Food Policy 106 (2022) 102168

Contents lists available at ScienceDirect

Food Policy

journal homepage: www.elsevier.com/locate/jfpo

Are small farms really more productive than large farms?[☆]

Fernando M. Aragón[a,1], Diego Restuccia[b,c,2], Juan Pablo Rud[d,e,*]

[a] Simon Fraser University, Canada
[b] University of Toronto, Canada
[c] NBER, United States of America
[d] Royal Holloway, University of London, UK
[e] IFS, UK

ARTICLE INFO

JEL classification:
O12
O13
Q12
Q15

Keywords:
Farm size
Productivity
Yields
Land markets
Distortions
Agriculture
Policy

ABSTRACT

This paper shows that using yields may not be informative of the relationship between farm size and productivity in the context of small-scale farming. This occurs because, in addition to productivity, yields pick up size-dependent market distortions and decreasing returns to scale. As a result, a positive relationship between farm productivity and land size may turn negative when using yields. We illustrate the empirical relevance of this issue with microdata from Uganda and show similar findings for Peru, Tanzania, and Bangladesh. In addition, we show that the dispersion in both measures of productivity across farms of similar size is so large that it renders farm size an ineffective indicator for policy targeting. Our findings stress the need to revisit the empirical evidence on the farm size-productivity relationship and its policy implications.

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; Eswaran and Kotwal, 1986; Barrett, 1996; Assuncao and Ghatak, 2003; Barrett et al., 2010). However, these results contrast with growing macroeconomic evidence of a positive relationship between farm size and agricultural productivity, both across and within countries.[3] A similar finding has been reported in microeconomic studies, mostly from developed countries, using measures of total factor productivity instead of yields (Alvarez and Arias, 2004; 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 argue that these divergent results reflect the limitation of using yields as a measure of productivity. Our contribution is to show that, in many empirical applications, yields are not informative of the size-productivity relationship, and can lead to qualitatively different insights. Our findings cast doubts on the interpretation of the inverse yield-size relationship as evidence that small farms are more productive, and stress the need to revisit the existing empirical evidence.

Our results also point out to a broader limitation of the size-productivity relationship as a policy tool. This relationship promises

☆ For useful comments, we are grateful to Tasso Adamopoulos, Christopher Barrett, Chad Jones, Yongs Shin, two anonymous referees 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. Rud gratefully acknowledges the support from the Economic and Social Research Council (UK Research and Innovation), Project ES/S014438/1. The views expressed herein are not necessarily those of the Bank of Canada and are the authors alone.

* Correspondence to: Department of Economics, Royal Holloway, University of London, Egham, Surrey, TW20 0EX, UK.
E-mail addresses: faragons@sfu.ca (F.M. Aragón), diego.restuccia@utoronto.ca (D. Restuccia), juan.rud@rhul.ac.uk (J.P. Rud).
[1] Department of Economics, Simon Fraser University, Burnaby, BC, V5A 1S6, Canada.
[2] Department of Economics, University of Toronto, 150 St. George Street, Toronto, ON M5S 3G7, Canada.

[3] See for instance, Adamopoulos and Restuccia (2014), Chen et al. (2017), Restuccia and Santaeulàlia-Llopis (2017) and Adamopoulos and Restuccia (2020).

https://doi.org/10.1016/j.foodpol.2021.102168
Received 12 June 2021; Received in revised form 23 September 2021; Accepted 1 October 2021
Available online 1 November 2021
0306-9192/

a tractable mechanism for policy implementation: if farm size is correlated with productivity, then size could be used to target farmers and enhance efficiency. We show, however, that there is substantial dispersion in measures of productivity across farms of similar size, sometimes as large as the productivity dispersion between land size classes. Thus, even if the size-productivity relationship is correctly estimated, farm size would still be a poor proxy for productivity.

Our starting point is the observation that yields pick up not only total factor productivity, but also deviations from constant returns to scale (CRS) and relative input use. We show that this feature has two relevant empirical implications. First, in the presence of size-dependent distortions in input markets, estimates of the size-productivity relation using yields are inconsistent. This occurs because the omitted input ratio reflects market distortions. Second, solutions to address market imperfections, such as controlling for input ratios (the so-called production function approach) or exploiting within-farm variation in plot size (plot-level regressions), only work in the knife-edge case of CRS, but would fail in other cases.

We assess the empirical relevance of this issue by comparing the estimated size-productivity relationship using 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. Due to data availability, our main empirical analysis focuses on Uganda. However, we replicate the core findings using data from other countries.

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. We document a similar pattern of results using microdata from Peru, Bangladesh and Tanzania.

We interpret these findings as evidence of the limitation of using yields to identify the size-productivity relationship due to deviations from CRS and size-dependent distortions. We evaluate the validity of this interpretation in several ways. First, we check that our results are not driven by measurement error on farm size or omitted soil characteristics. Second, we show that, after correcting for market distortions and deviations from CRS, the negative correlation between yields and farm size goes away (and in our case, becomes positive). Third, we exploit household variation in land tenure in Uganda together with district and region-by-year fixed effects to examine in more detail the role of local market distortions. We find that the yield-farm size relationship becomes less negative for households with stronger land property rights. We interpret this finding as suggestive evidence of the role of market distortions in driving the negative yield-farm size result.

The methodological shortcomings of using yields as a measure of productivity have long been acknowledged in the literature (Sen, 1962; Bardhan, 1973; Binswanger et al., 1995; Townsend et al., 1998). Despite this recognized limitation, a large body of the evidence on the farm size-productivity relationship comes from studies using yields or other measures of partial productivity.[4] Recently, some studies have re-started to question the use of partial measures of productivity to understand the size-productivity relation and suggest using measures of total factor productivity instead (Gautam and Ahmed, 2019; Julien et al., 2019; Rada et al., 2019; Helfand and Taylor, 2021). This paper contributes to this debate by highlighting the empirical relevance of this issue, and the role of size-dependent market distortions and deviations from CRS as key sources of endogeneity.

The paper is organized as follows. In the next section, we discuss under which conditions the yield is an appropriate measure capturing farm productivity. Section 3 presents the empirical evidence from Uganda, showing that alternative measures of productivity produce opposing estimates of the farm size-productivity relationship. In Section 4, we provide robustness checks and evidence for other countries. Section 5 examines theoretically and empirically the reasons for the inverse size-yield relationship and provides evidence of land tenure as an indirect measure of market distortions on the farm size-productivity relationship. Section 6 concludes.

2. Yields and the size-productivity relationship

The study of the relationship between farm size and productivity occupies a central place in the agriculture 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 and Deininger, 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 labor per unit of land).[5]

To examine the validity of these approaches, we derive the relationship between yields and farm size starting from the farm's production function. This allows us to distinguish two different measures of productivity. The first measure is what we call farm productivity (or total factor productivity), which captures the returns to all factors of production, e.g. the ability of a farmer to produce an amount of output with a given set of inputs, including land, labor, tools, fertilizers, etc. The second measure is yields, i.e. production per unit area of cultivated land. This is a partial measure of productivity, as yields can increase when either total factor productivity is higher or the use of other inputs is higher.

In some applications, when all inputs are fixed, changes to total and partial productivity due to external reasons (such as temperature or pollution) would be the same.[6] However, these productivity measures would diverge when other inputs change. For example, farmers can increase yields by using more labor in the same amount of land, in

[4] For example, out of the top 20 most cited empirical papers in the size-productivity literature, 16 used yields and another two used partial productivity measures (such as profits per acre), whereas only two papers used measures of total factor productivity. The group of highly cited empirical papers using yields includes analyses of possible explanations of the inverse relationship such as omitted variables, market distortions and measurement error (Assunção and Braido, 2007; Barrett et al., 2010; Carletto et al., 2013).

[5] 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) and Sheng and Chancellor (2019).

[6] See, for instance, the discussion in Aragón and Rud (2016) and Aragón et al. (2021).

which case, with diminishing returns to labor, a higher land productivity (yield) is associated with lower marginal and average productivity of labor, while total farm productivity remains the same. As the total factor productivity is a measure of the returns to all factors of production, it obviates the trade-offs between alternative measures of partial productivity.

Consider a farmer who produces a single, homogeneous, good Y according to the following Cobb–Douglas technology:[7]

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

where T_{it} and L_{it} stand for the amounts of land and labor used by farmer i in period t.[8] 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 $s_i e^{\omega_t + \epsilon_{it}}$, where ω_t are common productivity drivers (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:

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

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 researcher uses yields as a proxy for productivity.

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

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

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 $r(1+\tau_i)$.[9] 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:

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

where c is a function of common prices and parameters (w, r, α, γ).

Eq. (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 of productivity.

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

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

By construction, the error term is:

$$\mu_{it} = \gamma(1-\alpha)\ln(1+\tau_i) + \beta \ln(\bar{T}_i - T_{it}) + (\gamma - 1)\ln T_{it} + c + \omega_t + \epsilon_{it}.$$

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:

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

where the error term is: $\varepsilon_{it} = (\gamma - 1)\ln T_{it} + \epsilon_{it}$. 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.[10]

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).

[7] 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.

[8] 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.

[9] 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.

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

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 three ways. First, we eliminate the time dimension t to focus on within-farm variation. Second, we change the unit of observation to be plot p in farm i. Third, 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 can represent the relationship between plot-level yields and size as:

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

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 β. 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. Similarly, several studies suggest that in some contexts (like Thailand, China, Malawi, Ethiopia, and Bangladesh) the agricultural production function of subsistence farmers may exhibit decreasing returns to scale (Shenoy, 2017; Chari et al., 2020; Restuccia and Santaeulàlia-Llopis, 2017; Gautam and Ahmed, 2019; Chen et al., 2021). We document similar findings of DRS in our empirical analysis using data from Uganda, Tanzania, Bangladesh and Peru.

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 the empirical relevance of this issue.

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 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 (in kg) 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 (in Ugandan shilling) by the quantity sold of each crop (in kg). Then, we obtain the median unit value of each crop at the national level.[11]

We measure the area of land cultivated (in hectares) 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 the share of household's 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 (in degree Celsius) and precipitation (in mm per month). 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 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., 2021). 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

[11] The main results are qualitatively similar when using prices at regional and local level (Tables A.5 and A.6 in the Appendix) or when restricting the sample to single-crop households or to households specialized in one of the three main crops, i.e., cassava, maize or beans (Tables A.3 and A.4 in Appendix.)

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.

temperatures above 26°. The inclusion of HDD allows for potentially different, non-linear, effects of extreme heat.

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.[12] 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 (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 $\omega_{jt} = \exp(\delta \cdot \text{weather}_{jt} + \eta_{jt})$ 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:

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

We estimate equation (8) using panel data methods with household fixed effects.[13] 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).[14] 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.[15] 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 productivity of 0.86.[16] 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

Fig. 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.

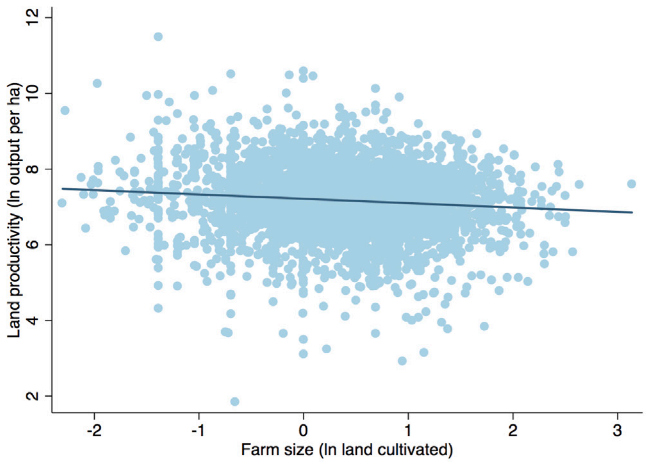
[12] We refer to our measure of real farm output per unit of operated land as land productivity or yield interchangeably.

[13] We prefer using panel data methods with household fixed effects than using proxy variable methods such as Olley and Pakes (1996), Levinsohn and Petrin (2003), Ackerberg et al. (2015), or Gandhi et al. (2020). Shenoy (2020) shows that these alternative methods fail in the presence of input market frictions and recommends instead using dynamic panel methods. We implement the dynamic panel method and replicate our main analysis estimating the production function as in Shenoy (2017). This alternative approach uses the Anderson and Hsiao (1981) dynamic panel estimator and lagged values of inputs as instruments. The results are very similar to our approach. See Tables A.1 and A.7 in Appendix.

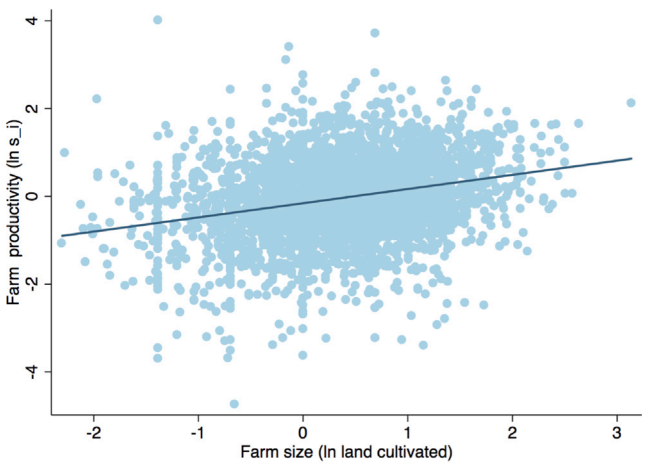
[14] Results remain virtually unchanged when including a continuous measure of capital using the value of farm implements and machinery used in last 12 months. See Table A.1 in Appendix. As shown in Table A.9, farmers in our sample mostly use tools, such as hoes and machetes.

[15] 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.

[16] See Figure A.3 in Appendix.



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



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

Fig. 1. Farm size and productivity.

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 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 Fig. 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 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 Fig. 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 productivity (farm productivity and yields) across farms within farm-size bins for different farm size categories.[17] 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.

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., 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.[18] 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.[19] 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

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

[18] 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 in the Appendix).

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

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	3249	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 taking a simple average. 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.

Table 4
Productivity dispersion by farm size.

Farm size (has)	% farms	Farm productivity (s_i)		Yields (Y/T)	
		Mean	90th/10th percentile	Mean	90th/10th percentile
0–1	28.8	1.348	11.2	3185.6	12.6
1–2	33.8	1.334	8.0	2712.6	8.6
2–5	32.6	1.624	6.7	2386.0	6.5
5+	4.8	2.296	6.4	2274.0	8.4
All farms	100.0	1.479	8.9	2698.5	8.8

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

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 4th degree polynomial of the GPS measures of available land and total labor, and include these variables as additional regressors when estimating s_i. This 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.

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.

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.

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).

4.2 Parcel-level regressions

Several studies estimate the yield-size relationship using plot or parcel 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.[20] 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. However, we cannot perform this analysis due to data limitations. In particular, we do not have a panel of plots (nor parcels) so we cannot reliable control for time-invariant unobserved characteristics as in our baseline household-level regressions.

We can, however, indirectly assess the importance of the CRS assumption. To do so, we estimate yield regressions using parcel-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).[21] According to Eq. (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 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).[22]

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 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.

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 negative relationship between yields and farm size is reversed. Second, we exploit variation in land tenure security across Ugandan households as an indirect measure of market distortions to assess their role in driving the negative yield-size relationship.

5.1 Correcting for market distortions and returns to scale

Eq. (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:

$$\ln \frac{Y_{it}}{T_{it}} = (\beta + \gamma - 1)\ln T_{it} + \gamma(1-\alpha)\ln \frac{L_{it}}{T_{it}} + \delta X_i + \omega_t + \epsilon_{it}. \tag{9}$$

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 Eq. (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).

[20] 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).

[21] Bevis and Barrett (2020) use a panel of plots using a different non-representative survey of farmers in Uganda and find qualitatively similar results. They show that the inverse relation at the plot level can be partially explained by the perimeter-area ratio, i.e. an edge effect.

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

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

	Peru		Tanzania		Bangladesh	
	ln(output per ha) (1)	Farm productivity (2)	ln(output per ha) (4)	Farm productivity (5)	ln(output per ha) (4)	Farm productivity (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	7899	7894	6506	6525
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.

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).

5.2 Using land tenure to proxy for market distortions

Our previous results implicitly use the input ratio L/T as proxy for market distortions. However, the validity of this proxy depends on assumptions of the production function.[23] As a complementary approach, we proxy for market distortions by exploiting variation in land tenure security across household farms. 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; Janvry et al., 2015; Restuccia and Santaeulàlia-Llopis, 2017; Chen, 2017). We note, however, that property rights can be the outcome of other factors affecting productivity and input choices (such as access to infrastructure and distance to markets). In this context, the results in this section do not necessarily have a causal interpretation, instead they are suggestive of the effects of property rights as an indirect measure of market distortions on the inverse size-productivity relationship.

Land tenure measure We distinguish between two broad 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 land are based on communal ownership, which 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). We construct a farm-level measure of land tenure, in particular, use the share of cultivated household land that is under non-customary rights as the main proxy for a household's exposure to market distortions.

Land tenure and market distortions We start by assessing whether farm-level land tenure captures 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, input use and productivity should be strongly positively correlated. A low correlation would be indicative of 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., 2021). For this reason, we also examine the separability of consumption and production decisions in farming households (Benjamin, 1992; Dillon and Barrett, 2017). In the presence of perfect input markets, input use in production should be independent of household endowments. In our context, this implies that households with more secure property rights should observe a weaker correlation between total labor demand and household size. In the absence of market distortions, this correlation should be zero, while positive correlation would indicate distorted or imperfect markets.

Table 9 displays the results. The main finding, from columns 1 and 2, is that the relationship between farm productivity and input use is larger (more positive) for households with higher proportion of land under non-customary (more secure) rights. These results are suggestive of market distortions being less severe for households with more secure property rights.

Columns 3 and 4 report the results for the alternative approach of testing for separability of household's consumption and production decisions. While there is a positive correlation between labor demand and household size, this relationship is significantly weaker for households with modern property rights. This finding rejects the separability hypothesis, a result also consistent with the presence of more severe market distortions for households with less secure land rights.

Land tenure and the yield-size relationship We re-examine the farm size-yield relationship across farm households that differ in land tenure. If the negative size-yield relationship is driven by market distortions, then we should observe a less negative relationship when households have stronger land rights. Table 10 presents our findings using both the yield (column 1) and the production function approach (column 2). In both cases, we maintain the CRS assumption as in the existing literature.

We find that the inverse relationship becomes less negative for households with stronger land rights. These results are consistent with our interpretation that the negative relationship between yields and farm size reflects, in part, the plausible effect of market distortions implied by restrictive land institutions. They should, however, be interpreted as suggestive evidence only, given the potential endogeneity of land tenure even at the household level.

[23] 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 parameters that can vary across farms. Then, the optimal land-labor ratio would be $[\frac{A_i}{B_i}\frac{w}{r(1+\tau_i)}]^{\frac{1}{-\rho}}$ and hence picks up not only market distortions, but also differences in input-specific productivity $\frac{A_i}{B_i}$.

Table 8
Correcting for market distortions and returns to scale.

	Outcome variable: ln(Y/T)					
	(1)	(2)	(3)	(4)	(5)	(6)
ln(T)	−0.257***	−0.257***	−0.064***	−0.629***	−0.629***	−0.181***
$\beta + \gamma - 1$	(0.014)	(0.014)	(0.016)	(0.016)	(0.016)	(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		
Assume CRS	Yes	No	No	Yes	No	No
Add input ratio			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.

Table 9
Assessing market distortions.

	ln(land available) GPS measure	ln(total labor)		
	(1)	(2)	(3)	(4)
Farm productivity	0.132**	0.179***		
	(0.052)	(0.020)		
Farm productivity × % non-custom. land in farm	0.340***	0.079**		
	(0.086)	(0.032)		
ln HH size			0.449***	0.382***
			(0.022)	(0.024)
ln HH size × % non-custom. land in farm			−0.080**	−0.147***
			(0.037)	(0.038)
ln(land available) GPS measure				0.190***
				(0.010)
No. obs.	1905	14,511	14,588	10,259
R-squared	0.397	0.184	0.223	0.287

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. Column 1 collapses the panel data to a cross section of households taking a simple average.

Table 10
Farm size-yield relationship and land tenure.

	ln(output per ha) GPS measure	
	(1)	(2)
ln(land available) GPS	−0.703***	−0.242***
	(0.024)	(0.025)
ln(land available) GPS × % non-custom. land in farm	0.140***	0.128***
	(0.033)	(0.028)
ln(labor/land available GPS)		0.586***
		(0.020)
No. obs.	10,042	9813
R-squared	0.401	0.477

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.

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 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 other less developed countries 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 (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.

CRediT authorship contribution statement

Fernando M. Aragón: Conceptualization, Methodology, Formal analysis, Data curation, Writing (original draft and reviewed draft). **Diego Restuccia:** Conceptualization, Methodology, Formal analysis, Data curation, Writing (original draft and reviewed draft). **Juan Pablo Rud:** Conceptualization, Methodology, Formal analysis, Data curation, Writing (original draft and reviewed draft).

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.foodpol.2021.102168.

References

Abay, Kibrom A., Abate, Gashaw T., Barrett, Christopher B., Bernard, Tanguy, 2019. Correlated non-classical measurement errors, 'second best' policy inference, and the inverse size-productivity relationship in agriculture. J. Dev. Econ. 139, 171–184.

Abay, Kibrom A., Bevis, Leah E.M., Barrett, Christopher B., 2021. Measurement error mechanisms matter: Agricultural intensification with farmer misperceptions and misreporting. Amer. J. Agric. Econ. 103 (2), 498–522.

Ackerberg, Daniel A, Caves, Kevin, Frazer, Garth, 2015. Identification properties of recent production function estimators. Econometrica 83 (6), 2411–2451.

Adamopoulos, Tasso, Brandt, Loren, Leight, Jessica, Restuccia, Diego, 2017. Misallocation, Selection and Productivity: A Quantitative Analysis with Panel Data from China. Technical Report, National Bureau of Economic Research.

Adamopoulos, Tasso, Restuccia, Diego, 2014. The size distribution of farms and international productivity differences. Amer. Econ. Rev. 104 (6), 1667–1697.

Adamopoulos, Tasso, Restuccia, Diego, 2020. Land reform and productivity: A quantitative analysis with micro data. Amer. Econ. J.: Macroecon. 12 (3), 1–39.

Aggarwal, Shilpa, Giera, Brian, Jeong, Dahyeon, Robinson, Jonathan, Spearot, Alan, 2018. Market Access, Trade Costs, and Technology Adoption: Evidence from Northern Tanzania. Working Paper 25253, National Bureau of Economic Research.

Ali, Daniel Ayalew, Deininger, Klaus, 2015. Is there a farm size–productivity relationship in african agriculture? evidence from rwanda. Land Econom. 91 (2), 317–343.

Alvarez, Antonio, Arias, Carlos, 2004. Technical efficiency and farm size: a conditional analysis. Agric. Econ. 30 (3), 241–250.

Anderson, Theodore Wilbur, Hsiao, Cheng, 1981. Estimation of dynamic models with error components. J. Amer. Statist. Assoc. 76 (375), 598–606.

Aragón, Fernando M., Oteiza, Francisco, Rud, Juan Pablo, 2021. Climate change and agriculture: Subsistence farmers' response to extreme heat. Amer. Econ. J.: Econ. Policy 13 (1), 1–35.

Aragón, Fernando M., Rud, Juan Pablo, 2016. Polluting industries and agricultural productivity: Evidence from mining in ghana. Econ. J. 126 (597), 1980–2011.

Assunção, Juliano J, Braido, Luis HB, 2007. Testing household-specific explanations for the inverse productivity relationship. Amer. J. Agric. Econ. 89 (4), 980–990.

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

Auffhammer, M, Hsiang, SM, Schlenker, W, Sobel, A, 2013. Using weather data and climate model output in economic analyses of climate change. Rev. Environ. Econ. Policy 7 (2), 181–198.

Bardhan, Pranab K, 1973. Size, productivity, and returns to scale: An analysis of farm-level data in Indian agriculture. J. Polit. Econ. 81 (6), 1370–1386.

Barrett, Christopher B, 1996. On price risk and the inverse farm size-productivity relationship. J. Dev. Econ. 51 (2), 193–215.

Barrett, Christopher B, Bellemare, Marc F, Hou, Janet Y, 2010. Reconsidering conventional explanations of the inverse productivity–size relationship. World Dev. 38 (1), 88–97.

Benjamin, Dwayne, 1992. Household composition, labor markets, and labor demand: Testing for separation in agricultural household models. Econometrica 60 (2), 287–322.

Benjamin, Dwayne, 1995. Can unobserved land quality explain the inverse productivity relationship? J. Dev. Econ. 46 (1), 51–84.

Berry, R Albert, Cline, William R, et al., 1979. 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.

Besley, Timothy, Ghatak, Maitreesh, 2010. Property rights and economic development. In: Handbook of Development Economics, Vol. 5. Elsevier, pp. 4525–4595.

Bevis, Leah E.M., Barrett, Christopher B., 2020. Close to the edge: High productivity at plot peripheries and the inverse size-productivity relationship. J. Dev. Econ. 143, 102377.

Binswanger, Hans P, Deininger, Klaus, Feder, Gershon, 1995. Power, distortions, revolt and reform in agricultural land relations. Handb. Dev. Econ. 3, 2659–2772.

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

Carletto, Calogero, Savastano, Sara, Zezza, Alberto, 2013. Fact or artifact: The impact of measurement errors on the farm size–productivity relationship. J. Dev. Econ. 103, 254–261.

Carter, Michael R, 1984. Identification of the inverse relationship between farm size and productivity: an empirical analysis of peasant agricultural production. Oxf. Econ. Pap. 36 (1), 131–145.

Chari, Amalavoyal, Liu, Elaine M, Wang, Shing-Yi, Wang, Yongxiang, 2020. Property rights, land misallocation, and agricultural efficiency in China. Rev. Econom. Stud. 88 (4), 1831–1862.

Chen, Chaoran, 2017. Untitled land, occupational choice, and agricultural productivity. Amer. Econ. J.: Macroecon. 9 (4), 91–121.

Chen, Chaoran, Restuccia, Diego, Santaeulàlia-Llopis, Raül, 2017. Land Markets, Resource Allocation, and Agricultural Productivity. Technical Report, Working Paper, University of Toronto.

Chen, Chaoran, Restuccia, Diego, Santaeulàlia-Llopis, Raúl, 2021. The effects of land markets on resource allocation and agricultural productivity. Rev. Econ. Dyn..

Coldham, Simon, 2000. Land reform and customary rights: the case of uganda. J. Afr. Law 44 (1), 65–77.

Collier, Paul, Dercon, Stefan, 2014. African agriculture in 50 years: Smallholders in a rapidly changing world? World Dev. 63, 92–101.

Deininger, Klaus, Castagnini, Raffaella, 2006. Incidence and impact of land conflict in uganda. J. Econ. Behav. Organ. 60 (3), 321–345.

Desiere, Sam, Jolliffe, Dean, 2018. Land productivity and plot size: Is measurement error driving the inverse relationship? J. Dev. Econ. 130, 84–98.

Dillon, Brian, Barrett, Christopher B., 2017. Agricultural factor markets in sub-saharan africa: An updated view with formal tests for market failure. Food Policy 67, 64–77.

Dillon, Brian, Brummund, Peter, Mwabu, Germano, 2019. Asymmetric non-separation and rural labor markets. J. Dev. Econ. 139, 78–96.

Eswaran, Mukesh, Kotwal, Ashok, 1986. Access to capital and agrarian production organisation. Econ. J. 96 (382), 482–498.

Feder, Gershon, 1985. The relation between farm size and farm productivity: The role of family labor, supervision and credit constraints. J. Dev. Econ. 18 (2–3), 297–313.

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

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

Gandhi, Amit, Navarro, Salvador, Rivers, David A, 2020. On the identification of gross output production functions. J. Polit. Econ. 128 (8), 2973–3016.

Gautam, Madhur, Ahmed, Mansur, 2019. Too small to be beautiful? The farm size and productivity relationship in Bangladesh. Food Policy 84, 165–175.

Gourlay, Sydney, Kilic, Talip, Lobell, David, 2017. Could the Debate Be over? Errors in Farmer-Reported Production and their Implications for the Inverse Scale-Productivity Relationship in Uganda. The World Bank.

Helfand, Steven M, Taylor, Matthew PH, 2021. The inverse relationship between farm size and productivity: Refocusing the debate. Food Policy 99, 101977.

Hsiang, Solomon, 2016. Climate econometrics. Annu. Rev. Resour. Econ. 8, 43–75.

Hsieh, Chang-Tai, Klenow, Peter J, 2009. Misallocation and manufacturing TFP in China and India. Q. J. Econ. 124 (4), 1403–1448.

Janvry, Alain De, Emerick, Kyle, Gonzalez-Navarro, Marco, Sadoulet, Elisabeth, 2015. Delinking land rights from land use: Certification and migration in Mexico. Amer. Econ. Rev. 105 (10), 3125–3149.

Julien, Jacques C, Bravo-Ureta, Boris E, Rada, Nicholas E, 2019. Assessing farm performance by size in malawi, tanzania, and uganda. Food Policy 84, 153–164.

Kagin, Justin, Taylor, J Edward, Yúnez-Naude, Antonio, 2016. Inverse productivity or inverse efficiency? Evidence from Mexico. J. Dev. Stud. 52 (3), 396–411.

Key, Nigel, 2019. Farm size and productivity growth in the United States corn belt. Food Policy 84, 186–195.

Lamb, Russell L, 2003. Inverse productivity: Land quality, labor markets, and measurement error. J. Dev. Econ. 71 (1), 71–95.

Levinsohn, James, Petrin, Amil, 2003. Estimating production functions using inputs to control for unobservables. Rev. Econom. Stud. 70 (2), 317–341.

Lucas, Robert E, 1978. On the size distribution of business firms. Bell J. Econ. 508–523.

Olley, G Steven, Pakes, Ariel, 1996. The dynamics of productivity in the telecommunications equipment industry. Econometrica 64 (6), 1263–1297.

Place, Frank, Otsuka, Keijiro, 2002. Land tenure systems and their impacts on agricultural investments and productivity in uganda. J. Dev. Stud. 38 (6), 105–128.

Rada, Nicholas, Helfand, Steven, Magalhães, Marcelo, 2019. Agricultural productivity growth in Brazil: Large and small farms excel. Food Policy 84, 176–185.

Restuccia, Diego, Rogerson, Richard, 2008. Policy distortions and aggregate productivity with heterogeneous establishments. Rev. Econ. Dyn. 11 (4), 707–720.

Restuccia, Diego, Santaeulàlia-Llopis, Raül, 2017. Land Misallocation and Productivity. Working Paper 23128, National Bureau of Economic Research.

Schlenker, Wolfram, Roberts, Michael J., 2006. Nonlinear effects of weather on corn yields. Rev. Agric. Econ. 28 (3), 391–398.

Schlenker, Wolfram, Roberts, Michael J., 2009. Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change. Proc. Natl. Acad. Sci. 106 (37), 15594–15598.

Sen, Amartya K, 1962. An aspect of Indian agriculture. Econ. Wkly 14 (4–6), 243–246.

Sheng, Yu, Chancellor, Will, 2019. Exploring the relationship between farm size and productivity: Evidence from the Australian grains industry. Food Policy 84, 196–204.

Shenoy, Ajay, 2017. Market failures and misallocation. J. Dev. Econ. 128, 65–80.

Shenoy, Ajay, 2020. Estimating the production function under input market frictions. Rev. Econ. Stat. 1–45.

Townsend, Robert F., Kirsten, Johann, Vink, Nick, 1998. Farm Size, Productivity and Returns to Scale in Agriculture Revisited: a Case Study of Wine Producers in South Africa, Vol.19. Publisher: Wiley Online Library, pp. 175–180, (1), ZSCC: 0000160.