6-fold. We show these large gains in the agricultural sector in Malawi are not due to differentials in TFP dispersion compared with other sectors or more developed countries, but to severe factor misallocation. We find that land size (and capital) are essentially unrelated to household-farm level TFP, which is perhaps not surprising given the egalitarian nature of land-use distributions and weak property rights over land. These restrictions imply that 83% of the total operated land in Malawi is not marketed. Indeed, our analysis provides a strong empirical connection between factor misallocation and restricted land markets. The productivity gains from reallocation are 2.6 times larger for farms with no marketed land than for farms with marketed land, which is roughly three times the reallocation gains found in the manufacturing sector of China and India in Hsieh and Klenow (2009).

We show that the increase in aggregate productivity from the efficient reallocation of factors could trigger of a profound process of structural change by which the agricultural sector in Malawi could approach levels of farm size and sectoral employment shares of the industrialized world. This result implies that factor misallocation in the agricultural sector is of first-order importance to understand productivity differences and economic development across countries. Further, in a counterfactual exercise we show that the introduction of rental markets where operational scales can deviate from land ownership not only increases aggregate productivity to its efficient level but also decreases income inequality; large but unproductive farmers are better off by renting-out land to small but productive farmers. These findings point to a pressing need to facilitate the reallocation of land to the more productive farmers without necessarily altering the ownership structure. This requires the development of well-functioning rental markets and well-defined property rights over land. What policies and institutions are best in promoting a better allocation of resources across farmers is of crucial importance for future research.

Looking ahead, while our analysis takes the distribution of land and productivity across farmers as given and asked about the efficiency gains of reallocation, 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 Restuccia and Rogerson (2016) for a discussion of the importance of the dynamic implications of misallocation. Further, while the gains from the reallocation of agricultural inputs across wives and husbands within farm households are small compared to the gains from reallocation across households, the quantitative role of women—who are potentially more restricted in land (and capital) inputs than men in many parts of the world—in understanding productivity differences across farms remains a very open but important question. We leave these interesting and important extensions of our analysis for future research.

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