The Effects of Land Markets on Resource Allocation and Agricultural Productivity*

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November 2017

Abstract

We assess the role of land markets on factor misallocation in Ethiopia—where land is owned by the state—by exploiting policy-driven variation in land rentals across time and space arising from a recent land certification reform. Our main finding from detailed micro data is that land rentals significantly reduce misallocation and increase agricultural productivity. These effects are nonlinear across farms—impacting more those farms farther away from their efficient operational scale. The effect of land rentals on productivity is 70 percent larger when controlling for non-market rentals—those with a pre-harvest rental rate of zero. Land rentals significantly increase the adoption of new technologies, especially fertilizer use.

Keywords: Productivity, agriculture, land markets, rentals, misallocation, micro data.
JEL classification: E02, O11, O13, O55, Q1.

*We thank Stephen Ayerst, Loren Brandt, Rui Castro, Murat Celik, Leandro De Magalhães, Margarida Duarte, Xiaodong Zhu, and seminar participants at Fudan University, University of Lausanne, McMaster University, Midwest Macro Conference at Louisiana State University, National University of Singapore, Singapore Management University, Syracuse University, and the World Bank for useful comments. 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. Raül Santaeulàlia-Llopis thanks the ERC AdG-GA324048, "Asset Prices and Macro Policy when Agents Learn (APMPAL)" and the Spanish Ministry of Economy and Competitiveness through the Severo Ochoa Programme for Centers of Excellence in R&D (SEV-2015-0563) for financial support.

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1 Introduction

A prevalent feature of land markets in many poor countries is that land transactions are either prohibited by law or face high transaction costs, preventing the allocation of land to best uses. This is relevant because factor misallocation stemming from imperfect land markets has been emphasized as a major obstacle limiting agricultural productivity in poor countries, and plays an important role in understanding differences in income per capita across countries.[1] Typically, the ownership of land resides with the state or the collective and use rights of land are distributed by local leaders on a fairly egalitarian basis, with all members of the collective assigned an equal amount of land-use rights. However, while long-lived land-use rights can help improve tenure security of farm land and create incentives for investment (Besley, 1995), they do not necessarily entail the right to sell or rent, which may prevent or limit land transactions. As a result, to the extent that households are heterogeneous in farming ability and that land allocations are not based on these differences, it is not surprising that land misallocation is a prevalent feature in poor countries (Restuccia and Santaeulàlia-Llopis, 2017).

We study whether land rentals—a specific form of land transactions across farms—alleviate factor misallocation, and by how much. Ethiopia provides a unique and relevant context to investigate these questions. From 1974 until the early-1990s, the Communist government in power expropriated and uniformly redistributed all of the rural land in the country, and prohibited land transactions by law. While land ownership still resides with the

[1]The importance of agricultural productivity in accounting for income per capita differences across countries has been emphasized in Gollin et al. (2002), Restuccia et al. (2008), among many others. The role of factor misallocation in accounting for agricultural productivity differences across countries has been emphasized in Adamopoulos and Restuccia (2014).

state and many of the restrictions to land transactions remain in place, a series of reforms in the 2000s were implemented to grant land certificates to farmers and to partially allow land to be reallocated across farmers via rentals (up to a limit) of the use rights. Since land sales are prohibited in Ethiopia, land rentals are the only channel allowing reallocation of farms' operational scale and hence constitute a measure of the extent of land markets. In addition, because the implementation of these reforms was decentralized to the level of local governments, instead of being implemented at the national level (Deininger et al., 2008), land rentals differ substantially across sub-regions and over time. For example, among the 65 sub-regions (i.e., zones) in the country, the percentage of rented land varies from zero to more than seventy percent, and its rates of increase over a two-year period vary from zero to more than fifteen percentage points. We exploit these policy-driven variations in land rentals across space and time in order to assess the effects of land markets on resource allocation and agricultural productivity. This approach follows an important existing literature exploiting location differences using data from different countries, such as Banerjee and Iyer (2005), Giné (2005), Deininger et al. (2011), and de Janvry et al. (2015).

There are two components to our analysis. First, we provide a comprehensive study of the cross-sectional relationship between land rentals and resource misallocation. We find that land rentals are strongly associated with lower resource misallocation. We do so by separating farmers who participate in land rental markets from farmers who do not, and find better resource allocation for farmers who rent land. We also quantify the extent of misallocation within regions and correlate it with the prevalence of land rentals across regions, finding a negative relationship. Applying cross-sectional variation of land rentals to farm-level outcomes, we find that a one percentage point increase in land rentals is, on average, associated with a 0.87 percent higher agricultural productivity per zone. Second, using the panel dimension of our data, we assess the impact of land rental markets on resource misallocation using a difference-in-difference approach that exploits the policy-driven variation in land rentals across time and space. Our main result is that a one percentage point increase in land rentals leads, on average, to an increase in agricultural productivity of 0.49 percent per zone. Although the panel effect qualifies the cross-sectional result downwards by roughly one half, it remains economically large and significant. Moreover, we show that the effect of land rentals is 70 percent higher when controlling for non-market rentals (i.e., those with a pre-harvest rental rate of zero). These results are important as they provide novel and direct comprehensive evidence of improved resource allocation and agricultural productivity as a result of land reallocations via rental activity.

Despite the positive effects of reallocations through rentals, aggregate rental activity remains tenuous (only 9 to 12 percent of the land is rented in our panel), non-market transactions remain high (12 to 21 percent of the rented land has a pre-harvest rental rate of zero), and misallocation is still severe in Ethiopia's agricultural sector. Indeed, we find that reallocating resources to best use can increase agricultural productivity by a factor of between 2.7 to 3.1-fold in the cross-section and panel data. Our results highlight the importance of land reforms in poor countries that specifically address the tradability of land to promote better resource allocation and not simply tenure security—which has been the main focus in most reform episodes.

We also assess the broader consequences of land markets on technology adoption in agriculture. Our cross-sectional results indicate that land rentals are associated with a higher proportion of farms utilizing fertilizer as well as more capital-intensive technologies such as livestock in land preparation. The intensive margin of technology use—for farmers who were already using the technology before the increase in rentals—provides mixed results. We find that increases in land rentals generate a significant increase in the intensity of fertilizer use, while the effects on livestock and other forms of capital are not significant along the intensive margin.

Our main results are robust to several checks. First, we confirm that our results on land rentals remain when controlling for potential output market distortions. Specifically, we re-estimate our difference-in-difference specification, controlling for variables related to farms' distance to markets, and do not find any meaningful change to the effect of land rentals on resource misallocation. Second, we exploit our rich data, which contains measures of inputs and outputs for each plot of land operated by the household, to provide alternative measures of farm TFP. We show that unobserved shocks and classical measurement error at the plot level are mitigated by aggregation across plots at the farm level—our main unit of analysis. For instance, the standard deviation of plot-level TFP and revenue productivity (TFPR) are 70 and 65 percent higher than the farm-level dispersion, and as a result, reallocation gains would be exaggerated at the plot level (551 percent) as compared to our baseline farm level (207 percent). We also construct alternative measures of farm-level TFP—such as average TFP in the panel—and show that our results are robust. Third, while farm households generally produce several different types of crops, each plot of land is typically used to produce a single crop, and therefore, we also explore the plot-level data to quantify misallocation within crops. We find that the pattern of misallocation within crops is consistent with our aggregate results. Fourth, while we control for land quality in our analysis, we verify that the land quality of rented plots is not significantly different from that of non-rented plots.

Our paper is related to a growing macroeconomic development literature on agricultural productivity.[2] Our point of departure is that we focus on land rentals as a vehicle to overcome imbalances between the allocation of land-use rights and the efficient operational scale of farms. In addition, our quantitative assessment is derived empirically from actual variation in land allocations across space and over time. More generally, our paper also contributes to the microeconomic development literature studying the role of institutions as an obstacle to economic development.[3] We specifically study how farmers transact land-use rights of state-owned land in Ethiopia through land rentals after a certification reform and assess its macro implications for resource allocation and agricultural productivity. In this context, our analysis also relates to a broad literature in development on the economic consequences of land reforms. We provide strong empirical results on the effect of land markets utilizing novel and comprehensive micro data on land rentals in Ethiopia.

The paper proceeds as follows. Section 2 describes the institutional background and the data for Ethiopia. In Section 3, we present the basic framework, calibration, and assessment of the degree of misallocation in the agricultural sector of Ethiopia. Section 4 presents our main results about the effects of land rentals on factor misallocation and agricultural productivity. Section 5 discusses the role of market versus non-market rentals, and Section 6 assesses the impact of misallocation on technology adoption in agriculture. Section 7 performs robustness checks. Section 8 concludes.

[2]For example, see Adamopoulos (2011), Lagakos and Waugh (2013), Adamopoulos and Restuccia (2015), Donovan (2016), Gottlieb and Grobovšek (2016), Chen (2017b), and Adamopoulos et al. (2017).

[3]See Acemoglu et al. (2001), Banerjee et al. (2002), and Banerjee and Iyer (2005), among others.

2 Institutional Background and Data

2.1 Institutional Background

Ethiopia is one of the poorest countries in the world. According to the World Bank's World Development Indicators, Ethiopia's real GDP per capita adjusted by purchasing power parity (PPP) is only about three percent of that of the United States. Agriculture is an important sector in Ethiopia, employing around 75 percent of the work force. Despite being a poor country, Ethiopia's recent economic performance is positive, with a strong annual real GDP per capita growth rate of 6.9 percent between 2005 and 2015. As a result, Ethiopia is sometimes referred to as a miracle of economic growth in Africa.

Ethiopia is also an interesting country to study because of its historical institutional background related to land policies and its more recent land certification reforms. Current land institutions in Ethiopia are shaped by historical events, but their prevailing characteristic has been state control over the allocation and use of land. The evolution of land institutions can be divided into three periods. The first period is the imperial period, spanning from the mid nineteenth century to 1974. During this period, land ownership was usually granted to political supporters regardless of occupation or use in farming, which created a feudal regime. Further emergence of private property during this period resulted in powerful landlords. The second period, from 1975 to 1991, resulted from the severe social injustices created by the feudal regime that lead to a Communist regime. A comprehensive land reform, "Land to the Tiller", was then implemented. The Communist government expropriated all of the land in the country and redistributed it to all rural households—adjusting for soil quality and family size—in the form of use rights. Land redistributions were frequent, every one to two years, to achieve an equitable allocation of use rights among the local rural populations, and land transactions were strictly prohibited.

The third period started with the collapse of the Communist regime in 1991, under a market-oriented government that has largely maintained land-related policies from the previous regime. Essentially, land ownership still resides with the state and households are assigned use rights by local authorities at the village (*kebele*) or district (*woreda*) level. Many of the restrictions to land transactions remain in place. However, land certification reforms have been implemented since the early 2000s to mainly promote tenure security by issuing land certificates of use rights. A key aspect of the land reform is that the implementation was decentralized to local authorities, so the timing and extent of certification as well as restrictions to rental activity have differed across regions. This context provides us with useful policy-driven heterogeneity in land rentals across space and time that we exploit in order to assess the effects of rentals on factor misallocation and agricultural productivity.

The land rental market is relatively under-developed in Ethiopia where severe restrictions on land rentals remain in place. For example, only a fraction of use rights can be rented and the renting household must dwell in the rural area as well as be engaged only in farming.[4] Using the Ethiopia 2013/14 round of data, we find that around 24.3 percent of households either formally or informally rent in some land for agricultural production, and only 2.6 percent of households operate solely on rented land.[5] Because some households may rent in

[4]See Holden and Ghebru (2016) for a discussion of a set of legal restrictions on land rentals present in Ethiopia since 2006.

[5]The data explicitly records how each parcel of land operated by the household was acquired. We consider a parcel of land to be rented if it is recorded either as "rent" or "borrowed for free" in the data. Focusing on plot-level information we find that the vast majority of land plots feature use rights that are either inherited or granted by a local leader (39.2 percent and 41.5 percent, respectively). Land plots that are rented or borrowed from other households represent 13.1 percent. Note that some of these rented land plots are not for agricultural purposes. As a result, only 8.8 percent of agricultural land plots are rented.

very small amounts of land compared to their total cultivated land, a more direct measure of land rental market activity is the percentage of land rentals, defined as the ratio between the size of rented land and the size of total cultivated land. Nationwide, we find that 9.3 percent of the total cultivated land is rented in.

Table 1: Rented Land across Time and Space

	Percent						Obs.
	Aggregate	Min.	10 pct	Median	90 pct	Max.	
$R_{z,2013/14}$	9.3	0.0	0.0	10.8	30.7	73.7	65
$R_{z,2015/16}$	12.1	0.0	0.0	8.7	37.2	88.7	65

Notes: Data from Ethiopia ISA 2013/14 and 2015/16. The share of land rentals R_z is defined as the ratio between the size of total rented land in cultivation and the size of total cultivated land in zone z. We show distributional statistics of the level of R_z separately for our two waves of data 2013/14 and 2015/16. We drop zones with less than 10 household observations in either year.

To document the separate evolution of rental market reforms across space, we compute the portion of rented land in total cultivated land, R_z, separately for each sub-region (i.e., zone) z in Table 1. In 2013/2014, the percentage of rented land differs greatly across space where many zones have no rented land and some zones have more than 70 percent of their total cultivated land as rented in. The median percentage of rented land is 10.8 percent. The 90 percentile of rented land is 30.7 percent with a maximum of 73.7 percent of zone land rented. Moreover, there is a substantial increase in land rental market activity across our two waves of data, i.e., between 2013/14 and 2015/16. The nationwide share of rented land in total cultivated land increases from 9.3 percent to 12.1 percent, i.e., an increase of roughly one-third across the two waves. More importantly for our empirical analysis, rental markets have developed at differential pace across regions. For example, while 37 zones out of 65 zones did not experience an increase in land rentals, 8 zones experienced land rental increases by at least 10 percentage points, and 6 zones experienced rental increases of more than 15 percentage points.

2.2 Data

We use household-level data from the World Bank, the Ethiopia Integrated Survey of Agriculture (ISA), for two available waves 2013/14 and 2015/16. These surveys provide information over the entire process of crop production, including physical measures of farm inputs and outputs. The Ethiopia ISA 2013/14 is a representative sample of 5,262 households of the population, among whom roughly 63 percent live in rural areas and participate in agricultural production.[6] Each household is surveyed twice in a year: the first round is during the planting season, and the second round is during the harvest season.

Almost all farms in Ethiopia are family farms. Therefore, we treat a family farm operated by a household as our basic unit of production. We construct our measures of inputs, outputs, and TFP at the farm (household) level.[7] A farm operated by a household typically consists of several different plots of land; we therefore aggregate the inputs and outputs of these plots to the household level. We also explore plot-level variations in productivity in the robustness check section. We next detail how we measure inputs and outputs from the data.

Agricultural output. Farm output is recorded in physical quantities (kilograms) of different crops.[8] The most common crops in Ethiopia based on the percentage of households who produce it are maize (57 percent), sorghum (43 percent), tea leaves (40 percent), coffee

[6]The corresponding numbers in Ethiopia ISA 2015/16 are very similar.

[7]We closely follow the procedure in Restuccia and Santaeulàlia-Llopis (2017) to construct our measures of inputs, outputs and TFP. We also control for rain and land quality in the same manner.

[8]Some farmers may not have finished harvesting at the time of survey. In those cases, they report the percentage of harvest that is pending. We adjust for that to estimate their total harvest.

(29 percent), and wheat (25 percent).[9] To aggregate farm production of different crops, we use common crop prices. For our purposes, the key is that aggregate production at the farm level reflects physical variation in output. Valuing output at common prices therefore allows us to compare output across farms, reflecting variation in quantities produced. Less important is what common price we use. Since we observe the prices of crops traded at local markets, we compute for each crop the median price among all transactions and use it as the common price of this crop. The value of the crop output of a farm is estimated by multiplying the physical quantity produced with its common price. We then sum up the values of all crop types produced by the farm to obtain the value of gross output of each farm. We also use common prices to estimate the value of intermediate inputs used by farms, such as fertilizers and seeds, in a similar way. Note that some fertilizers and seeds are from the farmers' home production; we evaluate these home-produced goods using common market prices as well. Again, the key in these assumptions is that the aggregate measure of intermediate inputs used on a farm tracks physical variation in inputs as best as possible. We calculate the value added of a farm by subtracting the value of intermediate inputs from the value of gross output. We use this measure of value added in our analysis as the net farm output.

Rain. To measure productivity, it is important to exclude transitory variation in output from value added. In agricultural production, the most important shock is precipitation. Rainfall information is provided in the data, recorded as the annual precipitation in millimeters, and we use it to identify shocks in rainfall. We create 10 dummies representing different

[9] We restrict our analysis to crops only and hence abstract from livestock as the production cycles of livestock are usually longer than one year, which is our data period.

levels of rainfall. Then, we regress the calculated farm value added on those dummies and obtain the residual of this regression as the value added excluding the transitory variation due to rainfall shocks. This is the measure of farm value added we ultimately use in our analysis.

Land. Land input of a farm (i.e., farm size) is the sum of the size of all land plots operated by this farm. The size of 93.8 percent of land plots is accurately measured by GPS or, in case of small fields, by compass and rope at a precision of 0.1 square meters, while the size of the remaining land plots is reported by farmers. Farms are in general very small in Ethiopia. The average farm size in our sample is around 1.3 hectares, compared to 169.2 hectares in the United States as reported in 2007 U.S. Census of Agriculture. The farm size distribution is skewed to very small sizes: 64.7 percent of households in our sample operate farms smaller than one hectare, 86 percent of households operate farms smaller than two hectares, and only two percent of households operate farms larger than five hectares. We note that a plot of land is treated as a part of a particular farm if it is operated by that farmer, regardless of whoever has the use rights of the land. In other words, the size of the farm is the operational scale and not the ownership or use rights of land. Therefore, when computing farm size, we include rented-in land plots and exclude rented-out plots for each household.

Land quality. The survey also records land quality and other geographical characteristics for each plot of land. For each plot, we have information on its elevation, slope, terrain roughness, nutrient availability, nutrient retention, rooting conditions, excess salts, toxicity, and workability. The issue is how to combine these measures of land characteristics into one aggregate measure of land quality. We regress log value added per labor hour on these variables of land quality, controlling for log capital and land input per labor hour. This regression estimates how each dimension of land quality affects farm value added per labor hour. Then, we take the coefficients from this regression to evaluate the land quality index q for each farm. This is an upper bound measure of land quality as some inputs may be correlated with the quality of the land and hence is conservative in our analysis of the extent of misallocation.

Capital. Farm capital has three components: agricultural tools, transportation tools, and some livestock. Agricultural tools include sickles, axes, pick axes, traditional or modern ploughs, and water pumps. We observe the physical quantity of these tools owned by each farmer, as well as their prices at local markets. Again, we construct common prices, defined as the median of sell prices, to evaluate these agricultural tools. Transportation tools include hand-pushed or animal-drawn carts and bicycles. The price of transportation tools are not directly available in the data, so we estimate their values using local prices from the internet.[10] The livestock used for agricultural crop production are a bit more complicated. The survey records the three most common livestock in Ethiopia, cattle, goats, and sheep, as well as their farm use. In our measure of capital, we only include cattle that are for agricultural or transportation purposes, and exclude goats and sheep, which are mainly used for meat, wool, or milk. We also observe the prices at which farmers sell their cattle. Given this, we construct common cattle prices separately for male and female cattle, to evaluate livestock value. Finally, we sum up the values of agricultural tools, transportation tools, and

[10]We assign the prices of transportation tools as follows: one hand-pushed cart is worth about 6 traditional ploughs; one animal-drawn cart is about 9 traditional ploughs; one bicycle is about 17 traditional ploughs. Note that very few farmers have these transportation tools, so excluding them in the measure of capital would only change our results slightly.

cattle as our measure of farm capital.[11]

Labor. The data provide labor input for every plot of land of a farm, in both the planting season and the harvest season. Labor input includes farmers' family labor, hired labor, and unpaid labor from other households. Family labor is recorded in hours (the data reports hours per day, days per week, and number of weeks per season); hired labor and unpaid labor, however, are only recorded in days. We assume that hired men work the same hours per day as family members, while hired women and children are assigned fewer hours, consistent with their lower wage bills per day.[12] We also assume that unpaid labor from other households work the same hours per day as hired workers of the same identity: for example, unpaid men work the same hours per day as hired men. Finally, we construct farm labor input as the sum of hours from all three types of labor for all land plots of this farm in both seasons. We find that, out of total labor input, 76.6 percent is supplied by household members, 14.3 percent by hired labor, and 9.1 percent by unpaid labor from other households.

Panel data. The panel dimension of the Ethiopia ISA data for 2013/14 and 2015/16 is crucial in our analysis. First, we use time variation of land rentals to provide direct evidence of the effects of rentals on aggregate productivity in a difference-in-difference analysis.[13] Second, we use the panel dimension to compute a permanent component of individual farm

[11] To deal with a set of farmers who have zero measured capital but report cultivated land and positive production, we follow Adamopoulos et al. (2017) in imputing an amount of capital to all farms representing a common set of very small tools and structures used by farmers that are not recorded in the data. The amount we assign to each farmer is set to equal ten percent of the median capital-land ratio of farms within the zone, multipled by the amount of land input of the farm. We have verified that our results are not sensitive to the size of adjusted capital or to dropping these households.

[12] We assume the ratio of hours worked by hired women and hired men equals the daily wage ratio between them. We also estimate hours per day of hired children in the same way.

[13] An earlier round of Ethiopia ISA is available which in principle would allow us to expand the panel dimension to 2011. Unfortunately, a key variable (farm gross output) was not recorded consistently in 2011.

TFP (fixed effects) and re-conduct our misallocation exercises to assess the robustness of the standard cross-sectional constructs of TFP. Note that the data from the more recent 2015/16 survey are available in the same structure as the data from the 2013/14 survey. We construct farm capital, labor, land, and output for the year 2015/16 in the same way we do for the 2013/14 survey. By combining these two rounds of data, we obtain a balanced panel comprising 80.2 percent of households from the 2013/14 round.

We have described our measures of value added, capital, labor, and land. These measures summarize inputs and outputs of farms, and are used in our quantitative analysis in the next section.

3 Framework of Analysis

We describe the framework for the analysis and our calibration strategy. We then use this framework to quantify the extent of misallocation in agriculture in Ethiopia and compare our results with related studies.

3.1 Framework and Calibration

We start by describing our framework for the analysis, which closely follows Restuccia and Santaeulàlia-Llopis (2017). Consider a farmer with productivity $s_i \in S$ with the following production function:

$$\tilde{y}_i = s_i^{1-\gamma}[k_i^{\alpha}(q_i l_i)^{1-\alpha}]^{\gamma}, \tag{1}$$

where $\tilde{y}_i$ is the net output of this farm (measured as value added excluding transitory components and intermediates such as fertilizer and seeds), k_i is the capital input, q_i is land quality, and l_i is the land input. The parameter γ governs returns to scale at the farm level, and α determines the share of capital. In our analysis, we focus on the allocation of capital and land across farms, hence, we abstract from the intensive margin of labor supply in our production function. For this reason, when we confront this production function with data, we normalize our measures of output (value added), capital, and land in the data by labor hours. In other words, the production function is in per-hour form. The farmer earns profits, which is a fraction $1-\gamma$ of the farm output; therefore, $1-\gamma$ can be interpreted as the labor share. We denote the output of a farm after controlling for land quality by $y_i = \tilde{y}_i / q^{(1-\alpha)\gamma}$. Given actual inputs and output (value added) of a farm from the data, the farm-level productivity s_i can be measured as

$$s_i = \left[\frac{y_i}{k_i^{\alpha\gamma} l_i^{(1-\alpha)\gamma}} \right]^{\frac{1}{1-\gamma}}. \tag{2}$$

We further denote $s_i^{1-\gamma}$ as farm-level TFP$_i$.

As a benchmark, we solve for the efficient allocations that maximize aggregate agricultural output subject to the total amount of capital K and land L, and the set of farmers who are heterogeneous in their ability $s_i \in S$. Given the span-of-control technology specified in (1), the efficient allocation of factors among farms is non-degenerate. In particular, we can show that the efficient allocation of capital and land among farms should satisfy:

$$k_i^e = \frac{s_i}{\sum_i s_i} K \quad \text{and} \quad l_i^e = \frac{s_i}{\sum_i s_i} L, \tag{3}$$

where k_i^e and l_i^e denote the *efficient* allocation of capital and land (as opposed to the *actual* allocation k_i and l_i in the data). The efficient allocations of capital and land are proportional to farmer's ability. Note also that the efficient allocations equalize the marginal products of capital and land across farms. The efficient output (value added) for each farm is given by

$$y_i^e = s_i \frac{(K^\alpha L^{1-\alpha})^\gamma}{(\sum_i s_i)^\gamma}.$$

Then aggregate output is given by

$$Y^e = \sum_i y_i^e = \left(\sum_i s_i\right)^{1-\gamma} (K^\alpha L^{1-\alpha})^\gamma,$$

where Y^e is aggregate output from the social planner's solution. Therefore, it is the maximum output this economy can obtain given the aggregate amount of resources (capital, land, and number of farmers).

In general, the actual allocation of capital and land from the data (k_i and l_i) are not identical to the efficient allocation from the planner's solution (k_i^e and l_i^e). The difference indicates resource misallocation. Furthermore, the actual aggregate output in the data, $Y^a = \sum_i y_i^a = \sum_i s_i^{1-\gamma}(k_i^\alpha l_i^{1-\alpha})^\gamma$, is lower than Y^e. The difference between the actual aggregate output Y^a and the efficient aggregate output Y^e provides a summary statistic of the impact of misallocation on aggregate output and TFP:

$$e = \frac{Y^e}{Y^a} \geqslant 1,$$

where e measures the efficiency gain this economy can achieve if factors are reallocated efficiently.

We also construct a summary measure of misallocation as the dispersion of farm-level revenue productivity ("TFPR"), which in our framework is defined as

$$\mathrm{TFPR}_i \equiv \frac{y_i}{k_i^{\alpha} l_i^{1-\alpha}}.$$

It is straightforward to verify that the efficient allocation (k_i^e, l_i^e) equates TFPR across farms. Therefore, we use the dispersion of TFPR across farms to measure the extent of misallocation. In fact, it can be shown that the dispersion of TFPR only depends on farm-level distortions and is independent of the underlying farmer productivity distribution S.[14]

For a quantitative assessment of misallocation, note that in our framework, the only structure we impose is the farm-level production function specified in equation (1). Therefore, we only have two parameters to calibrate: α and γ, governing the factor income shares of the production function. Estimation of factor income shares in agriculture varies in the literature. Valentinyi and Herrendorf (2008) find that in the United States, the capital, labor, and land shares in agriculture are 0.36, 0.46, and 0.18, respectively. Restuccia and Santaeulàlia-Llopis (2017) use micro data from Malawi and estimate the capital, labor, and land shares to be 0.190, 0.419, and 0.391, respectively. This discrepancy may arise from the fact that Malawi has a lower level of mechanization in agriculture compared to the United States. In fact, Chen (2017a) argues that the capital-output ratio (and therefore, the capital income share) in agriculture tends to increase as an economy develops. Ethiopia is typically considered to be at a stage of development similar to Malawi. We therefore assign factor

[14]See Hsieh and Klenow (2009) and Adamopoulos et al. (2017) for related definitions of revenue productivity.

shares according to the estimation of Restuccia and Santaeulàlia-Llopis (2017), which results in the parameter values $\alpha = 0.327$ and $\gamma = 0.581$.

Given values for α and γ, together with farms' actual inputs and outputs observed in the data (k_i, l_i, and y_i), we use equation (2) to solve for farm-level productivity s_i. We also trim around 1.4 percent of the farm TFP distribution to remove possible outliers that may reflect measurement error in inputs and outputs in the data.[15] We then use equation (3) to solve for the efficient allocation of capital and labor (k_i^e and l_i^e), and contrast it with the actual allocation (k_i and l_i).

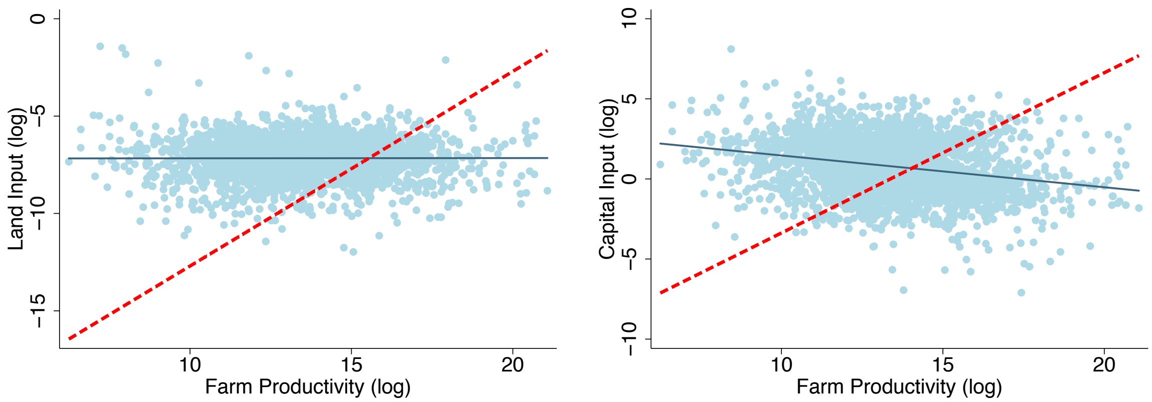
3.2 Misallocation and Efficiency Gain

We now use this framework to quantify the extent of misallocation in the agricultural sector in Ethiopia. We start by describing four sets of facts about factor allocation from the data: the patterns of farm inputs, farm output, marginal products of factors, and farm TFPR. We contrast these patterns with those of the efficient allocation discussed previously. We also compute the efficiency gain associated with factor reallocation as a summary measure of the cost of misallocation.

Farm inputs. Figure 1 reports farm inputs (land and capital) against farm productivity. Recall that the efficient allocation of land and capital should be proportional to farm-level productivity (red dashed line in the figure). The actual allocation in our sample, however, is very different from this efficient allocation: land input is virtually uncorrelated with farm-level productivity and capital input is negatively correlated with farm-level productiv-

[15] More aggressive trimming, say two percent of the TFP distribution, barely changes the dispersion of TFP with a standard deviation of 0.87, as opposed to our benchmark 0.91.

Figure 1: Farm-Level Factor Inputs



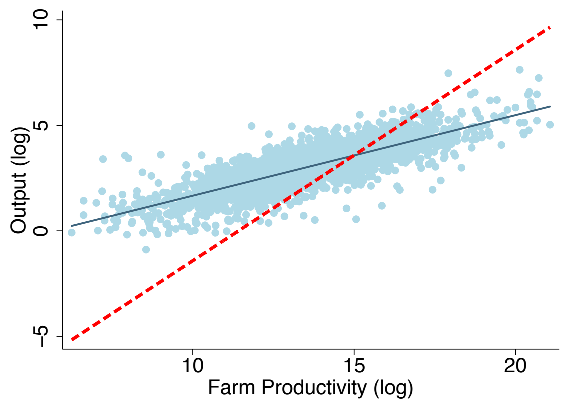
Notes: All variables are in log scale. The red dashed lines show the efficient allocation. The dark blue lines fit the data. The correlation between farm productivity and land (in log) is 0.003 and between farm productivity and capital (in log) is -0.25. Data for the Ethiopia ISA 2013/14 as described in Section 2.

ity. Therefore, this figure indicates severe factor misallocation in the agricultural sector in Ethiopia.

Farm output. Figure 2 reports farm output versus farm productivity. The planner's solution requires that farm output should be proportional to farm productivity, which is the red dashed line in the figure. The actual farm output is also increasing in farm productivity, but the slope is much flatter. This means that, compared to the efficient allocation, low productivity farms tend to be larger than they should be, and high productivity farms tend to be smaller. This pattern suggests that farms face distortions that are correlated with their productivity.

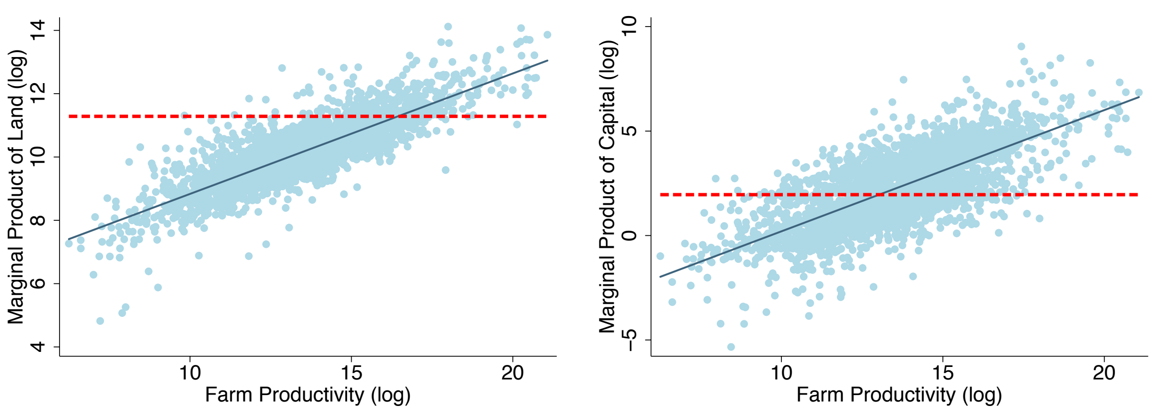
Marginal products of factors. Figure 3 shows the marginal products of land (MPLa) and capital (MPK) at the farm level. Recall that efficiency requires the marginal product of land (capital) to be equalized across farms, independent of farm-level productivity. First, there is a substantial amount of dispersion in MPLa, with a standard deviation of 0.993.

Figure 2: Farm-Level Output



Notes: All variables are in log scale. The red dashed line shows the efficient allocation. The dark blue line fits the data. Data for the Ethiopia ISA 2013/14 as described in Section 2.

Figure 3: Farm-Level Marginal Products



Notes: All variables are in log scale. The red dashed lines show the efficient allocation. The dark blue lines fit the data. Data for the Ethiopia ISA 2013/14 as described in Section 2.

Table 2: Revenue Productivity (TFPR)

	S.D.	75 – 25	90 – 10	Obs.
Ethiopia ISA 2013/14:	1.06	1.31	2.63	2,887
Manufacturing sector:				
United States, 1997	0.49	0.53	1.19	194,669
China, 2005	0.63	0.82	1.59	211,304
India, 1994	0.67	0.81	1.60	41,006

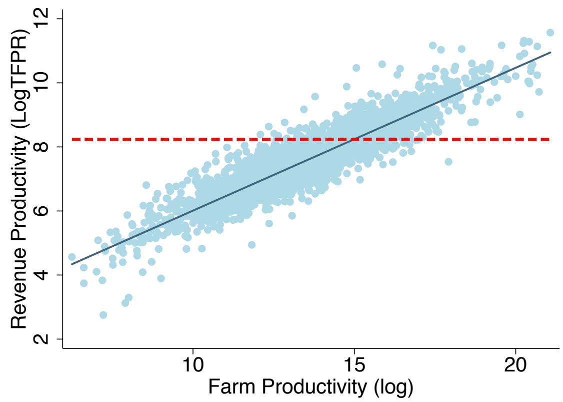
Notes: We compute TFPR as $y/(k^{\alpha}l^{1-\alpha})$. The table shows statistics on $\log \text{TFPR}$. "S.D." is standard deviation, "75 – 25" is the difference between the 75th and 25th percentiles, and "90 – 10" is that between the 90th and 10th percentiles. Data for the Ethiopia ISA 2013/14 as described in Section 2. The statistics for the manufacturing sectors in the US, China, and India are directly extracted from Hsieh and Klenow (2009).

Second, we find a strong positive correlation between the marginal product of land (capital) and farm-level productivity. Farms with higher productivity are not able to obtain enough inputs and therefore their marginal product of factors are higher.

TFPR. As discussed earlier, if factors are allocated efficiently, TFPR should be the same across farms in our framework. As a result, we use the dispersion in TFPR across farms as a measure of the extent of misallocation. Table 2 reports the dispersion of TFPR. The standard deviation of (log) TFPR is 1.06 in our sample. As a comparison, Hsieh and Klenow (2009) find this statistic to be 0.63 and 0.67 in the manufacturing sector of China and India. The 75 – 25 difference is 1.31 in our sample, compared to 0.82 and 0.81 in China and India, respectively. The 90 – 10 difference is also larger in our sample. This comparison indicates that the extent of misallocation is severe in Ethiopia. Severe factor misallocation in Ethiopia is largely associated with a uniform allocation of land-use rights and obstacles to reallocation of these rights as described in the institutional background for Ethiopia. We explore this source of misallocation in detail in the form of land rental markets in Section 4.

Figure 4 shows that farm TFPR—a summary measure of the implicit wedges facing each

Figure 4: Farm Revenue Productivity



Notes: All variables are in log scale. The red dashed line shows total factor revenue productivity (TFPR) of farms associated with the efficient allocation. The dark blue line fits the data. The correlation between log TFPR and log TFP is 0.91. Data for the Ethiopia ISA 2013/14 as described in Section 2.

farmer—tends to be increasing with farm productivity. This confirms our earlier characterization that more productive farms, unable to operate at larger scales, face larger implicit distortions. The correlation between log TFPR and log farm TFP is 0.91, indicating that correlated implicit distortions constitute a strong source of misallocation.

Efficiency gain. We compute the gain in aggregate output and productivity associated with an efficient reallocation of resources. The efficiency gain—which is equal to the ratio between the efficient output (Y^e) and the actual output (Y^a)—is 3.07 in Ethiopia. This estimate is tight with bootstrap standard deviation of 0.24 and is significant at 5% level, see Table 3. This means that reallocating resources from the actual allocation to the efficient allocation across existing farmers increases aggregate output by 207 percent. This efficiency gain is comparable to other contexts with severely underdeveloped land markets such as Malawi where efficiency gains are 3.59-fold (Restuccia and Santaeulàlia-Llopis, 2017).

The cost of factor-input misallocation in the agricultural sector in Ethiopia is somewhat

Table 3: Agricultural Output Gain (Y^e/Y^a)

	Full Sample	Median	5th pct.	95th pct.
Nationwide	3.07	3.00	2.59	3.54

Notes: Data for Ethiopia ISA 2013/14 as described in Section 2. Bootstrap median and confidence intervals are computed from 10,000 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.

larger than those estimated for the manufacturing sectors of China and India in Hsieh and Klenow (2009), where efficiency gains are between 1.9 to 2.3-fold, whereas Adamopoulos et al. (2017) estimate the efficiency gain in the agricultural sector in China in the 1990's to be around 1.8-fold. Since the dispersion of TFP in the agricultural sector in Ethiopia (0.91) is similar to that of China (1.06) and India (1.16), the larger efficiency gains in Ethiopia are driven by a larger degree of misallocation. This is consistent with the larger dispersion of TFPR in Ethiopia compared with that of China or India documented earlier.[16]

Our analysis has thus far focused on the sample for Ethiopia ISA 2013/14. We find similar results using the data for Ethiopia ISA 2015/16. For example, in this latter wave of data, the correlation between farm TFP and farm land input is -0.0132, and that between farm TFP and farm capital is -0.1927. Also, the standard deviation of farm TFPR is 0.983, and the efficiency gain is 2.65-fold, with a 5 percent confidence interval of $[2.41, 2.89]$ obtained from bootstrap.

Using our measures of farm productivity for each year in the panel, we calculate the geometric mean across years as the "persistent component" of farm productivity and use it as an alternative measure of farm productivity to calculate the efficiency gain in the year

[16]Larger factor-input misallocation is also documented for Malawi in Restuccia and Santaeulàlia-Llopis (2017). For instance, the variance of log TFPR is 1.25 in Malawi (1.13 in Ethiopia), reflecting the low prevalence of land markets in Malawi, where only 17 percent of household farms operate marketed land (24 percent in Ethiopia). This suggests that misallocation in the agricultural sector may be more severe in Sub-Saharan Africa than in other parts of the world.

2013/14. This "persistent component" of farm productivity is equivalent to the outcome of an estimation of household fixed effects of productivity (in log). When using this more permanent component of productivity we find that the efficiency gain is a factor of 3.01-fold, instead of 3.07 in our cross-sectional baseline.[17]

Within-zone misallocation. There are four levels of administrative divisions in Ethiopia: regions (states), zones (counties), woreda (districts), and kebele (wards). We have farm location information down to the kebele level. We have a total of 2,887 observations, located across 10 regions, 73 zones, and 273 woredas. Due to sample size, we mainly focus our analysis at the zone level since we have a reasonable number of zones and a relatively large number of observations within each zone. We decompose the nationwide efficiency gain of 3.07 into a component of reallocation within zones. To calculate the within-zone reallocation, we first treat each zone as a closed economy with given factor endowments of capital ($K_z = \sum_{i \in z} k_i$), land ($L_z = \sum_{i \in z} l_i$), and a fixed set of farmers. We then calculate the efficient output for each zone following the same procedure as for the efficient nationwide output: $Y_z^e = S_z^{1-\gamma}(K_z^{\alpha} L_z^{1-\alpha})^{\gamma}$, where $S_z = \sum_{i \in z} s_i$ is the sum of the productivity of farms in zone z. Y_z^e represents the maximum output a zone can obtain given its resources. Efficiency gains per zone are defined as $e_z = Y_z^e / Y_z^a$ where Y_z^a is actual aggregate output in zone z. On average, the efficiency gain per zone is 2.1-fold with a median of 1.9-fold. Because we compute the average gain using actual output as weights, the average gain is the country-level gain of eliminating within-zone misallocation. This implies that eliminating within-zone misallocation accounts for $\log(2.14)/\log(3.07) = 68$ percent of the overall efficiency gain. The

[17]We pursue further robustness alternatives with cross-sectional and panel measures of productivity in Section 7.

remaining 32 percent is accounted for by reallocating resources across zones.

In summary, our analysis provides evidence of substantial factor misallocation in the agricultural sector of Ethiopia in the form of TFPR and MPLa dispersion, and a substantial cost of misallocation in the form of large efficiency gains from reallocation. Interestingly, the institutional setting regarding land in Ethiopia is such that farmers have similar amounts of land-use rights and land sale transactions are prohibited (Section 2.1). Therefore, to the extent that farms are heterogeneous in their productivity, rental activity is essential in facilitating farm operational scales that are closer to efficiency. This is to say, rental activity is the only channel that allows for a reduction in the dispersion in the marginal product of land across farmers, and hence, an increase in aggregate agricultural productivity. Next, we investigate the role of land rentals on misallocation and productivity.

4 The Effects of Land Rental Markets

First, we provide a comprehensive study of the cross-sectional association between land rental markets and resource allocation. We do so in two ways by comparing the outcomes of farmers with and without land rentals and by exploiting variation in land rentals across geographical locations. Second, we investigate the impact of land rental markets on resource misallocation using the panel dimension of our data. To do so, we use a difference-in-difference strategy that exploits the variation in land rentals across locations and over time arising from a certification reform implemented by local governments with different timing and rules, instead of being implemented at the national level (Deininger et al., 2008).

4.1 Connecting Land Rentals to Resource Allocation

We document the cross-sectional relationship between land rentals and resource allocation. We start by comparing how households that rent land fare against those that do not, as in Restuccia and Santaeulàlia-Llopis (2017). We then use heterogeneity in land rental markets across locations to connect land rentals to resource allocation and agricultural productivity.

4.1.1 Farmers With and Without Land Rentals

The land market remains highly underdeveloped in Ethiopia, despite a comprehensive land certification reform intended to provide tenure security to farmers. In our sample, 67.6 percent of all household farms do not rent in or rent out any land, 24.3 percent of households formally or informally rent in some land for production, 10.6 percent of households rent out land, and 2.5 percent of households rent in and rent out land. We divide households into two groups: (a) farmers who do not rent in or rent out any land and (b) farmers that rent in or rent out some land. To the extent that rentals allow farmers to operate closer to their efficient scale, this classification highlights the role of land rentals in determining factor misallocation and efficiency gains.

Table 4 reports our results. First, we show the nationwide efficiency gains from reallocation separately for farmers who rent in or rent out some land and for those farmers who do not participate in rentals. That is, we conduct an efficient reallocation for the full sample and then compute the resulting efficiency gains associated with each group separately. The efficiency gain among farmers without rentals is 3.18, which is slightly larger than the aggregate efficiency gain of 3.07. In contrast, the efficiency gain is 2.61 among farmers who rent

Table 4: Misallocation for Farmers with/without Land Rentals

	Full Sample	No Rentals (0%)	Rentals (>0%)
Efficiency gain (Nationwide)	3.07	3.18	2.61
S.D. (log TFPR)	1.06	1.10	0.96
S.D. (log MPLa)	0.99	1.05	0.86
Observations	2,887	1,951	936
Sample (%)	100	67.6	32.4

Notes: Data for the Ethiopia ISA 2013/14 as described in Section 2. We conduct our baseline nationwide reallocation to compute efficiency gains separately for each group of farmers: those with no rental land and those with rented in or rented out land. S.D. is the standard deviation, TFPR is revenue productivity, and MPLa is the marginal product of land.

land. This comparison is our first direct evidence relating land rentals to improved factor allocation and agricultural productivity in Ethiopia. Second, the dispersion of TFPR—a direct measure of the extent of misallocation—is larger for farmers without rentals than for farmers with rentals. Precisely, the standard deviation of $\log \text{TFPR}$ is 1.10 for farmers without rentals, and is 0.96 for farmers with rentals. This difference is significant at the 1% level.[18] This difference implies that households renting in or renting out land have a lower degree of misallocation than households that do not rent land. Third, the standard deviation of $\log \text{MPLa}$ is also significantly lower for farmers who rent in or rent out land (0.86) than for those that do not rent (1.05). This difference is also significant at the 1% level.

The group of farmers that rent in land might have selected into renting as per their productivity.[19] To assess whether selection has an impact on the relationship between land rentals and resource misallocation, we consider the following regression at the household

[18]We obtain the significance level through bootstrap. Specifically, we randomly draw from the data each observation with replacement for the same number of observations as in our sample. We repeat this process 10,000 times to obtain a distribution that we use to compute the confidence intervals.

[19]For example, Restuccia and Santaeulàlia-Llopis (2017) show that farmers that rent land are roughly 20% more productive in terms of individual TFP than those that do not operate rented land.

Table 5: Farm-Level Land Rentals and Misallocation, Controlling for TFP_i

Dependent variable:	Farm-Level Misallocation		
	Efficiency Gain	TFPR	MPLa
Land Rentals (d_i)	-0.114	-0.082	-0.066
	(0.024)	(0.017)	(0.022)
R^2	0.83	0.83	0.69
Observations	2,887	2,887	2,887

Notes: Results of Regression (4) reported for: (a) efficiency gain $|\log(y_i^e/y_i^a)|$ where y_i^e is efficient output of farm i and y_i^a is actual output in the data; (b) log farm-level revenue productivity (TFPR_i) relative to the economy-wide average, $|\log(\text{TFPR}_i/\overline{\text{TFPR}})|$, and (c) log farm-level marginal product of land (MPLa_i) relative to the economy-wide average, $|\log(\text{MPLa}_i/\overline{\text{MPLa}})|$. Data for Ethiopia ISA 2013/14 as described in Section 2.

level that controls for farm-level TFP:

$$|\log e_i| = \alpha + \psi d_i + \beta \log \text{TFP}_i + \varepsilon_i, \tag{4}$$

where the dependent variable is an individual measure of farm-level misallocation resulting from a nationwide reallocation, d_i is a dummy that takes a value of one when farmer i rents in or rents out some land, and zero otherwise. The parameter of interest is ψ, which shows whether land rentals are positively or negatively associated with resource misallocation. We use three measures of individual farm-level misallocation. The first measure is the absolute value of the log individual efficiency gain/loss, $e_i = y_i^e/y_i^a$, where y_i^e is efficient output of farm i resulting from a nationwide efficient reallocation and y_i^a is actual output in the data. Deviations from efficient allocations may imply efficiency gains/loses (in log) so, for this reason, we consider the absolute value of the log efficiency gains. This implies that we can unambiguously interpret a negative (positive) estimate for ψ as a movement towards (away from) efficiency. The second measure is the absolute value of log farm-level revenue productivity (TFPR_i) relative to the economy-wide average, $|\log(\mathrm{TFPR}_i/\overline{\mathrm{TFPR}})|$. We define the economy-wide average of TFPR as $\overline{\mathrm{TFPR}} = Y^a/(K^\alpha L^{1-\alpha})$. The third measure, relating more specifically to land, is the log of farm-level marginal product of land (MPLa_i) relative to the economy-wide average, $|\log(\mathrm{MPLa}_i/\overline{\mathrm{MPLa}})|$, where $\overline{\mathrm{MPLa}} = (1-\alpha)\gamma Y^a/L$.

Using each of these measures as the dependent variable in Equation (4), we run ordinary least squares (OLS) regressions using our full sample and controlling for individual TFP_i. The estimated coefficients of ψ are -0.11 for efficiency gain, -0.08 for deviation in TFPR, and -0.07 for deviation in MPLa. All of these estimates are significant at the 1% level. Therefore, consistent with our previous analysis, renting land is significantly associated with lower resource misallocation, even after controlling for farm-level TFP.

Although land rentals alleviate resource misallocation, the extent of misallocation is still severe, even amongst farms that rent land. For example, the correlation between farm size and farm productivity is -0.019 among farmers that do not rent land and only 0.077 among farmers that rent land, whereas the efficient allocation entails a perfect correlation between farm size and farm productivity. Therefore, even though land rentals help direct land from less productive farms to more productive ones, farms are operating far from the efficient allocation overall, which suggests that land markets are still limited and subject to various frictions.

This should not be entirely surprising since, as discussed in our institutional background, substantial restrictions on rentals remain in place, such as the fact that only a fraction of land-use rights can be rented and farmers must still reside in the rural area and be engaged in agriculture. In addition, rental activity may be hindered by other imperfections such as weak legal institutions. Another way to characterize the limited role of rentals in the data is by noting two features of rentals required to achieve an efficient allocation of resources. The first property is that, given the distribution of land-use rights, 77.4 percent of the land should be rented in the efficient allocation, whereas in the data only 9.3 percent of land is rented. The second property is the concentration of rentals. In the efficient allocation, the top 10 percent most productive farms would operate 95.4 percent of the rented land, whereas in the data these farms operate only 14.9 percent. Hence, land rentals are not only insufficient, but also much less concentrated among productive farms, clearly indicating a limited role of rentals in directing resources to best uses.

Our cross-sectional results focus on the Ethiopia ISA 2013/14 data. However, we find similar results from Ethiopia ISA 2015/16. For example, the efficiency gain for farmers renting land is also lower than that of farmers not renting land (1.99 compared to 2.83) using the 2015/16 wave. The dispersion of log TFPR and log MPLa is also smaller among farmers renting land in 2015/16. The estimates of ψ from Regression (4) using dependent variables of efficiency gain, dispersion of TFPR, and dispersion of MPL from the 2015/16 data are -0.11, -0.08, and -0.10, respectively, and are all significant at the 1% level.

4.1.2 Land Rental Markets across Space

Our analysis of land rentals has so far focused on individual farmers across all of Ethiopia. We now exploit differences in land rentals across geographical locations. We mainly focus on results at the zone level, although our results also hold at the narrower woreda level.

We calculate efficient output ($Y_z^e = S_z^{1-\gamma}(K_z^\alpha L_z^{1-\alpha})^\gamma$) and actual output ($Y_z^a = \sum_{i \in z} y_i^a$) for each zone in the data. Then, the ratio $e_z = Y_z^e / Y_z^a \geqslant 1$ represents the efficiency gain at the zone level. We also compute the percentage of land rentals R_z in each zone, defined as the ratio between the size of rented land and total land size. This ratio measures directly the land rental market in each zone. There is large variation in the proportion of rented land across zones, ranging from zero percent to more than 70 percent.

The top panel of Figure 5 illustrates the relationship between the efficiency gain of each zone e_z and the percentage of land rentals in each zone R_z. Clearly, efficiency gains e_z are negatively correlated with land rentals R_z: a zone with more land rentals tends to have a lower efficiency gain. In particular, the elasticity between e_z and R_z (accuracy weighted by the number of observations in each zone) is -0.080, which is significant at the five percent level. Similarly, the bottom panels of Figure 5 show that the extent of misallocation—measured by the dispersion of farm revenue productivity ($\text{std}(\log \text{TFPR}_i)$) and marginal product of land ($\text{std}(\log \text{MPLa}_i)$)— significantly decreases with the percentage of land rentals in each zone with estimated elasticities of -.072 and -.076, respectively.[20]

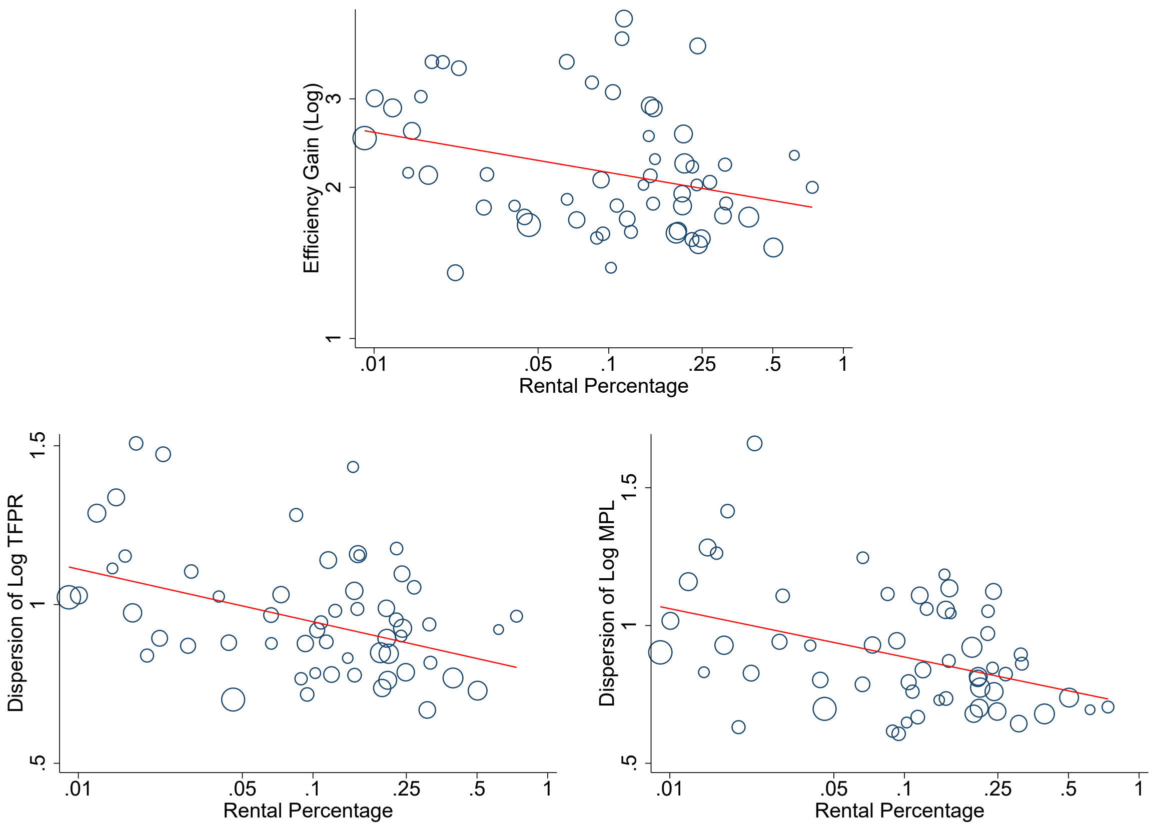
It is likely that the efficiency gain in a zone is related to the dispersion of farm-level TFP in the zone. We consider the following regression to address potential differences in farm TFP dispersion across zones:

$$\log e_z = \alpha + \psi \log R_z + \beta \text{std}_z^{\text{TFP}} + \varepsilon_z, \tag{5}$$

where R_z is the share of land rentals in zone z and $\text{std}_z^{\text{TFP}}$ is the dispersion of farm TFP within zone z defined as $\text{std}_z^{\text{TFP}} = \text{std}(\log(\text{TFP}_{zi}))$. We use as weights the number of observations in each zone. The parameter of interest is the elasticity ψ (the percentage change in efficiency

[20]The pattern between misallocation and land rentals is similar using the Ethiopia ISA 2015/16 data. In particular, the estimated elasticities are -0.161, -0.068, and -0.046 for the efficiency gain, dispersion in revenue productivity, and dispersion in marginal product of land, respectively.

Figure 5: Misallocation across Space



Notes: Plots within-zone efficiency gain, dispersions of farm-level revenue productivity (TFPR), and marginal product of land (MPLa) with respect to the fraction of rented land (in log). We report 57 zones that have a positive percent of rental land and more than 10 observations. We also trim zones with the highest and lowest efficiency gain. The size of the circles indicate the number of observations in each zone. The regression line is also accuracy weighted by the number of observations in each zone. The slopes of the regression line are -0.080, -0.072 and -0.076, respectively, and are all significant at the five percent level. Data for the Ethiopia ISA 2013/14 as described in Section 2.

Table 6: Land Rentals and Misallocation across Space—Zone-Level Outcomes

Dependent variable:	Efficiency Gain	Dispersion log TFPR	Dispersion log MPLa
Land Rentals (%)	-0.042	-0.030	-0.036
	(0.030)	(0.010)	(0.015)
R^2	0.31	0.81	0.65
Observations	57	57	57

Notes: Results for zone-level Regression (5), where each zone is treated as an observation. The first column refers to zone-level efficiency gain. We also repeat the regression with zone-level dispersion of log TFPR and dispersion of log MPLa as dependent variables. Regressions are accuracy weighted by the number of households within each zone. Standard deviations are in the parentheses. Data for the Ethiopia ISA 2013/14 as described in Section 2.

gains associated with a one percent change in the share of land rentals).

Table 6 shows the results of this zone-level outcome regression. The point estimate for ψ is -0.042, indicating that zones with a higher share of rented land tend to have lower efficiency gain, even after controlling for the dispersion in TFP. We replicate the Regression (5) using two additional summary statistics of misallocation as the dependent variable: the dispersion of log revenue productivity (TFPR) and the dispersion of log marginal product of land (MPLa) within each zone. We also find that more rentals in a zone are significantly associated with smaller dispersions of TFPR and MPLa with respective elasticities of -0.030 and -0.036. Conducting this analysis at the woreda level yields quantitatively similar results to that of this zone-level analysis, with woreda-level elasticities of -0.051, -0.021, and -0.027.[21]

To describe the relationship between land rentals and misallocation at a more disaggre-

[21] We focus on the zone-level analysis as opposed to the woreda level because, although there are more woredas, there are much fewer observations per woreda (only around 10), making statistics at the woreda level very noisy.

gate level, we use the heterogeneity in land rentals by zone with the following specification:

$$|\log e_{iz}| = \alpha + \psi \log R_z + \beta \log \mathrm{TFP}_{iz} + \varepsilon_{iz}, \tag{6}$$

where the dependent variable measures the degree of misallocation of farm i in zone z. We run this regression separately for the three measures of misallocation defined earlier: the absolute value of log farm-level efficiency gain/loss, the absolute value of log farm-level revenue productivity relative to the zone-level average, and the absolute value of log farm-level marginal product of land relative to the zone-level average.

Our findings are shown in panel (a) of Table 7. In all cases, we find a negative coefficient ψ suggesting a movement toward efficiency associated with land rentals. That is, zones with larger shares of rented land are associated with lower individual measures of misallocation. The coefficient of land rentals are -0.112, -0.135, and -0.176, on the efficiency gain, TFPR, and MPLa, respectively. These figures are all significant at the 1% level.

These results capture the average relationship between land rentals and individual measures of misallocation. However, our framework implies that efficiency gains are accrued when resources are reallocated among farmers with the largest deviations from efficient production. As a result, it is relevant to assess whether rental markets empirically ease misallocation disproportionally more for farmers farthest away from efficient production. To explore the potential non-linear relationship between land markets and misallocation across farmers, we divide the distribution of $|\log e_{iz}|$ into four quantiles (quartiles) and run the

Table 7: Land Rentals and Misallocation across Space—Farm-Level Outcomes

(a) Benchmark Specification

Dependent variable:	Farm-Level Misallocation		
	Efficiency Gain	TFPR	MPLa
Land Rentals (%), ψ	-0.112	-0.135	-0.176
	(0.014)	(0.011)	(0.011)
Observations	2,741	2,741	2,741
R^2	0.21	0.10	0.10

(b) Quantile Specification

Dependent variable:	Farm-Level Misallocation		
	Efficiency Gain	TFPR	MPLa
ψ_{Q1}	0.000	-0.003	0.004
	(0.004)	(0.003)	(0.003)
ψ_{Q2}	-0.002	0.000	-0.003
	(0.005)	(0.004)	(0.003)
ψ_{Q3}	-0.011	-0.003	-0.017
	(0.007)	(0.005)	(0.005)
ψ_{Q4}	-0.151	-0.193	-0.260
	(0.023)	(0.017)	(0.017)

Notes: Results of Regression (6) in panel (a) and of regression (7) in panel (b). We report the elasticity of land rentals and individual farm-level misallocation for these two specifications. We measure farm-level misallocation as the absolute value of log: (a) efficiency gain $|\log(y_{iz}^e/y_{iz}^a)|$ where y_{iz}^e is efficient output of farm i in a zone-level efficient reallocation and y_{iz}^a is actual output in the data, (b) revenue productivity (TFPR_i) relative to the zone-level average, $|\log(\mathrm{TFPR}_i/\overline{\mathrm{TFPR}})|$, and (c) marginal product of land (MPLa_i) relative to the zone-level average, $|\log(\mathrm{MPLa}_i/\overline{\mathrm{MPLa}})|$. Data for the Ethiopia ISA 2013/14 as described in Section 2.

following regression separately for each quartile:

$$|\log e_{iz}| = \alpha_Q + \psi_Q \log R_z + \beta_Q \log \mathrm{TFP}_{iz} + \varepsilon_{iz}. \tag{7}$$

The first quantile ($Q1$) represents farms that are closest to their optimal operational scale, and the last quantile ($Q4$) comprises farms that are farthest away from their efficient operational scale. Hence, the coefficient ψ_Q now depends on how far individual farms are from efficiency.

Our findings are shown in panel (b) of Table 7. The relationship between land rentals and resource misallocation is clearly nonlinear, consistent with the specification of our basic framework. As farmers approach their efficient operational scale, the beneficial relationship between land rentals and efficiency gains tends to diminish. Specifically, land rentals are not associated with changes in the efficiency gain for farmers that are already closest to their efficient allocation. The negative relationship between land rentals and efficiency gains starts to show up in the second quantile, with $\psi_{Q2} = -0.002$, and substantially increases as we move away from efficiency with significant elasticities of $\psi_{Q3} = -0.011$ and $\psi_{Q4} = -0.151$ for quantiles 3 and 4. The results remain similar, if not even larger, when using the absolute value of log farm-level revenue productivity (TFPR_{iz}) relative to the zone-level average and the log farm-level marginal product of land (MPLa_{iz}) relative to the zone-level average.

To provide a quantitative interpretation of our results, we first use our quantile specification for farm-level outcomes to compute the individual farm-level efficiency gain associated with a one percentage point higher share of land rentals as follows,

$$\Delta|\log e_{iz}| = \psi_Q \frac{\Delta R_z}{R_z}. \tag{8}$$

Then, using our zone-level data for R_z, we can plug our estimates for ψ_Q into Equation (8) to compute the individual efficiency that results from applying the reductions in the gains associated with a one percentage point increase in land rentals (i.e., $\Delta R_z = 0.01$) as $e^p_{iz} = e_{iz}(1+\Delta|\log e_{iz}|)$. Using the implied individual gains e^p_{iz}, we compute the implied individual output associated with a one percentage point increase in land rentals as $y^p_{iz} = y^e_{iz}/e^p_{iz}$ (noting that the efficient output y^e_{iz} is solved from the planner's problem and is therefore unchanged). The implied zone-level efficiency gain associated with an increase in rentals is calculated as $e^p_z = \sum_{i\in z} y^e_{iz}/\sum_{i\in z} y^p_{iz}$. Comparing the average of these implied efficiency gains (2.169) with our benchmark average efficiency gains per zone (2.183), we find that a one percentage point increase in land rentals is associated with 0.87 percent lower efficiency gains on average per zone (calculated as $1 - \log(2.169)/\log(2.183)$). Recall that the efficiency gain is simply defined as the ratio between efficient to actual output; therefore, our result can also be interpreted as one percentage point higher land rentals being associated with 0.87 percent higher agricultural productivity per zone on average.

4.2 Land Rental Markets across Time and Space

We have documented a negative association between land rentals and resource misallocation. It is possible that this relationship is being driven by another factor that affects both land rentals and misallocation. We now exploit the panel dimension of the Ethiopia ISA 2013/14 and 2015/16 in order to provide a more robust characterization of the effect of rental markets and resource misallocation.

As discussed earlier, the land certification reform was implemented by local governments with different timing and rules, so the variation of R_z across zones contains information on how the reform evolved across zones. Accordingly, we define the reform in terms of its observed outcome, i.e., the share of rented land by zone. Focusing on land rentals helps to capture the idea that zone-level institutions also shape the timing and intensity of the land reform implementation. Indeed, while the average increase in land rentals for the sample of zones is small across waves, the heterogeneity in land-rental growth is substantial. For example, while 37 out of 65 zones did not have any increase in land rentals, 8 zones had land rentals increase by at least 10 percentage points, and 6 zones had land rentals increase by more than 15 percentage points.

Panel specification and results We implement a standard difference-in-difference approach in our assessment. Since the share of rented land is a continuous variable between 0 and 100 percent, we define the indicator variable d_{zt} to equal one in the 2015/16 wave of our data if land rentals increased in zone z between the 2013/14 and the 2015/16 wave of the data, and zero otherwise. This implies the following benchmark panel specification to assess the impact of land rentals on resource misallocation:

$$|\log e_{izt}| = \alpha_z + \lambda_t + \psi d_{zt} + \beta \log \mathrm{TFP}_{iz} + \varepsilon_{izt}, \tag{9}$$

where e_{izt} is our measure of misallocation for farm i in zone z and time t, α_z is a zone fixed effect, λ_t is a year fixed effect, and dummy d_{zt}. The parameter of interest is ψ, which captures the effect of land rentals on individual farm-level misallocation. We also control for farm-level TFP.[22]

The results from our benchmark panel specification are reported in Table 8, panel (a). Using farm-level gains from zone-level efficient reallocations, we find that land rentals generate a significant decline in resource misallocation. The increase in land rentals generate a decline in efficiency gains with a significant coefficient of -0.058. We also apply this specification to the additional measures of farm-level misallocation: relative revenue productivity and relative marginal product of land. The estimated effect for each TFPR and MPLa is negative and significant with coefficients of -0.120 and -0.110, which reinforces our results that more land rentals reduce the extent of resource misallocation.[23]

In sum, the difference-in-difference analysis with panel data implies that a more active land market reduces resource misallocation and increases agricultural productivity. Our strong empirical results exploiting variation across zones and over time underscore alternative explanations for the relationship between land rentals and misallocation such as misspecification or measurement error.

[22]Note that for each household, we use average TFP across waves as described earlier in Section 3.2. Using the levels of TFP measured in each cross section yields similar results.

[23]There is substantial heterogeneity in the size of land rental increase across zones: while the average increase for zones with an increase in rentals is 10.9 percent, some zones barely have any increase in the share of rented land, and some zones have increases of more than 15 percent. This heterogeneity is not captured by our baseline reform dummy d_{zt}, which simply separates increases and non-increases in land rentals across waves in Regression (9). To explore potential nonlinear effects of land rentals on resource misallocation and productivity, we re-define d_{zt} in Regression (9) as a dummy that takes value one in the second period if rentals in zone z increase by more than the median among zones with an increase in rentals, and zero otherwise. The effects of land rentals on resource misallocation are larger with this specification. The relevant coefficients are -0.088 for farm-level efficiency gains, -0.174 for TFPR, and -0.159 for MPLa.

Table 8: Effects of Land Rental Markets on Misallocation and Productivity

(a) Benchmark Specification

Dependent variable:	Farm-Level Misallocation		
	Efficiency Gain	TFPR	MPLa
Land Rentals (d_z)	-0.058	-0.120	-0.110
	(0.039)	(0.031)	(0.033)
Observations	4,628	4,628	4,628
R^2	0.23	0.25	0.16

(b) Quantile Specification

Dependent variable:	Farm-Level Misallocation		
	Efficiency Gain	TFPR	MPLa
ψ_{Q1}	0.070	0.017	0.056
	(0.036)	(0.029)	(0.035)
ψ_{Q2}	-0.030	-0.007	-0.038
	(0.041)	(0.035)	(0.040)
ψ_{Q3}	-0.112	-0.031	-0.002
	(0.048)	(0.040)	(0.039)
ψ_{Q4}	-0.176	-0.395	-0.300
	(0.082)	(0.068)	(0.076)

Notes: Results of Regression (9) in panel (a) and of Regression (10) in panel (b) for the following measures of farm-level misallocation: (a) efficiency gain $|\log(y^e_{izt}/y^a_{izt})|$, where y^e_{izt} is efficient output of farm i in a zone-level efficient reallocation and y^a_{izt} is actual output in the data, (b) revenue productivity (TFPR_{izt}) relative to the zone-level average, $|\log(\text{TFPR}_{izt}/\overline{\text{TFPR}}_{zt})|$, (c) marginal product of land (MPLa_{izt}) relative to the zone-level average, $|\log(\text{MPLa}_{izt}/\overline{\text{MPLa}}_{zt})|$. Regressions are accuracy weighted by the number of households in each zone. Standard deviations are in the parentheses. Panel data for the Ethiopia ISA 2013/14 and 2015/16 waves are as described in Section 2.

Non-linear effects We also explore the potential non-linear effects of land rentals on farm-level misallocation as we have done in the previous section. To do so, we divide the distribution of $|\log e_{iz,2013}|$ into four quantiles (quartiles) and run the following regression separately for each quartile:

$$|\log e_{izt}| = \alpha_{Qz} + \lambda_{Qt} + \psi_Q d_{zt} + \beta_Q \log \mathrm{TFP}_{iz} + \varepsilon_{izt}, \tag{10}$$

where the first quantile ($Q1$) represents farms that are closest to their optimal operational scale, and the last quantile ($Q4$) consists of farms that are farthest from their optimal operational scale.

Consistent with our previous finding, the effect of land rentals on farm-level misallocation depends on how far farms are from their efficient operation scale (Table 8, panel(b)). In particular, the farther farmers are from their efficient operational scale, the larger the reduction in misallocation generated by increased rental activity at the zone level. While farmers in the first quartile (i.e., farmers closest to efficiency) have efficiency losses generated by increased land rentals ($\psi_{Q1} = 0.070$ significant at the 10% level), increased land rentals reduce efficiency gains in the second quartile ($\psi_{Q2} = -0.030$); there is an even stronger negative effect in the third quartile ($\psi_{Q3} = -0.112$ significant at the 5% level), and even stronger one in the fourth quartile ($\psi_{Q4} = -0.176$ significant at the 5% level). That is, the estimated effect of increased land rentals at the zone level is three times higher for farmers that are farthest away from their efficient operational scale than for the average effect. We obtain similar results using the other farm-level misallocation measures in revenue productivity and the marginal productivity of land (see the last two columns in Table 8).

Economic interpretation of results To provide a quantitative interpretation of the effects in our quantile specification, we calculate the farm-level efficiency gain generated by an increase in land rentals across waves as follows,

$$\Delta |\log e_{izt}| = \psi_Q. \tag{11}$$

The farm-level efficiency gain implied by the increase in land rentals across waves is $e^p_{iz} = e_{iz}(1 + |\Delta e_{iz}|)$ and the implied farm-level output is $y^p_{iz} = y^e_{iz}/e^p_{iz}$. We then calculate the implied zone-level efficiency gain as $e^p_z = \sum_{i \in z} y^e_{iz} / \sum_{i \in z} y^p_{iz}$. The increase in land rentals implies a reduction in the benchmark average efficiency gain from 1.692 to 1.681 for the 2013/14 wave.[24] That is, an increase in land rentals reduces efficiency gains by 1.28% on average per zone $(1 - \log(1.681)/\log(1.692))$.

Furthermore, to compare the reduction in efficiency gains from rentals with the cross-sectional relationship described in the previous section, we divide these effects by the aggregate growth in the share of rented land across our two waves, which is 2.6 percent (from 9.64 percent in 2013/14 to 12.25 percent in 2015/16). This implies that an increase in one percentage point of land rentals increases aggregate productivity by 1.28/2.61=0.49 percent. This effect is roughly half of that implied by the cross-sectional estimate discussed in the previous section.

Another way to quantitatively interpret our empirical results is by exploring how the within-zone efficiency gain evolves over time with systematic increases in land rentals from

[24]Note that the average value of efficiency gain from within-zone reallocation using the balanced panel (1.692) differs from the value using the cross-section in 2013/14 (2.183), see Section 3.2. The difference is mainly the result of the smaller panel sample, which is roughly 80 percent of the original cross-sectional sample.

Regression (10). We project forward the effects of land rentals on the distribution of farm-level efficiency gains, assuming that land rentals in all zones increase by the average in every period (i.e., $d_{zt} = 1$ for all z and t). We also keep the quantile effects ψ_Q constant over time (as well as the thresholds that apply to the coefficients). We initialize the distribution of farm-level efficiency gains in the Ethiopia ISA 2013/14 wave and solve for the distribution every period in order to track the aggregate within-zone efficiency gains. Increasing land rentals from 9.6 percent in the 2013/14 wave to 22.7 percent in 10 years and 35.7 percent in 20 years, we find that the within-zone efficiency gain falls from 1.69-fold in the 2013/14 wave to 1.57-fold in 10 years and to 1.44-fold in 20 years, corroborating the substantial improvement in resource allocation and agricultural productivity embedded in our empirical estimates.[25]

While the reduction in misallocation due to land rentals is economically substantial, our results suggest that land rental markets in Ethiopia may not be effectively directing resources to best uses. We explore the possibility that not all rented land may be efficiently allocated in the next section by distinguishing between market and non-market rentals.

5 Market versus Non-Market Rentals

We distinguish between land rentals that operate through the market versus land rentals that operate through personal connection, such as through relatives and friends.

A nice feature of our data is that detailed information is available on land rentals. This includes information about rental payments' amounts—both in cash and in kind—as well

[25]We note that by simply taking the effect of a 0.49 percent reduction in the efficiency gain with a one percent increase in rentals, the efficiency gain would fall to 1.64-fold in 10 years and to 1.58-fold in 20 years.

as from whom the land is rented (e.g., relative, friends, etc.). Despite the land certification reform discussed earlier, the land market in Ethiopia continues to be limited. For instance, not only is the percentage of farm households that operate rented land relatively small, but the vast majority of land rentals also occur between relatives and friends: among the households that rent in land, 46 percent rent from relatives and 36 percent rent from friends. This suggests that personal connections may be a key determinant of rental transactions rather than willingness to pay through a market process. If this is the case, then reallocations through rentals may not be as efficient in directing resources to best uses, and hence, would not have as strong a positive impact on agricultural productivity.

The prevalence of personal connection in rentals may be driven by market frictions such as fear of ownership insecurity—for example, land certificates may provide land tenure security in the operation of the land but may not give the same security on rentals as the outcome of land disputes may depend on the state of rule-of-law institutions—or rentals may obey other goals such as the provision of social insurance (De Magalhães and Santaeulàlia-Llopis, 2017).

Because land rentals from relatives and friends are not necessarily inefficient, we focus on the agreed upon payments agreed of the rental contract before harvest as a more direct indicator of whether land rentals are market-based or not.[26] For example, if a plot of land is rented for free, then it is likely that this rental is not market-based and that other considerations are at play. We construct the rental payment measured as the sum of both cash and in-kind payments. Based on this rental payment, we classify rentals that are free

[26]We focus on these rental payments, as opposed to actual payments, to avoid the possibility of renegotiation or default in the event of a weak harvest.

(zero payment) as non-market rentals.[27] We note that, in our data, the median payment of rent-in land among market rentals is about 52 percent of the output of a parcel of land. This is consistent with Otsuka et al. (1992), who argue that in poor countries farmers' payments to landlords are roughly half of their output.

We construct the indicator variable d_{nzt} to denote an increase of *non-market* rentals of a zone relative to market rentals. This is to say, we set $d_{nzt} = 1$ if non-market rentals increase more than market rentals in a zone (i.e., if rental increases in a zone are mainly non-market). Adding this dummy to Regression (9) controls for the effect of non-market rentals:

$$|\log e_{izt}| = \alpha_z + \lambda_t + \psi d_{zt} + \psi_n d_{nzt} + \beta \log \text{TFP}_{iz} + \varepsilon_{izt}, \tag{12}$$

where d_{zt} is as defined previously.

We find that the effects of rentals on misallocation are large and significant (Table 9). The effect of rentals is roughly 70 percent larger than our benchmark panel results in Section 4.2. Precisely, the effect of land rentals on efficiency gain is -0.099, compared to -0.058 in our benchmark specification which does not control for non-market rentals. In contrast, if the increase of rentals are mainly non-market, then the effect of these rentals, which is captured by the sum of the coefficients $\psi + \psi_n$, is not only small (e.g., 0.004 for efficiency gain) but also not significantly different from zero. Similar insights arise using measures of misallocation based on TFPR and MPLa. These results imply that, for zones where the increase in rentals are mainly non-market, misallocation is not significantly reduced.

We conclude that reductions in the degree of misallocation due to changes in operational

[27] Including rentals with small nominal payments as part of non-market rentals delivers similar results.

Table 9: Effects of Market versus Non-Market Rentals

Dependent variable:	Farm-Level Misallocation		
	Efficiency Gain	TFPR	MPLa
Land Rentals (d_z)	-0.099	-0.192	-0.168
	(0.046)	(0.036)	(0.038)
Non-Market Rentals (d_{nz})	0.104	0.181	0.147
	(0.059)	(0.047)	(0.049)
Observations	4,628	4,628	4,628
R^2	0.23	0.25	0.16
Added Inference: $d_z + d_{nz}$	0.004	-0.012	-0.021
Prob. $> F$	0.934	0.781	0.633

Notes: Results of Regression (12) with the following measures of farm-level misallocation: (a) efficiency gain $|\log(y^e_{izt}/y^a_{izt})|$ where y^e_{izt} is efficient output a farm i of a zone-level efficient reallocation and y^a_{izt} is actual output in the data, (b) revenue productivity (TFPR_{izt}) relative to the zone-level average, $|\log(\text{TFPR}_{izt}/\overline{\text{TFPR}}_{zt})|$, (c) marginal product of land (MPLa_{izt}) relative to the zone-level average, $|\log(\text{MPLa}_{izt}/\overline{\text{MPLa}}_{zt})|$. Regressions are accuracy weighted by the number of households in each zone. Standard deviations are in the parentheses. Panel data for waves Ethiopia ISA 2013/14 and 2015/16 described in Section 2.

scale via rentals largely operate through market forces and the effectiveness of rentals in allocating resources is still limited by other aspects of the institutional environment.

6 Land Rental Markets and Technology Adoption

The impact of land rental markets on agricultural productivity is also likely to come in the form of adopting new technologies and investment (e.g., fertilizers, tractors, and animals).[28] Ethiopia is a country at a very preliminary stage of development and this reflects on the low levels of technology adoption. In the 2013/14 wave, 51.1 percent of farmers use fertilizers, 62.0 percent use livestock in agricultural production, and 4.9 percent use tractors (either

[28] See, for instance, Restuccia and Rogerson (2017) for a discussion of the broader consequences of misallocation.

owned or rented).[29]

We separately investigate the effects of land rental markets on the extensive and intensive margins of technology adoption such as fertilizers use, livestock, and tractors. First, we explore the extensive margin by positing a probit regression among households, using an indicator for the adoption (or not) of a given technology. We estimate this specification separately for fertilizers, livestock, and tractors. Specifically, let us denote the indicator of using a given technology as $\mathbf{f}$: $\mathbf{f}_i = 1$ indicates that household i uses any positive amount of a given technology. To help illustrate the problem, consider the following equivalent latent variable model. Suppose there exists an auxiliary random variable $\mathbf{f}^*$ specified as

$$\mathbf{f}_i^* = \alpha + \psi d_i + \psi_n d_{ni} + \beta \log \mathrm{TFP}_i + \gamma \left| \log \left(\frac{\mathrm{TFPR}_i}{\overline{\mathrm{TFPR}}} \right) \right| + \varepsilon_i. \tag{13}$$

We can view $\mathbf{f}$ as an indicator for whether this latent variable is positive: $\mathbf{f} = 1$ if $\mathbf{f}^* > 0$. In this regression, d_i is an indicator of whether or not farmer i rents any positive amount of land, and d_{ni} is an indicator of whether or not farmer i rents in land with a pre-harvest rental rate of zero (as opposed to markets, as in the previous Section 5). Our key parameters of interest are then ψ and ψ_n. We also control for farm TFP (TFP_i) and farm TFPR (relative to the economy-wide average), the latter of which is as a summary measure of farm misallocation. Intuitively, higher farm TFP facilitates the adoption of better technology, while higher farm-level distortions reduce the return to adopting it.

Our results are in Table 10, panel (a). Farms with land rentals from the market are

[29] The Ethiopia ISA data about the use of capital (livestock and tractors) is restricted to land preparation activities. Land preparation lends itself to the adoption of capital as a substitute for labor since it is power intensive but not control intensive (Pingali, 2007). Whether substitution occurs also depends on relative factor prices.

Table 10: Effects of Land Rental Markets on Technology Adoption

(a) Extensive Margin: Probit Specification

	Fertilizers	Livestock	Tractors
Land Rentals (d_i)	0.469	0.595	-0.136
	(0.060)	(0.068)	(0.104)
Non-Market Rentals (d_{ni})	-0.460	-0.536	-0.013
	(0.087)	(0.094)	(0.156)
Observations	2,887	2,887	2,887
Pseudo R^2	0.03	0.11	0.01
Added Inference: $d_i + d_{ni}$	0.008	0.059	-0.150
Prob. $> F$	0.912	0.443	0.264
Δ Prob. (%)	18.3	20.6	-1.3

(b) Intensive Margin: Difference-in-Difference Specification

	Fertilizers	Livestock	Capital
Land Rentals (d_z)	0.234	-0.131	-0.006
	(0.099)	(0.086)	(0.089)
Non-Market Rentals (d_{nz})	0.012	-0.011	0.005
	(0.121)	(0.108)	(0.114)
Observations	2,421	2,214	4,628
R^2	0.31	0.28	0.43
Added Inference: $d_z + d_{zn}$	0.246	-0.142	-0.001
Prob. $> F$	0.025	0.148	0.992

Notes: Results of probit specification (13) in panel (a) and of difference-in-difference specification (14) in panel (b). Each specification estimated for different measures of technology adoption: fertilizer use, livestock use in agricultural production per unit of labor, and tractors per unit of labor. For the difference-in-difference specification, we use capital per unit of labor (as described in Section 2.2). Regressions are accuracy weighted by the number of households in each zone. Standard deviations are in parentheses. Panel (a) uses the Ethiopia ISA 2013/14 data, and panel (b) uses the panel Ethiopia ISA 2013/14 and 2015/16 described in Section 2.

more likely to use fertilizers in agricultural production than farms without rentals. This association, summarized by the estimate for ψ, is large and significant. Specifically, consider a farm of average TFP and TFPR; our estimate implies that such a farm is 18.3 percent more likely to use fertilizer if it operates with rented land.[30] In contrast, land rentals are not associated with the use of fertilizers when renting is done through non-market rentals as $\psi + \psi_n$ is small and not significantly different from zero.[31] Similar insights arise when looking at the probability of using livestock in agricultural production. That is, market rentals significantly increase the probability of using livestock, while non-market rentals have no effect. The case of tractors, however, is different since land rentals are not significantly associated with a higher probability of using tractors in agricultural production. We come back to this result below. Moreover, although not reported in Table 10, the estimation of the other parameters confirm our conjecture that farm TFP is positively associated with fertilizer use, while farm-level distortions are negatively associated with it.

Exploiting the panel dimension of our data set to estimate the effects of land rentals on the intensive margin of technology adoption, we focus on households that have already adopted the technology in the 2013/14 wave, and discuss how land rentals affect the intensity of technology use in the 2015/16 wave. We consider the following specification, which is analogous to Equation (12),

$$\log \tilde{f}_{izt} = \alpha_z + \psi d_{zt} + \psi_n d_{nzt} + \beta \log \mathrm{TFP}_{iz} + \gamma \left| \log \left(\frac{\mathrm{TFPR}_{izt}}{\overline{\mathrm{TFPR}}} \right) \right| + \varepsilon_{izt}. \tag{14}$$

[30] The probability of 18.3 percent is computed using our estimated ψ from probit Regression (13) reported in Table 10, panel (a), evaluated at the mean.

[31] The puzzling low take-up rate of fertilizers in poor countries has been emphasized by Duflo et al. (2011). Our results suggest that the return to fertilizer use depend on the efficiency of farm operational scale which, in the context of Ethiopia, depend crucially on rental markets for land.

where α_z is zone fixed effect, λ_t is year fixed effect, and d_{zt} is an indicator for land rental increases across waves in zone z, and d_{nzt} is an indicator for non-market land rental increases relative to market rentals across waves in zone z. We also control for farm TFP and farm TFPR as a summary measure of farm misallocation.

Our results are shown in Table 10, panel (b). We find that an increase in land rentals generates an increase in fertilizer use intensity, with a large and significant estimate $\psi = 0.239$. This is consistent with the cross-sectional probit results except that the distinction between market and non-market rentals has no implications on the effect of fertilizer use. In contrast, the effects of land rentals on livestock or aggregate capital are not significant along the intensive margin. These results can be partly explained by Ethiopia's small plot size and restrictive rental markets for capital assets. While fertilizers can boost agricultural productivity almost independently of the size of the cultivated plot, this is not the case for large animals, tractors, and other sizeable capital which, unless rented on a daily or hourly basis, are more likely to pay off in large operational scales (e.g., Chen, 2017a).

7 Robustness and Extensions

We provide a set of robustness checks. First, we discuss a potentially important qualification of our findings with regards to the presence of output market distortions. Second, a merit of the dataset that we use is that it records inputs and outputs for each plot operated by all households. We exploit this feature to check the robustness of our results to different measures of farm TFP. Third, we study the role of crop composition on the extent of misallocation. Fourth, we provide additional discussion on the role of land quality between rented and non-rented plots.

7.1 Output Market Distortions

It is important to recognize that other distortions, in addition to distortions on factor inputs, may be in place. Our emphasis has been on connecting misallocation with restrictions to land markets in Ethiopia, as well as on establishing a link from land rentals to misallocation. Even if Ethiopia's land certification reforms have been successful in providing tenure security as their primary objective, we have documented that strong restrictions in rentals remain in place and that, even if not everywhere enforced, rental activity remains tenuous. However, to the extent that there may be other frictions in the economy—such as poor infrastructure which would make markets in remote rural locations difficult to access—that may be driving the misallocation we document, it is relevant to assess the extent to which the land market is the dominant source of misallocation in the data as opposed to other frictions.

To this effect, we exploit the availability of data on farm distance to markets as a proxy for other frictions such as product market distortions and assess the extent to which these variables are related to farm-specific measures of distortions. In particular, we extend our benchmark difference-in-difference specification (9) to include farm distance to nearest city (or distance to the nearest major road) denoted by m_i as an additional control variable. This implies the following specification:

$$|\log e_{izt}| = \alpha_z + \lambda_t + \psi d_{zt} + \beta \log \mathrm{TFP}_{iz} + \gamma \log \ m_{iz} \ + \varepsilon_{izt}.$$

We find that controlling for output market distortions does not alter our benchmark results. The estimated coefficient ψ (and standard errors) for efficiency gains, TFPR, and MPLa barely change, with -0.058 (0.039), -0.121 (0.031), and -0.110 (0.033), respectively. The coefficients on log distance for dependent variables of efficiency gains, TFPR, and MPLa, are not significant with estimates of -0.002 (0.021), -0.021 (0.016), and 0.020 (0.017), respectively.

7.2 Alternative Measures of Farm Productivity

An important concern in the misallocation literature is the possibility of measurement error in individual inputs and outputs driving dispersion in the marginal products of production units. Also important is the measure of productivity which could potentially suffer from classical measurement error.[32]

Before we try to address these issues, we emphasize that our main focus has been on comparison across groups of farmers who differ on whether they rent land or not, the comparison across regions that differ on the extent of land rentals, and the comparison of household changes in rented land over time, while the relative size of measurement error should be similar across household groups, regions, and over time. Therefore, while the level of dispersion in marginal products may reflect some measurement error, differences in the dispersion of marginal products across differing groups (location and time) should not be as

[32] See related discussions in Restuccia and Santaeulàlia-Llopis (2017), De Magalhães and Santaeulàlia-Llopis (2017), and Gollin and Udry (2017). For instance, Restuccia and Santaeulàlia-Llopis (2017) assess the effect of recall bias in the ISA data, indicating a negligible effect on the degree of misallocation, whereas De Magalhães and Santaeulàlia-Llopis (2017) externally validate reported agricultural production in the ISA data with measures of food consumption, showing that underreporting of output is not quantitatively important. Gollin and Udry (2017) emphasize plot-level variation across and within farms by estimating measurement error in inputs and outputs assuming that farmers are equally efficient in operating each plot. We show that aggregating inputs and outputs at the farm-household level—our main unit of analysis—is critical in mitigating these potential concerns.

affected by measurement error. Nevertheless, we provide several alternative measures of farm productivity and conclude that our quantitative results are fairly robust to these alternatives.

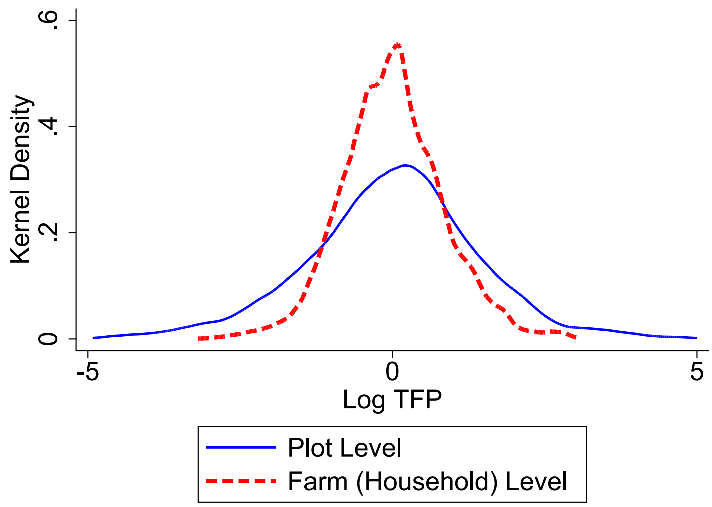
7.2.1 Cross-sectional farm productivity from plot-level data

Recall that our basic unit of production is the farm household. Since a household generally operates a farm spanning several plots of land in the data—specifically, an average of more than seven plots in the case of Ethiopia—we have aggregated inputs and outputs at the household level, and can thereby calculate a unique farm productivity for each household. An important implication of this aggregation at the farm level is that plot-level shocks and classical measurement error on inputs and outputs are averaged out. To illustrate the importance of this feature of our analysis, we contrast our results with the alternative, where the unit of production is instead the plot. In this alternative setup, each plot of operated land is assigned a unique productivity computed from its inputs and outputs as done previously for the farm household. In particular, the land and labor inputs and the value of output (value added) are available for each plot of land (a.k.a. a *field* in the data). The capital stock, however, is slightly more complicated since is measured at the household level. Furthermore, it is reasonable to assume that the capital (for example, a plough) of a given household can be used in multiple plots owned by this household. To assign capital services used in each plot, we assume that plot-level capital services are proportional to the size of plots (i.e., a larger plot uses more capital than a smaller plot). After obtaining plot-level inputs and outputs, we consider the plot as the basic unit of analysis and calculate the plot-level productivity as we do in Section 3.

Consistent with a large microeconomic development literature, there is a lot of plot-level variation in productivity, even within farm households. In particular, the dispersion in plot-level TFP is 70 percent higher than the dispersion in farm-level TFP (see Figure 6 for the distributions of plot-level and farm-level productivity). The dispersion in plot-level TFPR is also about 65 percent higher than the dispersion in farm-level TFPR. As a result, the efficiency gain from reallocation is much higher at the plot level (551 percent) than in our baseline using farm-level observations (207 percent). Hence, the aggregation of plot-level inputs and outputs within farm households, as done in our baseline results, is essential in providing a more robust characterization of the extent and consequences of misallocation in agriculture. Incidentally, we note that a key feature of the land institution we emphasize is the weak connection between land use and productivity reflected in a nearly zero correlation between land input and farm TFP. This pattern of misallocation is not much different when characterized at the plot level. Similarly, the correlation between log TFPR and log TFP is 0.935 when the unit of production is land plot and 0.908 when the unit of production is the farm household. The key difference is that the reallocation gains are magnified at the plot level because of the larger dispersion in plot-level TFP.

We can also exploit the plot-level data to explore alternative productivity measures at the farm level. Rather than aggregating inputs and outputs of all the plots operated by the household, we can instead use the mean, median, or the second highest value of these plot-level productivities as alternative measures of household-level productivity. Once we have these alternative measures, we aggregate inputs and outputs to the household level, and redo our previous analysis using these alternative measures of household productivity. Specifically, in Section 3, we have assigned each household i a unique household-level productivity s_i. Suppose household i operates several plots of land, and we calculate plot-level productivities

Figure 6: Distributions of Farm and Plot Level Productivity



Notes: Distributions of farm-level and plot-level TFP. The dispersion in plot-level productivity, represented by the standard deviation of log TFP, is 1.409, whereas for the farm-level productivity is 0.911.

s_{ij}. Given this, we can construct the following three alternative measures of household-level productivity:

$$s_i^1 = (\Pi_j s_{ij})^{\frac{1}{J}}, \quad s_i^2 = \text{median}_j(s_{ij}), \quad s_i^3 = \text{max}_j^2\{s_{ij}\}.$$

The first measure s_i^1 uses the geometric mean of plot-level productivity to approximate household-level productivity; the second measure s_i^2 uses the median of plot-level productivity as an approximation; the third measure s_i^3 uses the second highest value as an approximation. These measures are based on the assumption that a household should have the same productivity across plots. Therefore, variation in plot-level productivity within a household may reflect potential measurement error or misspecification. We take the mean, median, or the second highest value of plot-level productivity to minimize these measurement error.

Having calculated these alternative measures, we replace the household level productivity s_i with these three alternative measures and re-compute the efficiency gain. Note that

Table 11: Alternative Measures of Farm Productivity

Measure of Farm productivity s_i	Rank Corr. with Baseline s_i	Efficiency Gain	Observations
(a) Cross-Sectional Data (2013):			
(1) Benchmark s_i	–	3.07	2,887
(2) $s_i^1 = (\Pi_j s_{ij})^{\frac{1}{J}}$	0.74	3.64	2,876
(3) $s_i^2 = \text{median}_j(s_{ij})$	0.72	3.54	2,860
(4) $s_i^3 = \max_j^2\{s_{ij}\}$	0.59	3.58	2,859
(b) Panel Data:			
(1) Benchmark $\widetilde{s}_i = (s_i^{2013} s_i^{2015})^{\frac{1}{2}}$	0.77	3.01	2,314
(2) $\widetilde{s}_i^1 = ((\Pi_j s_{ij}^{2013})^{\frac{1}{J}}, (\Pi_j s_{ij}^{2015})^{\frac{1}{J}})^{\frac{1}{2}}$	0.57	3.02	2,309
(3) $\widetilde{s}_i^2 = (\text{median}_j(s_{ij}^{2013}), \text{median}_j(s_{ij}^{2015}))^{\frac{1}{2}}$	0.58	3.03	2,306
(4) $\widetilde{s}_i^3 = (\max_j^2\{s_{ij}^{2013}\}, \max_j^2\{s_{ij}^{2015}\})^{\frac{1}{2}}$	0.47	3.06	2,303

Notes: For each farm household, we construct four alternative measures of productivity based on plot-level productivity of operated plots: the geometric mean, median, and second largest value, in addition to the geometric mean of farm productivity between the 2013/14 and 2015/16 waves. The number of observations differ slightly across cases because we apply a consistent trimming of the farm-TFP distribution as described in Section 3.1.

we keep inputs unchanged while recalculating output using these new measures of farm productivity to be consistent. We find that all of the alternative plot-based measures of productivity yield very similar results to our benchmark efficiency gain, see Table 11, panel (a). The (geometric) average for instance produces an efficiency gain of 3.64-fold, which is slightly larger than our benchmark specification of 3.07-fold. The median yields an efficiency gain of 3.54-fold, and the second max of 3.58-fold. The Spearman's ranking correlation between the alternative measures of productivity and our baseline farm-level productivity are high: 0.74 for the (geometric) average plot, 0.72 for the median, and 0.59 for the second max.

7.2.2 Panel-based farm productivity

We also explore the panel structure of the data to construct a set of analogous measures of farm productivity. Ultimately, we want our re-allocation exercises to be conducted using measures of productivity that abstract from potential transitory variation. For example, although we control for temporary shocks, such as rainfall, it could be the case that, when computing our cross-sectional benchmark farm-level productivity, the cross-sectional variation does not net all temporary components of farm-level TFP. This is important, as we do not want to mistakenly attribute a larger optimal scale to farm i simply because it received a positive output shock relative to other farms.

As discussed earlier, we can calculate farm productivity separately for each year in the panel and calculate the geometric mean of farm productivity across years.[33] We also use our panel to construct (geometric) averages of plot-level productivity across waves where plot-level productivity per wave takes the form of averages, median and second max.

The results of this analysis are in Table 11, panel (b). In all cases, the efficiency gains are similar to the cross-sectional benchmark gains. The Spearman's ranking correlations between the panel-based productivities and the benchmark cross-sectional productivity are large and positive, between 0.47 and 0.77. Overall, we conclude that measurement error is unlikely to be driving our quantitative results.

[33] Note that not all farms in the 2013/14 wave are in the 2015/16 wave and so, for these farms, we use the 2013/14 productivity level in order to keep the sample of farms the same as in our cross-section analysis. If we focus on a balanced panel, the efficiency gains in 2013/14 would be larger at 3.20-fold, instead of 3.07-fold.

Table 12: Misallocation within Crops

Crop	Number of Farms (%)	Cultivated Land (%)	Dispersion in TFPR_i	Efficiency Gain
Maize	56.7	12.5	1.18	3.29
Sorghum	42.7	14.9	1.03	2.50
Tea Leaves	40.3	10.8	1.00	3.82
Coffee	29.3	7.3	1.53	4.22
Wheat	25.2	3.0	1.09	2.35

Notes: List of the five most common crops in Ethiopia. Column 1 reports the percentage of household farms cultivating at least one plot with a particular crop. Column 2 reports the percentage of land used to cultivate a given crop. The last two columns report the dispersion of TFPR and the efficiency gains, as defined in Section 3, when we focus only on farm plots of a single crop. Data for the Ethiopia ISA 2013/14.

7.3 Misallocation within Crops

Farmers in Ethiopia cultivate a variety of crops with maize, sorghum, and tea leaves being among the most produced crops by farms. Since our production function specification is common across farm households who may be producing different crops, differences in composition of production can generate dispersion in marginal products across farm households. To address this issue, we explore the extent of misallocation within each crop using our plot-level data.

The data records the crop cultivated in each plot operated by a household. We then focus on an individual crop indexed by c. We keep all land plots cultivating crop c, aggregate inputs and outputs of these plots to the household level, and then repeat the analysis in Section 3 to calculate the extent of misallocation and economy-wide efficiency gain.

Table 12 reports the results for five different crops, which are the most widely cultivated in Ethiopia. We find that within crops, both the extent of misallocation measured by the dispersion in log TFPR, and the efficiency gain from reallocation are fairly similar to our baseline farm aggregate. For instance, more than half of all farmers produce maize and, for this crop, the dispersion in log TFPR is 1.18 and the efficiency gain is 3.29-fold (compared with 1.06 and 3.07-fold in our baseline).

7.4 Land Quality Differences in Rented Land

Another concern is whether there are any land quality differences between rented and non-rented land. Recall that we control for land quality throughout our analysis so our computations of efficiency gains already incorporate direct data on land quality. The concern here is different and it has to do with the possibility that rented land is of higher quality. This might have implications for the effects of land rentals on aggregate productivity. We assess this possibility using our plot-level data. We construct land quality at the plot level in the same way we constructed land quality at the household level in Section 3 and then compare land quality between rented and non-rented plots. The Welch's t-test shows that land quality q is only about 3 percent higher among the rented land plots than the non-rented plots, and the difference is not statistically significant.

8 Conclusions

Land rentals provide a useful mechanism to overcome imbalances between the allocation of land-use rights and the efficient operational scale of farms. We reach this conclusion by exploiting policy-driven variation in land rentals across time and space in Ethiopia derived from a land certification reform implemented at the local level. The context is relevant because land sales are prohibited by law, and land-use rights are fairly uniformly distributed among rural farm households. Hence, land rental is the only channel that allows for the reallocation of farms' operational scale.

Our main finding from the variation in rentals across regions and time is that a one percentage point increase in land rentals leads, on average, to an increase in agricultural productivity of 0.49 percent per zone. We also find that the effect of land rentals is roughly three times larger for the quartile of farms farthest away from their efficient operational scale relative to the average. The effects of land rentals on misallocation and agricultural productivity are also much larger when controlling for non-market rentals—those with a pre-harvest rental rate of zero. These results highlight the importance of land reforms in poor countries that specifically address the tradability of the land through rentals to promote better resource allocation and not simply tenure security—the latter of which has been the main focus in most reform episodes. In particular, developing land rental markets can be a powerful policy instrument for countries aiming at increasing agricultural productivity while, at the same time, preserving the egalitarian nature of land ownership.

Despite the strong positive effect of land rentals on resource allocation and agricultural productivity, we have shown that substantial misallocation remains in Ethiopian agriculture. Therefore, even though land rentals help achieve a better allocation of resources, farms continue to operate far from their efficient allocation overall, suggesting that land markets are still limited and subject to various frictions. These frictions may include remaining restrictions on rentals but rental activity may be hindered by other imperfections in the economic environment such as weak legal institutions. The fact that more than 90 percent of rentals occur among relatives and friends and that a substantial portion of these rentals are set at a pre-harvest rental rate of zero are indicative of imperfections in the institutional environment. Further investigation of the determinants and characteristics of rentals is clearly warranted.

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