NBER WORKING PAPER SERIES

ARE SMALL FARMS REALLY MORE PRODUCTIVE THAN LARGE FARMS?

Fernando M. Aragon Sanchez
Diego Restuccia
Juan Pablo Rud

Working Paper 26331
http://www.nber.org/papers/w26331

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
September 2019

For useful comments, we are grateful to Tasso Adamopoulos, Yongs Shin, and seminar participants at several institutions and conferences. All errors are our own. Restuccia gratefully acknowledges the support from the Canada Research Chairs program and the Bank of Canada Fellowship program. Aragon gratefully acknowledges financial support from the Social Sciences and Humanities Research Council of Canada, grant 435-2018-0227. The views expressed herein are not necessarily those of the Bank of Canada or the National Bureau of Economic Research and are the author's alone.

Are Small Farms Really more Productive than Large Farms?
Fernando M. Aragon Sanchez, Diego Restuccia, and Juan Pablo Rud
NBER Working Paper No. 26331
September 2019
JEL No. C33,C55,D24,E02,E13,O11,O12,O13,O4,O5,Q15,Q18

ABSTRACT

We revisit the long-standing empirical evidence of an inverse relationship between farm size and productivity using rich microdata from Uganda. We show that farm size is negatively related to yields (output per hectare), as commonly found in the literature, but positively related to farm productivity (a farm-specific component of total factor productivity). These conflicting results do not arise because of omitted variables such as land quality, measurement error in output or inputs, or specification issues. Instead, we reconcile the findings emphasizing the role of farm-specific distortions and returns to scale in traditional farm production. We exploit unique regional variation in land tenure regimes in Uganda in evaluating the role of farm-specific distortions. Our findings point to the limited value of yields (or land productivity) in establishing the farm size-productivity relationship. More generally, we demonstrate the limitation of using farm size in guiding policy applications.

Fernando M. Aragon Sanchez
SFU, Dep. Economics
8888 University Drive
V5A 1S6, Burnaby, BC Canada
faragons@sfu.ca

Diego Restuccia
Department of Economics
University of Toronto
150 St. George Street
Toronto, ON M5S 3G7
CANADA
and NBER
diego.restuccia@utoronto.ca

Juan Pablo Rud
Dept of Economics, Royal Holloway
Egham Hill, Egham
Surrey TW20 0EX, UK
juan.rud@rhul.ac.uk

1 Introduction

An important and established literature has documented a robust inverse relationship between yields (i.e., output per unit of land) and farm size. The implication is that if yields proxy for farm productivity, a common presumption in the literature, then small farms are more productive than large farms (Berry et al., 1979; Barrett, 1996; Barrett et al., 2010). This interpretation of the inverse yield-size relationship has had a profound effect on agricultural policy whereby small landholder agriculture is considered a cornerstone of microeconomic development, as documented in Collier and Dercon (2014). This view contrasts sharply with the macroeconomic evidence whereby farming in developing countries operates predominantly at small scale and feature much lower agricultural productivity, compared to rich countries where the predominant unit of production is large scale farming (Adamopoulos and Restuccia, 2014).

In this paper, we demonstrate that using yields as a measure of productivity to evaluate the size-productivity relationship is not informative for agricultural policies and can lead to erroneous recommendations. This happens because yields pick up not only farm productivity, but also market distortions and technological features such as returns to scale. These issues can derive qualitatively different estimates of the farm size-productivity relationship.

Our analysis relies on rich microdata from Ugandan farmers. We construct two alternative measures of productivity: (1) yields, as is standard in the literature and (2) farm productivity, exploiting the detailed information from the microdata. In particular, farm productivity is constructed by estimating a farm-level production function and corresponds to the farm-specific component of total factor productivity (TFP). Using these two alternative measures, we evaluate the farm size-productivity relationship.

We find that the results are highly sensitive to the measure of productivity we use. We observe 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. But when using farm productivity instead of yields, we find a *positive* relationship with farm size. These conflicting results do not arise as a statistical artifact due to omitted soil characteristics or measurement errors in farm size or output.

Instead, our results reflect a more profound limitation of yields as a measure of productivity by farm size. Since yields are a measure of land productivity, they pick up farm productivity plus deviations from constant returns to scale (CRS) and market distortions. In practice, these considerations imply that estimates of the size-productivity relationship using yields are inconsistent when the farm technology exhibits decreasing returns to scale (DRS) or in the presence of size-dependent distortions. These are plausible conditions in most applications in developing countries.

We evaluate the validity of our interpretation of the results in two ways. First, 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 becomes positive. Second, we exploit unique variation in land tenure regimes to examine in more detail the role of market distortions. Uganda has two broad types of tenure regimes: non-customary and customary systems. Customary systems exhibit communal property rights, face higher transaction costs and are perceived as less secure.

We use the type of land tenure as a measure for the extent of market distortions. The key idea is that in places with modern, non-customary, land (such as Western and Central regions), markets distortions would be smaller and thus the yield-farm size relationship would be less biased. We start by showing that factor misallocation (measured by the correlation between farm productivity and input use) is smaller in regions with more non-customary land. Then, we find that the yield-farm size relationship becomes less negative in areas with non-customary property rights. We interpret this finding as suggestive evidence that market distortions play a role in driving the negative yield-farm size result.

Our paper is not the first to raise concerns on the use of yields as a measure of productivity when evaluating the size-productivity relationship. Early reviews on the size-productivity relationship have emphasized the use of yields as “flawed by methodological shortcomings” (Binswanger et al., 1995, p. 2706). More recently, Helfand et al. (2018) argue that partial measures of productivity, such as yields, may be inappropriate and advocate for using total factor productivity. Using data from Brazil, they also show that the sign of the size-productivity relationship depends of the measure used and suggest that deviations from CRS could be a possible source of discrepancy.

The contribution of our paper to this debate is twofold. First, we establish why yields are not informative of the size-productivity relationship and may lead to erroneous policy recommendations. In particular, we show the importance of size-dependent market distortions and deviations from CRS as key sources. Second, we provide empirical evidence on the relevance of these sources and examine their quantitative importance in explaining the negative size-productivity relationship. We also provide evidence that our results apply in other contexts around the world, by reproducing the main set of findings for Peru, Tanzania and Bangladesh.

Importantly, our results also point out a broader limitation of the size-productivity literature. The size-productivity relationship offers a tractable mechanism for policy implementation: if size is correlated to productivity then it can be used to target farmers and enhance efficiency. We show, however, that size is deeply confounded with distortions in developing countries. This issue makes farm size a poor proxy of 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, distortions imply substantial dispersion in productivity across farms of similar size. Thus, even if the relationship is correctly estimated, farm size becomes an uninformative proxy of farm productivity.

We demonstrate this point by documenting the dispersion in productivity (using both yields and farm productivity) across farms within farm-size categories. We show that this dispersion is very large for each farm-size class, and in some cases larger than the dispersion of productivity across the entire sample of farms. In addition, the scope of reallocation gains is much smaller across farm sizes than across farms with different productivity. For instance, the ratio of farm productivity between the 90th and 10th percentiles of farms is a factor of more than 8-fold, whereas the ratio of average farm productivity between the largest and smallest farm size classes is a factor of only 2.3-fold, and the ratio of average yields between the smallest and largest farm size categories is even smaller, only a factor of 1.4-fold.

The paper is organized as follows. In Section 2, we provide some background on the farm size-productivity relationship and its importance to guide economic policy. 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 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 5 provides a broader discussion of our findings and evidence from other countries. We conclude in Section 6.

2 Background

The study of the relationship between farm size and productivity occupies a central place in the agrarian and development economics literature (Barrett et al., 2010). An important finding in this literature is the inverse relationship between farm size and yields (output per unit of land). This result has been documented in several countries in Asia, Africa, and Latin-America (Berry et al., 1979; Barrett, 1996; Barrett et al., 2010) and has been interpreted as evidence that small farms are more productive.

There are several explanations in the literature for why small farms may be more productive. For instance, small farms may be able to solve a contractual problem (hidden effort) of farm workers (Feder, 1985; Eswaran and Kotwal, 1986). A complementary explanation is that small farms may be more productive due to selection: low-productivity farmers with small landholdings may be more likely to hit a minimum consumption threshold, and leave agriculture, than similar farmers with larger farms. As a result, in average, small farms would be more productive (Assuncao and Ghatak, 2003). A recent explanation emphasizes a behavioral phenomenon: farmers may put more effort on the edges of a plot. This “edge” effect would be proportionally larger in smaller plots—which have relatively more area on the edges—and thus explain why small farms are more productive (Bevis and Barrett, 2016).

The interest on the farm size-productivity relationship stems, in part, from its profound normative implication: if small farms are indeed more productive, then land redistribution from large to small farms can increase agricultural productivity and food availability (Barrett et al., 2010; Collier and Dercon, 2014). In addition, the farm size-productivity relationship provides a tractable approach to policy implementation. Since farm size is easily observable by the policy maker, whereas productivity is difficult to assess in real time, policies are often implemented based on size.

To fix ideas, consider a standard model of farm size and input allocation. The framework is based on Adamopoulos and Restuccia (2014), building on previous work from Lucas Jr (1978) and Hopenhayn (1992). There are n heterogeneous farmers producing a single homogeneous good according to the following production function:

$$y_i = s_i A (T_i^{\alpha} L_i^{1-\alpha})^{\gamma}, \tag{1}$$

where T_i and L_i stand for the amounts of land and labor used by farmer i. Total factor productivity is equal to $s_i A$, where A is a common productivity shock, such as weather, and

s_i is a farm-specific output shifter, such as farming ability or entrepreneurship. Henceforth, we call s_i farm productivity.

This framework provides a simple characterization of the efficient, first best, allocation of land and labor across farmers. Consider a static allocation in which the set of farmers and distribution of productivity are given, and the economy has fixed endowments of land (T^e) and labor (L^e). In this context, the efficient allocation maximizes aggregate output and solves the following social planner's problem:

$$\begin{aligned} \max_{\{T_i, L_i\}} \quad & \sum_i s_i A (T_i^{\alpha} L_i^{1-\alpha})^{\gamma}, \\ \text{subject to} \quad & \sum_i T_i = T^e, \ \sum_i L_i = L^e. \end{aligned}$$

The Pareto efficient allocation equates the marginal product of land and labor across farmers. By the first welfare theorem, this solution also corresponds to the allocation in a competitive market equilibrium with no distortions. Letting $z_i \equiv s_i^{1/(1-\gamma)}$, we can characterize the efficient allocations as:

$$T_i^* = \frac{z_i}{\sum z_i} T^e, \ L_i^* = \frac{z_i}{\sum z_i} L^e.$$

The main insight is that an efficient allocation requires resources to be *proportional* to farm productivity s_i, i.e., more productive farmers should operate more land and labor. It follows that if the relationship between farm size and farm productivity is indeed negative, then policies that redistribute land towards small landholders would enhance economic efficiency and increase aggregate productivity. The framework also suggests that an approach to assess the extent of factor misallocation in an economy involves comparing the relationship between farm size and farm productivity in the actual data to the efficient benchmark. This source of economic inefficiency has attracted attention as a quantitatively relevant determinant of income differences across countries (Restuccia and Rogerson, 2008; Hsieh and Klenow, 2009).

An important issue is that the evidence that small farms are more productive is based on estimates of the relationship between farm size and yields (or land productivity) instead of measures of farm total factor productivity s_i. We show below that, in many applications, this choice of variable results in misleading estimates of the size-productivity relationship and thus leads to erroneous policy recommendations. Moreover, we show that because of distortions and other market imperfections, farm size hides substantial heterogeneity in farm productivity, diminishing the effectiveness of size-related policy implementations.

3 Empirical evidence

We revisit the evidence that small farms are more productive than large farms using detailed microdata from Ugandan households. We start by replicating the inverse relationship between yields and farm size, as in the existing literature. Then, we re-examine this result with the same data but using estimates of farm productivity s_i.

3.1 Data

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). We focus on the farm as the production unit so our unit of observation is a household farm i in period t, where t refers to a season-round pair. A farmer may operate one or several parcels or plots of land and hence we aggregate any information at the parcel level to the household-farm level. Focusing on the farm as the production unit is critical in measuring productivity since many issues of measurement arise at the plot 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 (i.e., 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.

We measure 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 use and farm size. In addition, we obtain measures of available land from self-reported information and from 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 in 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 use of fertilizers, pesticides, or intercropping), soil characteristics and land tenure regimes. Regarding soil characteristics, the survey asks farmers to classify each parcel according to soil type (sand loan, sandy clay loan, back clay or other), quality (good, fair, or poor) and topography (hilly, flat, gentle slope, valley or other). We aggregate the parcel-level indicators to the farm level to obtain a share of farm land in each category.

Similarly, we obtain indicators of the share of land (at the farm and district level) under different tenure regimes. We distinguish two types of tenure regimes: customary and non-customary. Non-customary tenure regime includes freehold, leasehold, and Mailo.[1] Later, we use these variables as a measure of property rights to assess the role of land market imperfections.

We complement the household survey with weather data: temperature and precipitation. These variables are relevant determinants of agricultural productivity (see, for example, 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 al., 2015). We combine the weather and survey data using the location of the sub-county (n=967) of residence of the household.[2]

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 domestic instead of hired labor. Third, there is a limited use of capital inputs (such as oxen) and productivity-enhancing inputs such as fertilizers, pesticides, and improved seeds. Finally, there is substantial variation in land property rights: around 27% of the land is held under non-customary, modern, regimes (like freehold, leasehold, and Mailo) while the rest is held under customary,

[1] The Mailo tenure system is a form of leasehold in which land owners hold their land in perpetuity and have similar rights to freeholders, while tenants have security of occupancy as in common-law arrangements (sometimes backed by a certificate). A tenant can only be removed if the land is unattended for at least three years (Coldham, 2000).

[2] 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°C and 26°C while harmful degree days (HDD) captures exposure to temperatures above 26°C. The inclusion of HDD allows for potentially different, non-linear, effects of extreme heat.

communal, property rights, which are prevalent in Africa and developing countries.

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
Degree days (°C)	15.1	1.8
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.

Measures of productivity We construct two alternative measures of productivity: land productivity (or yield) and farm productivity.[3] 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 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 (land or labor) to individual crops.

Second, we obtain estimates of farm productivity s_i. To do so, we estimate the following production function $Y_{ijt} = s_i A_{ijt}(T_{it}^{\alpha} L_{it}^{1-\alpha})^{\gamma}$, where the unit of observation is a household farm i, in location j, and period (season-year) t. We assume that the common productivity shock is $A_{ijt} = \exp(\delta \cdot \text{weather}_{jt} + \eta_{jt} + \epsilon_{ijt})$ where weather_{jt} is a set of temperature and precipitation variables, η_{jt} is a region-season-year fixed effect, and ϵ_{ijt} is the error term. Taking logs, we obtain:

$$\ln Y_{ijt} = \ln s_i + \alpha\gamma \ln T_{it} + (1-\alpha)\gamma \ln L_{it} + \delta \text{weather}_{jt} + \eta_{jt} + \epsilon_{ijt}. \tag{2}$$

We estimate equation (2) using panel data methods with household fixed effects. Our preferred specification is a Cobb-Douglas production function with land and labor inputs and with the same parameters for all regions (see Column 1 in Table A.1).[4] The estimated

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

[4] 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 domestic 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.

production function parameters are $\hat{\alpha} = 0.526$ and $\hat{\gamma} = 0.709$, which are close to the values calibrated in the context of similar economies such as Restuccia and Santaeulalia-Llopis (2017) for Malawi and Adamopoulos et al. (2017) for China.[5] We use the estimated fixed effects of our baseline specification as measures of $\ln s_i$, the log of farm productivity.

We note that there is a strong positive correlation between land productivity and farm productivity of 0.86.[6] Despite these similarities, we show below that they produce qualitatively different estimates of the farm size-productivity relationship.

3.2 Conflicting findings depending on the measure of productivity

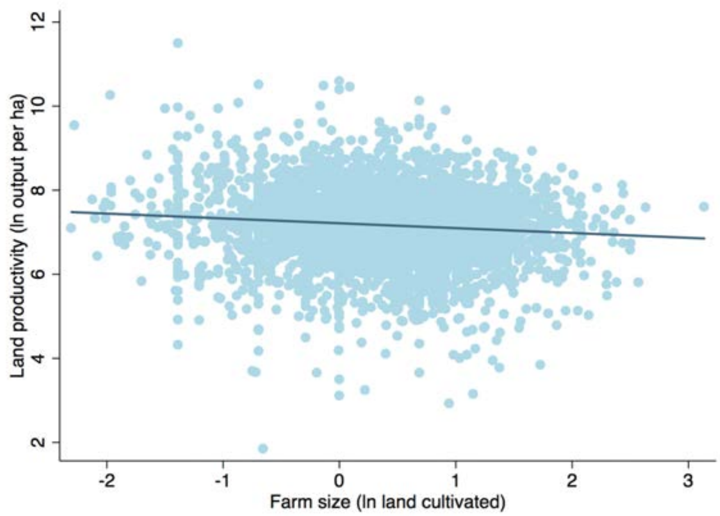
Figure 1 displays the relationship between the log of cultivated area, our baseline measure of farm size, and the two measures of productivity. An important observation is that the relationship is qualitatively different depending of the measure of productivity used. Using yields (panel A), we observe 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 (Carter, 1984; Assunção and Braido, 2007; Barrett et al., 2010; Ali et al., 2015). The yield approach regresses log of yields on log of land cultivated and includes a host of control variables. We include a rich set of soil characteristics, weather controls (temperature and precipitation), farmer characteristics (such as age, literacy and gender), as well as region-by-period and district fixed effects. The production function approach adds to the previous specification the log of the labor-land

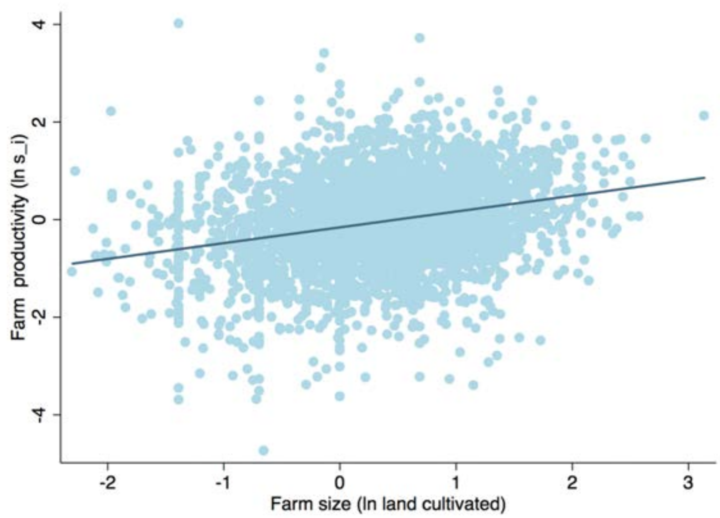
[5]Table A.1 in the Appendix presents detailed results of the production function estimation. Figure A.2 in the Appendix reports the resulting distribution of the estimated household-farm fixed effects.

[6]See Figure A.3 in the Appendix for a 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 ($\ln s_i$)

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 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 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 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 seem to be driving the 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 measure of farm size (see Table A.2 in the Appendix.)

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***	-0.270***	-0.491***	-0.035**	-0.075***	-0.298***
	(0.015)	(0.015)	(0.019)	(0.016)	(0.016)	(0.022)
ln(labor/land)				0.422***	0.384***	0.335***
				(0.016)	(0.017)	(0.018)
Controls	No	Yes	Yes	No	Yes	Yes
Household FE	No	No	Yes	No	No	Yes
No. obs.	16,063	14,576	15,787	15,806	14,333	15,532
R-squared	0.029	0.176	0.109	0.087	0.216	0.144

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 farm land 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)	0.191***	0.255***	0.185***	0.185***	0.152***	0.182***
	(0.011)	(0.023)	(0.011)	(0.011)	(0.011)	(0.011)
Prod. function used to estimate s_i	CD	CD	CD + agric. practices	CD by region	CD + IV	Translog
No. obs.	15,361	3,249	15,291	15,291	15,210	15,291
R-squared	0.399	0.349	0.585	0.525	0.685	0.579

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 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.

3.3 A statistical artifact?

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., 2019). This error 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.[7] 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. The results are, however, qualitatively similar (see columns 1 and 2 in Table 4).[8]

Finally, we examine the role of systematic measurement error in self-reported output.[9] We do so indirectly by 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 control for it when estimating the relationship between farm productivity and farm size.

In particular, we modify equation (2) by assuming that $\epsilon_{ijt} = v_{ijt} + M(T_i, L_i)$, i.e., there

[7] 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.3 in the Appendix). We find that the measurement error is decreasing in farm size. This negative relationship between farm size and measurement error is smaller in regions with modern land tenure regimes such as Western and Central.

[8] Note that we lose some observations because GPS measures are only available for a random sub-sample of farmers.

[9] Abay et al. (2019) show the importance of accounting for correlated non-classical measurement errors in output and land size. They find that the inverse relationship disappears in a sample of Ethiopian farmers when correcting for both sources of measurement error. Interestingly, accounting for measurement error in one variable only may exacerbate the inverse relationship.

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 address this issue by approximating M with a 4^{th} degree polynomial of the GPS measures of available land and total labor, and including these variables as additional regressors when estimating s_i. Note that this approach also addresses biases due to unobserved inputs (such as labor quality or capital) that could be correlated to farm size.

Columns 3 and 4 in Table 4 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 opposite findings on the farm size-productivity relationship documented in Tables 2 and 3 are not due to omitted variables or systematic measurement error. So, what explains these different results?

Table 4: Farm size and productivity

	ln(output per ha) GPS measure	farm productivity ($\ln s_i$)		
	(1)	(2)	(3)	(4)
ln(land available) GPS measure	-0.629*** (0.016)	0.140*** (0.010)	0.138*** (0.010)	0.136*** (0.010)
Prod. function used to estimate s_i		CD	CD + land polyn.	CD + land and labor polyn.
No. obs.	10,087	11,149	11,149	11,149
R-squared	0.391	0.424	0.429	0.431

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 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.

4 What explains the different results?

We show that, in many 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 returns to scale. These issues can lead, as in the case of Uganda, to wrongly inferring a negative relationship.

To illustrate this point, consider a researcher who wants to examine the farm size-productivity relationship. The 'true' model the researcher wants to estimate is:

$$\ln s_i = \beta \ln T_i + \epsilon_i, \tag{3}$$

where as before s_i is farm productivity, T_i is farm land size, and ϵ is an error term. Assume that farms have a production function as described in equation (1), that is $y_i = s_i A \left(T_i^{\alpha} L_i^{1-\alpha}\right)^{\gamma}$, and face potentially imperfect markets. Following 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 $r(1+\tau_i)$. 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. We allow for these distortions to be (potentially) different across farms. The wedge τ_i measures the relative distortion in input markets and so we are implicitly normalizing the distortion in labor prices equal to one. The special case of efficient markets occurs when $\tau_i = 0$.

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

$$\frac{L_i}{T_i} = \frac{1-\alpha}{\alpha} \frac{r}{w} (1+\tau_i). \tag{4}$$

Using this result and taking logs, we can re-write yields $\frac{Y_i}{T_i} = s_i \frac{\left(T_i^{\alpha} L_i^{1-\alpha}\right)^{\gamma}}{T_i}$ as:

$$\ln \frac{Y_i}{T_i} = \ln s_i + \gamma(1-\alpha)\ln(1+\tau_i) + (\gamma - 1)\ln T_i + c, \tag{5}$$

where c is a constant, which is a function of common prices and parameters (w, r, α, γ) and the common productivity shock (A).

The researcher uses yields as a proxy for farm productivity s_i. The estimated model is equivalent to the yield approach regression used in the farm size-productivity literature. Replacing (3) into (5), the estimated model is:

$$\ln \frac{Y_i}{T_i} = c + \beta \ln T_i + \mu, \tag{6}$$

where the error term is: $\mu = \gamma(1-\alpha)\ln(1+\tau_i) + (\gamma - 1)\ln T_i + \epsilon$. Equation (6) highlights two reasons why, in general, using yields, can lead to inconsistent (wrong) estimates of the relationship between productivity and farm size: (1) size-dependent market distortions, or (2) decreasing returns to scale.

These are plausible conditions in many applications, especially in the context of subsistence farmers in developing countries. In either case, the error term μ would be, by construction, correlated with farm size and OLS estimates of β would be inconsistent. OLS estimates of β would be consistent only in very special cases such as (1) efficient markets ($\tau_i = 0$) and constant returns to scale (CRS), or (2) CRS and distortions independent of farm size (i.e., τ_i uncorrelated to T).

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, if the technology exhibits DRS, 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. Yields can be affected by size-dependent market distortions and by properties of the technology such as DRS. As we document below, when correcting for these issues, the original negative relationship between yields and farm size is reversed and instead we obtain a positive relationship between yields and farm size.

4.1 Correcting for market distortions and DRS

Equation (4) suggests that the observed labor-land ratio is proportional to the market distortion. Using the input ratio as a proxy for $(1 + \tau_i)$ and the 'true' farm-size productivity relationship (equation 3), we can rewrite expression (5) as follows:

$$\ln \frac{Y_i}{T_i} = \text{constant} + (\beta + \gamma - 1) \ln T_i + \gamma(1 - \alpha) \ln \left(\frac{L_i}{T_i} \right) + \epsilon. \tag{7}$$

This expression suggests using a specification similar to the production function approach in the existing literature. That is, regressing yields on farm size and the input ratio. A key distinction, however, is that we do not impose CRS. Instead, we use a value of $\hat{\gamma} = 0.711$ obtained from estimating the production function (see column 1 in Table A.1). This is relevant, because the estimate associated with farm size is $\beta + \gamma - 1$. Thus, to recover β, the farm-size productivity relationship, we also need to account for possible deviations from CRS. We do so by subtracting $(\hat{\gamma} - 1)$ from the estimates associated with farm size.

Table 5 presents the estimates of equation (7) using two alternative measures of farm size, T_i: (self-reported) area cultivated and GPS measures of available land. We start by replicating the "yield approach" (column 1 and 4) and then gradually adding the input ratio, our proxy for market distortions, (columns 2 and 5) and relax the CRS assumption (columns 3 and 6). The main result is that the initially negative estimate of the slope coefficient between yields and farm size becomes less negative after correcting for market imperfections, and eventually becomes positive when relaxing the assumption of CRS.

Table 5: Correcting for DRS and market distortions

	Outcome variable: ln(Y/T)					
	(1)	(2)	(3)	(4)	(5)	(6)
ln(T)	-0.274***	0.018	0.213***	-0.630***	-0.106***	0.322***
	(0.015)	(0.015)	(0.016)	(0.015)	(0.015)	(0.020)
ln(L/T)			0.381***			0.552***
			(0.017)			(0.020)
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
No. obs.	14,580	14,580	14,337	10,259	10,259	10,063
R-squared	0.178	0.154	0.195	0.404	0.192	0.284

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. $\hat{\gamma} = 0.711$ obtained from Column 1 Table A.1.

These results support our conclusion that, in many applications, yields are not useful to examine the farm size-productivity relationship. Yields pickup not only farm productivity but also size-dependent distortions and features of the farm technology. These issues are quantitatively important and, as shown in the case of Uganda, can lead to substantially different implications.

4.2 Using land tenure regimes as proxies of market distortions

Our previous results 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.

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 $\frac{B_i}{A_i}\frac{r}{w}(1+\tau_i)$. Thus, the input ratio would pick up not only the market distortion but also differences in input-specific productivity $\frac{B_i}{A_i}$.

Similarly, it is also possible that land market distortions are highly correlated with other input distortions (like capital), making the land-labor ratio a poor proxy of land market distortions. This is indeed what the evidence suggests from different contexts in agriculture (Restuccia and Santaeulalia-Llopis, 2017; Adamopoulos et al., 2017; Chen et al., 2017).[10]

As an alternative approach, we exploit variation in land tenure regimes as a proxy of market distortions. This approach is motivated by the Coase theorem, and existing evidence suggesting that property rights play an important role on allocative efficiency (Besley and Ghatak, 2010; De Janvry et al., 2015; Restuccia and Santaeulalia-Llopis, 2017; Chen, 2017).

There are four types of land tenure in Uganda: freehold, leasehold, Mailo (form of freehold), and customary land. The first three tenure systems 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).

These differences in land tenure seem to matter for economic activity. For instance, Place and Otsuka (2002) find that customary land is associated with less agricultural investment. In our data, we also observe that in regions with more prevalent use of non-customary tenure systems around 47% of land holdings have been marketed, i.e., acquired through purchase or rented. In contrast, in regions with more customary land, this figure is much lower, around 27%.

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

[10]The results in Hsieh and Klenow (2009) for the manufacturing sector in China and India also indicate that distortions to the capital-labor ratio account for a small fraction of the dispersion in overall distortions, implying that input wedges are highly correlated between them or have the same underlying source.

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 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.

We start by assessing whether land rights capture meaningful differences in market distortions. We use an indirect approach evaluating whether the magnitude of factor misallocation is related to differences in land tenure regimes. To do so, we estimate the relationship between input use (land and labor) and farm productivity ($\ln s_i$). As discussed in Section 2, in an efficient allocation, these variables should be positively correlated. We allow for different values by type of land tenure by including an interaction term with indicators of modern land rights. We use two proxies: an indicator of being in the Western or Central region (regions with a prevalent use of non-customary tenure regimes) and the share of farm land under non-customary regimes in the district.

Table 6 displays the results.[11] 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. These results are consistent with modern property rights improving allocative efficiency, and justify using measures of land rights as proxies of market distortions.

Note, however, that these results do not imply that there is no misallocation in some parts of Uganda, only that the magnitude is different across regions with markedly different land tenure regimes. Indeed, our results suggest a substantial amount of factor misallocation in Ugandan agriculture. Assuming a Cobb-Douglas technology in land and labor, the estimated relationship between input use and farm productivity in the case with no distortions should

[11] Note that the regressions in Table 6 use the GPS measure of available land as a proxy for farm size. We use this variable to reduce concerns of measurement error in self-reported data as discussed in Section 3.3.

be equal to $\frac{1}{1-\gamma}$. Given our estimate of $\hat{\gamma} = 0.709$, the implied slope is around 3.4. In contrast, the estimated slope in the data is quite small. For instance, using the results from column (1) in Table 6, the estimated slope for the land input is 0.159 in the entire sample and 0.493 in the region with modern land rights. These results echo similar findings in other contexts (Restuccia and Santaeulalia-Llopis, 2017; Adamopoulos et al., 2017; Adamopoulos and Restuccia, 2019).

Table 6: Assessing factor misallocation

	ln(land available) GPS		ln(total labor)	
	(1)	(2)	(3)	(4)
Farm productivity	0.159***	0.126**	0.137***	0.166***
	(0.044)	(0.053)	(0.018)	(0.022)
Farm productivity × modern land rights	0.334***	0.403***	0.109***	0.046
	(0.071)	(0.098)	(0.027)	(0.042)
Proxy of modern land rights	Western or Central	% non-custom. land in district	Western or Central	% non-custom. land in district
No. obs.	2,237	2,237	15,194	15,194
R-squared	0.380	0.379	0.213	0.212

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.

Next, we re-examine the farm size-yield relationship allowing for differences by land tenure, our proxy for market distortions.[12] 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 7 presents our findings using both the yield

[12]We check the robustness of our results to using alternative indicators of market distortions, such as presence of local market places (see Tables A.4 and A.5 in the Appendix). The results are qualitatively similar, albeit this indicator accounts for a much smaller magnitude of misallocation and the negative size-yield relationship.

(columns 1 and 2) and production function approach (columns 3 and 4). In both cases, we do not correct for DRS, but instead maintain the assumption of CRS as in the existing literature.

We document the inverse relationship. Importantly, we find that it becomes less negative in regions with modern land rights. This evidence is consistent with our interpretation that the negative relationship between yields and farm size reflects, in part, market distortions.

Table 7: 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	-0.698***	-0.673***	-0.265***	-0.227***
	(0.023)	(0.025)	(0.025)	(0.027)
ln(land available) GPS $\times$ modern land rights	0.137***	0.103**	0.130***	0.070*
	(0.029)	(0.041)	(0.025)	(0.038)
ln(labor/land available GPS)			0.555***	0.558***
			(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.	10,255	10,255	10,059	10,059
R-squared	0.405	0.403	0.474	0.473

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.

5 Discussion

We discuss the broader implications of our results and assess whether our findings are specific to Uganda or whether they apply more generally to other countries.

5.1 Farm size deeply confounded by market distortions

The broad literature on the inverse size-productivity relationship has had a profound influence on agricultural policy. 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 provides a tractable mechanism for policy implementation.

We have shown that yields are not informative of the size-productivity relationship and hence can produce erroneous policy recommendations. But our evidence points to a more general conclusion: farm size is deeply confounded by distortions and hence, it is an ineffective instrument for policy. This conclusion is general because it applies to both measures of productivity. To illustrate this point, Table 8 documents the mean and dispersion of the two measures of productivity (farm productivity and yields) across farms within farm-size bins for different farm size categories.[13] To characterize dispersion, we use the ratio of the 90th and 10th percentiles.

The main observation is that there is substantial dispersion in both measures of productivity within a farm-size class. This 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 when using the measure of yields (Y_i/T_i) for which 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.

The implication of these results is that there is not a simple instrument for policy. Effective policy should facilitate better resource allocation by farm productivity, but productivity is difficult to observe for the policy maker. Our results suggest that policy should focus on fostering and improving markets, in particular, markets for land where even an egalitarian distribution of ownership rights can be decoupled from farm operational scales via

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

Table 8: Productivity dispersion by farm size

Farm size (has)	% farms	Farm productivity (s_i) Mean	Farm productivity (s_i) 90th / 10th percentile	Yields (Y/T) Mean	Yields (Y/T) 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.

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).

5.2 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 countries: Peru, Tanzania, and Bangladesh (see Table 9).

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). Additional results are available in Appendix B.

In all cases, we find a similar patterns as in Uganda: a negative correlation between yields and farm size, but a positive relationship between farm size and farm productivity ($\ln s_i$). These results are robust to several specifications and, similar to the Ugandan case, we find that the negative yield-size relationship becomes positive when correcting for DRS and market distortions (see Tables B.1, B.2 and B.3 in the Appendix).

Further, we note that although not directly comparable since we do not have access to the micro data, we find similar patterns for the United States. Using the 2017 US Census 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 in the Appendix. 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 9: 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 & 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 includes set of location 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.

6 Conclusions

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 by features of the farm technology, such as decreasing returns to scale. These issues limit the usefulness of the inverse relationship to inform agricultural policies in developing countries and may lead to counterproductive policy recommendations.

Our analysis relies on detailed microdata from Uganda that allow us to compute two alternative measures of productivity at the farm level: the yield (land productivity) and farm's total factor productivity. We first show that these measures of productivity produce different patterns where the yield is negatively related with farm size whereas farm productivity is positively related with farm size. These contradictory results do not arise from omitted variables or measurement error. Instead, we show empirically that the difference arises because of the presence of market distortions and decreasing returns to scale in the farming technology. We also provide direct empirical evidence of the importance of market distortions by exploiting unique regional variation in the extent of land markets in Uganda. While we show that our findings also apply to other countries, more work remains in order to establish the patterns on a large cross-section of countries.

A more general conclusion from our findings is that farm size is not a useful instrument for policy implementation since size is deeply confounded by market distortions, a prevalent feature in developing countries. Since farm size is not a useful instrument for policy, an important area for future work consists in establishing the mechanisms that would allow a more efficient use of resources in developing countries.

References

Abay, Kibrom A., Gashaw T. Abate, Christopher B. Barrett, and Tanguy Bernard, "Correlated non-classical measurement errors, âSecond bestâ policy inference, and the inverse size-productivity relationship in agriculture," *Journal of Development Economics*, 2019, *139*, 171 – 184.

Adamopoulos, Tasso and Diego Restuccia, "The size distribution of farms and international productivity differences," *American Economic Review*, 2014, *104* (6), 1667–97.

_ and _ , "Land Reform and Productivity: A Quantitative Analysis with Micro Data," Working Paper 25780, National Bureau of Economic Research April 2019.

_ , Loren Brandt, Jessica Leight, and Diego Restuccia, "Misallocation, selection and productivity: A quantitative analysis with panel data from China," Technical Report, National Bureau of Economic Research 2017.

Ali, Daniel Ayalew, Klaus Deininger et al., "Is There a Farm Size–Productivity Relationship in African Agriculture? Evidence from Rwanda," *Land Economics*, 2015, *91* (2), 317–343.

Aragón, Fernando M., Francisco Oteiza, and Juan Pablo Rud, "Climate Change and Agriculture: Subsistence Farmers' Response to Extreme Heat," *arXiv e-prints*, Feb 2019, p. arXiv:1902.09204.

Assunção, Juliano J and Luis HB Braido, "Testing household-specific explanations for the inverse productivity relationship," *American journal of agricultural economics*, 2007, *89* (4), 980–990.

Assuncao, Juliano J and Maitreesh Ghatak, "Can unobserved heterogeneity in farmer ability explain the inverse relationship between farm size and productivity," *Economics Letters*, 2003, *80* (2), 189–194.

Auffhammer, M, SM Hsiang, W Schlenker, and A Sobel, "Using Weather Data and Climate Model Output in Economic Analyses of Climate Change," *Review of Environmental Economics and Policy*, June 2013, *7* (2), 181–198.

Barrett, Christopher B, "On price risk and the inverse farm size-productivity relationship," *Journal of Development Economics*, 1996, *51* (2), 193–215.

_ , Marc F Bellemare, and Janet Y Hou, "Reconsidering conventional explanations of the inverse productivity–size relationship," *World Development*, 2010, *38* (1), 88–97.

Benjamin, Dwayne, "Can unobserved land quality explain the inverse productivity relationship?," *Journal of Development Economics*, 1995, *46* (1), 51–84.

Berry, R Albert, William R Cline et al., *Agrarian structure and productivity in developing countries: a study prepared for the International Labour Office within the framework of the World Employment Programme.*, Johns Hopkins Univ. Press, 1979.

Besley, Timothy and Maitreesh Ghatak, "Property rights and economic development," in "Handbook of development economics," Vol. 5, Elsevier, 2010, pp. 4525–4595.

Bevis, Leah EM and Christopher B Barrett, "Close to the edge: do behavioral explanations account for the inverse productivity relationship?," 2016.

Binswanger, Hans P, Klaus Deininger, and Gershon Feder, "Power, distortions, revolt and reform in agricultural land relations," *Handbook of development economics*, 1995, *3*, 2659–2772.

Carleton, Tamma A and Solomon M Hsiang, "Social and economic impacts of climate," *Science*, 2016, *353* (6304), aad9837.

Carletto, Calogero, Sara Savastano, and Alberto Zezza, "Fact or artifact: The impact of measurement errors on the farm size–productivity relationship," *Journal of Development Economics*, 2013, *103*, 254–261.

Carter, Michael R, "Identification of the inverse relationship between farm size and productivity: an empirical analysis of peasant agricultural production," *Oxford Economic Papers*, 1984, *36* (1), 131–145.

Chen, Chaoran, "Untitled land, occupational choice, and agricultural productivity," *American Economic Journal: Macroeconomics*, 2017, *9* (4), 91–121.

_ , Diego Restuccia, and Raül Santaeulàlia-Llopis, "Land markets, resource allocation, and agricultural productivity," Technical Report, working paper, University of Toronto 2017.

Coldham, Simon, "Land reform and customary rights: the case of Uganda," *Journal of African Law*, 2000, *44* (1), 65–77.

Collier, Paul and Stefan Dercon, "African Agriculture in 50 Years: Smallholders in a Rapidly Changing World?," *World Development*, 2014, *63*, 92 – 101. Economic Transformation in Africa.

Desiere, Sam and Dean Jolliffe, "Land productivity and plot size: Is measurement error driving the inverse relationship?," *Journal of Development Economics*, 2018, *130*, 84–98.

Eswaran, Mukesh and Ashok Kotwal, "Access to capital and agrarian production organisation," *The Economic Journal*, 1986, *96* (382), 482–498.

Feder, Gershon, "The relation between farm size and farm productivity: The role of family labor, supervision and credit constraints," *Journal of development economics*, 1985, *18* (2-3), 297–313.

Fischer, G., F. Nachtergaele, S. Prieler, H.T. van Velthuizen, L. Verelst, and D. Wiberg, "Global Agro-ecological Zones Assessment for Agriculture," Technical Report, IIASA 2008.

Funk, Chris, Pete Peterson, Martin Landsfeld, Diego Pedreros, James Verdin, Shraddhanand Shukla, Gregory Husak, James Rowland, Laura Harrison, Andrew Hoell, and Joel Michaelsen, "The climate hazards infrared precipitation with stations: a new environmental record for monitoring extremes," *Scientific Data*, 2015, *2.*

Gourlay, Sydney, Talip Kilic, and David Lobell, *Could the debate be over? errors in farmer-reported production and their implications for the inverse scale-productivity relationship in Uganda*, The World Bank, 2017.

Helfand, Steven, Matthew Taylor et al., "The Inverse Relationship between Farm Size and Productivity: Refocusing the Debate," Technical Report 2018.

Hopenhayn, Hugo A, "Entry, exit, and firm dynamics in long run equilibrium," *Econometrica: Journal of the Econometric Society*, 1992, pp. 1127–1150.

Hsiang, Solomon, "Climate econometrics," *Annual Review of Resource Economics*, 2016, *8*, 43–75.

Hsieh, Chang-Tai and Peter J Klenow, "Misallocation and manufacturing TFP in China and India," *The Quarterly journal of economics*, 2009, *124* (4), 1403–1448.

Janvry, Alain De, Kyle Emerick, Marco Gonzalez-Navarro, and Elisabeth Sadoulet, "Delinking land rights from land use: Certification and migration in Mexico," *American Economic Review*, 2015, *105* (10), 3125–49.

Jr, Robert E Lucas, "On the size distribution of business firms," *The Bell Journal of Economics*, 1978, pp. 508–523.

Place, Frank and Keijiro Otsuka, "Land tenure systems and their impacts on agricultural investments and productivity in Uganda," *Journal of Development Studies*, 2002, *38* (6), 105–128.

Restuccia, Diego and Raul Santaeulalia-Llopis, "Land Misallocation and Productivity," Working Paper 23128, National Bureau of Economic Research February 2017.

_ and Richard Rogerson, "Policy distortions and aggregate productivity with heterogeneous establishments," *Review of Economic dynamics*, 2008, *11* (4), 707–720.

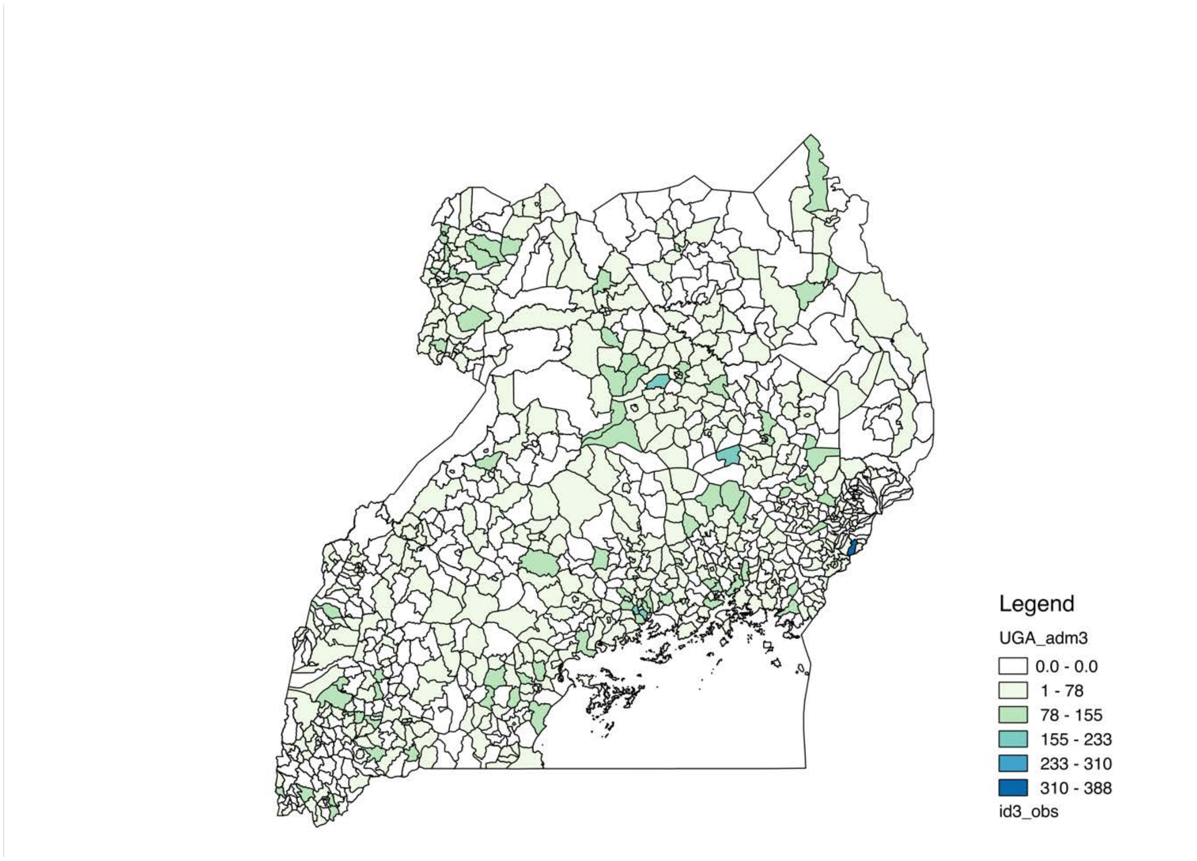
Schlenker, Wolfram and Michael J. Roberts, "Nonlinear Effects of Weather on Corn Yields," *Review of Agricultural Economics*, 2006, *28* (3), 391–398.

_ and _ , "Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change," *Proceedings of the National Academy of Sciences*, 2009, *106* (37), 15594–15598.

ONLINE APPENDIX - Not for publication

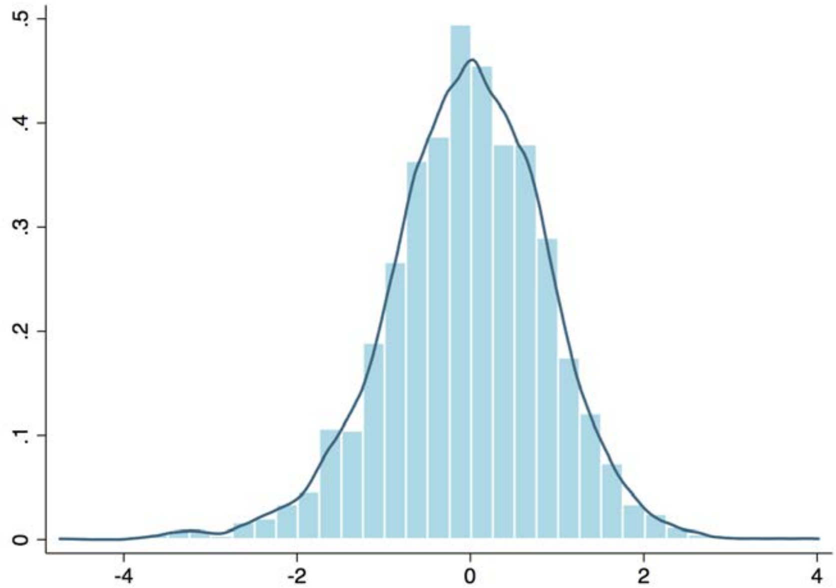
A Additional figures and tables

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 $\hat{\gamma} = 0.709$. The difference between the 90^{th} and 10^{th} percentile is 2.23.

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

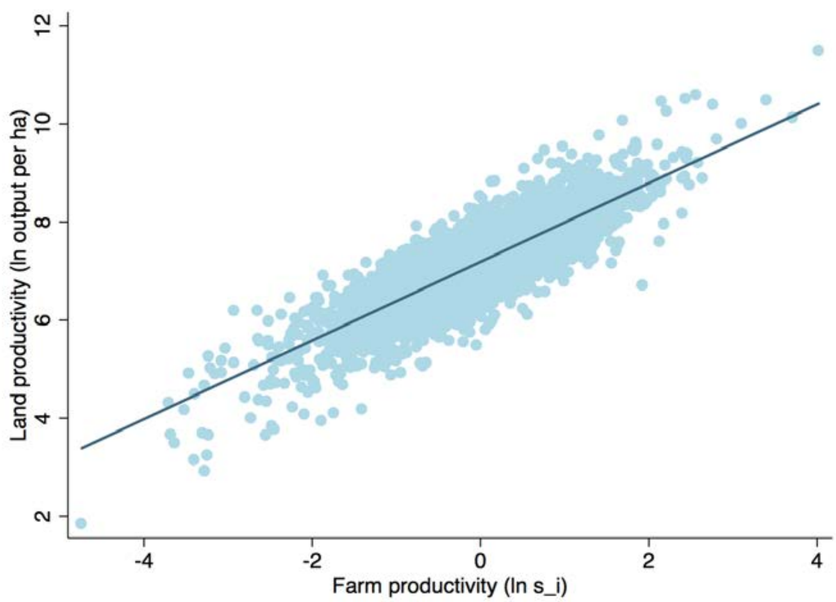
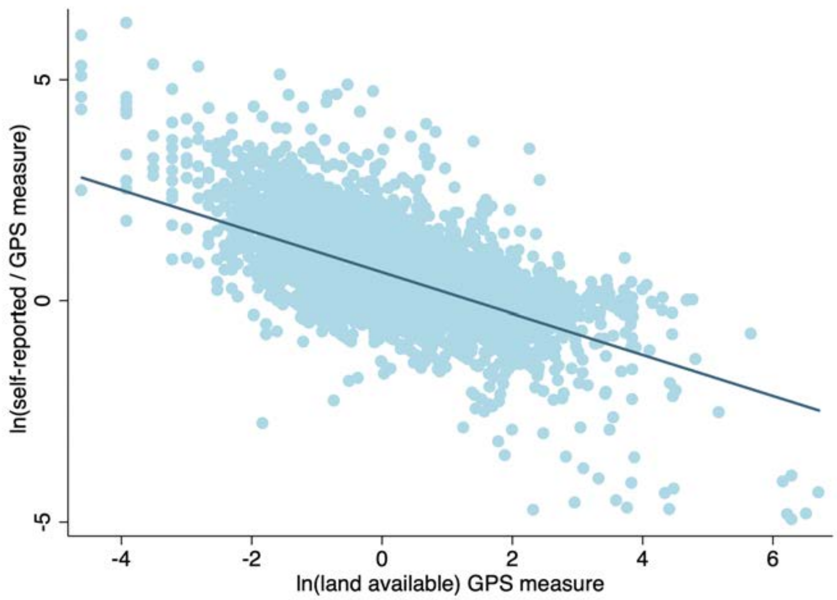
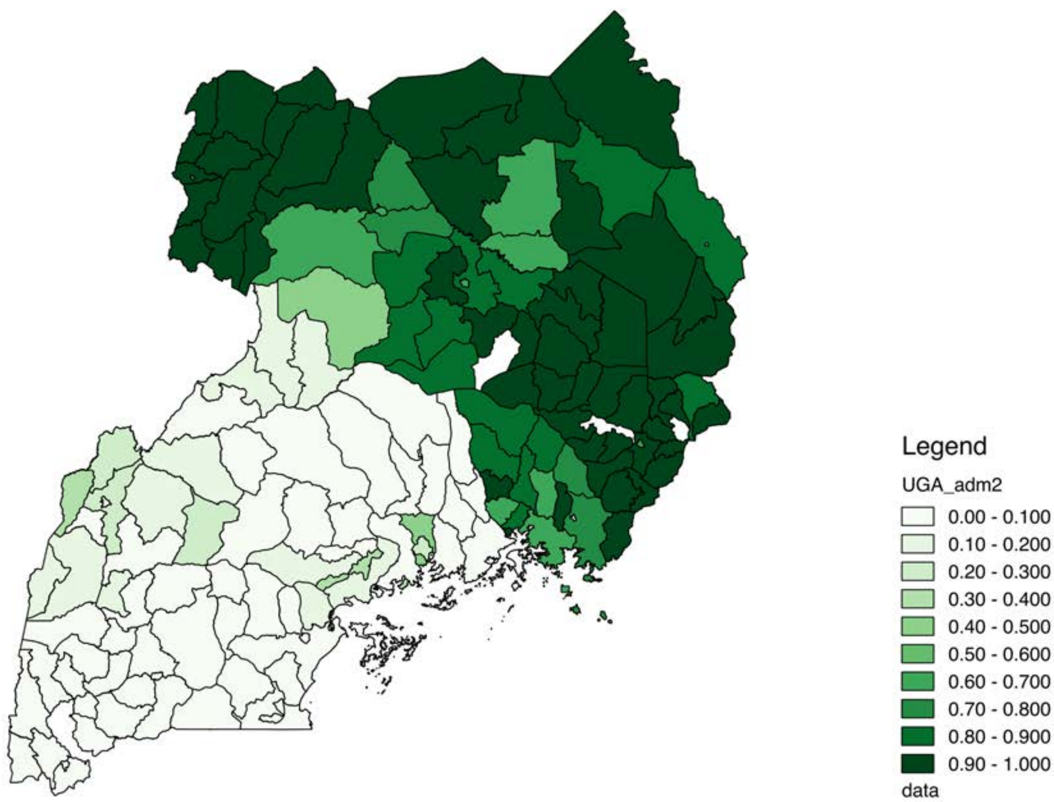


Figure A.4: Systematic measurement error in available land



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)	0.373***	0.347***	0.362***	0.394***	
	(0.020)	(0.020)	(0.020)	(0.068)	
ln(total labor)	0.336***	0.333***			0.428***
	(0.017)	(0.019)			(0.021)
ln(land available) GPS measure					0.048**
					(0.020)
ln(domestic labor)			0.236***	0.299**	
			(0.017)	(0.141)	
ln(hired labor)			0.117***	0.113***	
			(0.012)	(0.012)	
Method	OLS	OLS	OLS	IV	OLS
Control for agric. practices	No	Yes	Yes	Yes	No
Implied γ	0.709	0.680	0.715	0.806	0.476
Implied α	0.526	0.510	0.506	0.488	0.101
Observations	15,541	14,413	14,413	13,988	10,789
No. farmers	3,457	3,407	3,407	3,361	2,617
R-squared	0.154	0.157	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***	-0.107***	-0.232***	-0.038*	0.184***	0.249***
	(0.013)	(0.013)	(0.022)	(0.021)	(0.011)	(0.021)
Controls	No	Yes	Yes	Yes	Yes	Yes
Household FE	No	No	Yes	No	No	No
No. obs.	16,010	14,530	15,739	3,252	16,371	3,249
R-squared	0.003	0.152	0.055	0.248	0.390	0.349

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: 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)	(0.013)	(0.016)	(0.018)
ln(land available) GPS			0.087***	0.136***
× 1(Western/Central region)			(0.021)	(0.025)
Control variables	No	Yes	No	Yes
Observations	12,134	11,175	12,134	11,175
R-squared	0.382	0.498	0.385	0.504

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.4: Assessing factor misallocation - robustness

	ln(land available) GPS		ln(total labor)	
	(1)	(2)	(3)	(4)
Farm productivity	0.127**	0.087	0.142***	0.164***
	(0.053)	(0.063)	(0.022)	(0.026)
Farm productivity × modern land rights	0.331***	0.415***	0.114***	0.066
	(0.076)	(0.107)	(0.031)	(0.047)
Farm productivity × has local market	0.145**	0.141*	-0.016	-0.014
	(0.074)	(0.074)	(0.026)	(0.026)
Proxy of modern land rights	Western or Central	% non-custom. land in district	Western or Central	% non-custom. land in district
No. obs.	1,983	1,983	11,498	11,498
R-squared	0.393	0.392	0.228	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%. 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.

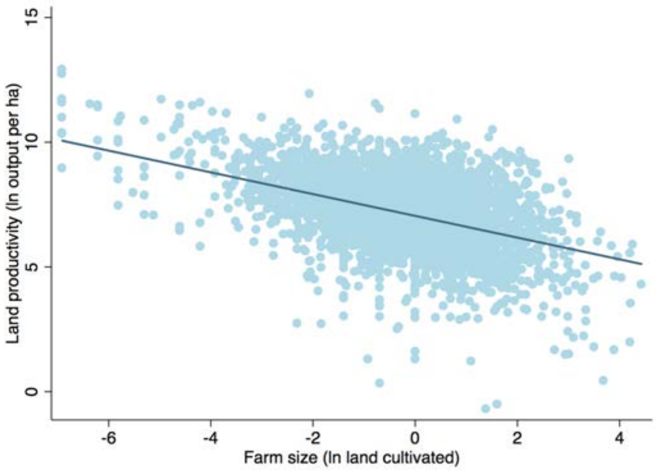
Table A.5: Farm size-yield relationship and land tenure - robustness

	ln(output per ha) GPS measure			
	Yield approach		Production function approach	
	(1)	(2)	(3)	(4)
ln(land available) GPS	-0.699***	-0.668***	-0.278***	-0.238***
	(0.027)	(0.029)	(0.029)	(0.031)
ln(land available) GPS × modern land rights	0.111***	0.071	0.108***	0.053
	(0.032)	(0.043)	(0.028)	(0.039)
ln(land available) GPS × has local market	0.051*	0.042	0.056**	0.048*
	(0.031)	(0.031)	(0.028)	(0.028)
ln(labor/land available GPS)			0.547***	0.550***
			(0.022)	(0.022)
Proxy of modern land rights	Western or Central	% non-custom. land in district	Western or Central	% non-custom. land in district
No. obs.	8,245	8,245	8,080	8,080
R-squared	0.416	0.415	0.481	0.481

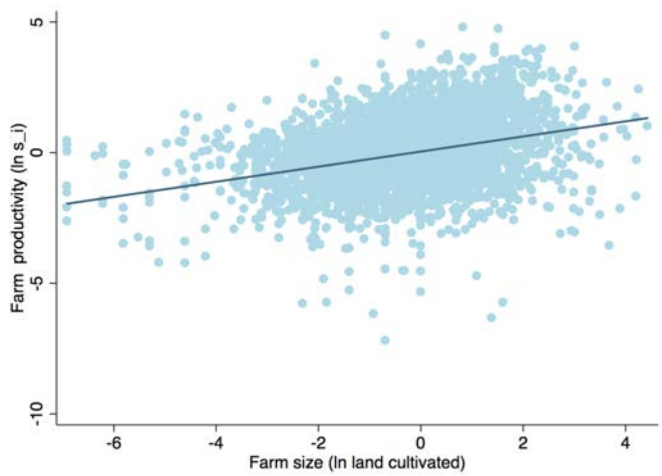
Notes: Robust standard errors in parentheses. Standard errors are clustered at the household level. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. All regressions use GPS measure of available land as proxy for farm size and include soil and farmer controls, as well as region-by-period 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

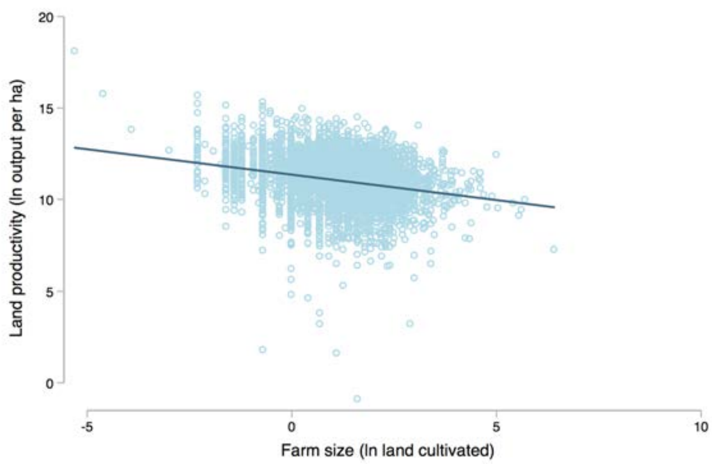


(a) Land productivity ($\ln(Y/T)$)

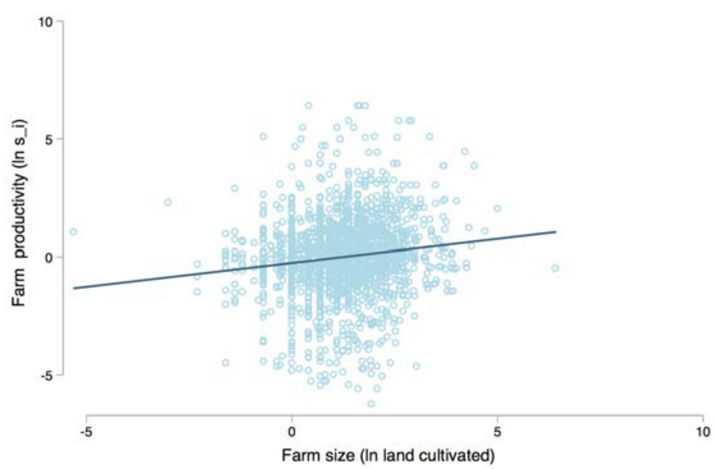


(b) Farm productivity ($\ln s_i$)

Figure B.2: Farm size and productivity - Tanzania

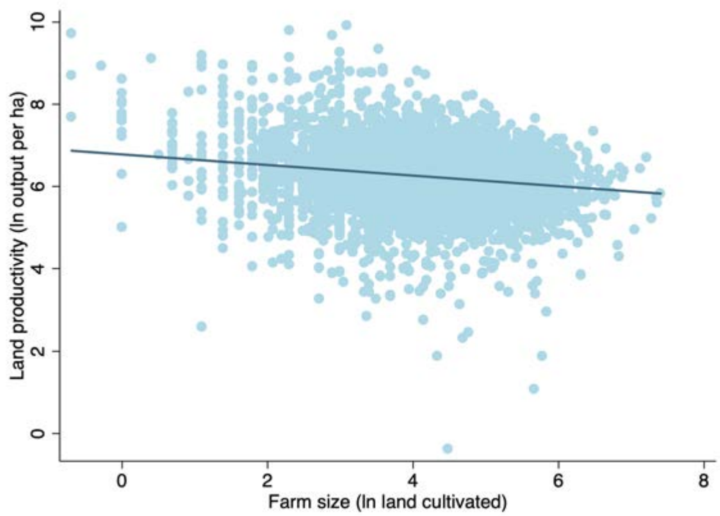


(a) Land productivity ($\ln(Y/T)$)

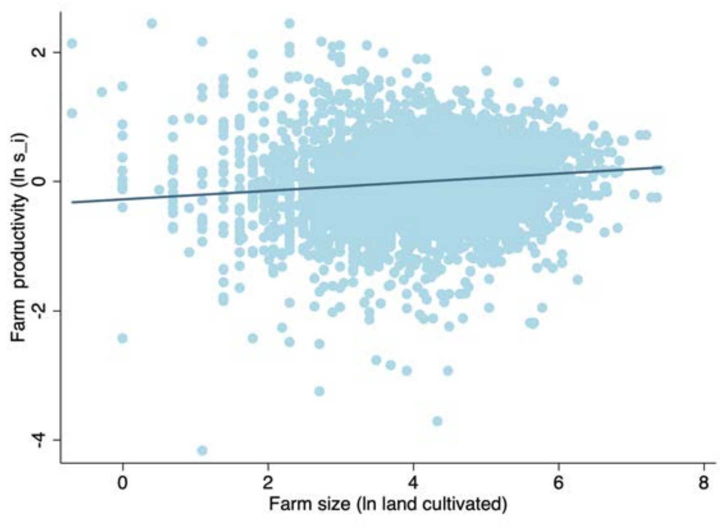


(b) Farm productivity ($\ln s_i$)

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 5: 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***	0.083***	0.330***	-0.403***	-0.094***	0.157***	-0.103***	-0.014	0.128***
	(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***
			(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
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 5. Regressions includes same controls as baseline results in Table 9. 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 9. 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 9. 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).