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

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Abstract

We assess the effects of land markets on misallocation and productivity using a quantitative macroeconomic model with heterogeneous household-farms facing institutional barriers to land markets. We combine our model with micro panel data in order to exploit effective variation in land rentals across time and space in Ethiopia—where land remains owned by the state. A policy experiment in the model that reduces zone-specific institutional barriers to land markets that replicates actual changes in land rentals across time and space shows that rentals have substantial effects on misallocation and agricultural productivity. Further, eliminating existing rentals reduces agricultural productivity by 15 percent, whereas increasing rentals to the efficient level would attain an additional productivity gain of 18 percent. The model also shows that land rentals significantly *reduce* farm income inequality.

Keywords: Land, Markets, Rentals, Effects, Misallocation, Productivity, Inequality, Panel Data, Formal, Informal.
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1 Introduction

What are the effects of land markets on resource allocation and agricultural productivity? This question is important for many poor countries in which land transactions are either prohibited by law or face high transaction costs (Binswanger and Rosenzweig, 1986; Rosenzweig and Binswanger, 1993). The advocates of these prohibitions base their arguments on the lack of evidence in favor of the efficient use of resources generated from land markets and on the notion that common or customary tenure—as opposed to the private titling of land—keeps inequality and landlessness in check. Indeed, many governments and institutions justify "against-market" land policy on these grounds in poor countries. In these settings, the ownership of land typically resides with the collective or the state and land use rights are distributed by local leaders on an egalitarian basis. However, although long-lived land-use rights can help improve land tenure security and generate investment (Besley, 1995), they do not necessarily entail the right to sell or rent, which prevents land transactions and reallocations (Galiani and Schargrodsky, 2011). Unfortunately, despite the importance and large efforts devoted into understanding land markets, the answer to whether land markets improve resource allocation and productivity as well as its implications for equity remain elusive. We study the effects of land rental markets on agricultural productivity and inequality using both empirical microeconomic evidence and a quantitative macroeconomic model. We find that increases in land rentals substantially improve agricultural productivity and reduce farm income inequality.

Ethiopia provides a unique and relevant context to investigate the effects of land markets on productivity. 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. Although land ownership still resides with the state, many of the restrictions to land transactions remain in place and in a manner that differs across regions in Ethiopia. Indeed, using representative panel data that catches the reform in the 2010s—in three waves 2011/12, 2013/14, and 2015/2016—we find large variation in land rental market activity across space and time. A potential explanation for this variation in land market activity is the land certification reform launched in the 2000s that granted land certificates to farmers that allowed land to be reallocated across farmers via rentals (up to a limit) of the use rights (Holden and Ghebru, 2016). An interesting aspect of this land reform is that the granting of land certificates—and, hence, the lifting of barriers to land rental market activity—was decentralized and implemented by local governments with different intensity and timing across zones (i.e., sub-regions) as opposed to being contemporaneously implemented by the central government (Deininger et al., 2008). In addition, land rental decisions may depend on factors other than the holding of a land-use certificate such as the state of rule of law, complementary institutions, and remaining fears of expropriation.[1] Altogether, this layout provides us with unique variation in land rentals across time and space that we exploit in our analysis.

We provide micro empirical evidence on how changes in land rental market activity relate to changes in resource allocation comparing (reference) zones that do not feature increases in land rentals with (non-reference) for which land rentals increase. Our main empirical finding is that increases in land rentals are associated with reductions in resource misallocation. These effects are non-linear as they are stronger for farms further away from their efficient operational scale. We further evaluate the empirical effects for zones that initiate land rental markets and across zones that differ in the maturity of their land markets. In both cases we reach similar insights that adopting and maturing land rental markets contribute to a reduction in resource misallocation and increases in agricultural productivity.

We then develop a quantitative macroeconomic model with household-farms that are heterogeneous in their permanent productivity and face zone-specific institutional barriers to accessing land rental markets summarized by a cost parameter. We calibrate the level of these institutional costs separately for each zone in order to match the extent of land rental market activity in each zone. We denote the implied allocations in this calibration procedure as *status quo*. Then, we conduct a policy experiment on the *status quo* allocations through a land reform that we formalize as an exogenous and unexpected reduction in the institutional costs. Specifically, we change the costs in each zone in order to match the

[1] For example, our panel data collected in the 2010s potentially captures a lagging behavior between the granting of land certificates and the farms' engagement in land rental activity. A plausible explanation for this lagging is the potential lack of trust in the institutional reform (Ostrom, 2010), which could be driven by the fact that Ethiopian farmers have witnessed a recent past with recurrent governmental land expropriations (Gottlieb and Grobovšek, 2018).

actual zone-level changes over time in land rental activity observed in the data. This policy experiment generates a new set of *counterfactual* allocations in which the zone-level land rental activity in the model matches the land rentals in the data after the reform. We then use the model-generated farm-level *status quo* and *counterfactual* allocations in each zone to estimate the effects of land rental markets on resource misallocation and agricultural productivity using the same empirical specification as the one previously implemented on the data. Our main result is that an increase in land rentals generates a significant decline in resource misallocation. On average, a one percentage point increase in land rentals generates an increase in productivity of 2.9% within zones. Moreover, these model-generated effects are very close in magnitude to the empirical evidence which gives us confidence that our model is a useful tool to further assess the effects of land rentals. In particular, we use our model to assess the scalability of the land markets effects and the implications for inequality.

We study the scalability of the land markets effects by either increasing or decreasing the institutional costs through a set of model *counterfactual* experiments. We find that eliminating rentals—i.e. increasing the institutional costs from *status quo* to infinity—reduces agricultural productivity by 15 percent on average. Instead, increasing rentals to the efficient level—i.e., decreasing the institutional cost from *status quo* to zero—we attain an additional productivity gain of 18 percent. These effects are quite heterogeneous across zones since the gains depend on the pre-existing extent of misallocation. This context-dependence shows that zones without land market activity that face the largest efficiency gains require a land market activity of a scale similar to the that of the median (in terms of efficiency gains) zone with land market activity suggesting that the land market effects are relatively scalable.

A critical aspect of the political discourse on land policy in poor countries is whether land rentals enhance or reduce farm income inequality (Deininger and Binswanger, 1999; Deininger and Feder, 2001). A complete assessment of the effects of land rental markets on inequality is challenging as it requires data that is typically not available such as the record of all land rental payments and receipts. Instead, we use our model-generated *status quo* and *counterfactual* allocations to construct measures of within-zone farm-income inequality and assess the effects of land markets on inequality with a difference-in-difference strategy on model-generated data. We find that the increase in land rental market activity substantially reduces zone-level inequality for a wide range of inequality measures.

Our paper is related to a growing macroeconomic literature on agricultural productivity and its importance in accounting for cross-country income per capita differences.[2] The measurement of the extent of misallocation in poor countries has been emphasized using micro panel data in Restuccia and Santaeulàlia-Llopis (2017) and Gollin and Udry (2017). In sharp contrast, our interest is on the changes in the extent of misallocation due to the effects of land markets—and not on the extent of misallocation *per se*. If emerging land markets produce positive effects on resource allocation and productivity, then we have identified underdeveloped land markets as one source—among potentially many others—of factor misallocation (Restuccia and Rogerson, 2017). In this context, our paper also relates to the studies on the role of institutions that impede economic development (Acemoglu et al., 2001; Banerjee et al., 2002; Banerjee and Iyer, 2005). We focus on barriers to accessing land markets and how this micro distortion matters for macro agricultural productivity using effective variation across space and time in land market activity, an approach common in development (Besley and Burgess, 2000; Banerjee and Iyer, 2005; Giné, 2005; de Janvry et al., 2015). Further, land reforms have been studied extensively (Deininger et al., 2008, 2011; Chari et al., 2017). Our contribution is the integration of micro empirical evidence and quantitative macroeconomic theory, providing a comprehensive aggregate assessment of land reallocation effects triggered at the micro level. In this context, our work relates to a recent strand of the development literature that combines empirical approaches and theory such as Mobarak and Rosenzweig (2014), Bryan et al. (2014), Lagakos et al. (2018), and Meghir et al. (2019).

In Section 2, we describe the data, the institutional background and the land market activity in Ethiopia. Section 3 presents the theoretical framework and the qualitative effects of land markets. Section 4 discusses the empirical evidence. Section 5 quantifies the effects of land markets on resource allocation and productivity using *counterfactual* policy experiments. Section 6 studies the inequality implications of land rentals. Section 7 concludes.

[2] See, for example, Gollin et al. (2002, 2004, 2007), Restuccia et al. (2008), Adamopoulos (2011), Lagakos and Waugh (2013), Adamopoulos and Restuccia (2014), Gollin et al. (2014), Donovan (2016), Chen (2017), Adamopoulos et al. (2017), and Chen (2020).

2 Data and Institutional Background

Data. We use household-level panel data from the World Bank, the Ethiopia Integrated Survey of Agriculture (ISA), for all available waves 2011/12, 2013/14, and 2015/16. The ISA's provide information over the entire process of crop production, including physical measures of farm inputs and outputs. These are representative surveys of the population, with approximately 5,250 households interviewed per wave of which two thirds live in rural areas and work in agricultural production. Households are surveyed twice in a year: the first round occurs during the planting season, and the second round 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 factor inputs, outputs, and total factor productivity (TFP) at the household-farm level. A household-farm typically consists of several plots of land; we therefore aggregate the inputs and outputs of these plots to the household level. We describe in detail our variables of output, capital, land quality, land, and labor input, as well as transitory shocks such as rain, in Appendix A.

The panel dimension of the Ethiopia ISA data is key in two aspects of our analysis. First, we use the panel dimension of our survey data to compute a permanent component of individual farm TFP. This permanent component—or fixed effect—captures unobserved heterogeneity in productivity. We use this benchmark productivity to conduct our reallocation exercises. Second, we use the land market activity variation across time and space of land rentals in Ethiopia to provide empirical evidence of the relationship of rentals on aggregate productivity with an empirical strategy that requires the household-farm panel structure.

Institutional Background. 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. Farmers with these land certificates are allowed to rent out land with varied restrictions, but not to sell land because land is entirely owned by the state.

Land market activity across space and time. We measure land rental market activity, $R_{z,t}$, as the ratio between the size of total rented land and the size of total cultivated land in a given zone z and period t. Despite the land reform, the land rental market is relatively under-developed in Ethiopia. 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 (Holden and Ghebru, 2016). We find a rich variation in land rentals in Ethiopia, see Table 1.[3] The nationwide percentage of rented land is 10.9 in 2013/14. This percentage differs greatly across space with many zones with no land rental market activity, there are 8 zones with no rental market activity in 2013/14, and other zones with more than 60 percent of cultivated land being rented. Across time between 2013/14 and 2015/16, there is a substantial and heterogeneous increase in land rental market activity. While 34 zones out of 67 zones did not experience an increase in land rentals, 7 zones experienced land rental increases by at least 10 percentage points, and 3 zones experienced rental increases of more than 15 percentage points. Out of the 8 zones

[3] There are four levels of administrative divisions in Ethiopia: regions (states), zones (counties), woreda (districts), and kebele (wards). For the 2013/14 sample, we have farm location information down to the kebele level. We have a total of 2,877 observations, located across 10 regions, 73 zones, and 272 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.

Table 1: The Share of Land Rentals across Time and Space (Zones)

	Percent						Obs.
	Aggregate	Min.	10 pct	Median	90 pct	Max.	#
$R_{z,2013/14}$	10.9	0.0	0.0	5.2	24.7	66.0	67
$R_{z,2015/16}$	11.5	0.0	0.0	6.3	27.7	73.2	67

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

with zero rentals in 2013/14, 6 zones have positive rental market activity in 2015/16.

The fact that the lifting of barriers to land rental market activity was implemented by local governments with different intensity and timing across zones (i.e., sub-regions) is likely to contribute to the current landscape of land market activity across space and time in Ethiopia. This is however hard to determine. For example, the granting of land certificates does not necessarily generate immediate land market activity, which is our object of interest. Indeed, we find that although land certificates have been already granted in all zones (at least partially), there are zones with granted land certificates where we do not observe land rental market activity at all through our entire sample period (from 2011/12 to 2015/16). We find that the certificates in these zones where (on average) granted in 2008. That is, we find zones in which farms do not engage in land rentals in the 2010s even though land certificates were granted in those zones in the 2000s. This suggests that certain lagging behavior between the granting of land certificates and land rental activity exists. That is, it is plausible that it takes time for farmers—who throughout their lifetime have been subject to recurrent land expropriations by the government in Ethiopia—to trust and use the new land rental entitlements. Indeed, during the launching of the land reform, local governments still illegally evicted landholders with de-facto imprisonment threats (ELTAP, 2007), which further depletes trust (Ostrom, 2010). For this reason, our analysis focuses on land rentals. Nevertheless, land rentals are clearly associated with the land certificate reform with a contemporaneous correlation within each year is also positive and significant: The Spearman's rank correlations between the two are 0.44 and 0.37 for the 2013/14 and 2015/16 waves, respectively, both of which are significant at the one percent level.

3 A Theoretical Framework

We develop a quantitative macroeconomic model to assess the effects of land rental markets on resource misallocation and productivity in Ethiopia.

3.1 Setup

Production. Our economy is populated by heterogeneous household farms indexed by i that differ in their permanent productivity, $s_i \in \{1, ..., S\}$. Each farm produces a homogeneous agricultural good using the following decreasing returns to scale technology:

$$\widetilde{y}_{it} = (s_i \zeta_{it})^{1-\gamma} \left(k_{it}^{\alpha} \ell_{it}^{1-\alpha}\right)^{\gamma},$$

where $\widetilde{y}_{it}$ is the output of farm i in period t (measured as value added net of intermediates such as fertilizer and seeds), k_{it} is the capital input and $\ell_{it} = q_{it} l_{it}$ is quality adjusted land input, where q_{it} is land quality and l_{it} is land size. Notice that household-farm productivity consists of a permanent component, s_i, that does not change over time and a transitory component ζ_{it} (e.g., rain shocks and illnesses). All variables are in per capita (hourly) terms following the idea that the reallocations of capital and land that we conduct across household farms are not accompanied by the reallocation of household members across farms since agricultural production is largely provided within family. Nevertheless, we conduct robustness to this assumption in Appendix C.

Two remarks are in order. First, we are interested in reallocations guided only by the permanent component of productivity s_i. For this reason, we use our panel data to recover this permanent fixed-effect component and measure the transitory shocks ζ_{it} as residual deviations from the permanent component. Second, we also use our rich data on land quality at the plot level to net its effects on output (see Appendix A). As a result, we define our benchmark output y_{it} as output net of transitory shocks and land quality,

$$y_{it} = \frac{\widetilde{y}_{it}}{\zeta_{it}^{1-\gamma} q_{it}^{(1-\alpha)\gamma}} = s_i^{1-\gamma} \left(k_{it}^{\alpha} l_{it}^{1-\alpha}\right)^{\gamma}, \qquad (1)$$

where $\gamma \in (0, 1)$ governs returns to scale at the farm level and α is a factor share parameter.

Measuring farm productivity. We use the micro data to estimate factor income shares to pin down the values for α and γ and use these parameters to measure farm productivity. We find that the capital, labor, and land shares are 0.147, 0.464, and 0.389, respectively. This implies that $\alpha = 0.274$ and $\gamma = 0.536$ (see Appendix B for details and a discussion of robustness to alternative values). Given values for α and γ, together with farms' actual inputs (including land quality) and outputs in the data, we recover farm-level productivity separately for each year, $s_i\zeta_{it}$, which is the product of a permanent s_i and transitory component ζ_{it}. We then use the panel data to recover our benchmark measure of permanent farm-level productivity s_i, which is constructed as the geometric mean of farm-level productivity across years. That is, our benchmark productivity measure s_i is equivalent to the outcome of an estimation of household-farm fixed effects of productivity (in logs) and, hence, it captures permanent unobserved heterogeneity across farms. After observing the implied distribution of productivity we trim approximately 0.8 percent of the farm productivity distribution to remove candidate outliers which may reflect measurement error in inputs and outputs. A more systematic (and aggressive) trimming of one percent of the productivity distribution on both tails barely changes the dispersion in log productivity, a standard deviation of 0.75 compared with a benchmark 0.79. Notice that although farm productivity s_i is invariant to time, farm output and factor inputs can change over time (see equation (1)). However, for the ease of notation, we drop time subscripts for all variables in our analysis from now on.

Farm problem. Extending the production framework, we assume that each household farm is endowed with $\bar{l}$ units of land and can rent capital and land taking costs as given. Farms choose their operational scale solving the following profit maximization problem:

$$\max_{k_i, l_i} \pi(s_i, \bar{l}_i) = s_i^{1-\gamma} \left(k_i^{\alpha} l_i^{1-\alpha}\right)^{\gamma} - rk_i - c(l_i, \bar{l}_i), \tag{2}$$

where l_i and $\bar{l}_i$ denote the land operational scale and endowment. The function $c(l_i, \bar{l}_i)$ represents the cost of changing the amount of land operated relative to the endowment. This cost combines the rental cost of land with a land transaction cost that captures the institutional barriers to accessing land rental markets determined by, for example, the amount of land certificates distributed in given zone that allow for rentals. We write this cost as

$$c(l_i, \bar{l}_i) = q(l_i - \bar{l}_i) + b(l_i, \bar{l}_i), \tag{3}$$

where q is the rental rate of land, $q(l_i - \bar{l}_i)$ the rental payment (receipt) of land if $l_i > \bar{l}_i$

($l_i < \bar{l}_i$), and $b(l_i, \bar{l}_i)$ represents the institutional barrier to accessing land rental markets. We assume a standard quadratic adjustment cost function $b(l, \bar{l}) = \frac{\chi_z}{2}(l - \bar{l})^2$, where $\chi_z \in [0, \infty)$ is a zone-specific component capturing the difficulty of accessing to land rental markets within a given zone (a geographical area) z. Note that this functional form satisfies basic properties such that $b(\bar{l}_i, \bar{l}_i) = 0$, $b(l_i, \bar{l}_i) > 0$ for all $l_i \neq \bar{l}_i$, and increasing in the distance between l_i and $\bar{l}_i$ at an increasing rate.

Equilibrium. Denote the optimal inputs solved from the profit maximization problem (2) as $l^*(s_i, \bar{l}_i)$ and $k^*(s_i, \bar{l}_i)$. Given a a set of land endowments and productivity among S farmers $(s_i, \bar{l}_i)$ and the aggregate amount of capital K, an equilibrium is a set of allocations (l_i^*, k_i^*) and prices (r, q) such that: (i) Given prices (q, r), farm allocations (l_i^*, k_i^*) solve problem (2) and (ii) land and capital rental markets clear, that is, $\sum_i l^*(s_i, \bar{l}_i) = L = \sum_i \bar{l}_i$. and $\sum_i k^*(s_i, \bar{l}_i) = K$. We describe a solution algorithm for the equilibrium in Appendix D.

3.2 Theoretical Effects of Land Rental Markets

We use our theoretical framework to qualitatively examine the effects of access to land rental markets in order to guide us in the empirical and quantitative analyses. Since we are interested in resource allocations within zones z, we separately solve for equilibrium allocations within zones—subject to aggregate zone-specific capital K_z and land L_z.

We define the total amount of rentals (share of rented land) in a given zone as

$$R_z = \frac{\sum_i (l^*(s_i, \bar{l}_i) - \bar{l}_i)\mathbb{1}(l^*(s_i, \bar{l}_i) > \bar{l}_i)}{\sum_i \bar{l}_i}, \tag{4}$$

where $\mathbb{1}(l^*(s_i, \bar{l}_i))$ is a binary variable which is equal to one if farmer i rents in land and zero otherwise. We use this binary variable to prevent double counting rented land.

Efficient allocation ($\chi_z = 0$). We start by focusing on the efficient allocation, achieved in equilibrium when $\chi_z = 0$. It is straightforward to show that when $\chi_z = 0$, equilibrium allocations are, after solving for the equilibrium prices, given by

$$l^*(s_i, \bar{l}; \chi_z = 0) = l^e(s_i) = \frac{s_i}{S_z} L_z, \tag{5}$$

where $S_z = \sum_{i \in z} s_i$. That is, operated land is proportional to farmer's productivity s_i. The solution for capital is analogous. Notice that in this case the initial endowment $\bar{l}_i$ does not affect the operational scale of land which is solely a function of individual productivity s_i. Clearly, in this case, land rentals are positive ($R_z > 0$) as long as land endowments $\bar{l}_i$ differ from the efficient allocations $l_i^e(s_i)$ for each and all i.

Farm output associated with the efficient allocation is

$$y^e(s_i) = s_i^{1-\gamma}(k_i^e(s_i)^\alpha l_i^e(s_i)^{1-\alpha})^\gamma = s_i\Big(\frac{K_z^\alpha L_z^{1-\alpha}}{S_z}\Big)^\gamma.$$

The zone-level aggregate output associated with the efficient allocation is

$$Y_z^e = \sum_{i\in z} y_i^e = S_z^{1-\gamma}(K_z^\alpha L_z^{1-\alpha})^\gamma,$$

which is the maximum aggregate output subject to the aggregate resource constraints.

Allocations with imperfect land markets ($\chi_z > 0$). When the institutional cost $\chi_z > 0$, the optimal farm operational land is the solution to following equation which results from operating the first order conditions from problem (2),

$$l_i^* = s_i \gamma^{\frac{1}{1-\gamma}} \left(\frac{\alpha}{r}\right)^{\frac{\alpha\gamma}{1-\gamma}} \left(\frac{1-\alpha}{q(1+\tau(l_i^*, \bar{l}_i))}\right)^{\frac{1-\alpha\gamma}{1-\gamma}}, \tag{6}$$

where $\tau(l, \bar{l}) = \chi_z(l - \bar{l})/q$ represents an *endogenous* land wedge (i.e., an implicit "distortionary tax" on the rental price of land). Since this wedge is increasing in l_i^*, there is a unique solution to this equation. Further, the optimal land operational scale depends on s_i and $\bar{l}_i$, hence we denote the solution as $l_i^*(s_i, \bar{l}_i)$. We can similarly solve for the capital input which is also indirectly affected by the land wedge.

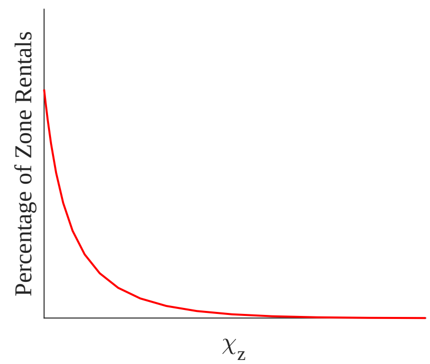
Recall that, absent the institutional cost ($\chi_z = 0$), land rentals are generally positive ($R_z > 0$) as long as the land endowments $\bar{l}_i$ differ from the efficient allocations $l_i^e(s_i)$ for each and all i. On the contrary, if the institutional cost is prohibitively high ($\chi \to \infty$), then the operational land of each farm is simply given by the land endowment,

$$l_i^*(s_i, \bar{l}_i : \chi_z \to \infty) = \bar{l}_i,$$

and rental markets collapse ($R_z = 0$). In the intermediate cases where $\chi_z \in (0, 1)$, land rentals R_z decrease with χ_z, see Figure 1. Provided land endowments are not efficient, then the amount of land rentals R_z indicates the institutional cost of land rentals χ_z.

Measures of misallocation. Equilibrium farm output is given by $y_i^* = (s_i^*)^{1-\gamma}[(k_i^*)^\alpha(l_i^*)^{1-\alpha}]^\gamma$.

Figure 1: Institutional Land Rental Costs (χ_z) and Equilibrium Land Rentals (R_z)



As long as $\chi_z > 0$, this output level $y_i^*(s_i, \bar{l}_i)$ is different from the efficient allocation $y^e(s_i)$, unless the distribution of $\bar{l}_i$ coincides with $l^e(s_i)$. Aggregate equilibrium output is then

$$Y_z^* = \sum_{i \in z} y_i^*(s_i, \bar{l}_i) \neq Y_z^e.$$

which differs from efficient aggregate output Y_z^e. Since efficient output is the maximum that can be attained with the given resources, $Y_z^* \neq Y_z^e$ must imply that $Y_z^* < Y_z^e$. The ratio of efficient to equilibrium output, indicating the *efficiency gain* of relocating resources,

$$e_z = \frac{Y_z^e}{Y_z^*} \geqslant 1, \tag{7}$$

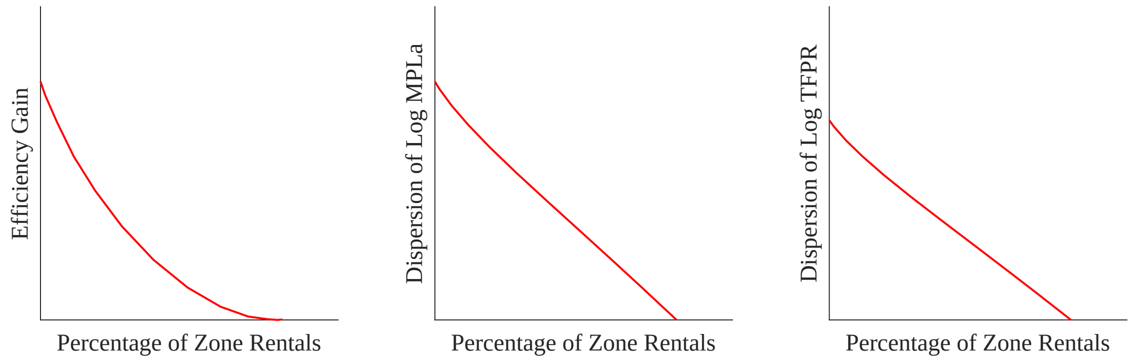
is our first measure of misallocation, with $e_z = 1$ only if $\chi_z = 0$. Intuitively, $\chi_z > 0$ reduces equilibrium land rentals R_z and hence prevents land from being allocated efficiently. As a result, e_z decreases with equilibrium rentals R_z, as illustrated in the left panel of Figure 2.

An alternative direct measure of the extent of misallocation is the dispersion in the marginal product of land among farmers within a zone. To see this, notice that if $\chi_z = 0$, then our economy reaches the *efficient* allocations by equalizing the marginal product of land across all farms in zone z. The *efficient* marginal product of land for each farm i is

$$\text{MPLa}_i^*(\chi_z = 0) = \text{MPLa}_i^e = (1-\alpha)\gamma \frac{y^e(s_i)}{l^e(s_i)} = (1-\alpha)\gamma \frac{Y_z^e}{L_z},$$

which is identical across farmers. This implies that the dispersion (standard deviation) of the MPLa_i across farms is zero in *efficiency* within a given zone, and strictly positive otherwise, i.e., with $\chi_z > 0$. Deviations from this *efficient* zero dispersion can be used to measure the extent of misallocation. Furthermore, it implies the negative relationship between equilibrium land rentals R_z and the dispersion of the MPLa_i as illustrated in the

Figure 2: Effects of a Land Rental Markets on Zone-Level Misallocation



Note: Zone-level misallocation, measured as the zone-level efficiency gain and the dispersion of marginal product of land or revenue productivity, against the percentage of zone rentals.

middle panel of Figure 2.

We also construct a widely used summary measure of misallocation as the dispersion of farm-level revenue productivity ("TFPR"). Under the *efficient* allocations in our framework, TFPR is give by

$$\text{TFPR}_i^*(\chi = 0) = \text{TFPR}_i^e = \frac{y_i^e(s_i)}{(k_i^e(s_i)^\alpha (l_i^e(s_i))^{1-\alpha}} = \frac{Y_z^e}{(K_z^e)^\alpha \,(L_z^e)^{1-\alpha}},$$

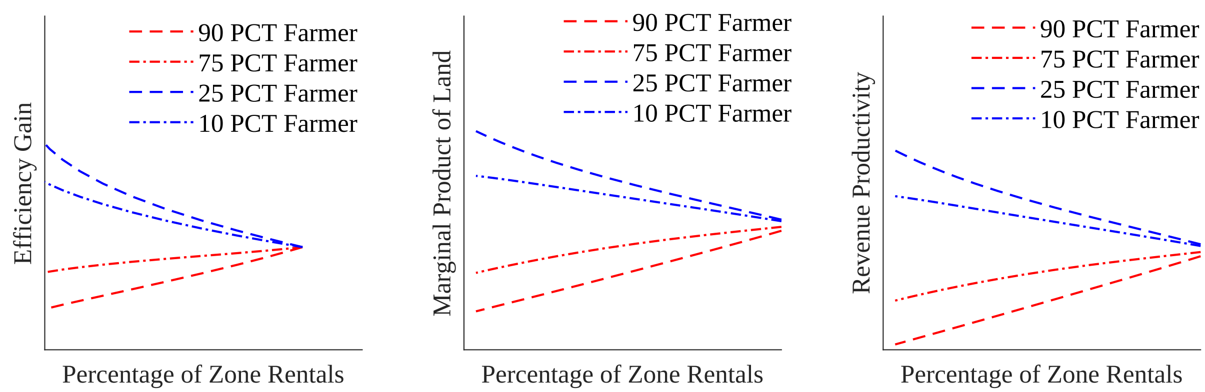
which is a constant and hence also equalized across farms. Therefore, we also use the dispersion (standard deviation) of TFPR across farms within a given zone to measure the extent of misallocation (Hsieh and Klenow, 2009; Adamopoulos et al., 2017). Similarly, a higher institutional cost χ_z reduces equilibrium rentals R_z, and then increases the dispersion of TFPR. The negative relationship between equilibrium rentals and the dispersion of TFPR is illustrated in the right panel of Figure 2.

We use the above three zone-level measures of misallocation in the quantitative analysis. In addition, we also construct corresponding measures of misallocation at the farm level to facilitate our empirical analysis. To do so, we define the farm-level efficiency gain as the ratio of efficient to equilibrium output, $e_i = y_i^e(s_i)/y_i^*(s_i, \bar{l}_i)$, which is equal to one when there is no misallocation. Similarly, we define the farm-level MPLa and TFPR as

$$\text{MPLa}_i = \frac{y_i^*(s_i, \bar{l}_i)}{l_i^*(s_i, \bar{l}_i)}, \quad \text{TFPR}_i = \frac{y_i^*(s_i, \bar{l}_i)}{l_i^*(s_i, \bar{l}_i)^{1-\alpha} k_i^*(s_i, \bar{l}_i)^\alpha}.$$

Absent misallocation, farm-level MPLa and TFPR should equal to their zone-level average and any deviation from zone average indicates misallocation. Intuitively, a land reform that

Figure 3: Effects of Land Rental Markets on Farm-Level Misallocation



Notes: The left panel plots the relationship between farm-level efficiency gain and zone-level land rentals. We sort farmers according to the ratio of equilibrium to efficient operational scale and plot the 10th, 25th, 75th, and 90th percentile of the distribution. The middle and right panels show the same relationship for the marginal product of land and the revenue productivity.

reduces χ_z increases land rentals within a zone which moves farm-level efficiency gains towards unity. The same occurs for MPLa and TFPR that move toward the zone average. Furthermore, the effects are non-linear in that the farmers that benefit most from the institutional change brought by the land reform are the ones that are the farthest away from their efficient operational scale. Figure 3 illustrates how the farm-level measures of misallocation converge across farms as the amount of land rentals increases within zones. Sorting farmers by the ratio of their equilibrium to efficient operational scale indicates that farms farther away from their efficient operational scale (10 and 90 percentiles Figure 3) benefit more from land rentals compared to those relatively closer to their efficient operational scales (25 and 75 percentiles in Figure 3).

4 Empirical Evidence

We exploit the variation in land rentals across time and space in the data to assess how changes in land market activity relate to changes in resource allocation and productivity. Our empirical analysis shows that increasing land rentals is associated with improvements in the efficiency of resource allocation and productivity. Land rentals clearly respond to effective barriers in rental markets but their changes may potentially also reflect a source of variation that affects misallocation and productivity. As a result, we are limited to interpret our empirical results as causal and instead assess the causal effects of rental markets in our quantitative analysis.

4.1 Main Empirical Results

To assess how changes in land market activity relate to changes in resource allocation and productivity we separate zones into two groups in our sample according to their behavior in terms of land market activity across waves. We define a reference group that consists of zones for which the share of rented land, R_z, does not increase between 2013/14 and 2015/16, and a complement non-reference group that consists of those zones for which land rentals increase in that period. We are interested in assessing whether there are differential changes over time in productivity across these two groups of zones, and by how much.

Empirical specification and main results. We focus on the following benchmark empirical specification:

$$m_{izt} = \alpha_z + \lambda_t + \psi d_{zt} + \beta \log \mathrm{TFP}_{iz} + \varepsilon_{izt}, \tag{8}$$

where m_{izt} is an individual measure of the degree 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} captures changes in land rentals. In the zones where the land market activity increases across waves the indicator variable d_{zt} equals one in the second wave, and in the reference zones d_{zt} equals zero. The parameter of interest is ψ, which captures how changes in land rentals relate to changes in individual farm-level misallocation. We also control for the permanent component of individual farm-level TFP.

We use three specific measures of farm-level misallocation: (a) farm-level efficiency gain, $|\log(y^e_{izt}/y^a_{izt})|$, where y^e_{izt} is efficient output of farm i in a zone and y^a_{izt} is actual output in the data; (b) farm-level marginal product of land (MPLa_{izt}) relative to the zone-level average, $|\log(\mathrm{MPLa}_{izt}/\overline{\mathrm{MPLa}}_{zt})|$; and (c) farm-level revenue productivity (TFPR_{izt}) relative to the zone-level average, $|\log(\mathrm{TFPR}_{izt}/\overline{\mathrm{TFPR}}_{zt})|$. Notice that deviations from efficient allocations may imply efficiency gains or loses and therefore the ratio in logs between efficiency values and actual data can take positive or negative values. For this reason, we consider the absolute value of the log efficiency gains. This implies that we can unambiguously interpret a negative

Table 2: Land Rental Markets, Misallocation, and Productivity

(a) Benchmark Specification

Dependent variable:	Farm-Level Misallocation		
	Efficiency Gain	MPLa	TFPR
Land Rentals (d_z)	-0.132	-0.192	-0.151
	(0.048)	(0.065)	(0.065)
Observations	4,712	4,712	4,712
R^2	0.23	0.12	0.16

(b) Quantile Specification

Dependent variable:	Farm-Level Misallocation		
	Efficiency Gain	MPLa	TFPR
ψ_{Q1}	-0.034	-0.087	-0.007
	(0.041)	(0.067)	(0.067)
ψ_{Q2}	-0.054	-0.062	-0.077
	(0.045)	(0.048)	(0.050)
ψ_{Q3}	-0.128	-0.098	-0.099
	(0.048)	(0.048)	(0.055)
ψ_{Q4}	-0.278	-0.379	-0.362
	(0.105)	(0.138)	(0.137)

Notes: Results of regression (8) in panel (a) and of regression (9) in panel (b) for the following measures of farm-level misallocation: (1) efficiency gain $|\log(y^e_{izt}/y^a_{izt})|$, where y^e_{izt} is efficient output and y^a_{izt} is actual output in the data, (2) marginal product of land (MPLa_{izt}) relative to the zone-level average, $|\log(\text{MPLa}_{izt}/\overline{\text{MPLa}}_{zt})|$, (3) revenue productivity (TFPR_{izt}) relative to the zone-level average, $|\log(\text{TFPR}_{izt}/\overline{\text{TFPR}}_{zt})|$. Standard errors are calculated using block-bootstrap clustering at the zone level and are reported in parentheses. Data from Ethiopia ISA 2013/14 and 2015/16 waves.

(positive) estimate for ψ as a movement towards (away from) efficiency.

Our main empirical findings are reported in Table 2, panel (a), where standard errors are calculated using block-bootstrap clustering at the zone level and are reported in the parentheses. Using farm-level efficiency gains, we find that land rentals are associated with a significant decline in resource misallocation. The increase in land rentals is related to a decline in efficiency gains with a significant coefficient of ψ equal to -0.132. The estimated ψ using the other measures of farm-level misallocation, MPLa and TFPR, is also negative and significant with respective values of -0.192 and -0.151. Stinger selection of zones into the non-reference group renders larger effects, in particular, restricting the set of non-reference zones to those that increase rentals by more than one percent, we find estimates of ψ of -0.156 for efficiency gains, -0.236 for MPLa, and -0.212 for TFPR.

The previous results captures how land rentals relate to farm-level measures of misallocation on average. However, our theoretical framework implies that efficiency gains are larger when resources are reallocated among farmers with the larger 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 our measure of misallocation in the base year, m_{iz}, into four quantile groups (quartiles) and run the following regression separately for each group:

$$m_{izt} = \alpha_{Qz} + \lambda_{Qt} + \psi_Q d_{zt} + \beta_Q \log \text{TFP}_{iz} + \varepsilon_{izt}, \tag{9}$$

where the first quantile ($Q1$) represents farms that are closest to their efficient operational scale, and the last quantile ($Q4$) consists of farms that are farthest from their efficient operational scale. In this quantile specification, the non-reference and reference groups are defined within each quantile. For instance, for Q4, we compare the farmers farthest from efficiency in zones where rentals increase to those who are also farthest from efficiency in zones whose rentals do not increase.

Our findings are reported in panel (b) of Table 2. The relationship between land rentals and misallocation is nonlinear, consistent with the theoretical framework. Specifically, land rentals are not associated with much changes in efficiency gains for farmers that are already close to their efficient allocation. The negative relationship between land rentals and efficiency gains starts to be significant in the third quantile, with $\psi_{Q3} = -0.128$, and substantially increases as we move away from efficiency with significant elasticities of $\psi_{Q4} = -0.278$ in the fourth quantile. With a simple back of the envelope calculation, these coefficients imply that a one percentage point increase in land rentals is associated with 3.2% higher productivity (see Appendix E). The results are stronger with other farm-level measures of misallocation, MPLa and TFPR, see the last two columns in panel (b) of Table 2.

In sum, our empirical analysis shows that a more active land market is associated with reductions in resource misallocation and therefore increases in agricultural productivity. These empirical findings are robust to alternative measures of misallocation. Also, the fact that we exploit variation across zones and over time underscores alternative explanations for the relationship between land rentals and misallocation such as mis-specification or measurement error in inputs or output, particularly in the average specification although to a lesser extent in the non-linear specification. Further, our results continue to hold if we additionally control for other household characteristics or potential output market frictions; see Appendix C.

4.2 Additional Empirical Results

In addition to our main empirical results that more active land rentals are overall associated with reductions in resource misallocation, we also use our data to explore more specific aspects of this relationship. Particularly, we assess how the magnitude of the correlation between land rentals and misallocation vary in the following contexts: (1) focusing on zones starting from zero rentals—the extensive margin, (2) comparing zones with mature versus emerging rental markets, and (3) comparing formal versus informal land rentals.

The extensive margin. Our sample contains zones for which the land market activity is nonexistent throughout and zones with no active rental market in 2013/14 that become active in 2015/16. This allows us to assess the relationship between the "extensive" margin of land markets and resource misallocation. There are eight zones for which rented land is zero in 2013/14, with two zones featuring zero land market activity in 2015/16 (reference group) and six zones featuring positive land market activity in 2015/16 (non-reference group). We use our empirical specification (8) with dummy $d_{zt} = 1$ for the non-reference group defined by $R_{z,2013/14} = 0$ and $R_{z,2015/16} > 0$, and $d_{zt} = 0$ for the reference group defined by $R_{z,2013/14} = R_{z,2015/16} = 0$. Clearly, the extensive margin analysis is much more demanding on our data than the one focused on the overall land market as our sample reduces to a total of 332 households. We find that, compared with the reference group without land rentals, zones that start land market activity in 2015/16 largely reduce misallocation in all measures, see panel (a) of Table 3. Interestingly, the point estimates are approximately 50 percent larger with this smaller sample than those obtained for the overall land marekts. Not surprisingly, given the fewer number of observations, the standard errors are larger in the current specification, but still find a significant association at the ten percent level for efficiency gain and MPLa.

Maturity of land markets. We also assess the relevance of the maturity of land markets.

Table 3: Land Rentals and Misallocation, the Extensive Margin

	(a) Extensive Margin			(b) Maturity of Land Markets		
	Eff. Gain	MPLa	TFPR	Eff. Gain	MPLa	TFPR
Land Rentals, ψ	-0.184	-0.240	-0.241	-0.135	-0.259	-0.252
	(0.108)	(0.135)	(0.243)	(0.075)	(0.118)	(0.135)
Observations	332	332	332	1,378	1,378	1,378
R^2	0.10	0.15	0.16	0.23	0.18	0.17

Notes: Results of regression (8) for three measures of farm-level misallocation: (a) efficiency gains, (b) marginal product of land, (c) revenue productivity. Standard errors are calculated using block-bootstrap clustering at the zone level and are reported in parentheses. Data from Ethiopia ISA 2013/14 and 2015/16 waves. Panel (a) compares zones without no land rentals with zones with positive rentals in 2015/16 but not in 2013/14. Panel (b) compares zones with substantial (mature) land rentals in both waves to zones with emerging land rentals.

To do so, we instead compare zones with substantial and established land rentals (zones where land rentals are consistently above 20% in both 2013/14 and 2015/16) with zones featuring emerging land rentals (zones where rentals increase but have less than 10% of land rentals in 2015/16). The threshold choices follow the idea that after the land reform the amount of land rentals increase only gradually and hence the extent of land rentals reflects at least partially the maturity of land markets. The implied sample comprises approximately one third of our original sample of households. The results are reported in panel (b) of Table 3. Compared with mature zones where land market activity is more established, emerging zones largely and significantly reduce misallocation in all measures.

Formal and informal land rentals. Land markets in economies with rich histories of tensions in land arrangements such as Ethiopia may not effectively direct resources to best uses. A nice feature of our dataset is that it provides information about whom the land is rented from. Using this information we find that among the households that rent in land the vast majority rent land from relatives (46 percent) and friends (36 percent). This suggests that land reallocations may obey other goals such as redistribution or the provision of social insurance (Kinnan and Townsend, 2012; Munshi and Rosenzweig, 2016).[4] Since land rentals from relatives and friends are not necessarily ineffective, we instead use the available information on land rental payment arrangements agreed before cultivation between the

[4]See also Rosenzweig and Stark (1989), Townsend (1994); Udry (1994), De Magalhães and Santaeulàlia-Llopis (2018) and Morten (2019); Kinnan (2019).

renter and the rentier to attribute a land rental as either formal or informal. In particular, if a rental contract specifies a plot to be rented for free, then it is likely that this land rental is not market-based and that other considerations are at play. Following this idea, we define informal land rentals as those that are stipulated to be for free (zero rental payments) in the rental contract and formal rentals as those for which the rental contract stipulates a non-zero rental payment. Extending the definition of informal rentals as those with small nominal payments agreed in the rental contract delivers similar results. Notice that our definition of formal rentals—which adds stipulated payments in cash and in kind—includes sharecropping contracts (Shaban, 1987; Sadoulet et al., 1997; Burchardi et al., 2018) as long as the ex-ante agreed amount of shared crops between the renter and the rentier is nonzero.

We construct the indicator variable d_{mzt} to denote an increase of formal (market-based) land rentals of a zone: $d_{mzt} = 1$ if formal rentals increase in a zone and $d_{mzt} = 0$ otherwise. Similarly, we construct the indicator variable d_{nzt} to denote an increase of informal land rentals of a zone. Using these two dummies in our benchmark specification (8) controls for the effect of informal rentals:

$$m_{izt} = \alpha_z + \lambda_t + \psi_m d_{mzt} + \psi_n d_{nzt} + \beta \log \mathrm{TFP}_{iz} + \varepsilon_{izt}. \tag{10}$$

Results are in Table 4. In all three measures of farm-level misallocation, the effects of formal rentals on misallocation, captured by ϕ_m, is significant and approximately 25 percent larger than our benchmark results. In contrast, the role of informal rentals, captured by the coefficient ψ_n, is not only smaller but also not significant. Our results indicate that rentals reduce misallocation mainly operate through market forces rather than informal land rentals.

5 Quantitative Analysis

We use our quantitative macroeconomic model to study the effects of land markets. First, we assess the effects of a policy reform that consists of a reduction in the barriers to accessing land markets—which endogenously increases land rental activity—on resource allocation and productivity. Second, we assess the scalability of land rental market activity by considering *counterfactual* policy experiments on the barriers to land rental markets from scenarios where land rentals are strictly prohibited to scenarios where there are no barriers to land markets.

Table 4: Formal versus Informal Land Market Activity and Misallocation

Dependent variable:	Farm-Level Misallocation		
	Efficiency Gain	MPLa	TFPR
Formal Rentals (d_{mz})	−0.140	−0.207	−0.090
	(0.051)	(0.079)	(0.073)
Informal Rentals (d_{nz})	−0.004	−0.053	−0.054
	(0.047)	(0.074)	(0.072)
Observations	4,712	4,712	4,712
R^2	0.23	0.13	0.16

Notes: Results of econometric specification (10) with the three measures of farm-level misallocation: (a) efficiency gain, (b) marginal product of land, (c) revenue productivity. Standard errors are calculated using block-bootstrap clustering at the zone level and are reported in parentheses. Data from Ethiopia ISA 2013/14 and 2015/16 waves.

Third, we quantify how much the estimated barriers to land rental markets account for the full extent of misallocation within zones.

5.1 The Effects of Land Markets

Recall that the institutional cost χ_z—which represents barriers to accessing land rentals markets such as the granting of land certificates (or their lack of) or implicit institutional barriers to land markets—is endogenously related to land rentals in the model such that a reduction in χ_z generates an increase in the amount of land rentals. We use this theoretical relationship between χ_z and land rentals to calibrate χ_z in order to match actual land rentals, R_z, by zone in 2013/14 (see Appendix D for details of this calibration procedure). The calibrated model then matches the amount of land rentals per zone, R_z, for each of the 67 zones under study in 2013/14. The implied median value for χ_z is 1.67 and the range spans from 0.09 in the 5th percentile to more than 100 in the 95th percentile for the zones for which there are no rentals. Farm-level productivity and endowment $\{(s_i, \bar{l}_i\})$ are given by data. We refer to the calibrated equilibrium allocations as *status quo*.

In order to assess the effects of land markets on resource allocation and productivity, we conduct a policy experiment on the *status quo* allocations. We implement an unexpected reduction in the institutional costs, χ_z, that is, we change χ_z so as to match the change in land rental activity by zone between the two waves of data 2013/14 and 2015/16. We then

Table 5: Effects of Land Rental Markets on Productivity, Model *Conterfactual*

(a) Benchmark Specification

Dependent variable:	Farm-Level Misallocation		
	Efficiency Gain	MPLa	TFPR
Land Rentals (d_z)	-0.151	-0.171	-0.130
	(0.022)	(0.025)	(0.019)
Observations	4,712	4,712	4,712
R^2	0.52	0.47	0.52

(b) Quantile Specification

Dependent variable:	Farm-Level Misallocation		
	Efficiency Gain	MPLa	TFPR
ψ_{Q1}	-0.057	-0.071	-0.049
	(0.018)	(0.020)	(0.015)
ψ_{Q2}	-0.149	-0.164	-0.129
	(0.033)	(0.037)	(0.029)
ψ_{Q3}	-0.186	-0.211	-0.161
	(0.032)	(0.036)	(0.028)
ψ_{Q4}	-0.197	-0.223	-0.170
	(0.044)	(0.050)	(0.038)

Notes: Results of regression (8) in panel (a) and of regression (9) in panel (b) for the three measures of farm-level misallocation: (1) efficiency gain, (2) marginal product of land , (3) revenue productivity. Standard errors are calculated using block-bootstrap clustering at the zone level and are reported in parentheses. Model generated data calibrated to Ethiopia ISA 2013/14 wave.

compute the *counterfactual* factor input allocations at the farm level that result from this policy experiment. Note that this policy experiment, which is solely based on variation in χ_z to match variation over time in rentals by zone, does not target our empirical findings.

We use the model-generated *status quo* and *counterfactual* allocations to estimate the empirical specifications (8)-(9). Our main finding is that the results from the policy experiment in the model are very similar to our empirical findings. Panel (a) of Table 5 shows a significant average effect on efficiency gains of -0.151. Notice that the model-generated effect is not significantly different from the empirical findings on efficiency gains of -0.132 reported earlier. On average, a one percentage point increase in land rentals generates an increase in productivity of 2.9% within zones in the model and 3.2% in the data. Similarly, the quantile model-generated effects, reported in panel (b) of Table 5, are also similar to their empirical counterparts. Similar insights are obtained with the other two measures of misallocation.

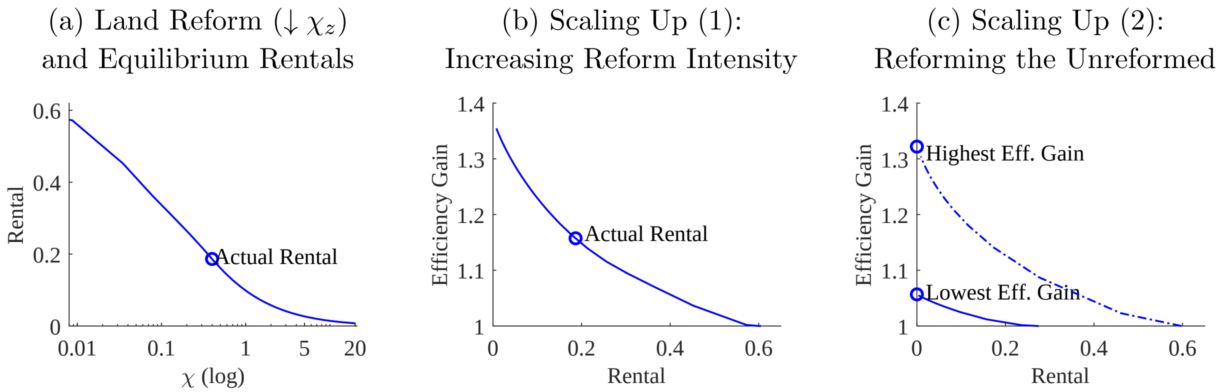
We emphasize that the model generated effects are entirely driven by our policy experiment, an unexpected change in a zone-specific policy parameter χ_z. Our finding that the model-generated and empirical results are similar validates our quantitative model and provides confidence on the implications of the model for other variables of interest and for counterfactual analysis. Importantly, the fact that the model-generated results account for most of the empirical findings indicates that other factors potentially driving the relationship between land rentals and misallocation are unlikely to be quantitatively important.

5.2 Scalability of the Land Market Effects

An important aspect for our macroeconomic policy analysis is the scalability of locally-implemented changes in the institutional costs associated with land markets. Scalability is not necessarily straightforward because of equilibrium effects and context dependence (e.g., the extent of pre-market resource misallocation). As a result, we cannot empirically assess the scalability of reducing the institutional costs that are a barrier to land rental market activity, but an advantage of our model-based analysis is that we can use our framework to conduct a set of *conterfactuals* that addresses this question.

First, we study whether scaling up the intensity of land markets, i.e., further reductions of the institutional barriers to land markets (i.e., χ_z), in zones with already land market activity imply further gains from reallocation. We show the effects of institutional barriers on the equilibrium rentals of our median zone (i.e., zone with median efficiency gains), see panel (a) of Figure 4. The *status quo* equilibrium is calibrated with χ_z so as to match the actual land rentals in the median zone (19 percent of total land) which implies efficiency gains of 16% in that zone. Clearly, *counterfactual* reductions in the institutional costs increase equilibrium land-rental market activity. In this context, we find that scaling up the intensity of land market activity beyond the *status quo* rentals generates further efficiency gains, see panel (b) of Figure 4. However, the scaling-up effects diminish in economies with larger land rental market activity. For example, a reduction in institutional barriers that generates equilibrium land rentals above 57 percent imply additional efficiency gains below 1%, setting an upper bound for scalability. Clearly, economies with substantial land rental market activity are

Figure 4: Scaling Up or Down the Land Reform via Changes in χ_z



Note: Panel (a) shows how land rentals change with the institutional cost χ_z for the zone with median efficiency gain using our calibrated model. The circle indicates the actual level of rentals and the associated calibrated χ_z. Panel (b) shows the model-implied efficiency gain, the ratio of efficient to equilibrium output with a given rentals, with respect to equilibrium rentals in the median zone. Panel (c) shows the relationship of efficiency gain and rentals for zones with zero rentals in the data. The lines refer to zones with the highest and lowest efficiency gains among the zones with no rentals.

closer to efficiency and hence feature smaller gains from additional land reallocation.

Second, we focus on zones without land market activity and plot the equilibrium relationship between efficiency gains and rentals for the highest and lowest efficiency gains zones in panel (c) of Figure 4. The reform is scalable in that reducing institutional costs in zones where there is no land market activity increases productivity substantially. But the results by zone are quite heterogenous. Whereas in one zone efficiency gains are exhausted with relatively few rentals (17 percent), another zone requires substantial rentals (54 percent) to exhaust the larger efficiency gains. Note that even in this extreme zone the level rentals required to lower efficiency gains to 1% is similar to those of the median zone, which we argue makes land market activity relatively scalable. These results indicate that not all zones need the same reduction in the barriers to accessing land markets to reduce efficiency gains.

Third, we assess how the existing land rentals have improved efficiency. We shut down land rentals ($\chi = +\infty$) and calculate the implied zone-level TFP without rentals. When compared to the calibrated zone-level TFP, the existing rentals increase aggregate zone-level TFP by 14.9% on average and 11.1% for the median. These results likely underestimate the effect of rentals due to selection (Lagakos and Waugh, 2013). In our model, we assess the allocation of rentals for the currently existing farmers, abstracting from the notion that some farmers may completely rent out their land and migrate. This extensive margin can

Table 6: The Extent of within-zone Misallocation, Ethiopia ISA 2013/14 2013/14

	Average	Median	5th pct.	95th pct.
Efficiency Gain	1.66	1.64	1.28	2.81
MPLa (Std. log)	0.84	0.81	0.55	1.15
TFPR (Std. log)	0.84	0.82	0.61	1.13

Notes: We compute the average efficiency gain using actual output as weights, hence the average gain is the country-level gain of eliminating within-zone misallocation.

be quantitatively important for resource allocation (Chen, 2017; Adamopoulos et al., 2017).

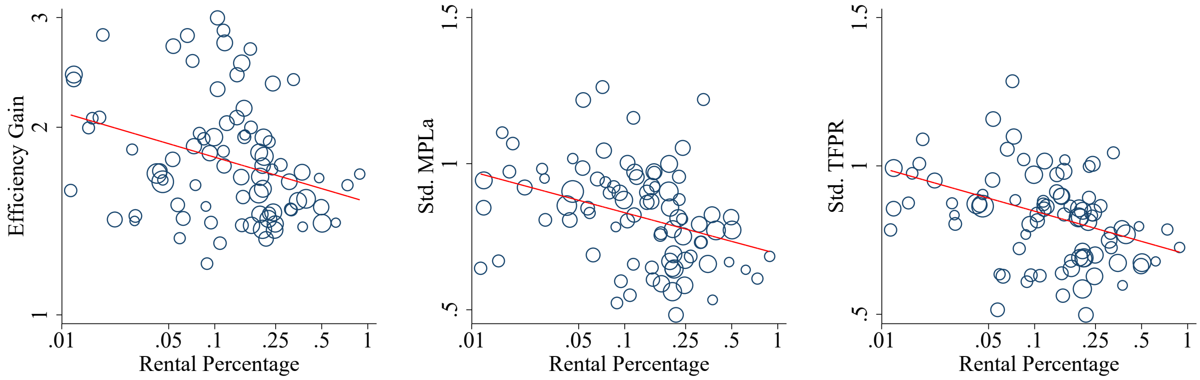
5.3 Accounting for Overall Misallocation

Whereas in our theoretical framework we restrict our analysis to a specific wedge—an institutional barrier to accessing land markets—distorting the allocations of factor inputs, there is potentially a myriad of others reasons that contribute to explain factor input misallocation (Restuccia and Rogerson, 2017). In this context, we now assess how much the specific institutional cost on land rentals χ_z—calibrated to match the actual rental activity from the data—accounts for the full extent of within-zone misallocation in Ethiopian agriculture.

To start, we report several statistics for the distribution of within-zone efficiency gains—the ratio of efficient to actual output in each zone in the data—in Table 6. The efficiency gains summarize the full extent of observed within-zone factor input misallocation. For the 2013/14 wave data, The full efficiency gain is 1.66-fold on average over the zones, with a median of 1.64-fold. This median estimate is tight with bootstrap standard deviation of 0.03, significant at the one percent level. We obtain similar within-zone efficiency gains in 2015/16 wave with an average within-zone efficiency gain 1.67-fold and a median of 1.59-fold. These efficiency gains are not driven by crop composition (see Appendix C). Efficiency gains vary substantially across zones: 2.81-fold for 95th percentile and 1.28-fold for the 5th percentile. Further, from an aggregate perspective, there exists a clear cross-sectional association between the within-zone efficiency gains and the within-zone percentage of land rentals R_z (i.e. the proportion of rented land of total land in zone z) as illustrated in the left panel of Figure 5, in line with the empirical evidence. The within-zone dispersion in MPLa and TFPR is also correlated with within-zone land rentals R_z.

How much the specific institutional cost on land rentals χ_z—calibrated to match the

Figure 5: Land Rentals and the Extent of within-zone Misallocation



Notes: The relationship between the fraction of rented land R_z by zone and three separate measures of within-zone misallocation: within-zone efficiency gain (left), dispersion in the marginal product of land (center), and dispersion of farm-level revenue productivity (right). We report 84 zone-year observations with nonzero rentals and more than 10 observations. We also trim zones with the highest and lowest levels of misallocation. The size of the circles indicate the number of observations in each zone. The solid line corresponds to the line of best fit after controlling for year fixed effects for the pooled samples of two waves. The estimated elasticities are -0.072, -0.061, and -0.063, all significant at 1% level.

rental activity in 2013/14—accounts for the full extent of within-zone misallocation? To answer this question we first compute the efficiency gains of eliminating in the model the institutional cost on land rentals χ_z. The efficiency gain is on average 1.18-fold and it varies substantially among zones. We then compute the log ratio of efficiency gains in the model to the full efficiency gains in the data. We find that the efficiency gains in the model generated by the institutional cost χ_z accounts for 34 percent of the extent of misallocation for the median zone (6 and 70 percent the 5th and 95th percentile zones). Although the institutional cost in accessing land rental markets, χ_z, cannot fully explain the observed extent of misallocation, it accounts for an important part of this misallocation which adds further relevance to our study of barriers to accessing land markets.

6 The Effects of Land Markets on Inequality

Our analysis shows that active land markets imply higher efficiency in resource allocation and productivity, but a common and important concern for policy makers is that opening land markets might result in higher inequality (Deininger and Binswanger, 1999; Deininger

Table 7: Effects of Land Rental Markets on Income Inequality

Dependent variable:	Zone-level inequality measure			
	Variance of logs	Gini index	90-10 ratio	75-25 ratio
Land Rentals, ψ	-0.093	-0.012	-0.142	-0.077
	(0.028)	(0.003)	(0.036)	(0.025)
Observations	138	138	138	138
R^2	0.97	0.99	0.98	0.98

Notes: We calculate measures of income dispersion at the zone-level: variance of logged farm income, Gini index of farm income, the 90-10 ratio of log farm income, and the 95-75 ratio and estimate the impact of rentals on income inequality in equation (11) at the zone level using model-generated data. Standard errors are in parentheses. In all regressions we control for zone fixed effects.

and Feder, 2001; André and Platteau, 1998; Otsuka, 2007). The idea is that land markets might put plenty of land ownership and, hence, farm income in the hands of few highly productive farms. We now assess the effects of land markets on inequality associated with the increase in rental market activity in Ethiopia.

The assessment of the effects of land markets on income inequality is challenging in terms of data requirements. First, the assessment requires data on both land rental payments paid and received by each farm. Second, the assessment also requires that the sum of rental payments paid by those that rent in land be identical to the total receipts from renting out land, which can also be an important constraint for non-administrative survey data. Unfortunately, although our data contains the payments paid by farmers that rent in land, it does not collect the data on income generated from renting out land, which unambiguously limits the empirical assessment on inequality. In addition, it is possible that some households renting out are not even in the survey, as we generally find that the share of land rented in is larger than that of renting out. Fortunately, our model-generated *status quo* and *counterfactual* allocations resulting from our main policy experiment in the previous section satisfy the requirements to analyze inequality. As a result, we now conduct an assessment of land markets on inequality using our quantitative framework.

We construct measures of within-zone inequality for farming income separately in the *status quo* and *counterfactual* scenarios using a definition of farm income that is the sum of farming production (value added) minus capital factor payments and the land rental costs $c(\bar{l}, l)$. Recall that the land rental costs incorporates the possibility of non-negative income generated from renting out land. Based on this income measure, we construct four measures of income inequality: the variance of log farm income, the Gini index, the 90-10 percentile ratio, and the 75-25 percentile ratio. We run the following difference-in-difference specification on four measures of farm income inequality:

$$\text{Inequality}_{zt} = \alpha_z + \lambda_t + \psi d_{zt} + \varepsilon_{zt}, \tag{11}$$

where the non-reference zones are defined as those for which there is an increase in the extent of land market activity as in our empirical section. Table 7 shows the results. Across all inequality measures, we find that land rentals significantly reduce farm income inequality. The reason is that more rentals reduce inequality is that, despite agricultural production and profit being more centralized among productive farms, less productive farmers benefit by renting out their land which generates income.

7 Conclusions

We show that land rentals provide a useful mechanism to overcome imbalances between the allocation of land-use rights and the efficient operational scale of farms. A policy reform experiment that reduces institutional barriers to land markets in manner that replicates the actual changes of land rentals across time and space in Ethiopia shows that land rentals substantially reduce resource misallocation and increase agricultural productivity.

Despite the strong positive effects of land rentals on resource allocation and agricultural productivity, land markets are still underdeveloped in Ethiopia. The limited use of land rentals can arise from various frictions which may include restrictions on other factor inputs, remaining imperfections in land markets (e.g., purchases and sales are prohibited) or weak legal institutions that limit the credibility of the land reform.

Finally, although our analysis strictly belongs to the context of land rental market activity in Ethiopia, we do think that our results generally 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—which has been the main focus in most reform episodes. We hope that our work generates further research on the effects of land market activity and its limitations in other contexts.

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Online Appendix

A Ethiopia LSMS-ISA Data

Agricultural output. Farm output is recorded in physical quantities (kilograms) of different crops. Some farmers may not have finished harvesting at the time of the survey. In those cases, they report the percentage of harvest that is pending which we use to estimate their total output. In the 2013/14 wave, 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 (29 percent), and wheat (25 percent). 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. 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 for our purpose 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 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 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. In the 2013/14 wave, 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. In the 2013/14 wave, The average farm size in our sample is around 1.3 hectares, compared to 169.2 hectares in the United States as reported in the 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 farm, 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. These observed dimensions capture the most important features of land quality. 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 all these indicators of land quality, controlling for log capital and land input per labor hour. This regression estimates how these dimensions of land quality affect farm value added per labor hour. Then, we take the coefficients from this regression to construct a land quality index q for each farm. This coefficient q summarizes land quality using the best possible observed information in our data. We recognize that there may still be other unobserved dimensions of land quality differences among plots, and hence our goal with this approach is to control on land quality differences as much as possible based on the observed information, without asserting conclusions on the specific measure of land quality.

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. 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. 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 cattle as our measure of farm capital. 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, multiplied 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.

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 male family members, and hired women and children work the same hours as female and children family members, respectively. Furthermore, we adjust labor hours of women and children as efficiency units of men hours using the median wage ratios relative to men to obtain the male-equivalent hours. 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, and we apply the same quality adjustment as well. 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, 75.3 percent is supplied by household members, 14.7 percent by hired labor, and 10.0 percent by unpaid labor from other households.

B Factor Income Shares

We document our procedure to estimate factor shares using the Ethiopian micro data. Factor shares are calculated as the share of cost of each factor in production. We also discuss robustness of our results with respect to the their values.

Labor share. We observe the wage payments for hired labor, separately for male, female, and children. We then calculate the cost per day for these three types of labor by taking the median wage rate of each type. For household members and free labor from other households, we do not observe the cost. We hence impute the cost by assigning the same wage rate as hired labor of the same type. For example, we assume that using male household members has the same cost as using the same amount of hired male individuals. By doing this, we calculate the labor cost of each farm. We then take the ratio between this labor cost and the farm output (value added), and take the median (0.464) as the labor income share.

Land share. We observe the land payments, both cash and in-kind, for some land rentals. There is a substantial portion of rentals that are non-market, that is involving no payment in cash or in kind. We therefore calculate the land share using the portion of rentals that are market, i.e., the payment is not zero. The cost of land is then as the ratio between rental payments and rental size. We take the median of this ratio to be our measure of land price. Then for all land plots, regardless of rented or own, we apply this price to calculate the implied cost of land. We next aggregate this land cost to the farm level to obtain the shadow land cost of each farm, including both rented land and own land. Finally, we calculate the ratio between this implied land cost and the farm output (value added), and take the median (0.389) as the land income share.

Capital. We do not directly observe the capital cost. We therefore use the residual as the capital share, which is $1 - 0.464 - 0.389 = 0.147$.

To summarize, we estimate that capital, labor, and land income shares are 0.147, 0.464, and 0.389, respectively. Note that estimates of factor income shares in agriculture varies in the literature. Valentinyi and Herrendorf (2008) find that in the United States, capital, labor, and land income shares in agriculture are 0.36, 0.46, and 0.18. Restuccia and Santaeulàlia-Llopis (2017) use micro data from Malawi and estimate capital, labor, and land shares to be 0.190, 0.419, and 0.391. The discrepancy among the shares may arise from the fact that the capital income share in agriculture tends to increase as an economy develops (Chen, 2020). Ethiopia is typically considered to be at a stage of development similar to Malawi, and our estimated factor income shares are close to those of Restuccia and Santaeulàlia-Llopis (2017).

A difficulty with estimating factor income shares in poor and developing countries is the fact that only a subset of factor services are transacted in a market for which we observe factor payments. To the extent that there may be selection in the set of observed transactions, factor income shares may be biased. A similar bias may arise if observed transactions are subject to distortions. We recognize the difficulty of dealing with these issues given our current data and to even assign the direction of the bias. To address the importance of factor shares values for our results, we conduct the following robustness checks. First, we use factor income shares from Restuccia and Santaeulàlia-Llopis (2017). These shares are estimated using only capital and land payments, not labor payments, in a larger sample of market transactions for Malawi, and hence, less subject to selection issues on land income. Using these shares we re-estimate farm productivity and find it to be highly correlated with our baseline productivity with the Spearman's rank correlation of 0.99. We also re-estimate

Table 8: Robustness on Factor Shares in Production

	Correlation with Baseline	Efficiency Gain	MPLa	TFPR
Baseline	–	−0.132	−0.192	−0.151
		(0.048)	(0.065)	(0.065)
Malawi shares	0.99	−0.133	−0.187	−0.142
		(0.058)	(0.063)	(0.065)
No capital	0.97	−0.100	−0.167	−0.167
		(0.052)	(0.063)	(0.063)
Half land share	0.96	−0.102	−0.211	−0.131
		(0.054)	(0.069)	(0.095)
DRS = 0.7	0.98	−0.147	−0.170	−0.131
		(0.081)	(0.059)	(0.058)
DRS = 0.5	0.99	−0.121	−0.202	−0.152
		(0.042)	(0.066)	(0.073)

Notes: The first column reports the rank correlation of farm productivity in each case with respect to our baseline measure. The remaining columns report the results of regression (8) for the three measures of farm-level misallocation: (a) efficiency gain, (b) marginal product of land, and (c) revenue productivity. Standard errors are calculated using block-bootstrap clustering at the zone level and are reported in parentheses. Data for the Ethiopia ISA 2013/14 and 2015/16 waves.

our main empirical specification and obtain coefficients of efficiency gain, MPLa, and TFPR that are significant and very close in magnitude to our baseline, see Table 8.

Second, note that the implicit returns to scale parameter in our farm production function is the sum of the capital and the land shares and our estimate for the decreasing returns parameter is similar to that in Restuccia and Santaeulàlia-Llopis (2017) and Gollin and Udry (2017) using different identification strategies. In this context, we hold the value of the decreasing returns parameter and consider variations in the shares between capital and land. We consider two alternative cases: (a) assigning zero share to capital which implies a larger role for land than in our baseline and (b) reducing the land share by one half and assigning it to capital, implying a larger role for capital and lesser role for land than in our baseline. In both cases, farm productivity is highly correlated with our baseline, 0.97 and 0.96; and the main empirical results are similar as well, see Table 8. Third, we use alternative values for the returns to scale parameter, a higher value of 0.7 and a lower value of 0.5 relative to our basline. We re-estimate farm productivity in each case and again find it highly correlated with our baseline (with rank correlation of 0.98 and 0.99) and similar significant empirical results (see Table 8). We hence conclude that our main results are robust to reasonable variations in the values of factor shares parameters.

C Robustness and Extensions

We provide a set of robustness checks and discuss some extensions to our empirical analysis.

C.1 Controlling for Household-Level Observables

We repeat the difference-in-difference regression specified in equations (8) and (9) explicitly controlling for a set of household-level observables such as the household head's age, gender, education, marriage status, health status, and the household's size. Note that further controlling for land quality measures, such as elevation or slope, does not change our results since they are already taken into account when removing land quality from farm level measures of output. The results are displayed in Table 9. The results are very similar to those in Table 2. Including household-level observables as controls does not alter the effects of land rental markets on resource misallocation.

C.2 Output Market Distortions

Our emphasis has been on connecting misallocation with restrictions to land markets in Ethiopia. However, to the extent that there may be other frictions in the economy that may be driving the misallocation we document—such as poor infrastructure which would make markets in remote rural locations difficult to access—it is relevant to assess the extent of 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 (8) to include farm distance to nearest market denoted by dist_i as an additional control variable. This implies the following specification:

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

Table 9: Effects of Land Rentals on Misallocation, wiht other Controls

(a) Benchmark Specification

Dependent variable:	Farm-Level Misallocation		
	Efficiency Gain	MPLa	TFPR
Land Rentals (d_z)	−0.135	−0.203	−0.163
	(0.050)	(0.069)	(0.068)
Observations	4,534	4,534	4,534
R^2	0.24	0.14	0.17

(b) Quantile Specification

Dependent variable:	Farm-Level Misallocation		
	Efficiency Gain	MPLa	TFPR
ψ_{Q1}	−0.029	−0.087	−0.017
	(0.043)	(0.062)	(0.069)
ψ_{Q2}	−0.066	−0.079	−0.069
	(0.044)	(0.048)	(0.047)
ψ_{Q3}	−0.116	−0.106	−0.117
	(0.050)	(0.050)	(0.057)
ψ_{Q4}	−0.314	−0.414	−0.403
	(0.105)	(0.147)	(0.143)

Notes: Results of regression (8) in panel (a) and of regression (9) in panel (b) for the three measures of farm-level misallocation, after controlling for household-level observables: (a) efficiency gain, (b) marginal product of land, and (c) revenue productivity. Standard errors are calculated using block-bootstrap clustering at the zone level and are reported in parentheses. Data for the Ethiopia ISA 2013/14 and 2015/16 waves.

We find that controlling for output market distortions does not alter our benchmark results. The estimated coefficient ψ (and standard errors) for efficiency gains, MPLa, and TFPR barely change, with −0.132 (0.048), −0.192 (0.065), and −0.151 (0.065), respectively. The coefficients on log distance for dependent variables of efficiency gains, MPLa, and TFPR are insignificant with estimates of −0.030 (0.042), −0.019 (0.039), and −0.044 (0.035), respectively. These results should not be entirely surprising since the bulk of overall misallocation in Ethiopia occurs within narrow geographical areas, such as a zone in our analysis, that share similar market access. Particularly, we calculate in Section 5.3 that the level of efficiency gain across zones is on average 1.66-fold. This average is weighted by zone-level actual output, and hence it is also the country-level gain of eliminating within-zone misallocation. The nationwide efficiency gain is 2-fold if we also allow for across zone reallocation, implying that within-zone misallocation accounts for $\log(1.66)/\log(2.00) = 73\%$ of the overall efficiency gain.

C.3 Explicit Labor Input

That the functioning of labor markets in poor countries is far from perfect is well known (Rosenzweig, 1978, 1988; Rosenzweig and Wolpin, 1985; Behrman, 1999). We abstracted from labor input in our analysis because most farm labor is family labor and hence have avoided the notion of splitting families in reallocation. We show that our results are robust to explicitly including labor in the production function. Recall that in our benchmark production function output (y_i) and inputs (k_i, l_i) are all normalized to labor input. Alternatively, we consider an expanded production function where we explicitly include the labor input:

$$y_i = s_i^{1-\gamma}(k_i^{\alpha} n_i^{\theta} l_i^{1-\alpha-\theta})^{\gamma}, \tag{12}$$

where n_i is labor input and $\theta\gamma$ is the corresponding factor share. In this case, the farm productivity can be calculated as $s_i = \left[\frac{y_i}{(k_i^{\alpha} n_i^{\theta} l_i^{1-\alpha-\theta})^{\gamma}}\right]^{\frac{1}{1-\gamma}}$, and the efficient allocation requires $k_i^e = \frac{s_i}{\sum_i s_i}K, \quad n_i^e = \frac{s_i}{\sum_i s_i}N, \quad l_i^e = \frac{s_i}{\sum_i s_i}L$, where $N = \sum_i n_i$ denotes the aggregate labor endowment. The efficient aggregate output per zone is $Y^e = \sum_i y_i^e = \left(\sum_i s_i\right)^{1-\gamma}(K^{\alpha}N^{\theta}L^{1-\alpha-\theta})^{\gamma}$. Analogously, farm revenue productivity (TFPR) is now defined as $\text{TFPR}_i \equiv \frac{y_i}{k_i^{\alpha} n_i^{\theta} l_i^{1-\alpha-\theta}}$.

In this alternative specification, we have three parameters to calibrate: γ, α, θ. Note that the labor income share is now given by $1-\gamma+\theta\gamma$, where $1-\gamma$ is the profit of the farm and $\theta\gamma$ is the share of labor input. We therefore set $1-\gamma+\theta\gamma = 0.464$ to match the labor share of 0.464 as in our benchmark specification. Recall that family labor accounts for 75.3 percent of total farm labor. We then choose the first component $1-\gamma$ to be 75.3 percent of the total labor share, which means $\gamma = 0.651$. The capital share, $\alpha\gamma$ is 0.147, and hence we choose $\alpha = 0.202$.

Our results remain largely unchanged in this alternative specification. On average, the efficiency gain per zone is 1.83, compared to 1.66 in our benchmark case, which implies that there is also misallocation in the labor input. Notice that in assessing efficiency gains, we reallocate factor inputs (including labor) within zones. That is, we are not allowing for reallocation gains potentially generated from (internal) migration which we think deserves

Table 10: Effects of Land Rentals on Misallocation with Explicit Labor Input

(a) Benchmark Specification

Dependent variable:	Farm-Level Misallocation		
	Efficiency Gain	MPLa	TFPR
Land Rentals (d_z)	−0.084	−0.168	−0.070
	(0.052)	(0.085)	(0.055)
Observations	4,716	4,716	4,716
R^2	0.16	0.16	0.13

(b) Quantile Specification

Dependent variable:	Farm-Level Misallocation		
	Efficiency Gain	MPLa	TFPR
ψ_{Q1}	0.012	−0.129	−0.053
	(0.038)	(0.058)	(0.038)
ψ_{Q2}	−0.110	−0.078	−0.082
	(0.048)	(0.054)	(0.042)
ψ_{Q3}	−0.090	−0.113	−0.050
	(0.079)	(0.065)	(0.050)
ψ_{Q4}	−0.127	−0.386	−0.155
	(0.125)	(0.258)	(0.155)

Notes: Results of regression (8) in panel (a) and of regression (9) in panel (b) for the three measures of farm-level misallocation: (a) efficiency gain, (b) marginal product of land, (c) revenue productivity. Standard errors are calculated using block-bootstrap clustering at the zone level and are reported in the parentheses. Data from Ethiopia ISA 2013/14 and 2015/16 waves. The results shown in this table are under the setup where the labor input enters production explicitly.

further exploration. For such analysis in different contexts, see Munshi and Rosenzweig (2016) for India and Bryan and Morten (2019) for Indonesia. For a cross-country analysis, see Hendricks and Schoellman (2018). The results of our difference-in-difference analysis when we add labor are in Table 10. We obtain similar results to our benchmark. Land rentals significantly reduce misallocation and the effects are again non-linear.

C.4 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 our analysis to calculate the extent of misallocation and zone-level efficiency gain.

Table 11 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 MPLa or 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 1.03 and the efficiency gain is 1.79-fold (compared with 0.84 and 1.66-fold in our baseline).

Table 11: Crop-Level Analysis of Misallocation

Crop	Number of Farms (%)	Cultivated Land (%)	Efficiency Gain within Zones	Dispersion in MPLa$_i$ within Zones	Dispersion in TFPR$_i$ within Zones
Maize	56.6	17.5	1.79	1.02	1.03
Sorghum	42.7	18.6	1.74	0.84	0.88
Tea Leaves	40.2	13.5	1.51	0.84	0.86
Coffee	29.3	16.6	2.16	1.13	1.12
Wheat	25.2	8.7	1.61	0.91	0.94

Notes: The table lists 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 three columns report the average efficiency gains and the dispersion of MPLa and TFPR within zones weighted by zone-level output, focusing only on farm plots of a single crop. Data from Ethiopia ISA 2013/14.

D Model Solution and Calibration Strategy

We describe the solution algorithm we use for the model equilibrium and the algorithm we use in our calibration strategy to pin down χ_z by zone.

D.1 Solution Algorithm

Given a set of parameter values (α, γ, χ_z), an initial set of farm-level land endowments and permanent productivity for a large number of farmers $\{(s_i, \bar{l}_i)\}$, and an aggregate amount of capital K:

1. Guess land and capital rental prices, respectively, q and r.

2. Solve the farm profit maximization problem (equation (2)). That is, find the farm-specific optimal demands of land and capital (l_i^*, k_i^*) that solve the first order conditions (equation (6)).

3. Check whether land and capital market clears for each zone, that is,

$$\sum_i l^*(s_i, \bar{l}_i) - \sum_i \bar{l}_i = 0$$
$$\sum_i k^*(s_i, \bar{l}_i) - K = 0.$$

4. If factor markets clear, then STOP. Otherwise, update the guess of factor prices (q, r) and GO TO step 2.

Notice that to generate the update in step 4 if the aggregate demand of land exceeds the aggregate supply of land, then we need to increase the rental price of land, q. Analogously for capital. Also, notice that there is no analytical solution to the first order condition in step 2. We numerically search for roots.

D.2 Calibration Strategy for χ_z

Our calibration strategy aims at finding the institutional cost χ_z such that the model land rentals match the actual land rentals by zone. We apply the following calibration algorithm.

1. Guess the institutional cost by zone, χ_z.

2. Solve the model by zone, applying the solution algorithm discussed previously.

3. Compute the model-generated land rentals as equation (4) by zone.

4. If the model-generated rentals by zone equate their data counterparts, then STOP. Otherwise, update guess of χ_z and GO TO step 2.

To generate the update in step 4, if the model-generated rentals are smaller (larger) than their data counterparts, then we decrease (increase) the institutional cost χ_z. Notice that this procedure is computationally intense and that, further, we need to follow it separately for each zone. To ease the computational burden we parallelize our computation with multiple cores.

E Economic Interpretation of Empirical Results

To provide a quantitative interpretation of our regression results, we use our quantile specification for farm-level outcomes to compute the changes in individual farm-level MPLa generated by an increase in land rentals across waves as follows:

$$\Delta \left| \log \left(\frac{\text{MPLa}_{izt}}{\overline{\text{MPLa}}_{zt}} \right) \right| = \psi_Q. \tag{13}$$

Then, we plug our estimates for ψ_Q into equation (13) to compute the projected individual MPLa generated by an increase in land rentals, denoted as MPLa^p_{iz}. Note that we have $\text{MPLa}^p_{iz} \propto s_{iz}^{1-\gamma} k_{iz}^{\alpha\gamma} (l^p_{iz})^{(1-\alpha)\gamma-1}$. We can then solve out the projected land input associated with rental l^p_i as

$$l^p_{iz} \propto \left(\frac{\text{MPL}^p_{iz}}{s_{iz}^{1-\gamma} k_{iz}^{\alpha\gamma}} \right)^{\frac{1}{(1-\alpha)\gamma-1}}. \tag{14}$$

Notice that equation (14) solves l^p_i up to a scalar, which is determined by the land market clearing condition of each zone $\sum_{i\in z} l^p_{iz} = L_z$. We then substitute l^p_{iz} into the production function to solve out the projected output $y^p_{iz} = s_{iz}^{1-\gamma} k_{iz}^{\alpha\gamma} (l^p_{iz})^{(1-\alpha)\gamma}$ for the 2013/14 wave.

The projected zone-level efficiency gain associated with rental 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 (1.423) with our benchmark average efficiency gains per zone (1.527), we find that an increase in land rentals reduces efficiency gains by 16.6% on average per zone (calculated as $1-\log(1.423)/\log(1.527)$).

Because the land rental dummy (i.e., $d_{z,t} = 1$) is associated with different growth rates of rentals per zone R_z, we divide the estimated effects by the aggregate growth in the share of rented land across our two waves within non-reference groups, which is 5.1 percent. This implies that an increase in one percentage point of land rentals increases aggregate productivity by 16.6/5.1=3.2 percent.