Are Small Farms Really more Productive than Large Farms?
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ABSTRACT

In this paper we show that the study of the farm size-productivity relationship hinges on the choice of productivity measure. Our main insight is that using yields, a partial measure of productivity, may not be informative for the size-productivity relationship because, in addition to total factor productivity, yields pick up input markets distortions and deviations from constant returns to scale. We examine the empirical relevance of this insight using detailed microdata from Uganda. We find an inverse relationship between yields and farm size. We show the relationship turns positive when accounting for market distortions and returns to scale; or when using a farm-specific component of total factor productivity.

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Abstract

In this paper we show that the study of the farm size-productivity relationship hinges on the choice of productivity measure. Our main insight is that using yields, a partial measure of productivity, may not be informative for the size-productivity relationship because, in addition to total factor productivity, yields pick up input markets distortions and deviations from constant returns to scale. We examine the empirical relevance of this insight using detailed microdata from Uganda. We find an inverse relationship between yields and farm size. We show the relationship turns positive when accounting for market distortions and returns to scale; or when using a farm-specific component of total factor productivity.

JEL classification: O12, O13, Q12, Q15

Keywords: Farm size, productivity, yields, land markets, distortions, agriculture, policy.

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1 Introduction

An important and established microeconomic literature has documented a robust inverse relationship between yields (i.e., output per unit of land) and farm size. This finding has been interpreted as evidence that small farms are more productive (Berry et al., 1979; Barrett, 1996; Barrett et al., 2010; Assuncao and Ghatak, 2003; Eswaran and Kotwal, 1986). These results contrast with growing macroeconomic evidence of a positive relationship between farm size and agricultural productivity, both across and within countries (Adamopoulos and Restuccia, 2014; Chen et al., 2017; Restuccia and Santaeulàlia-Llopis, 2017; Adamopoulos and Restuccia, 2020). A similar finding has been reported in microeconomic studies from developed countries using measures of total factor productivity instead of yields (Sheng and Chancellor, 2019; Key, 2019).

What explains these divergent findings? Answering this question is important given its consequential policy implications. If small farms are indeed more productive, then policies that encourage small landholdings (such as land redistribution) could increase aggregate productivity (see the discussion in Collier and Dercon, 2014).

We propose a simple framework that allows to reconcile these different results. We show, theoretically and empirically, why the choice of measure of productivity matters for understanding the size-productivity relationship. Because yields is a partial measure of productivity, it picks up not only total factor productivity, but also deviations from constant returns to scale (CRS) and other phenomena that affect relative input use, such as input markets' imperfections. We show that even with CRS technologies, estimates of the size-productivity relationship using yields would be inconsistent in the presence of size-dependent market distortions. These are plausible in many contexts, such as subsistence farming in developing countries (Dillon and Barrett, 2017; Aggarwal et al., 2018; Dillon et al., 2019; Julien et al., 2019). As a consequence, even if larger farms produce more output conditional on inputs used, their yields may be lower.

To illustrate our main insight, consider the following simple example. Farmers have access to identical CRS technology, the same total factor productivity and labor endowment but differ only in the amount of land they can operate. There are no input markets so farmers use all their endowment of inputs (both land and labor). In this scenario, small farms use, by construction, relatively more labor per unit of land than large farms, and obtain higher output per unit of land. We then observe an inverse relationship between yields and farm size but this relationship, however, is simply reflecting the (inefficient) allocation of inputs (land in this scenario), not differences in total factor productivity.

We assess the empirical relevance of this issue using microdata from Ugandan farmers. We construct two alternative measures of productivity: (1) yields, as is standard in the literature, and (2) farm productivity. Farm productivity is the farm-specific component of total factor productivity (TFP) obtained by estimating a farm-level production function. Then, we evaluate the farm size-productivity relationship using these two alternative measures.

We find that the results are highly sensitive to the measure of productivity we use, despite both measures being strongly correlated (i.e., 0.86). We find a negative relationship between yields and farm size, consistent with the broad findings documented in the literature. Interestingly, the quantitative magnitude of the relationship for Uganda is quite close to that reported for other countries. However, when using a measure of farm productivity instead of yields, we find a *positive* relationship between farm size and productivity. We show that these conflicting results reflect the inconsistent estimates obtained when using yields as a measure of productivity in the presence of deviations from constant returns to scale and size-dependent market distortions. We document a similar pattern of results using microdata from Peru, Bangladesh and Tanzania.

Recent studies have challenged the inverse relationship between yields and farm size by identifying potential sources of statistical bias, such as non-classical measurement error or omitted soil characteristics (Carletto et al., 2013; Gourlay et al., 2017; Abay et al., 2019a). In this paper, we take a step back and show that the use of yields in the regression analysis has a more profound economic limitation. In particular, we find that technology and market distortions may render yields uninformative of the size-productivity relationship and using it can lead to wrong policy recommendations. We also point out an important limitation of two strategies used to empirically address market imperfections: controlling for relative input use (the so-called production function approach) and exploiting within-farm variation in plot size (Assunção and Braido, 2007; Barrett et al., 2010). While these strategies account for size-dependent distortions, they do not address possible deviations from CRS and could still deliver inconsistent estimates.

We evaluate the validity of this interpretation in several ways. First, we show that our results are robust to using GPS measures of farm size and other proxies for output measurement error and to including a rich set of soil and farmer characteristics. These are standard fixes to measurement error and omitted variable problems discussed in the literature. Second, we revisit our estimates of the size-productivity relationship and show that, after correcting for market distortions and returns to scale, the negative correlation between yields and farm size goes away (and in our case, becomes positive). Third, we show that our conclusions hold when controlling for relative input use or when using plot level yield regressions. Fourth, we exploit unique variation in land tenure regimes in Uganda to examine in more detail the role of market distortions. We find that the yield-farm size relationship becomes less negative in areas with better-defined private property rights. We interpret this finding as suggestive evidence of the role of market distortions in driving the negative yield-farm size result.

Our results point out to a broader limitation of the size-productivity relationship as a policy tool. This relationship promises a tractable mechanism for policy implementation: if farm size is correlated with productivity then size can easily be used to target farmers and enhance efficiency. However, we show that in several contexts farm size a poor proxy for productivity for at least two reasons. First, the relationship between farm size and productivity can be wrongly estimated (as it is the case when using yields). Second, there is substantial dispersion in productivity across farms of similar size, sometimes as large as the productivity dispersion between land size classes, which arise for example from restrictive land institutions and other market distortions prevalent in poor and developing countries. Thus, even if the relationship is correctly estimated, in our context, the size of a farm is not very informative about its productivity.

Our paper is not the first to raise concerns on the use of yields when evaluating the size-productivity relationship. Some early reviews of the literature acknowledged that the use of yields as a measure of productivity was "flawed by methodological shortcomings" (Binswanger et al., 1995, p. 2706). Recent papers also recognize this limitation. For example, in their study of farm size classes in Brazilian municipalities Helfand and Taylor (2018) discuss the importance of the CRS assumption and propose a regression of yields controlling for a land-adjusted measure of inputs, similar to the production function approach. Other recent papers have also used a measure of total factor productivity to look into the farm size-productivity relationship, using aggregate or micro-data and different methodologies (Gautam and Ahmed, 2019; Julien et al., 2019; Rada et al., 2019). In this paper, we show under which specific circumstances using yields would be appropriate, highlighting the role of size-dependent market distortions and deviations from CRS as key sources of endogeneity, and illustrate their empirical relevance using data from Uganda and other countries.

The paper is organized as follows. In Section 2, we discuss under which conditions yields is an appropriate measure to capture farm productivity. Section 3 presents the empirical evidence from Uganda and show that using alternative measures of productivity produces different estimates of the farm size-productivity relationship. In Section 4 we present robustness checks and evidence for other countries. In Section 5, we examine, theoretically and empirically, the reasons for these conflicting results and provide direct empirical evidence about the role of land markets on the farm size-productivity relationship. Section 6 concludes.

2 Using yields to estimate the size-productivity relationship

The study of the relationship between farm size and productivity occupies a central place in the agrarian and development economics literature. The interest on this relationship stems, in part, from its profound normative implications. In the presence of heterogeneous farmers, the efficient factor allocation that maximizes aggregate output requires that farm size is proportional to productivity (Lucas, 1978; Adamopoulos and Restuccia, 2014; Restuccia and Santaeulàlia-Llopis, 2017). Thus, if small farms are more productive, then policies that redistribute land into smaller farms would increase aggregate productivity.

A large literature using micro-data from small-scale traditional farmers in developing countries has indeed found an inverse relationship between farm size and productivity measured by yields (output per unit of land). This result has been documented in several countries in Asia, Africa, and Latin-America and has been interpreted as evidence that small farms are more productive (Berry et al., 1979; Barrett, 1996; Barrett et al., 2010).

There are two common econometric specifications used to estimate the farm size-productivity relationship: the yield approach and the production function approach (Carter, 1984; Assunção and Braido, 2007; Ali et al., 2015). The yield approach regresses yields on farm size (usually cultivated area) and a set of control variables. The production approach adds to the previous specification the input ratios (usually land and labor).[1]

[1] These are not the only approaches used in the literature. For example, some studies regress profits or labor demand on farm size (Benjamin, 1995; Lamb, 2003), while others use estimates of total factor productivity, e.g., Key (2019); Julien et al. (2019); Sheng and Chancellor (2019).

To examine the validity of these approaches, we derive the relationship between yields and farm size starting from the farm's production function. Consider a farmer who produces a single, homogeneous, good Y according to the following Cobb-Douglas technology:[2]

$$Y_{it} = s_i A_t (T_{it}^{\alpha} L_{it}^{1-\alpha})^{\gamma} e^{\epsilon_{it}}, \tag{1}$$

where T_{it} and L_{it} stand for the amounts of land and labor used by farmer i in period t.[3] Note that parameter α measures the contribution of land to total output, while γ captures returns to scale at the farm level.

In this specification, total factor productivity (TFP) is equal to $s_i A_t e^{\epsilon_{it}}$, where A_t is a common productivity driver (such as weather or local public goods), ϵ_{it} is an unanticipated productivity shock, and s_i is a farm-specific output shifter, such as farming ability or entrepreneurship. Henceforth, we call s_i farm productivity.

Consider the 'true' relationship between farm productivity and size:

$$\ln s_i = \beta \ln \bar{T}_i + \gamma X_i, \tag{2}$$

where $\bar{T}_i$ is a measure of farm size (such as average cultivated land or size of land holdings), and X_i is a set of observable farm characteristics (such as soil quality or farmer's education).

Note that a researcher interested in the relationship between farm size and productivity would need to estimate β. If a measure of farm productivity s_i is available, then the researcher could directly estimate equation (2). Instead, we consider the case where the resercher uses yields as a proxy for productivity.

Dividing (1) by T_{it}, taking logs, and using (2), we obtain a expression linking yields to

[2] We use a Cobb-Douglas functional form in land and labor inputs for ease of exposition. We relax this assumption in our empirical analysis to check the robustness of our results to using more flexible specifications.

[3] Consistent with our empirical analysis, our discussion assumes that the researcher uses panel data. The implications are identical, however, if we assume cross sectional data and drop the subscript t.

farm size:

$$\ln \frac{Y_{it}}{T_{it}} = \beta \ln \bar{T}_i + \gamma X_i + \ln A_t + \gamma(1-\alpha) \ln \frac{L_{it}}{T_{it}} + (\gamma - 1) \ln T_{it} + \epsilon_{it}, \tag{3}$$

We can further simplify this expression using standard results linking input ratios to relative input prices. We consider a general case in which farmers face (potentially) imperfect input markets. Following Restuccia and Rogerson (2008) and Hsieh and Klenow (2009), we model market distortions as 'wedges' or taxes on input prices. Without loss of generality, we assume that the price of labor is w while the price of land is $r(1+\tau_i)$.[4] The wedge τ_i measures the relative distortion in input markets. Thus, we are implicitly normalizing the distortion in labor prices equal to one. We allow for these distortions to be different across farms.

Profit maximization implies that farmer i chooses the following input ratio:

$$\frac{L_{it}}{T_{it}} = \frac{1-\alpha}{\alpha} \frac{r}{w} (1+\tau_i).$$

Using this result, we can re-write expression (3) as:

$$\ln \frac{Y_{it}}{T_{it}} = \underbrace{\beta \ln \bar{T}_i + \gamma X_i}_{\text{farm productivity}} + \underbrace{\gamma(1-\alpha) \ln(1+\tau_i)}_{\text{market distortions}} + \underbrace{(\gamma - 1) \ln T_{it}}_{\text{deviations from CRS}} + c + \epsilon_{it}, \tag{4}$$

where c is a constant that is a function of common prices and parameters $(w, r, \alpha, \gamma, A)$.

Equation (4) summarizes the main insight of our paper. It shows that yields pick up not only farm productivity, but also factors that affect input ratios (such as market distortions), and deviations from constant returns to scale. These issues could lead to inconsistent (wrong) estimates of the farm size-productivity relation (β) when using yields as a measure

[4] Note that τ_i has a broad interpretation. It can be interpreted as subsidies or taxes, but also as any other market imperfection or institutional feature that distorts effective relative input prices.

of productivity.

The yield approach Consider a researcher who uses the yield approach and estimates the following model

$$\ln \frac{Y_{it}}{T_{it}} = \beta \ln T_{it} + \gamma X_i + \mu_{it}, \tag{5}$$

By construction, the error term is: $\mu_{it} = \gamma(1-\alpha)\ln(1+\tau_i) + \beta \ln(\bar{T}_i - T_{it}) + (\gamma - 1)\ln T_{it} + \epsilon_{it}$.

There are two reasons why estimating this model would lead to inconsistent estimates of β: (1) presence of size-dependent market distortions (i.e., a correlation between τ_i and farm size), and (2) deviations from constant returns to scale (CRS). In either case, the error term μ would be, by construction, correlated with farm size and OLS estimates of β would be inconsistent.

This problem cannot be solved by adding better controls of soil quality or other determinants of farm productivity, nor by reducing measurement error on land or output. Similarly, in the presence of decreasing or increasing returns to scale, the problem would persist even after using instruments or even randomizing farm size. The source of the problem is more profound: it arises from using yields, a proxy of land productivity, instead of measures of productivity of the production unit, i.e., farm productivity.

The production function approach and plot-level regressions The potential problems associated with decreasing input ratios and imperfect markets have been recognized in the literature as early as Sen (1962). There have also been important work examining whether imperfect markets could explain the inverse yield-size relationship (Barrett et al., 2010; Eswaran and Kotwal, 1986; Feder, 1985).

There are two main approaches used to account for imperfect markets. First, researchers add input ratios to the yield regression. This is called the production function approach since, under the assumption of a Cobb-Douglas technology with CRS, it is equivalent to estimating the production function. The validity of this approach, however, crucially depends on the CRS assumption. To see this, re-write expression (3) as follows:

$$\ln \frac{Y_{it}}{T_{it}} = \beta \ln \bar{T}_i + \gamma X_i + \gamma(1-\alpha) \ln \frac{L_{it}}{T_{it}} + \varepsilon_{it}, \tag{6}$$

where the error term is: $\varepsilon = (\gamma - 1) \ln T_{it} + \epsilon$. Given that in most applications the measure of farm size ($\bar{T}_i$) is correlated with land used (T_{it}), this specification does not identify β except in the special case of CRS.[5]

A second strategy estimates the yield-size relationship comparing different plots within the same farm holding. This approach exploits within-farm variation and involves estimating a yield regression using plot-level data and including farm fixed effects (in the case of cross-sectional data) or farm-period fixed effects (in the case of panel data).

The key idea is that markets are not involved in the allocation of inputs within the farm. Thus, imperfect markets (and other farm-level factors) could not affect the yield-plot size relationship. This view has important implications: findings of an inverse yield-plot size relationship have led some researchers to reject imperfect markets as an explanation of the farm size-productivity results (Assunção and Braido, 2007; Kagin et al., 2016).

This approach, however, also relies on the assumption of CRS to identify the size-productivity relationship. To see this, let us modify expression (3) in two ways. First, we change the levels so that the unit of observation is plot p in farm i. Second, profit maximization and the Cobb-Douglas assumption imply that the plot-level input ratio $\frac{L_{ip}}{T_{ip}}$ is equalized across plots. Let us denote this unobserved input ratio as κ_i. With these modifications, we

[5] For instance, in studies using cross-sectional data and using cultivated land (crop area) as a measure of farm size, by construction $\bar{T}_i = T_{it}$.

can represent the relationship between plot-level yields and size as:

$$\ln \frac{Y_{ip}}{T_{ip}} = \beta \ln \bar{T_{ip}} + \underbrace{\gamma X_i + \gamma(1-\alpha) \ln \kappa_i}_{\text{farm fixed effect}} + \ln A + (\gamma - 1) \ln T_{ip} + \epsilon_{ip}. \tag{7}$$

Note that, conditional on farm fixed effects, yields would no longer pick up market distortions. However, it would still capture deviations from CRS. Thus, a yield regression using plot-level data would still produce inconsistent estimates of the size-productivity relationship, except in the special case of constant returns to scale.

This discussion does not imply that yields would always produce inconsistent estimates of the size-productivity relationship. If the technology exhibits CRS, then either the production function approach or plot-level regressions are informative. If, in addition, input markets are well-functioning or distortions are not size-dependent, then regressing yields on farm size would be enough.

We argue, however, that these conditions may not be met in several applications, especially in the context of subsistence farmers in developing countries. For instance, Dillon and Barrett (2017), Aggarwal et al. (2018) and Dillon et al. (2019) document quantitatively important distortions in agricultural input markets in Africa. Recent work by Julien et al. (2019) documents distortions in input markets (measured using shadow prices) correlated with farm size in Malawi, Tanzania, and Uganda.

In these cases, using yields (instead of farm productivity) would lead to inconsistent estimates of the farm size-productivity relationship, and erroneous policy recommendations. Whether this issue is quantitatively relevant or not remains an empirical question. Below, we examine this issue using data from Ugandan farmers.

3 Empirical evidence

Our main analysis uses detailed microdata from Ugandan households to examine whether the choice of measure of productivity affects the estimates of the farm size- productivity relationship. We use two measures: yields and an estimate of farm productivity (s_i). We also replicate the main findings using comparable data from Peru, Tanzania, and Bangladesh.

3.1 The Ugandan case

We use data from the Uganda Panel National Survey (UPNS), a household-level panel dataset collected with support from the World Bank, as part of the LSMS-ISA project. This survey is representative at the urban/rural and regional level and covers the entire country. We use the four available rounds: 2009-10, 2010-11, 2011-12, and 2013-14. Every round collects agricultural information for each of the two cropping seasons (i.e., January to June and July to December), potentially providing 8 observations per household.

We focus on the household farm as the production unit. A farmer may operate one or several parcels or plots of land, hence we aggregate any information at the parcel level to the household-farm level. Our dataset contains a panel of around 3,400 farming households observed, on average, for four periods. Figure A.1 in the Appendix displays the map of Uganda and sample coverage.

Output and inputs We construct measures of agricultural output and input use (land and labor) for each farm in a given period. To measure real agricultural output at the farm level, we construct a Laspeyres index of production that aggregates the quantity produced of each crop by the household farm using proxies of prices in 2009 as weights. We use unit values as proxies of prices. To calculate these proxies, we divide the value of sales by the quantity sold of each crop. Then, we obtain the median unit value of each crop at the national level.[6]

We measure the area of land cultivated by adding up the size of parcels planted by the household. Similar to previous studies, we use this variable as our main measure of land input and farm size. We also obtain measures of available land from self-reported information and GPS data. The available land corresponds to all the parcels of land the farmer has access to either because the farmer owns the land or has user rights, for instance, due to rental agreements. We use these variables as measures of land endowment and as alternative proxies of farm size.

Our measure of labor input is the total number of person-days used on the farm. The survey distinguishes between work done by household members and by hired workers. We use this information to construct measures of family and hired labor.

Other variables The survey also provides information on agricultural practices (such as the use of fertilizers, pesticides, or intercropping), and soil characteristics. The survey asks farmers to classify each parcel according to soil type, quality and topography. We aggregate these parcel-level indicators to the farm level to obtain a share of farmland in each category. We also obtain indicators of the share of land (at the farm and district level) under different tenure regimes.

We complement the household survey with weather data on temperature and precipitation. These variables are relevant determinants of agricultural productivity (Auffhammer et al., 2013; Hsiang, 2016; Carleton and Hsiang, 2016). We use high-frequency satellite imagery and gridded data to obtain measures of cumulative exposure to heat and water. For temperature, we use the MOD11C1 product provided by NASA. The satellite data provides daily estimates of land surface temperature (LST). Precipitation data comes from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) product (Funk et

[6]The main results are qualitatively similar when using prices at regional and local level (see Tables A.3 and A.4 in the Appendix).

al., 2015). We combine the weather and survey data using the location of the sub-county (n=967) of residence of the household.

Our approach to model exposure to weather is similar to previous work (Schlenker and Roberts, 2006, 2009; Aragón et al., 2019). In particular, we obtain average precipitation, degree days, and harmful degree days during the last cropping season for each farmer. Degree days (DD) measures the cumulative exposure to temperatures between 8℃ and 26℃ while harmful degree days (HDD) capture exposure to temperatures above 26℃. The inclusion of HDD allows for potentially different, non-linear, effects of extreme heat. Results, available upon request, are robust to using alternative temperature thresholds for HDD.

Table 1 presents summary statistics of our main variables. There are several relevant observations. First, farmers have small scale operations (the average cultivated area is 2.3 hectares). Second, farmers use practices akin to subsistence agriculture such as inter-cropping (i.e, cultivation of several crops in the same plot) and reliance on family instead of hired labor. Third, there is limited use of capital inputs (such as oxen) and productivity-enhancing inputs such as fertilizers, pesticides, and improved seeds. Finally, there is a substantial variation on land tenure regimes: around 27% of the land is held under non-customary, modern, regimes (like freehold, leasehold, and Mailo) while the rest is held under customary, communal, property rights.

Measures of productivity We construct two alternative measures of productivity: land productivity (or yields) and farm productivity.[7] First, we calculate yields (Y/T) by dividing real farm agricultural output, at 2009 prices, by the area of land cultivated. This variable is similar to measures of crop yields used in previous work. The key distinction is that we use the value of total agricultural farm output (using time-invariant and common prices across farms) instead of the quantity produced of a single crop. This distinction arises because of

[7] We refer to our measure of real farm output per unit of operated land as land productivity or yield interchangeably.

Table 1: Summary statistics (UPNS 2009-2014)

Variable	Mean	Std. Dev.
HoH age	47.2	15.2
HoH can read and write	0.657	0.475
HoH is female	0.222	0.416
Household size	6.1	2.9
Total output (in 2009 Ush, 000s)	2854.4	6118.0
Yields (output per ha.)	5013.6	7510.0
Land cultivated (has)	2.300	2.136
Land available (has)	4.247	10.713
Land available GPS (has)	2.606	17.015
Total labor (person-day)	125.5	97.0
Domestic labor (person-day)	124.0	119.4
Hired labor (person-day)	14.1	170.6
% hire workers	28.0	44.9
% have bulls or oxen	19.1	39.3
% use org. fertilizer	6.6	24.9
% use inorg. fertilizer	1.8	13.3
% use pesticides	6.4	24.4
% use improved seeds	9.1	28.7
% farm land intercropped	35.3	42.0
% farm land non-customary tenure	27.3	38.8
Average degree days (°C)	15.1	1.8
Average harmful degree days (°C)	1.0	1.0
Precipitation (mm/month)	105.8	50.7

Notes: Sample restricted to farming households. HoH = Head of household. Non-customary land tenure includes freehold, leasehold, and Mailo. Average degree days are calculated by dividing the total degree days by the number of days in the growing season.

our focus on the farm rather than the plot as the main production unit and the presence of multi- and inter-cropping: farmers usually cultivate several crops, sometimes even in the same plot. These features make it difficult to attribute inputs (either land or labor) to individual crops.

Second, we obtain estimates of farm productivity s_i. We use the same functional assumptions as in Section 2 but modify it so that the unit of observation is a household farm i, in location j, and period (season-year) t. In addition, we parametrize the common productivity shock $A_{jt} = \exp(\delta \cdot \text{weather}_{jt} + \eta_{jt})$ where weather_{jt} is a set of weather (temperature and precipitation) variables, and η_{jt} is a region-season-year fixed effect. Taking logs, we obtain:

$$\ln Y_{it} = \ln s_i + \alpha\gamma \ln T_{it} + (1-\alpha)\gamma \ln L_{it} + \delta \text{weather}_{jt} + \eta_{jt} + \epsilon_{it}. \tag{8}$$

We estimate equation (8) using panel data methods with household fixed effects. Our preferred specification is a Cobb-Douglas production function in land and labor inputs and with the same parameters for all regions (see Column 1 in Table A.1). We check the robustness of our results using estimates of farm productivity s_i obtained from alternative specifications (see Columns 2 to 6 in Table 3). In particular, we (1) include as additional controls indicators of using other inputs such as oxen, fertilizers, pesticides and improved seeds, (2) decompose labor into family and hired workers, (3) allow for heterogeneous parameters (α, γ) by region, (4) use input endowments (available land and household size) as instruments for land and labor, and (5) estimate a more flexible translog production function.

The estimated production function parameters are $\hat{\alpha} = 0.526$ and $\hat{\gamma} = 0.708$, which are close to the values calibrated in the context of similar economies, such as Restuccia and Santaeulàlia-Llopis (2017) for Malawi and Adamopoulos et al. (2017) for China.[8] We use the estimated fixed effects of our baseline specification as measures of $\ln s_i$, the log of farm productivity.

There is a strong positive correlation between land productivity and farm productiv-

[8]Table A.1 in the Appendix presents detailed results of the production function estimation. Figure A.2 in the Appendix reports the resulting distribution of the estimated household-farm fixed effects.

ity of 0.86.[9] Despite this strong correlation, we show below that both measures produce qualitatively different estimates of the farm size-productivity relationship.

3.2 Conflicting findings depending on the measure of productivity

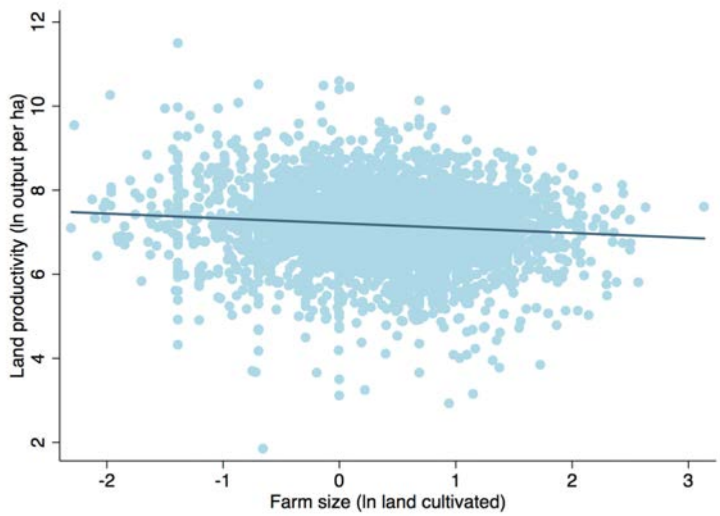
Figure 1 displays the relationship between the log of cultivated area, our baseline measure of farm size, and the two measures of productivity. An important observation is that the relationship is qualitatively different, depending on the measure of productivity used. Using yields (panel A), we observe a negative relationship. This finding is consistent with previous results of an inverse farm size-productivity relationship. However, when using farm productivity (panel B), the relationship is positive.

Table 2 presents a formal analysis of the inverse relationship between yields and farm size. We employ two specifications commonly used in the farm size-productivity literature: the yield approach and the production function approach. The yield approach regresses log of yields on the log of land cultivated and includes a rich set of control variables such as soil and farmer characteristics, weather, region-by-period and district fixed effects. The production function approach adds to the previous specification the log of the labor-land ratio. Assuming a Cobb-Douglas technology with constant returns to scale, this specification is equivalent to estimating the production function.

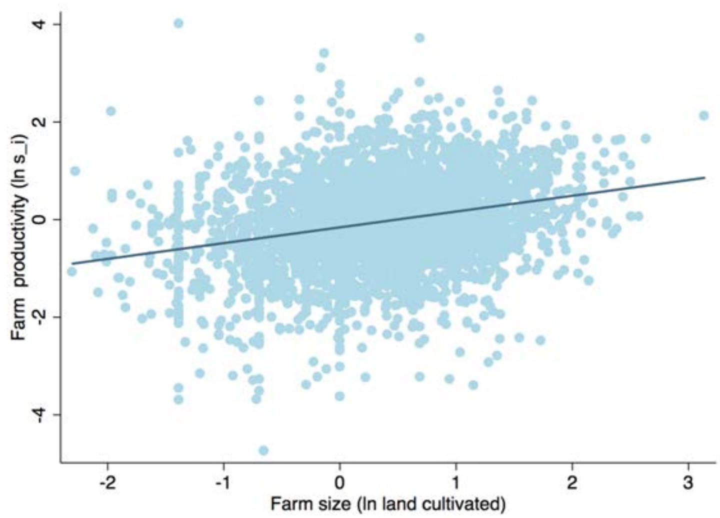
We present results using both specifications and varying the set of covariates. We also check the robustness of our results to using (self-reported) available land as a measure of farm size, and to collapsing the panel data by taking the average for each household (see Table A.2 in the Appendix). In all cases, we find a negative and significant relationship between farm size and yields. Interestingly, the estimated coefficient (around -0.27 in our preferred specification in column 2 in Table 2) is similar in magnitude to previous estimates

[9] See Figure A.3 in the Appendix for documentation of the relationship between our two measures of productivity.

Figure 1: Farm size and productivity



(a) Land productivity ($\ln(Y/T)$)



(b) Farm productivity ($\ln s_i$)

using data from other countries (Barrett et al., 2010; Desiere and Jolliffe, 2018).

We replicate the analysis using farm productivity ($\ln s_i$) instead of yields and report the results in Table 3. The results confirm the conflicting patterns observed in Figure 1: there is a robust and significant positive relationship between farm size and farm productivity (see results in columns 1 and 3 in Table 3 for specifications without and with controls). One potential concern with these last results is that we are artificially obtaining statistically significant results by duplicating the time-invariant measure of farm productivity in the panel data. However, this turns out not to be an issue as we obtain qualitatively similar results collapsing the panel data at the household level (column 2 in Table 3).

Our baseline specification uses estimates of s_i obtained from a production function that is Cobb-Douglas in land and labor. However, this choice of functional form does not drive our results. We obtain similar results using estimates of s_i obtained with more flexible specifications, such as translog production function, a Cobb-Douglas with heterogeneous parameters by region or estimating the production function using endowments as instruments for input used (columns 4 to 6 in Table 3). Our findings are also robust to using land available as a measure of farm size (see Table A.2 in the Appendix.)

3.3 Substantial dispersion in productivity measures

To the extent that policy makers do not observe productivity (either land or farm productivity), but instead can easily observe farm size, the inverse size-productivity relationship promises a tractable mechanism for policy implementation that has been highly influential.

Our previous results, however, point to an important limitation: there is substantial dispersion in both measures of productivity across farms of similar size (see Figure 1). This feature renders farm size a poor proxy of productivity and an ineffective instrument for policy. This conclusion is general because it applies to both measures of productivity. To illustrate this point, Table 4 documents the mean and dispersion of the two measures of

Table 2: Yields and farm size

	Outcome variable: ln(output per ha)					
	Yield approach			Production function approach		
	(1)	(2)	(3)	(4)	(5)	(6)
ln(land cultivated)	-0.239***	-0.257***	-0.487***	-0.035**	-0.064***	-0.295***
	(0.015)	(0.014)	(0.019)	(0.016)	(0.016)	(0.021)
ln(labor/land)				0.422***	0.390***	0.336***
				(0.016)	(0.017)	(0.017)
Controls	No	Yes	Yes	No	Yes	Yes
Household FE	No	No	Yes	No	No	Yes
No. obs.	16,063	14,578	15,788	15,806	14,335	15,533
R-squared	0.029	0.176	0.110	0.087	0.217	0.145

Notes: Robust standard errors in parentheses. Standard errors are clustered at the household level. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. All regressions (except in column 1) include district and region-by-year fixed effects as well as soil, farmer, and weather controls. Soil controls= % of farmland of different types, quality, and topography. Farmer controls = age, literacy, gender, ethnic group. Weather controls: DD, HDD, and log of precipitation. Columns 3 and 6 also include household fixed effects.

Table 3: Farm productivity and farm size

	Outcome variable = farm productivity ($\ln s_i$)					
	(1)	(2)	(3)	(4)	(5)	(6)
ln(land cultivated)	0.198***	0.295***	0.179***	0.181***	0.160***	0.175***
	(0.011)	(0.022)	(0.010)	(0.011)	(0.011)	(0.010)
Prod. function used to estimate s_i	CD	CD	CD + agric. practices	CD by region	CD + IV	Translog
No. obs.	15,363	3,249	15,332	15,332	15,251	15,332
R-squared	0.399	0.352	0.348	0.333	0.831	0.352

Notes: Robust standard errors in parentheses. Standard errors are clustered at the household level. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. All regressions include soil and farmer controls similar to Table 2, as well as district fixed effects. CD=Cobb-Douglas in land and labor inputs. Column 2 uses a cross-section of farmers obtained by collapsing the panel data at the household level. Column 3 estimates a CD specification adding indicators of agricultural practices such as the use of bulls/oxen, fertilizers, pesticides, improved seeds, and intercropping. Column 4 estimates s_i using a flexible CD specification with different parameters by region, column 5 uses a CD specification that instruments input use with input endowments (land available and household size), while column 6 uses a translog production function.

productivity (farm productivity and yields) across farms within farm-size bins for different farm size categories.[10] To characterize dispersion, we use the ratio of the 90th and 10th percentiles.

The main observation is that the within-class dispersion is similar to, or even greater, than the dispersion of the overall distribution. For instance, within very small farms (0 to 1 ha), the ratio of productivity between farms in the 90th and 10th percentiles is 11.2, whereas the ratio for the whole distribution is 8.9. We observe a similar pattern using yields. In that case, the ratio of productivity between the 90th and 10th percentile is around 12.6 for the very small farms, but 8.8 for the whole distribution.

Table 4: Productivity dispersion by farm size

		Farm productivity (s_i)		Yields (Y/T)	
Farm size (has)	% farms	Mean	90th / 10th percentile	Mean	90th / 10th percentile
0-1	28.8	1.348	11.2	3,185.6	12.6
1-2	33.8	1.334	8.0	2,712.6	8.6
2-5	32.6	1.624	6.7	2,386.0	6.5
5+	4.8	2.296	6.4	2,274.0	8.4
All farms	100.0	1.479	8.9	2,698.5	8.8

Notes: Farm size classes are calculated using average area planted. Yields (Y/T) refer to average yields per farmer.

4 Robustness checks

4.1 Omitted soil characteristics and measurement error

Existing work suggests that the inverse yield-farm size relationship may be driven by omitted variables, e.g. soil quality (Benjamin, 1995), or systematic measurement error (Carletto et al., 2013; Gourlay et al., 2017; Desiere and Jolliffe, 2018; Abay et al., 2019a). This error

[10] To facilitate comparison, we transform the farm productivity measure $\ln(s_i)$ into s_i.

arises if small farmers over-report output or under-report land. The measurement error could generate the inverse relationship between yields and farm size, even if the actual relationship is insignificant.[11] A relevant concern is that the pattern of results we observe may be a statistical artifact of these identification problems.

We examine this possible explanation in several ways. First, our regressions control for a rich set of soil characteristics, and are robust to including district or household fixed effects. These findings weaken the argument that our results are affected by omitted variables. Second, we replicate our baseline results using, as proxies of farm size, the area of available land measured using a GPS device. Arguably, this variable is less prone to have a systematic measurement error than self-reported land.[12] The results are, however, qualitatively similar (see columns 1 and 2 in Table 5).

Finally, we examine the role of systematic measurement error in the self-reported output. In the absence of crop-cut measures or other variables to address measurement error in output (as in Gourlay et al. (2017), for example), we use an indirect approach exploiting the observation that, to affect the estimates of farm-size and productivity, the measurement error needs to be correlated with farm size. Thus, we can proxy the measurement error using a function of land and labor.

In particular, we modify equation (8) by assuming that $\xi_{ijt} = v_{ijt} + M(T_i, L_i)$, i.e., there is systematic measurement error which is a function of farm size. Note that omitting $M(\cdot)$ as a regressor would create an endogeneity problem and we would not obtain consistent estimates of farm productivity (s_i).

We proxy M with a 4^{th} degree polynomial of the GPS measures of available land and total labor, and include these variables as additional regressors when estimating s_i. This

[11] We check whether this is a potential issue and find evidence of a sizable and systematic measurement error between self-reported and GPS measures of available land (see Figure A.4 and Table A.5 in the Appendix).

[12] It is not clear, however, that GPS measures are always preferable to self-reported land size. As pointed out by Abay et al. (2019a), in the presence of correlated measurement errors, using objective measures (such as GPS) could aggravate the bias when estimating the size-productivity relationship.

Table 5: Addressing measurement error

	ln(output per ha) GPS measure	farm productivity ($\ln s_i$)		
	(1)	(2)	(3)	(4)
ln(land available) GPS measure	-0.628***	0.140***	0.139***	0.137***
	(0.016)	(0.010)	(0.010)	(0.010)
Prod. function used to estimate s_i		CD	CD + land polyn.	CD + land and labor polyn.
No. obs.	10,070	11,146	11,146	11,146
R-squared	0.392	0.423	0.428	0.430

Notes: Robust standard errors in parentheses. Standard errors are clustered at the household level. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. Column 1 same controls as column 2 in Table 2. Columns 2 to 4 use same controls as column 1 in Table 3. Column 3 uses a measure of s_i estimated from CD production function with a 4th degree polynomial of land cultivated while column 4 further adds a 4th degree polynomial of total labor.

approach is similar in flavor to using polynomials of inputs to account for unobservables as in Levinsohn and Petrin (2003). Note that this approach also addresses biases due to unobserved inputs (such as labor quality or capital) that could be correlated with farm size.

Columns 3 and 4 in Table 5 show the results adding only the 4th degree polynomial of land (column 3), and for land and labor (column 4). In both cases, we still observe the positive relationship between farm productivity and farm size. Taken together, we interpret these results as evidence that the conflicting findings on the farm size-productivity relationship documented in Tables 2 and 3 are unlikely to be driven by omitted variables or systematic measurement error.

4.2 Plot-level regressions

Several studies estimate the yield-size relationship using plot-level data and exploiting within-farm variation. This approach effectively controls for all farm-specific variable and thus reduce concerns of bias due to market distortions.[13] However, as shown in Section 2, the validity of this approach still relies on the assumption of constant returns to scale.

How relevant is this issue in our context? Ideally, we would like to replicate the previous analysis and compare the estimated size-productivity relationship using measures of yield and s_i at the plot level or obtain measures of plot-level returns to scale. However, we cannot perform this analysis due to data limitations. In particular, we have plot-level information on output and land use, but lack data on other inputs, such as labor. Thus, we can calculate yields at plot level but cannot obtain input ratios nor estimate a plot-level production function.

We can, however, indirectly assess the importance of the CRS assumption. To do so, we estimate yield regressions using plot-level data and including household-period fixed effects (see Table 6). Column 1 does not include any control except for the fixed effects, while column 2 adds indicators of plot characteristics (soil type, quality, and topography). According to equation (7), the estimated parameter is equal to $\beta + \gamma - 1$, where γ measures economies of scale and β is the size-productivity relation. We can use this expression to calculate the implied value of β under different assumptions about economies of scale.

Under the CRS assumption, the implied $\beta = -0.271$ is negative. However, if returns to scale are sufficiently small ($\gamma \leq 0.72$) the size-productivity relation would become weakly positive. Interestingly, using our preferred farm-level estimates of $\gamma = 0.708$, we cannot reject the hypothesis that β is equal to zero.

4.3 Evidence from other countries

Are our results applicable in other contexts or are they specific to the Ugandan case? We explore this issue by replicating our analysis using household panel data from three different

[13] The use of farm fixed effect does not eliminate all relevant identification concerns. There is, for example, suggestive evidence that plot-level regressions may be biased due to systematic measurement error (Desiere and Jolliffe, 2018).

Table 6: Plot-level yield regressions

	Outcome variable: ln(output per ha.)	
	(1)	(2)
ln(land cultivated)	-0.271***	-0.272***
	(0.018)	(0.018)
Plot characteristics	No	Yes
Household-period FE	Yes	Yes
Assuming $\gamma = 0.708$		
Implied β	0.021	0.020
p-value $H_0: \beta = 0$	0.248	0.285
No. obs.	28,144	27,804
R-squared	0.021	0.025

Notes: Robust standard errors in parentheses. Standard errors are clustered at the household-period level. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. Period refers to season-year pair. All regressions include household-period fixed effects. Column 2 adds indicators of plot characteristics (soil type, soil quality, and topography).

countries: Peru, Tanzania, and Bangladesh. These countries expand our analysis across different regions in the world. For Peru, we use data from the National Household Survey (ENAHO) years 2007 and 2011. For Tanzania, we use the National Panel Survey (TNPS) which was carried out biannually from 2008 to 2012. For Bangladesh, we use data from the 2011 and 2015 Bangladesh Integrated Household Survey (BIHS).

In all cases, we find similar results as in Uganda: a negative correlation between yields and farm size, but a positive relationship between farm size and farm productivity (see Table 7). Similar to our main result, these findings are robust to alternative specifications of the production function (see Tables B.2 and B.3 in the Appendix).[14]

We also note that, although not directly comparable, since we do not have access to the microdata, we find similar patterns for the United States. Using the 2017 US Census

[14] Additional figures and estimated are available in Appendix B.

of Agriculture and the disaggregated information by farm size following the analysis in Adamopoulos and Restuccia (2014), we find a negative relationship between yields and farm size, whereas the relationship between labor productivity and farm size is strongly positive (see Table B.4). The implied elasticities with respect to farm size are -0.37 for the yield and 0.51 for labor productivity.

While the analysis so far relies on a few different countries, these results indicate that our findings may be broadly applicable to different developing countries, and highlight the need to revisit the interpretation of the negative yield-farm size relationship and its policy implications.

Table 7: Replication of main results using data from other countries

	Peru		Tanzania		Bangladesh	
	ln(output per ha)	farm productivity	ln(output per ha)	farm productivity	ln(output per ha)	farm productivity
	(1)	(2)	(4)	(5)	(4)	(5)
ln(land cultivated)	-0.759***	0.197***	-0.403***	0.151***	-0.103***	0.081***
	(0.014)	(0.011)	(0.019)	(0.016)	(0.012)	(0.010)
Soil controls	Yes	Yes	Yes	Yes	Yes	Yes
Farmer controls	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	No	No
Fixed effects	Strata & region-by-growing season & month of interv.		Season (short-long), district & survey round		District & survey round	
No. obs.	11,359	11,364	7,899	7,894	6,506	6,525
R-squared	0.433	0.358	0.287	0.573	0.224	0.229

Notes: Robust standard errors in parentheses. Standard errors are clustered at the household level. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. Columns 1, 3, and 5 replicate the yield approach of column 2 in Table 2. Columns 2, 4, and 5 replicate the regression in Column 1 of Table 3. This specification uses as dependent variable the farm productivity ($\ln s_i$) obtained from estimating a Cobb-Douglas production function. All regressions include a set of locations and time fixed effects. Soil controls: (Peru) indicators of soil quality from Fischer et al. (2008) (nutrient availability, nutrient retention, rooting conditions, oxygen availability, salinity, toxicity, and workability) and the share of irrigated land share of land. (Tanzania) share of loam soil, flat plot, and self-reported good soil. Indicators of whether the farm has irrigation, oxen, or tractor. (Bangladesh) share of arable land of different types (clay, loam, and sand). Farmer controls: age, age^2, gender, educational attainment (or literacy). Weather controls: degree days, harmful degree days, average monthly rainfall, and its square.

5 What explains the different results?

We show that, in several applications, using yields as a measure of productivity is not informative of the farm size-productivity relationship. This occurs because yields pick up not only farm productivity, but also market distortions and deviations from constant returns to scale. These issues can lead, as in the case of Uganda, to wrongly inferring a negative relationship between farm size and productivity.

We explore the validity of this interpretation in two ways. First, we modify the yield approach to account for market distortions and relax the CRS assumption. We show that, when correcting for these issues, the original negative relationship between yields and farm size is reversed. Second, we exploit variation in Ugandan land tenure regimes to indirectly assess the role of market distortions on driving the negative yield-size relationship.

5.1 Correcting for market distortions and returns to scale

Equation 3, derived in section 2, provides the correct specification linking yields to farm size. Using land cultivated (T_i) as measure of farm size, we can rewrite this expression as:

$$\ln \frac{Y_i}{T_i} = (\beta + \gamma - 1) \ln T_i + \gamma(1 - \alpha) \ln \frac{L_i}{T_i} + \gamma X_i + \ln A + \epsilon_i. \tag{9}$$

This specification is similar to the production function approach since it regresses yield on farm size and the input ratio. It does not, however, impose constant returns to scale. This implies that the estimate associated with farm size is equal to $\beta + \gamma - 1$, where β captures the farm size-productivity relationship and γ measures economies of scale.

Table 8 presents the estimates of equation (9) using two alternative measures of farm size: (self-reported) area cultivated and GPS measures of available land. We start by replicating the "yield approach" which suggests a negative relation between yields and farm size (columns

1 and 4). Then, we relax the CRS assumption and recover β by subtracting $(\hat{\gamma} - 1)$ from the estimates associated with farm size (columns 2 and 5). We use a value of $\hat{\gamma} = 0.708$ obtained from estimating the production function (see column 1 in Table A.1). Finally, we add the input ratio, our proxy for market distortions (columns 3 and 6).

The main result is that the initial negative estimate of β becomes less negative after relaxing the assumption of CRS and eventually becomes positive when correcting for market distortions. We obtain similar sign reversal of the yield-size relationship in the cases of Peru, Tanzania, and Bangladesh (see Table B.1 in the Appendix).

Table 8: Correcting for market distortions and returns to scale

	Outcome variable: ln(Y/T)					
	(1)	(2)	(3)	(4)	(5)	(6)
ln(T)	-0.270***	-0.270***	-0.075***	-0.630***	-0.630***	-0.200***
$\beta + \gamma - 1$	(0.015)	(0.015)	(0.016)	(0.015)	(0.015)	(0.020)
ln(L/T)			0.390***			0.578***
$\gamma(1 - \alpha)$			(0.017)			(0.019)
Measure of T	area planted (self reported)			GPS measure of available land		
Relax CRS assumption		Yes	Yes		Yes	Yes
Add input ratio L/T			Yes			Yes
Assumed γ	1.000	0.708	0.708	1.000	0.476	0.476
Implied β	-0.257	0.035	0.228	-0.629	-0.105	0.343
No. obs.	14,578	14,578	14,335	10,256	10,256	10,060
R-squared	0.176	0.152	0.195	0.392	0.176	0.279

Notes: Robust standard errors in parentheses. Standard errors are clustered at the household level. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. All regressions include district, region-by-year fixed effects and soil, weather and farmer controls as column 2 in Table 2. $\hat{\gamma} = 0.708$ obtained from Column 1 Table A.1.

5.2 Using land tenure regimes as proxies of market distortions

Our previous results implicitly use the input ratio L/T as a proxy for market distortions. However, the validity of this proxy depends on the functional form assumption of the production function.[15] As a complementary approach, we proxy for market distortions by exploiting variation in land tenure regimes. This approach is motivated by the Coase theorem and existing evidence suggesting that property rights play an important role in allocative efficiency (Besley and Ghatak, 2010; De Janvry et al., 2015; Restuccia and Santaeulàlia-Llopis, 2017; Chen, 2017).

A word of caution is, however, needed. Property rights themselves are the outcome of other factors that could affect productivity and input choices (such as access to infrastructure, distance to markets, among others). Thus, the results in this section should not be given a causal interpretation. Instead, we use property rights only as an indirect measure of the severity of market distortions.

Land tenure regimes There are two types of land tenure in Uganda: customary and non-customary land. Non-customary land includes tenure regimes such as freehold, leasehold, and Mailo,a form of leasehold in which landowners hold their land in perpetuity a while tenants have security of occupancy (Coldham, 2000). Non-customary tenure regimes offer some degree of formal, secure, property rights. In contrast, customary systems are based on communal ownership, are perceived as less secure and may face higher transaction costs due to lack of formal land registries and community approval requirements (Coldham, 2000; Place and Otsuka, 2002; Deininger and Castagnini, 2006).

These tenure systems are spatially concentrated in Uganda (see Figure A.5 in the Ap-

[15] For example, consider an alternative CES specification $f(T_i, L_i) = [A_i T^\rho + B_i L^\rho]^{\frac{\gamma}{\rho}}$ where A_i and B_i are input-specific productivity shifters that can vary by farmer. In that case, the land-labor ratio would be $[\frac{A_i}{B_i}\frac{w}{r(1+\tau_i)}]^{\frac{1}{-rho}}$. Thus, the input ratio would pick up not only the market distortion but also differences in input-specific productivity $\frac{B_i}{A_i}$.

pendix). Customary land is dominant in the Northern and Eastern regions, where more than 90% of land holdings are under this regime. In contrast, non-customary systems are mostly found in the Western and Central regions. In these regions, less than 7% of the land is held under customary systems. In our empirical analysis, we use regional indicators as the main proxies for the quality of property rights and development of land markets.

Land tenure and market distortions We start by assessing whether land tenure regimes capture meaningful differences in market distortions. To do so, we follow the literature on factor misallocation and evaluate the correlation between input use (land and labor) and farm productivity (Restuccia and Santaeulàlia-Llopis, 2017; Adamopoulos et al., 2017; Adamopoulos and Restuccia, 2020). In an efficient allocation, these variables should be positively correlated. A lower correlation in some areas would then be indicative of more severe market distortions.

A concern, however, is that the dispersion in productivity may be picking up not only market distortions but also unobserved heterogeneity or measurement error (Abay et al., 2019b). For that reason, we also examine this issue by testing for the separability of consumption and production decisions in farming households (Benjamin, 1992; Dillon and Barrett, 2017). This literature posits that, in the presence of perfect input markets, input use in production should be independent of household endowments. In our context, this implies that in areas with better functioning markets we should observe a weaker correlation between total labor demand and household size. In the absence of market distortions, this correlation would be zero, while stronger positive correlations would indicate more severe market failures.

In both approaches, we allow for different estimates by type of land tenure by including an interaction term with an indicator of being in the Western or Central region (regions with a higher incidence of non-customary tenure regimes). We also check the robustness of our findings to using a continuous variable: the share of farmland under non-customary regimes in the district (see Table A.6 in the Appendix).

Table 9 displays the results. The main observation is that the relationship between farm productivity and input use is larger (more positive) in places with modern rights, especially in regards to land (columns 1 and 2). These results are consistent with market distortions being less severe in places with modern property rights. This result is consistent with previous studies documenting a negative relation between customary land and agricultural investment, and more conflicts over land rights and fewer land purchases in areas with higher incidence of customary tenure (Place and Otsuka, 2002; Deininger and Castagnini, 2006).

Columns 3 and 4 confirm this finding. While there is a positive correlation between labor demand and household size, this relationship is significantly weaker in places with modern property rights. This finding rejects the separability hypothesis, a result consistent with the presence of market distortions. Taken together, these results justify using measures of land rights as proxies of market distortions.

Yield-size relationship under different land tenure regimes We re-examine the farm size-yield relationship allowing for differences by land tenure. The key idea is that if the negative size-yield relationship is driven by market distortions, then we would observe a less negative relationship in places with modern land rights. Table 10 presents our findings using both the yield (columns 1 and 2) and production function approach (columns 3 and 4). In both cases, we maintain the CRS assumption as in the existing literature.

We find that the inverse relationship becomes less negative in regions with modern land rights. This finding is robust to using alternative indicators of market distortions, such as the presence of local market places (see Tables A.7 and A.8 in the Appendix). This evidence is consistent with our interpretation that the negative relationship between yields and farm size reflects, in part, market distortions.

Table 9: Assessing market distortions

	ln(land available) GPS	ln(total labor)		
	(1)	(2)	(3)	(4)
Farm productivity	0.125**	0.166***		
	(0.051)	(0.020)		
Farm productivity × Western/Central region	0.390***	0.100***		
	(0.079)	(0.029)		
ln HH size			0.464***	0.393***
			(0.022)	(0.024)
ln HH size × Western/Central region			-0.069**	-0.129***
			(0.031)	(0.034)
ln(land available) GPS measure				0.193***
				(0.009)
No. obs.	1,968	15,235	15,331	10,524
R-squared	0.366	0.184	0.229	0.292

Notes: Robust standard errors in parentheses. Standard errors are clustered at the household level. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. All regressions include soil and farmer controls, as well as region-by-period and district fixed effects. Farm productivity ($\ln s_i$) is estimated using a flexible Cobb-Douglas in land and labor inputs with different parameters by region. Differences in sample size are due to columns 1 and 2 collapsing the sample to one observation per farmer. *Western or Central* is an indicator of being in one of the two regions.

Table 10: Farm size-yield relationship and land tenure

	ln(output per ha) GPS measure			
	Yield approach		Production function approach	
	(1)	(2)	(3)	(4)
ln(land available) GPS	-0.702***	-0.679***	-0.251***	-0.214***
	(0.023)	(0.027)	(0.025)	(0.028)
ln(land available) GPS × modern land rights	0.139***	0.110**	0.131***	0.075*
	(0.030)	(0.043)	(0.026)	(0.039)
ln(labor/land available GPS)			0.577***	0.579***
			(0.019)	(0.019)
Proxy of modern land rights	Western or Central	% non-custom. land in district	Western or Central	% non-custom. land in district
No. obs.	10,256	10,256	10,060	10,060
R-squared	0.395	0.393	0.471	0.470

Notes: Robust standard errors in parentheses. Standard errors are clustered at the household level. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. All regressions use GPS measure of available land as a proxy for farm size and include soil and farmer controls, as well as region-by-period and district fixed effects. Columns 3 and 4 include the log of input ratio as an additional control variable. *Western or Central* is an indicator of being in one of the two regions.

6 Conclusion

A prevalent view in development economics is that small farms are more productive than large farms. This view is rooted in the widely-held empirical finding of an inverse relationship between yields, as a measure of productivity, and farm size.

We show, however, that using yields is not informative as to whether small farms are more or less productive. This occurs because yields are affected by market distortions and deviations from constant returns to scale. These issues limit the usefulness of the inverse relationship to inform agricultural policies in developing countries and may lead to erroneous policy recommendations. We illustrate this limitation using data from Uganda and show that the use of yields (instead of measures of farm productivity) leads to qualitatively different results.

Our evidence also points to a more general limitation of the size-productivity relationship as a policy tool. We show for the case of Uganda that there is substantial dispersion in productivity across farms of similar size. This feature renders farm size a poor proxy of productivity, even if the size-productivity relationship is correctly estimated.

These results imply that there is not a simple instrument for policy. An effective policy should facilitate better resource allocation by farm productivity, but productivity is difficult to observe for the policymaker. Our results suggest that policy should focus on fostering and improving markets, in particular, markets for land. Even with an egalitarian distribution of property rights, land ownership can be decoupled from farm operational scales via rental markets or other decentralized mechanisms. Decoupling land use from land rights can also have substantial effects on migration and occupation decisions, further contributing to productivity growth in agriculture (De Janvry et al., 2015; Adamopoulos et al., 2017). How to achieve these outcomes in poor and developing countries is a challenging endeavor that merits the focus of future research.

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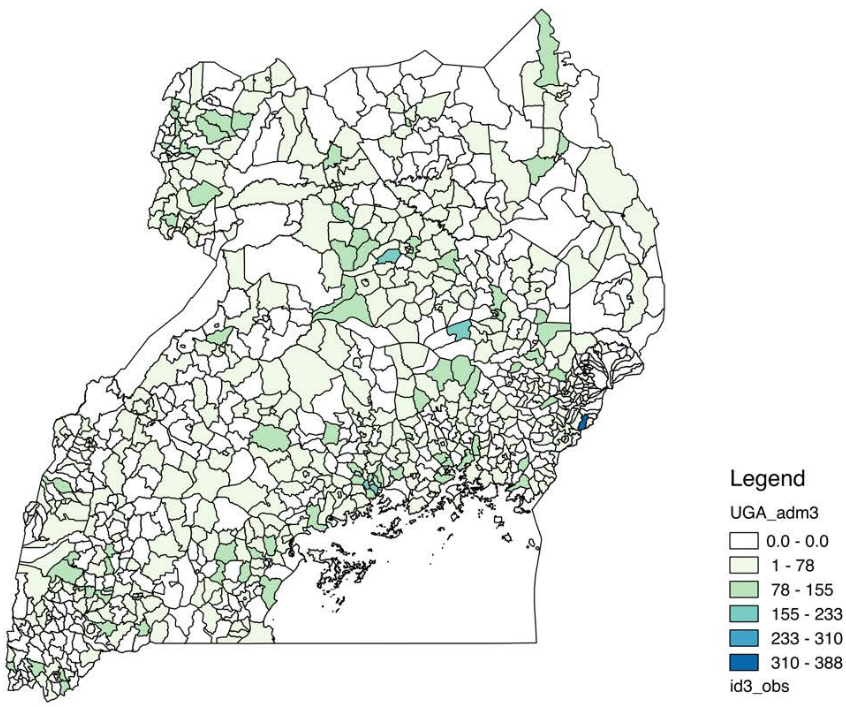
ONLINE APPENDIX - Not for publication

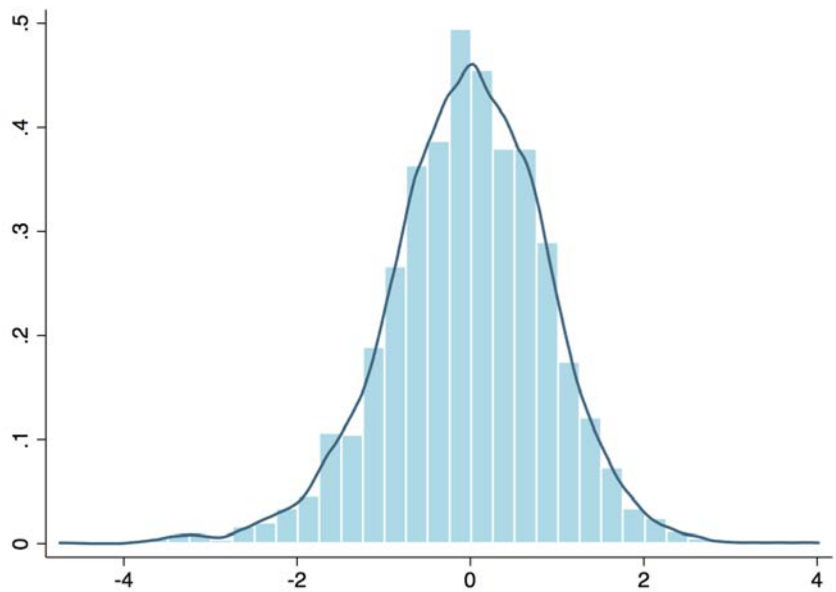
A Additional figures and tables

Figure A.1: Sample coverage



Notes: Figure depicts the number of observations per county.

Figure A.2: Distribution of farm productivity ($\ln s_i$)



Notes: The estimated production function parameters are $\hat{\alpha} = 0.526$ and $\hat{\gamma} = 0.708$. The difference between the 90^{th} and 10^{th} percentile is 2.23.

Figure A.3: Yields ($\ln Y/T$) and farm productivity ($\ln s_i$)

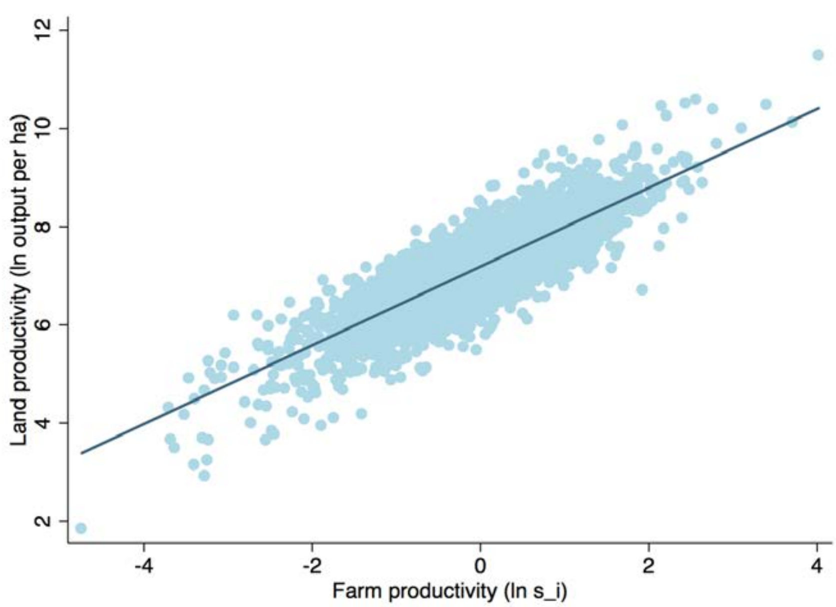
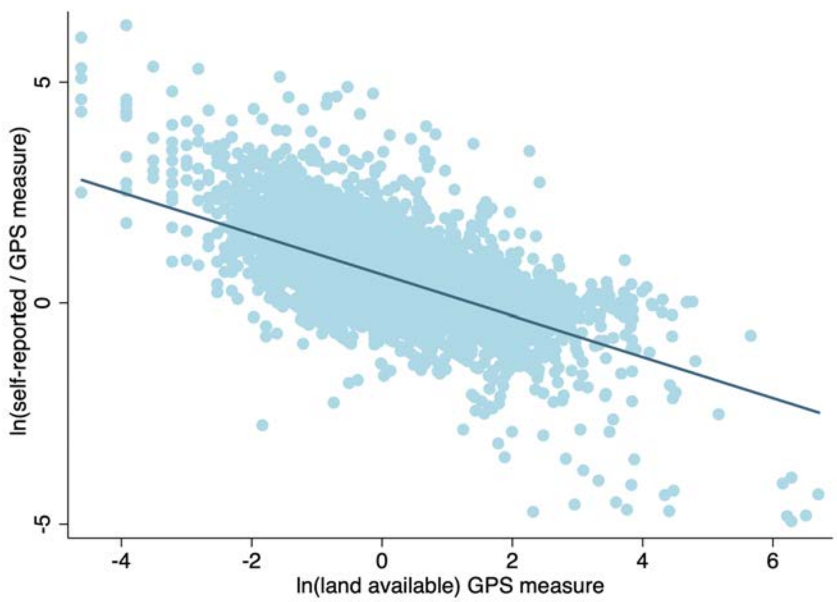
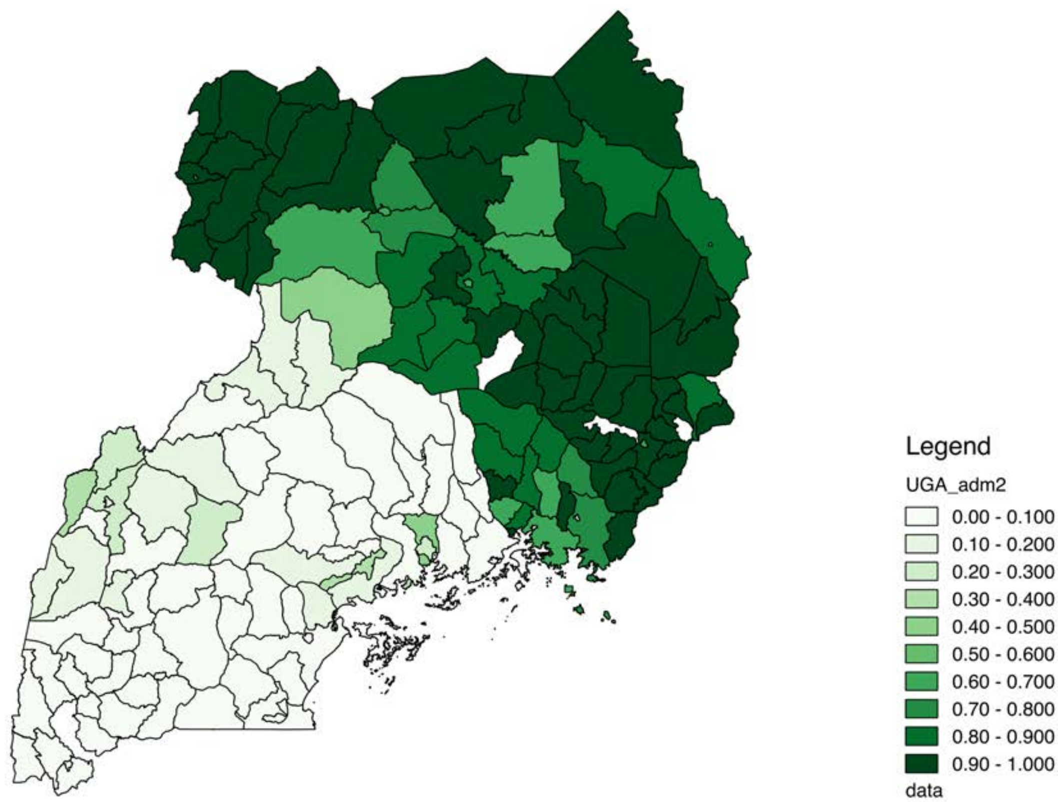


Figure A.4: Systematic measurement error in available land



Notes: Vertical axis is a proxy of measurement error = log of ratio of self-reported to GPS measure of available land.

Figure A.5: Land tenure regimes in Uganda



Notes: Figure depicts the share of customary land in district (as % of agricultural land).

Table A.1: Production function estimates

	ln(output)				
	(1)	(2)	(3)	(4)	(5)
ln(land cultivated)	0.372***	0.341***	0.355***	0.392***	
	(0.020)	(0.020)	(0.020)	(0.071)	
ln(total labor)	0.336***	0.339***			0.428***
	(0.017)	(0.019)			(0.021)
ln(land available)					0.048**
GPS measure					(0.020)
ln(domestic labor)			0.237***	0.296**	
			(0.017)	(0.149)	
ln(hired labor)			0.132***	0.131***	
			(0.011)	(0.011)	
Method	OLS	OLS	OLS	IV	OLS
Control for agric. practices	No	Yes	Yes	Yes	No
Implied γ	0.708	0.681	0.724	0.819	0.476
Implied α	0.526	0.502	0.490	0.479	0.101
Observations	15,541	14,361	14,361	13,933	10,789
No. farmers	3,457	3,403	3,403	3,356	2,617
R-squared	0.154	0.155	0.155		0.120

Notes: Robust standard errors in parentheses. Standard errors are clustered at household level. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. All regressions include household and region-by-period fixed effects, plus weather controls. Columns 2 to 4 also include indicators of using fertilizers, pesticides, improved seeds, intercropping, hired labor, and tenure of bulls/oxen. Column 4 uses land available and no. of household members who work in farm in last year as instruments for land cultivated and domestic labor. Column 5 replicates baseline specification in Column 1 but uses GPS measure of land available instead of self-reported cultivated land. Land measured in has. Labor measured in person-days.

Table A.2: Using available land as measure of size

	ln(output/land cultivated)				Farm productivity	
	(1)	(2)	(3)	(4)	(5)	(6)
ln(land available)	-0.073***	-0.101***	-0.230***	-0.037*	0.188***	0.251***
	(0.013)	(0.013)	(0.022)	(0.020)	(0.011)	(0.019)
Controls	No	Yes	Yes	Yes	Yes	Yes
Household FE	No	No	Yes	No	No	No
No. obs.	16,010	14,532	15,740	3,252	16,373	3,249
R-squared	0.003	0.153	0.057	0.250	0.392	0.350

Notes: Robust standard errors in parentheses. Standard errors are clustered at household level. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. All regressions (except column 1) include soil and farmer controls similar to Table 2, as well as district fixed effects. Columns 2 to 4 also includes region-by-period fixed effects, while column 3 adds household fixed effects. Columns 4 and 6 use a cross-section of farmers obtained by collapsing the panel data at household level.

Table A.3: Yields and farm size using regional and local prices

	Outcome variable: ln(output/land cultivated)			
	(1)	(2)	(3)	(4)
ln(land cultivated)	-0.160***		-0.282***	
	(0.018)		(0.025)	
ln(land available) GPS		-0.583***		-0.637***
		(0.019)		(0.023)
Output prices	Regional (n=5)		District (n=109)	
No. obs.	14,685	10,330	7,582	5,601
R-squared	0.235	0.365	0.276	0.422

Notes: Robust standard errors in parentheses. Standard errors are clustered at household level. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. All regressions include soil, farmer and weather controls similar to column 2 of Table 2, as well as district fixed effects. Columns 1 to 2 calculate real agricultural output (at 2009 prices) using median prices by region, while columns 3 and 4 use median prices by district.

Table A.4: Farm productivity and farm size using regional and local prices

	Outcome variable = farm productivity			
	(1)	(2)	(3)	(4)
ln(land cultivated)	0.226***		0.177***	
	(0.014)		(0.020)	
ln(land available) GPS		0.157***		0.142***
		(0.013)		(0.019)
Output prices	Regional (n=5)		District (n=109)	
No. obs.	15,368	11,146	13,640	9,986
R-squared	0.442	0.495	0.465	0.478

Notes: Robust standard errors in parentheses. Standard errors are clustered at household level. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. All regressions include soil and farmer controls similar to column 1 of Table 3, as well as district fixed effects. Columns 1 to 2 calculate real agricultural output (at 2009 prices) using median prices by region, while columns 3 and 4 use median prices by district.

Table A.5: Systematic measurement error in self-reported land available

	ln(self-reported land available / GPS measure)			
	(1)	(2)	(3)	(4)
ln(land available) GPS	-0.465***	-0.505***	-0.503***	-0.573***
	(0.012)	(0.014)	(0.016)	(0.019)
ln(land available) GPS × 1(Western/Central region)			0.087***	0.134***
			(0.021)	(0.026)
Control variables	No	Yes	No	Yes
Observations	12,134	11,172	12,134	11,172
R-squared	0.382	0.466	0.385	0.472

Notes: Robust standard errors in parentheses. Standard errors are clustered at household level. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. Outcome variable is the log of the ratio of self-reported land available and the corresponding GPS measure. Mean of outcome variable = 0.427. Columns 2 and 4 include as control variables: weather, soil and farmer characteristics as well as district and region-by-period fixed effects.

Table A.6: Assessing market distortions - using continuous measure of land tenure

	ln(land available) GPS	ln(total labor)		
	(1)	(2)	(3)	(4)
Farm productivity	0.142**	0.193***		
	(0.067)	(0.024)		
Farm productivity × % modern land in district	0.376***	0.042		
	(0.129)	(0.045)		
ln HH size			0.459***	0.396***
			(0.028)	(0.030)
ln HH size × % modern land in district			-0.066	-0.150***
			(0.051)	(0.056)
ln(land available) GPS measure				0.192***
				(0.009)
No. obs.	1,968	15,235	15,329	10,524
R-squared	0.359	0.184	0.230	0.292

Notes: Robust standard errors in parentheses. Standard errors are clustered at the household level. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. All regressions include soil and farmer controls, as well as region-by-period and district fixed effects. Farm productivity ($\ln s_i$) is estimated using a flexible Cobb-Douglas in land and labor inputs with different parameters by region. Differences in sample size is due to columns 1 and 2 collapsing the sample to one observation per farmer.

Table A.7: Assessing market distortions - using presence of local markets

	ln(land available) GPS		ln(total labor)	
	(1)	(2)	(3)	(4)
Farm productivity	0.079	0.132*	0.176***	0.202***
	(0.061)	(0.079)	(0.024)	(0.029)
Farm productivity × modern land rights	0.388***	0.291**	0.104***	0.051
	(0.087)	(0.140)	(0.033)	(0.050)
Farm productivity × has local market	0.141	0.124	-0.027	-0.028
	(0.091)	(0.089)	(0.032)	(0.032)
Proxy of modern land rights	Western or Central	% non-custom. land in district	Western or Central	% non-custom. land in district
No. obs.	1,631	1,631	11,536	11,536
R-squared	0.400	0.391	0.201	0.202

Notes: Robust standard errors in parentheses. Standard errors are clustered at the household level. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. All regressions include soil and farmer controls, as well as region-by-period and district fixed effects. Farm productivity ($\ln s_i$) is estimated using a flexible Cobb-Douglas in land and labor inputs with different parameters by region. Differences in sample size is due to columns 1 and 2 collapsing the sample to one observation per farmer. *Western or Central* is an indicator of being in one of the two regions. *has local market* is an indicator of having a market place (for either agricultural or non agricultural goods) in the community.

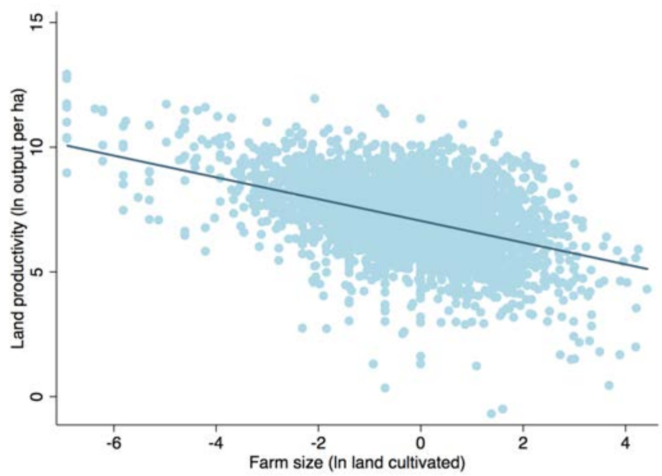
Table A.8: Farm size-yield relationship and land tenure - using presence of local markets

	ln(output per ha) GPS measure			
	Yield approach		Production function approach	
	(1)	(2)	(3)	(4)
ln(land available) GPS	-0.703***	-0.672***	-0.265***	-0.224***
	(0.028)	(0.030)	(0.029)	(0.031)
ln(land available) GPS × modern land rights	0.117***	0.078*	0.112***	0.057
	(0.032)	(0.045)	(0.028)	(0.040)
ln(land available) GPS × has local market	0.052	0.041	0.055**	0.045
	(0.032)	(0.032)	(0.028)	(0.028)
ln(labor/land available GPS)			0.569***	0.572***
			(0.021)	(0.021)
Proxy of modern land rights	Western or Central	% non-custom. land in district	Western or Central	% non-custom. land in district
No. obs.	8,246	8,246	8,081	8,081
R-squared	0.406	0.405	0.478	0.478

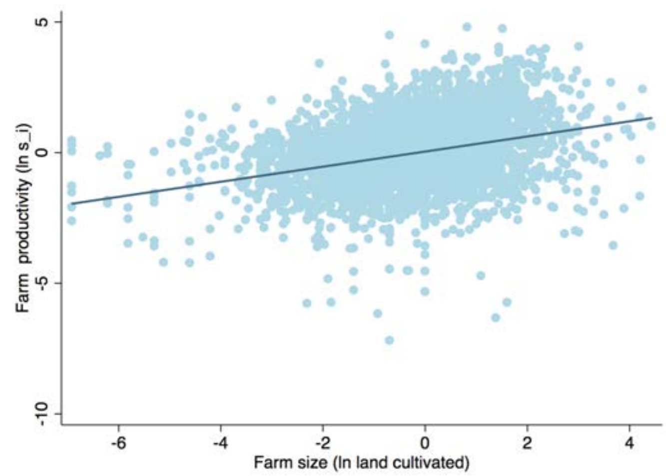
Notes: Robust standard errors in parentheses. Standard errors are clustered at the household level. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. All regressions use GPS measure of available land as proxy for farm size and include soil and farmer controls, as well as region-by-period and district fixed effects. Columns 3 and 4 include log of input ratio as an additional control variable. *Western or Central* is an indicator of being in one of the two regions. *has local market* is an indicator of having a market place (for either agricultural or non agricultural goods) in the community.

B Evidence from other countries

Figure B.1: Farm size and productivity - Peru

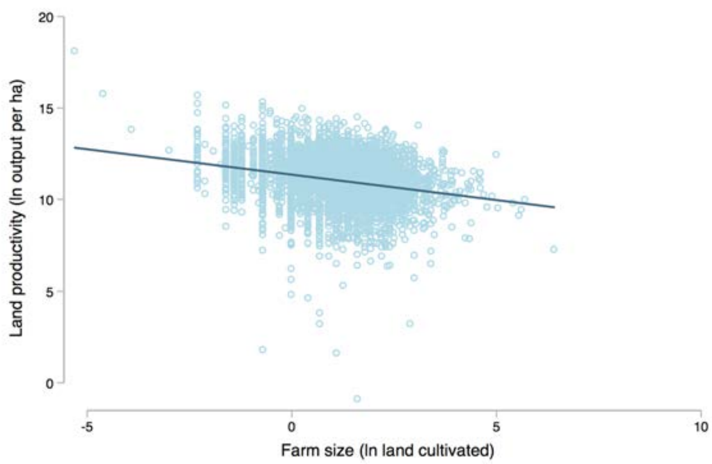


(a) Land productivity ($\ln(Y/T)$)

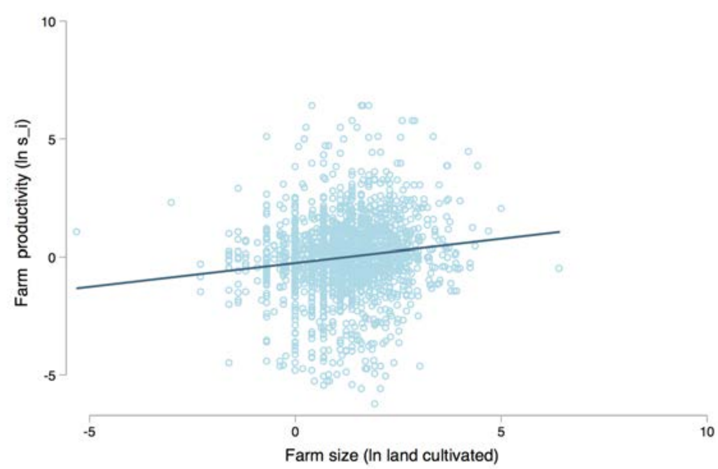


(b) Farm productivity ($\ln s_i$)

Figure B.2: Farm size and productivity - Tanzania

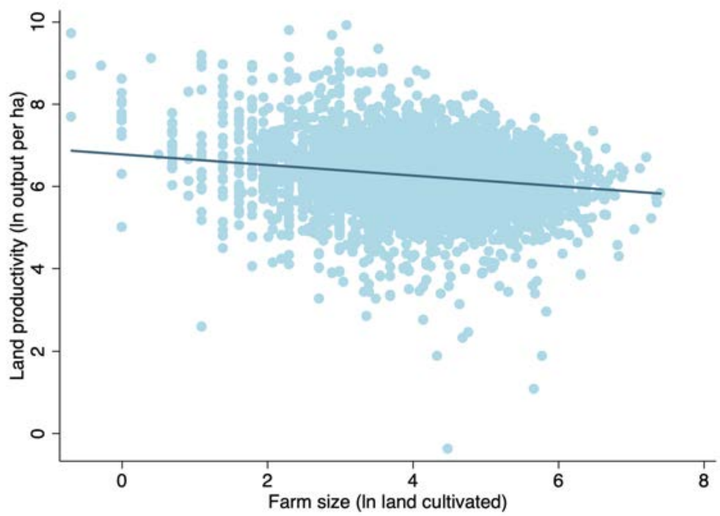


(a) Land productivity ($\ln(Y/T)$)

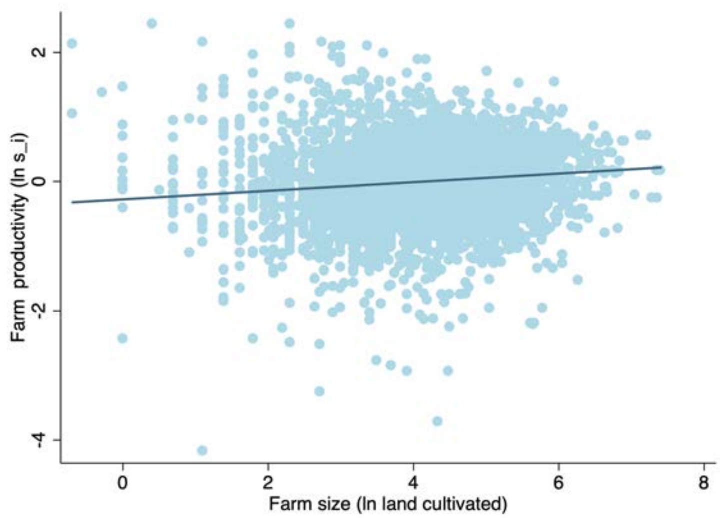


(b) Farm productivity ($\ln s_i$)

Figure B.3: Farm size and productivity - Bangladesh



(a) Land productivity ($\ln(Y/T)$)



(b) Farm productivity ($\ln s_i$)

Table B.1: Replication of Table 8: Correcting by DRS and market distortions countries

	Peru			Tanzania			Bangladesh		
	ln(output per ha.)			ln(output per ha.)			ln(output per ha.)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ln(land cultivated)	-0.533***	-0.533***	-0.286***	-0.403***	-0.403***	-0.152***	-0.103***	-0.103***	0.032***
$\beta + \gamma - 1$	(0.012)	(0.012)	(0.030)	(0.019)	(0.019)	(0.020)	(0.012)	(0.012)	(0.010)
ln(labor/land)			0.259***			0.447***			0.476***
$\gamma(1-\alpha)$			(0.029)			(0.017)			(0.016)
Relax CRS assumption		Yes	Yes		Yes	Yes		Yes	Yes
Add input ratio			Yes			Yes			Yes
Assumed γ	1.000	0.384	0.384	1.000	0.691	0.691	1.000	0.904	0.904
Implied β	-0.533	0.083	0.330	-0.403	-0.094	0.157	-0.103	-0.014	0.128
No. obs.	11,359	11,359	11,357	7,899	7,899	7,890	6,506	6,506	6,506
R-squared	0.384	0.205	0.213	0.287	0.234	0.334	0.224	0.201	0.360

Notes: Robust standard errors in parentheses. Standard errors are clustered at the household level. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. Results replicate columns 1-3 of Table 8. Regressions includes same controls as baseline results in Table 7. Assumed γ obtained from estimation of production function.

Table B.2: Robustness checks of yield-size relationship

	Peru			Tanzania			Bangladesh		
	ln(output per ha.)			ln(output per ha.)			ln(output per ha.)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ln(land cultivated)	-0.759***		-0.286***	-0.613***		-0.152***	-0.213***		0.040***
	(0.014)		(0.030)	(0.031)		(0.020)	(0.025)		(0.010)
ln(land available)		-0.498***			-0.363***			-0.083***	
		(0.012)			(0.020)			(0.011)	
ln(labor/land)			0.259***			0.447***			0.476***
			(0.029)			(0.017)			(0.016)
Household FE	Yes	No	No	Yes	No	No	Yes	No	No
No. obs.	11,359	11,359	11,357	7,899	7,899	7,890	6,506	6,506	6,506
R-squared	0.384	0.205	0.213	0.172	0.272	0.379	0.052	0.218	0.378

Notes: Robust standard errors in parentheses. Standard errors are clustered at the household level. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. Results replicate columns 2-4 of Table 2. Regressions includes same controls as baseline results in Table 7. Column 1 also adds household fixed effects. Columns 3, 6 and 9 use the production function approach , while other columns use the yield approach.

Table B.3: Robustness checks of farm productivity-size relationship

	Peru			Tanzania			Bangladesh		
	ln(output per ha.)			ln(output per ha.)			ln(output per ha.)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ln(land cultivated)	0.183***	0.136***	0.176***	0.163***	0.201***	0.154***	0.078***	0.111***	0.083***
	(0.011)	(0.011)	(0.011)	(0.017)	(0.017)	(0.016)	(0.010)	(0.020)	(0.009)
Prod. function used used to estimate s_i	CD by department	CD + IV	Translog	CD by region	CD + IV	Translog	CD by division	CD + IV	Translog
No. obs.	11,364	11,364	11,364	7,894	7,055	7,894	6,525	6,525	6,525
R-squared	0.301	0.333	0.314	0.868	0.450	0.576	0.430	0.246	0.234

Notes: Robust standard errors in parentheses. Standard errors are clustered at the household level. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. Results replicate columns 4-6 of Table 3. Regressions includes same controls as baseline results in Table 7. No. of departments in Peru = 24. No. regions in Tanzania=26. No. divisions in Bangladesh=7.

Table B.4: Yields and labor productivity by farm size – United States

Farm size (acres)	Average farm size	Farm distribution (%)	Land share (%)	Value added per acre	Value added per worker
1−9	4.8	13.4	0.1	23.3	1.0
10−49	25.4	28.5	1.6	6.6	1.5
50−69	58.1	6.6	0.9	4.7	2.3
70−99	82.2	8.0	1.5	3.8	3.0
100−139	116.0	7.3	1.9	3.0	3.3
140−179	157.4	5.7	2.0	2.6	3.8
180−219	197.7	3.6	1.6	2.9	5.0
220−259	238.0	2.8	1.5	2.6	5.4
260−499	357.8	9.0	7.3	2.6	7.5
500−999	696.6	6.5	10.3	2.8	13.3
1,000−1,999	1376.6	4.3	13.4	2.4	19.3
2,000+	6103.4	4.2	57.7	1.0	22.7

Notes: Value added per acre and value added per worker are normalized relative to the lowest value. Data is from the 2017 US Census of Agriculture, Table 71, Summary by Size of Farm. Value added and adjusted farm labor are computed following Adamopoulos and Restuccia (2014).