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Fact or artifact: The impact of measurement errors on the farm size–productivity relationship☆

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ABSTRACT

This paper revisits the role of land measurement error in the inverse farm size and productivity relationship (IR). By making use of data from a nationally representative household survey from Uganda, in which self-reported land size information is complemented by plot measurements collected using Global Position System (GPS) devices we reject the hypothesis that IR may just be a statistical artifact linked to problems with land measurement error. In particular, we explore: (i) what are the determinants of the bias in land measurement, (ii) how this bias varies systematically with plot size and landholding, and (iii) the extent to which land measurement error affects the relative advantage of smallholders implied by the IR. Our findings indicate that using an improved measure of land size strengthens the evidence in support of the existence of the IR.

1. Introduction

The controversy over the existence of an inverse relationship between farm size and productivity (IR henceforth) is one of the longest standing and more ideologically charged debates of the agricultural development literature. Should smallholders be found to be more efficient, policies to facilitate the redistribution of land towards small farmers may be justified not only on equity but also on efficiency grounds. Binswanger et al. (1995) and Eastwood et al. (2010) provide comprehensive reviews of the arguments and a historical account of the empirical evidence on the IR. In the context of African agriculture, the relationship has been most recently questioned by Collier and Dercon (2009: p. 3) who maintain that "there are (only) a handful of reasonably careful studies showing the inverse farm-size/productivity relationship in African settings, but also some showing the reverse (i.e. positive) farm-size/productivity relationship".

A substantial part of the debate, particularly in recent years, has focused on whether the IR may be a statistical artifact, stemming from problems with the available data. The possible role of the omission or imprecise measurement of land quality traits in determining the empirical findings on the IR has been examined by several authors (Benjamin, 1995; Bhalla and Roy, 1988; Binswanger et al., 1995; Lamb, 2003; Walker and Ryan, 1990). Barrett et al. (2010) have probably put an end to that aspect of the controversy using laboratory tests on soil samples to show that only a minimal part of the IR can be explained by differences in land quality. We are aware of only one study (Lamb, 2003) that attempts to empirically test the robustness of the IR to possible errors in land area measurement. The conclusion of that study, which controls for errors in land measures indirectly by comparing fixed and random effect estimates, is that when errors in self-reported farm size are accounted for the IR can be completely explained by factor market imperfections and differences in land quality.

In this paper, we revisit the role of land measurement error in the IR controversy by drawing on data from a nationally representative household survey from Uganda, in which self-reported land size information was complemented by plot measurements collected using Global Position System (GPS) devices. This allows us to systematically analyze the differences in land area data using both measurements, and discuss the impact of such differences on estimates of agricultural productivity. In particular, we explore: (i) what are the determinants of the bias in land measurement, (ii) whether this bias varies systematically with plot size and landholding, and (iii) whether the data

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support the IR hypothesis, and the extent to which land measurement error affects the relative advantage of smallholders implied by the IR. Preliminary empirical evidence (Goldstein and Udry, 1999) suggests that the differences between GPS and self-reporting may be substantial, and that such difference varies by farm size. If this intuition is correct, using GPS data can have considerable implications for the much debated and contentious relationship between farm size and productivity.

The paper is organized as follows. The next section succinctly reviews the main strands of literature this paper relates to. Section 3 provides a description of the data. The econometric models used are sketched in Section 4 and the results discussed in Section 5. The final section summarizes the contributions of the analysis to the literature and to the policy discussion around smallholders' productivity.

2. The inverse farm size–productivity relationship: smallholder advantage or statistical artifact?

Starting with the seminal work of Sen (1962, 1966) who observed an inverse relationship between farm size and output per hectare in Indian agriculture, a large number of empirical studies have presented evidence that appears to corroborate that hypothesis (Barrett, 1996; Benjamin and Brandt, 2002; Berry and Cline, 1979; Carter, 1984; Eswaran and Kotwal, 1985, 1986; Lau and Yotopoulos, 1971). A smaller set of empirical studies however does not find evidence of such a relationship (Hill, 1972; Kevane, 1996; Zaibet and Dunn, 1998). Binswanger et al. (1995) and Eastwood et al. (2010) provide careful discussions of both the theory and the empirics of the IR debate, a full review of which is beyond the scope of this paper.

It will suffice here to note that, following Barrett et al. (2010), an inverse relation between farm size and productivity may have three main explanations: (i) imperfect factor markets, (ii) omitted variables and, in particular, omitted controls for land quality, and (iii) statistical issues related to the measurement of plot size. Imperfect factor markets (labor, land, insurance) are linked to differences in the shadow price of production factors that in turn lead to differences in the application of inputs per unit of land, in ways that are correlated with farm size. Much of the earlier contributions to the IR debate focused on testing this type of explanation. Assuncao and Ghatak (2003) demonstrate how theoretically unobserved heterogeneity in farmer quality may explain the observed differences in productivity. Other studies (e.g. Benjamin, 1995; Bhalla and Roy, 1988) have challenged the existence of the IR based on the observation that when land quality controls are introduced in the analysis, the strength of the IR often diminishes substantially or vanishes altogether. Barrett et al. (2010) utilize a dataset that includes laboratory measures of soil testing to conclude that in fact only a very limited proportion of the IR can be explained by differences in land quality. Lastly, attention has been drawn to the possibility that the existence of the IR may be a statistical artifact deriving by measurement error in land data (Lamb, 2003). A similar explanation is also hinted at by Barrett et al. (2010), after failing to explain the observed IR otherwise.

For the IR to be partially or fully explained by errors in land measurements, smaller farmers would have to systematically underreport land area with respect to larger farmers, thus resulting in artificially inflated yields in the bottom part of the distribution. However, as reported by De Groote and Traoré (2005), small farmers tend to overestimate their land holding—while large farmers tend to underreport—hence increasing the likelihood of analysts finding an even stronger inverse relationship in empirical studies based on more accurate measures.

Land area measurement is one of the fundamental components of agricultural statistics, and it is therefore not surprising that the interest of agricultural statisticians in the possibility of applying technological innovations such as satellite imagery and GPS devices to land area measurement is growing exponentially with the increasing affordability and precision of these technologies and their applications. Kelly et al. (1995) have long identified the use of GPS as having the potential to contribute to making land area measurement a much less costly and time consuming exercise than traditional methods. An early study mentioning a comparison of GPS and self-report plot measures is Goldstein and Udry (1999). They only refer to this in passing in a study of agrarian innovation in the Eastern Region of Ghana, reporting a very low correlation coefficient of just 0.15 between the two measures. They explain the result with the fact that traditional land measures in the region were based on length only (ropes), and as land became more scarce local farmers found it difficult to translate that to a two dimensional measure (hectares).

Keita and Carfagna (2009) provide a discussion of the performance of different GPS devices compared to traditional methods (rope and compass), which they consider the 'gold standard'. Their evidence confirms that GPS devices allow measuring farm size with enough accuracy compared to traditional and objective land measurement methods such as compass and meters. They conclude that the GPS is a reliable alternative to traditional measures (80% of the plots in their sample are measured with negligible error), but that on average GPS measures tend to underestimate plot area somewhat. The main reasons for errors in GPS measures detected by this study are the density of plot tree canopy cover and to some degree weather conditions at the time of measurement.

In a somewhat different application in the context of Peruvian market access self-reported data vis a vis "true travel time" using GPS, Escobal and Laszlo (2008) show how if the error is correlated with the main outcomes of interest the conclusions of the analysis may be biased and driven by a spurious correlation. That is because the deviation between the 'true' travel time and the respondents' estimate is determined by observable socio-economic variables related to the outcome of choice. Gibson and Mckenzie (2007) show evidence of the non-random distribution of measurement error in several of the distance and location studies they review, and demonstrate how the use of GPS aids can help overcome problems of measurement in data collection efforts.

GPS measurements are of course not immune from problems themselves. Possibly the most important issue is the fact that it is generally not practical and too costly to measure all the plots owned by a household. Some plots may be distant from the place of the interview (usually the household's dwelling), and respondents may not have the time or be willing to accompany the enumerators to all the plots. Even if they were, the operational costs and travel time required to record GPS measures for all plots are likely to be prohibitive for most survey operations. This raises some analytical concerns, in the form of biased estimates, if the plots that are not measured are systematically different from the ones that are measured. We do find evidence of such bias in our data, and in the next section we discuss how we dealt with the issue.

Another issue with GPS measures is that their accuracy deteriorates on very small plots. Bogaert et al. (2005) apply Monte Carlo simulation methods to experimental measurement data from Poland and show that for plots between 0.5 and 5 ha the coefficient of variation (CV) decreases with size but remains within the 1–5% range. For smaller plots the CV increases steeply even though it does not appear do exceed 15% in the plausible range of plot sizes. They also show how GPS measures are only modestly affected by the experience of the operator taking the measure, the shape of the plot, and the possible bias of the GPS device itself.

3. Data source and descriptive statistics

The data for this paper come from the Uganda National Household Survey (UNHS) round implemented by the Uganda Bureau of Statistics (UBOS) in 2005–2006. The UNHS is a multi-purpose household survey with a sample of 7500 households, selected following a stratified sample design that identified 753 enumeration areas (UBOS, 2009). One

Table 1
Summary of statistics at the plot level.
Source: Authors' calculations based on UNHS 2005.

	Nb of Plots	Unit	Mean	Std. Dev.	Min	Max
GPS	5767	Acre	2.24	12.43	0.01	600
Self-reported	5767	Acre	2.13	12.75	0.01	600
Discrepancy (GPS-self reported)	5767	Acre	0.11	2.28	−49	45
Negative discrepancy (Negative error = >GPS < self reported)	3121	Acre	−0.67	1.82	−49	−0.01
Positive discrepancy (Positive error = >GPS > self reported)	2545	Acre	1.07	2.47	0.01	45

special feature of this survey that makes our analysis possible is that it contains plot level information on agricultural land area measured through both GPS and farmers' own estimates.

Some 5714 of the survey households are located in rural areas and cultivate land. The total number of plots with self estimated measure is 13,959 and about 65% of these (9173 plots) have a corresponding GPS measure.[2] The agricultural production section, however, only contains information gathered at the household/farm level. Thus, the analysis in this paper is carried out partly at the plot level, and partly at the household/farm level. We use the former to analyze the difference between land area measurement using farmers' estimate and GPS, since it is at the plot level that the two measures are collected. The household/farm level analysis is more suitable to investigate the consequences of the bias in land measurement on the IR, since key farm input and output data are only available in the survey at this level, not allowing the calculation of plot-specific productivity measures.

To be able to run the analysis maintaining a consistent sample throughout, we therefore restricted our sample further to 5767 plots for which we have complete information on both types of measures for all the plots cultivated by the household. In the farm level analysis, for which we also drop 42 households with negative farm profits (equivalent to 1.5% of the sample), we end up with a sample of 2860 rural households for which we have both non-zero land area measures for the entire households' landholdings.

Table 1 reports key summary statistics for the plots for which we have information on both types of area measurements, along with the mean and standard deviation (in acres) of plot size measured through GPS, self-reporting, and the absolute and relative difference between the two measures. For simplicity of presentation, we will take the GPS measure as the benchmark and talk of farmers over- (or under-) reporting plot size whenever the area self-reported is larger (smaller) than the area measured by GPS. We do acknowledge however that the GPS measure may also be subject to a certain degree of inaccuracy (Keita and Carfagna, 2009).

On average the two methods produce strikingly similar estimates of land area. The average size of plots using GPS is 2.24 acres, a mere 0.11 acres (equivalent to 4.9%) larger than the area reported by farmers. The sample level means however mask pervasive differences in measurement that emerge at closer scrutiny. In the overall sample, farmers overestimate plot size in 54.12% of the cases (or 3121 plots), and underestimate it in 44.13% of plots (equivalent to 2545 plots). For the remaining 101 plots (1.75%) the survey reports identical measures with either method. For the plots where a ‘positive discrepancy’ is observed, namely a GPS measure larger than self reporting, the amount of area overestimated is larger in absolute value (1.07 acres on average, or 35.1%) than for the plots for which the bias is negative (−0.67 acres or 47.2%).

The fact that we dropped a substantial number of plots from our analysis because of gaps in the GPS measurement raises some concerns regarding whether this may introduce a source of bias in our analysis. This intuition is partially confirmed by an inspection of the summary statistics for the two sets of plots. The plots that we had to exclude from the analysis because of gaps in the GPS measure are on average smaller than those we did include, they are more likely to be on a steep slope, and less likely to be protected by a fence. The heads of households to which these plots belong are somewhat older and less educated, and more likely to be female. Also, these plots belong to households that are on average smaller. These plots are therefore not randomly selected, which is what one would expect, since taking the actual GPS measurement of a plot requires a household member and enumerator to move for the site of the main interview to the location of the plot to take the GPS measurement. More distant, less accessible plots are therefore more likely to be excluded. These statistically significant differences in plot characteristics between the part of the sample we use and the part we had to discard suggest the presence of possible sample selection issues arising from these restrictions and impacting on the analysis of farm productivity.[3] We will return to this point in the result section, to show how these issues do not in fact appear to be affecting our results. The non-random selection of GPS-measured plots, however, does represent a challenge that future surveys employing these methodologies will have to find ways to confront.

Table 2 summarizes land measurement statistics at the household level. We report statistics for deciles of landholding to investigate how measurement bias plays out at different points of the distribution. This information will be important later, when we analyze the impact of land measurement bias on the IR. The last column of Table 2 reports the discrepancy in percentage terms. According to this measure, the magnitude of the discrepancy appears to increase monotonically as one moves from the bottom (smallest landholders, −97%) to the top deciles (largest landholders, 19%). Up to 4.57 acres of farm size (the seventh decile), the bias is on average negative, whereas it becomes positive in the top three deciles. There is therefore a pattern in the direction of the bias, with smaller farmers generally over reporting their land relatively more than larger farmers, and with the largest farmers actually under reporting land size.

These findings go in the same direction as the results of De Groote and Traoré (2005) for Southern Mali. As stated above, De Groote and Traorè find that there is an approximate linear negative relationship between measurement error and plot size. Farmers have a tendency to overestimate small plots (which they define as below 1 ha[4]) compared to larger ones, which they somewhat underestimate. Also, the GPS and self-reported plot area measures in our sample display a correlation of 0.97 (which drops to a more reasonable, but still respectable, 0.77 when we trim the right end of the distribution of a few very large plots), well above the 0.15 found by Goldstein and Udry (1999) in their Ghana dataset.

One additional issue in our data, that is immediately apparent from the visual inspection of the distributions of the two land measures in

[2] A Garmin 12XL GPS device was used by the survey teams to collect plot area data.

[3] A table with the result of the t-tests of difference in means for key plot characteristics is available from the authors on request, and is also included in the working paper version of this article.

[4] 1 ha is equal to 2.47 acres.

Table 2
Mean farm size and discrepancy characteristics by decile of landholding (GPS measure).
Source: Authors' calculations based on UNHS 2005.

Deciles	Area of HH landholding	Nb. of plots per hh	Mean farm area using GPS	Mean farm area using self-reported	Farm discrepancy (GPS-self reported)	Discrepancy in % terms
1	0.01–.65	1.70	0.37	0.73	−0.36	−97%
2	0.66–1.12	2.33	0.90	1.43	−0.53	−59%
3	1.13–1.62	2.40	1.37	1.78	−0.41	−30%
4	1.63–2.09	2.70	1.84	2.36	−0.52	−28%
5	2.09–2.69	2.94	2.38	2.91	−0.52	−22%
6	2.7	2.80	3.04	3.53	−0.48	−16%
7	3.44–4.57	2.74	3.96	4.10	−0.14	−4%
8	4.59–6.16	2.94	5.31	5.18	0.13	2%
9	6.17–9.13	3.20	7.46	7.08	0.39	5%
10	9.14–600	3.40	21.03	17.07	3.96	19%
Total	*0.01–600*	*2.70*	*4.75*	*4.60*	*0.15*	*3%*

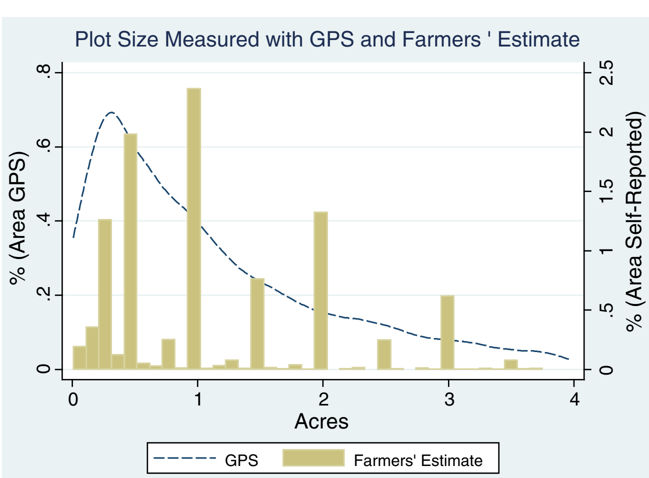
Note: area is expressed in acres, and computed for total household landholding.

Fig. 1, is the considerable tendency of respondents (or enumerators) to round their reported plot size to the nearest acre or half acre. This ‘heaping’ in the response pattern is not uncommon (Roberts and Brewer, 2001) but we suspect that it may be particularly important in the case of land measurement since it is bound to matter proportionally more to the left of the distribution, as the same amount of rounding represents a larger percentage of the actual plot size.

Fig. 1 also confirms that the two distributions are, overall, quite similar. However, while the means are not much different, at specific points the distributions deviate considerably, in a way that appears to be driven by heaping in the self-reporting distribution as opposed to a smooth curve for the GPS measure. Finally, the comparison of the two distributions appears to support the case for treating the GPS measure as the more accurate of the two.

The systematic patterns in the difference between land measurements we have observed above have the potential to introduce a bias in the estimation of agricultural/land productivity. Reasoning through the data it is apparent, as we already mentioned, that the kind of pattern we observe in our data should, if anything, generate a bias opposite in sign to that needed to corroborate the IR hypothesis. If small farmers report to be cultivating more land than they actually are, their ‘true’ yields are actually even larger than what one would compute using self-reported land quantities.

Table 3 summarizes level of output per acre computed using GPS and self-reported land areas. Farms are categorized as either small, medium or large. Small farms, those cultivating landholdings smaller than 1.45 acres exhibit systematically higher yields when area cultivated is measured through GPS as compared to self-reporting. The distance is reduced for medium farms, whereas large farms have lower yields measured with GPS than those obtained through farmers' estimate.



Source: Authors' calculations based on UNHS 2005

Fig. 1. Bias in land measurement: rounding problems.

The inclusion of a more accurate measure of land area in this dataset seems to be strengthening the empirical case for the existence of an inverse farm size productivity relationship, rather than weakening it. This is consistent with what we expected after looking at the distribution of the discrepancies in the two measures, but appears to contradict the discussion in Barrett et al. (2010) and the analysis in Lamb (2003), who finds that the IR disappears after introducing random effects which he hypothesizes capture the influence of measurement error.

Finally, while the land data we use in most of the paper come from the “access to land” section of the questionnaire, for the parts of the analysis focusing on maize yields we rely on the section on cultivation during the first cropping season January–June 2005. From this section of the survey we can use a sample of 5386 plots for which data is available for both the self-reported and the GPS measures.[5]

4. The econometric approach

In order to deepen the analysis of (a) the characteristics and determinants of the discrepancy between our two land measures, and (b) the implications of measurement bias on the robustness of the IR hypothesis, we estimate the two models specified below.

As in Deininger et al. (2012), to identify what are the factors affecting the difference between the two measures we estimate the following function, at the plot level:

$$e_j = \beta x_j + u_j \tag{1}$$

where e_j is the plot size specific difference between the GPS and the self-reported measure, x_j is a $(K+1)$-row vector of control variables with ‘1’ as its first element, $\beta = (\beta_0, \beta_1, \ldots, \beta_K)'$ is vector of parameters to be estimated. u_j is a two-sided error term representing white noise. The controls used in this regression include a set of characteristics of the household head (age, education, and gender) to proxy respondents' characteristics that are deemed to influence the ability to accurately report land size. We also include plot size, and its squared term, to test whether the relationship observed in the descriptive analysis holds in a multivariate framework, and a dummy reflecting whether the self-reported land variable is a round number, to capture the impact of rounding. The rounding variable is equal to 1 if the self-reported land measure is a number that clearly represents a response that

[5] Data for the July–December 2004 cropping season contain only area self-reported by farmers and hence do not allow a comparison with the GPS measure.

Table 3
Relation between output per acre and farm size.
Source: Authors' calculations based on UNHS 2005.

	Landholding	Average land area	Yields (GPS)	Output per acre (self reported)	Bias in yields (GPS-self reported)
	Acres	Acres	US$/acre	US$/acre	%
Small farms	0.01–1.45	0.7	236	170	28%
Medium farms	1.46–3.57	2.4	208	193	7%
Large farms	3.58–600	10.3	77	100	−30%

approximated land size with a 'round' number or a commonly reported fraction of a round number (0.25; 0.5; 1; 1.5; 2; etc.). We include this variable to control for the heaping in the response patterns identified in Fig. 1: for all observations that correspond to a heap in the self-reported land distribution, the rounding variable is equal to 1. We do not have a priori expectations for the sign of this variable, but we include it to check if there is any systematic heaping pattern (e.g. reporting to the next higher or next lower round number) that can contribute to explaining the discrepancy between the self-reported and GPS measures.

Furthermore, we include information on whether the household is involved in disputes over land ownership, as we expect such households to have less information or interest in these plots. Topography will also affect land estimate by farmers, as steep plots may be more likely to be subject to measurement error. Finally, we also add PSU dummies to control for idiosyncratic differences across survey teams and supervisors and for possible environmental and geographic factors.

Next we estimate a standard model for testing the existence of the IR, and to understand how land measurement error weakens, eliminates or reinforces this empirical evidence. Our model is based on the one originally proposed by Binswanger et al. (1995), and not dissimilar from the approach used by several others including, most recently, Barrett et al. (2010). We estimate the following function at the household level:

$$\ln\frac{Y_i}{A_i} = \beta_0 + \beta_1 \ln A_i + \beta_2 X_i + \beta_3 R + u_i \tag{2}$$

where Y_i represents net agricultural revenues for each household i, A_i the total area operated, X_i denotes a vector of households' characteristics that influence production such as the availability of family labor, the gender, age and education of the household head, value of inputs per acre used, and a set of land quality variables, R is the rounding effect when net revenues per acre of area cultivated are measured with land size as reported by farmers,[6] and u_i is the error term. We estimate two versions of this relationship, one using GPS and the other one with the self-reported land measure, and compare the two to gauge the impact of differences in measurement on the IR, which is captured by the coefficient on the land size variable. A negative coefficient on the land area variable indicates the presence of the IR. The further below 0 the coefficient, the stronger the IR. As in the previous model, we also include PSU fixed effects to control for survey team and local environmental effects.

The left hand side term—net agriculture revenues per acre—is computed as the value of total crop production net of value of variable inputs (hired labor, seeds, organic and inorganic fertilizers, chemicals, and animals rented for plowing), divided by the amount of land cultivated. While we maintain that this is the preferred way to calculate net revenues, some may argue that subtracting hired but not family labor may give an unfair advantage to small farmers who rely mainly on the latter. We therefore also tried running our estimates without subtracting hired labor costs from gross revenues and the results (not reported) did not change to any significant extent. Furthermore, as much of the literature on the IR focuses on yields rather than profits (e.g. Feder, 1985), we complement these estimates with the results of an alternative set of specifications using maize yields as the dependent variable.[7,8]

Regarding the terms on the right hand side, we expect productivity to be positively related to the use of variable farm inputs, including hired labor. Given the supportive evidence provided by several of the contributions to the inverse farm size productivity debate (Barrett, 1996; Benjamin and Brandt, 2002; Berry and Cline, 1979; Carter, 1984; Eswaran and Kotwal, 1985, 1986; Kutcher and Scandizzo, 1981; Lau and Yotopoulos, 1971; Udry, 1996), we expect labor market imperfections to give an advantage to farms able to rely on family labor, and hence a positive sign on the coefficient on this variable.

To control for various aspects of land quality, variables on farmer-assessed soil quality, steepness and irrigation of the plots are included as regressors. The soil quality variable is computed as the share of total cultivated land the farmer reports being in plots with good soil quality. The share of steep land is similarly computed using plot level data, and taking the sum of plot size with steep slope as a share of the total landholding. In the same fashion the share of land irrigated is constructed dividing the area of the cultivated plots reported to be irrigated by the total cultivated acreage. The obvious expectations concerning the regression coefficients on these variables are that good quality, irrigated land will be associated with larger profits per acre, whereas greater shares of steep land will, other things equal, be associated with lower levels of productivity per unit of cultivated land.

The final set of variables in the regression relates to household characteristics. The age of the household head is normally expected to reflect farming experience and therefore be positively related to farm productivity. It is also possible that older age may be related to reduced physical strength, health problems and hence reduced ability to farm the land, but the experience aspect usually dominates. Education should clearly affect positively farmers' productivity and welfare, while the expectation is for female headed households to be less productive because of a wide variety of factors ranging from discrimination in input and output markets to unfavorable family composition. Where the female headship is due to the presence of a migrating husband sending remittances back home that can be invested in farming, however, the impact on farming and productivity may in fact be positive. The summary statistics for all variables used in the regressions are reported in Appendix A.

[6] We include the rounding variable in this regression to avoid that any systematic pattern of rounding by the respondents may affect the estimates. The results presented below show that this is not the case. We have also run a specification without this variable, and results are unaffected. Given heteroskedasticity concerns we report robust standard errors for all regression results.

[7] We thank the Editor and an anonymous reviewer for this suggestion.

[8] In performing the log transformation of the net revenue variable we drop about 1% of observations with net revenues of zero or negative. Key results do not change if we include these observations by rescaling the level variables before taking the logs, or by and using a cubic root transformation.

Table 4
Determinants of difference in plot measurement (dependent variable: GPS-self reported plot size, in acres).
Source: Authors' calculations based on UNHS 2005.

	Bias in level with PSU fixed effects
Plot size (GPS)	0.04***
	[0.000]
Plot size (GPS) squared	−0.001***
	[0.000]
Rounding in self reported	0.26***
	[0.001]
Dummy: parcel has a fence	0.45***
	[0.006]
Head's age	0.73***
	[0.000]
Head's education	−0.01
	[0.566]
Dummy: female household head	0.07
	[0.362]
Dummy: plot was/is in dispute with relatives	0.67***
	[0.004]
Dummy: Plot is steep	0.20
	[0.349]
Constant	−0.55***
	[0.000]
Observations	5767
R-squared	0.229

p values in brackets.
* significant at 10%; ** significant at 5%; *** significant at 1%.

5. Empirical results

The results of the estimation of model (1) are reported in Table 4. Confirming the results of the descriptive analysis in Section 3, the data show a positive association between plot size and the difference between GPS and self-reported land measurements in levels. This discrepancy increases with farm size: larger farms have a tendency to under-report, while small farms tend to over-state the size of their landholdings.

The other signs are also as expected. The presence of rounding contributes to increasing measurement error, as we hypothesized based on the heaping displayed by the distribution of self-reported plot size in Fig. 1. While the education and gender of the household head variables are not significant, head's age matters. Older heads are likely to be less accurate in their reporting of plot size. Households who are involved in disputes over land are also likely to make larger errors in self-reporting, which we hypothesize is due to the fact that such disputes diminish their interest, access, and in general knowledge of plot characteristics. Contrary to expectations the demarcation of the plot with a fence does not seem to reduce the error in land self reporting; the coefficient of the dummy if the plot has a fence is positive and significant thereby suggesting a larger error for those plots. Finally, the steepness of the plot does not appear to significantly influence measurement bias.

Table 5 presents the results estimating model (2) using alternatively net revenues and maize yields as dependent variables. In columns (1) and (3) land is measured with the traditional respondent self-report, whereas columns (2), and (4) are based on the GPS measure of land size. In columns (1) and (2) the dependent variable is the log of net revenues per acre, whereas in columns (3) and (4) it is the log of maize yields (in kg per acre). Robust standard errors are reported in all specifications to account for heteroskedasticity.

The main variable of interest in this model is the (log) of land size, as it is this coefficient that captures the size–productivity relationship, with a negative coefficient pointing to the existence of an inverse relationship. The estimated coefficients are −0.24 in the specification using self-reported land size and −0.37 in the specification using the GPS measure of agricultural plots. Both estimates therefore support the IR hypothesis. When the GPS measure of farm size is used, however, the absolute value of the coefficient increases, indicating an even stronger IR.

The inclusion of hired labor and inputs on the right hand side poses problems as they may capture part of the effect of market imperfections, not allowing for their full effect to be reflected in the farm size coefficient.[9] To check for the extent to which this problem might affect our results we run the same regression without these variables and the key results (not reported) confirmed the presence of the IR. In both specifications, the coefficient of land size remains negative and statistically significant (to −0.312 and −0.479 in the SR and GPS specifications respectively).

The hypothesis according to which the IR would be a statistical artifact due to small farmers under-reporting their farm size is therefore strongly rejected by the data. In our sample, small farmers in fact over-report land size, and it is the very large famers who are actually more likely to under-estimate their holdings, thus resulting in artificially higher yields. When more accurate land measures are used thanks to the introduction of GPS devices, the estimated slope of the function becomes steeper indicating an even stronger IR than what one would conclude based on similar estimates performed using farmers' self-reporting.

As expected, good soil quality shows a positive association with farm profits, which remains stable across specifications. The irrigation and steepness variables, on the other hand, have the expected signs (positive for irrigation, negative for steep land) but the estimated coefficients are not statistically significant.

As discussed in Section 3 above, one issue with our data is the sample selection bias introduced by dropping from the productivity analysis the households for which we do not have both measures for all plots. To investigate whether this may be a factor invalidating our main findings we re-estimated model (2) using the entire sample, and tested (a) whether the group means of predictors estimated using the two samples are equal, and (b) whether the main coefficients of interest for the IR (i.e. the coefficients on the land variable) are equal.[10]

The Wald test rejects the null hypothesis that all coefficients are equal for both samples, which one would expect given the systematic differences between the two samples we discussed earlier in the paper. What matters for our key results, however, is that the test fails to reject the null for the land coefficient. In other words, the IR estimated using the self-reported measure is as strong on the full sample as it is on the restricted sample for which we have complete GPS information. For productivity analysis at large, however, the rejection of the test of equality between the two runs of the model does point towards the need for future surveys to solve the selection issues related to GPS measurement of plots, as that is bound to matter for specific aspects of the analysis.

One final concern relates to the possibility that larger farms be concentrated in remote and unfavorable agricultural areas, or that market imperfections leading to the IR may be confined to particular regions. We investigated whether that appears to be the case in our data, by running our analysis separately for the four macro-regions for which the UNHS is statistically representative (Central, Eastern, Northern and Western Uganda). The specification is the same as that described in model (2) and reported in Table 5 for the full sample, with the same explanatory variables included but not reported. Results are not reported for reasons of space, and are available from the authors. In all regions the IR holds regardless of the specification, but it is stronger

[9] The input variables also pose possible endogeneity problems being choice variables for the farmers.
[10] Results are available from the authors upon request.

Table 5
Testing the IR hypothesis. Dependent variable log of net agriculture revenue per acre and log of maize yields (kg/acre).

Variables	(1)	(2)	(3)	(4)
	Log net revenues per acre SR	Log net revenues per acre GPS	Log maize yields (Kg per acre SR)	Log maize yields (Kg per acre GPS)
Log land size	−0.236***	−0.374***	−0.975**	−1.036**
	(0.035)	(0.054)	(0.104)	(0.107)
Rounding	−0.014		−0.17	
	(0.063)		(0.099)*	
Log head's age	0.126**	0.070	−0.026	−0.077
	(0.060)	(0.061)	(−0.113)	(−0.114)
Log head's education	−0.106*	−0.083	0.073	0.068
	(0.054)	(0.053)	(−0.053)	(−0.055)
Dummy female head	−0.150***	−0.140***	−0.342**	−0.271**
	(0.047)	(0.046)	(0.092)	(0.094)
Log value of purchase inputs/acre	0.015***	0.013***	0.023**	0.022**
	(0.005)	(0.005)	(0.008)	(0.008)
Log value of hired labor/acre	0.017***	0.016***	0.024**	0.022**
	(0.004)	(0.004)	(0.009)	(0.009)
Log value of family labor/acre	0.298***	0.285***	0.061	0.111**
	(0.042)	(0.040)	(−0.039)	(0.039)
Share of land with poor soil quality	−0.003***	−0.002***	−0.063	0.029
	(0.001)	(0.001)	(−0.126)	(−0.097)
Share of land flat	−0.001*	−0.001	0.027	−0.275
	(0.000)	(0.000)	(−0.096)	(−0.442)
Share of land swamp/wetland	−0.001	−0.001	0.198	−0.031
	(0.002)	(0.002)	(−0.519)	(−0.128)
Share of plots intercropped			−0.343**	−0.381**
			(0.119)	(0.120)
Constant	3.022***	3.570***	4.486**	4.48**
	(0.300)	(0.320)	(0.501)	(0.505)
Observations	2825	2825	2609	2609
R-squared	0.567	0.620	0.386	0.395

Robust standard errors in parentheses.
Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Dummies for communities estimated but not reported.

when the GPS area measured is used. Our results do not therefore appear to be sensitive to the effect of possible socio-economic or agro-ecological differences across regions.

6. Conclusions

The hypothesis that the inverse relationship between farm size and productivity may just be a statistical artifact, linked to problems with land measurement error, is rejected by the analysis presented in this paper. Contrary to earlier conjectures, we find that the empirical validity of the IR hypothesis is strengthened, not weakened, by the availability of better measures of land size collected using GPS devices. Lamb (2003) concludes that by controlling for measurement error in land size, the statistical case for the IR disappears. This paper has shown that introducing rigorous controls for land *quantity* does not affect the evidence concerning the IR, which is in fact strengthened when the better land data are used.

We also explored how farmers' self-reporting of plot size varies systematically with the size of their holdings and other household and land characteristics. We conclude that in Uganda small farmers tend to over-report plot size relative to medium-sized land-holders, while the largest farm groups under-report plot size on average. This is consistent with earlier evidence from Mali reported by De Groote and Traoré (2005).

Self-reported measures of land size are notoriously imprecise. In large household surveys in developing countries, however, they have for a long time been the only option available to practically collect data on the physical dimension of the plots owned or cultivated by the household. More recently the availability of affordable and more reliable GPS devices has made GPS measurement a practical alternative that is increasingly being applied in surveys worldwide.

Being able to measure land with any degree of accuracy is clearly of outmost importance in economies that are largely agricultural based and for communities that derive a large share of their livelihood from agriculture and for whom land constitutes the main, when not the only, capital asset. In particular, an accurate measure of land size is necessary if one is to measure agricultural productivity with any degree of confidence.

This paper has shown that GPS technologies clearly hold promise for improving the accuracy in the collection of land size measures in the context of large household surveys. On the other hand, while we are not able to account in full for the determinants of the deviation between GPS and self-reported measures, we do find that self-reported land measures are a reasonable alternative in a well conducted survey, particularly for medium-sized farmers. The overall distribution as well as their mean and standard deviation, are fairly close to each other, and the measurement error did not change the substance of our productivity analysis. The respondents' rounding of responses can however create fairly serious differences in measurements, particularly when plots are small, as is the case here (but also in most of the developing regions).

The continuing fall in the price and increasing precisions and reliability of GPS devices make them an increasingly attractive element of every survey team toolbox. For mainly logistic reasons, however, GPS readings are hardly ever taken on all plots, and this raises concerns on the potential selectivity bias resulting from measuring only a sub-set of plots. While allocating adequate resources could go a long way in ensuring that this bias is reduced, farmer's self-reported measures must also be collected possibly together with information on the possible sources of the bias, to complement the GPS estimates and correct for potential biases. How to do that in practice is a subject that warrants further investigation.

Appendix A

Appendix Table 1
Descriptive statistics: net revenues regressions (n = 2825).
Source: Authors' calculations based on UNHS 2005.

	Mean	Standard deviation
Net revenues from crop production (US$/acre SR)	148.97	793.66
Net revenues from crop production (US$/acre GPS)	168.53	1073.69
Farm size (acres SR)	4.18	17.39
Farm size (acres GPS)	4.4	17.18
Dummy: rounding	0.87	0.34
Age of household head	45.41	16.87
Education of household head	0.36	1.58
Dummy: female head	0.28	0.45
Value of purchase inputs (US$/acre SR)	9.29	20.71
Value of purchase inputs (US$/acre GPS)	10.35	42.37
Value of hired labor (US$/acre SR)	2.59	8.66
Value of hired labor (US$/acre GPS)	2.70	9.17
Family labor (person days/acre SR)	77.09	90.02
Family labor (person days/acre GPS)	89.07	149.85
Share of land GPS with poor soil quality	12.17	30.48
Share of land SR with poor soil quality	12.06	30.26
Share of land GPS flat	45.57	46.93
Share of land SR flat	45.62	46.73
Share of land GPS swamp/wetland	1.54	9.62
Share of land SR swamp/wetland	1.50	9.28

Appendix Table 2
Descriptive statistics: maize yield regressions (n = 2609).
Source: Authors' calculations based on UNHS 2005.

	Mean	Standard deviation
Maize yields SR (kg/acre)	219.97	1774.69
Maize yields GPS (kg/acre)	201.44	678.75
Plot area (acres SR)	1.17	1.35
Plot area (acres GPS)	1.10	1.27
Dummy: rounding	0.75	0.41
Age of household head	44.68	15.71
Education of household head	7.35	5.05
Dummy: female head	0.25	0.44
Value of purchase inputs (US$/acre SR)	32.90	817.20
Value of purchase inputs (US$/acre GPS)	33.81	641.43
Value of hired labor (US$/acre SR)	3.52	13.29
Value of hired labor (US$/acre GPS)	3.97	17.38
Family labor (person days/acre SR)	57.32	76.81
Family labor (person days/acre GPS)	78.75	274.16
Share of land GPS with poor soil quality	11.20	30.76
Share of land SR with poor soil quality	11.22	30.73
Share of land GPS flat	50.11	49.00
Share of land SR flat	50.16	48.91
Share of land GPS swamp/wetland	1.36	1.07
Share of land SR swamp/wetland	1.37	10.72
Share of plots intercropped	80.82	40.01

References

Assuncao, J., Ghatak, M., 2003. On the inverse relationship between farm size and productivity. Economics Letters 80 (2), 189–194 (August 2003).

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

Barrett, C., Bellemare, M.F., Hou, J.Y., 2010. Reconsidering conventional explanations of the inverse productivity–size relationship. World Development 38 (1), 88–97 (2010).

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

Benjamin, D., Brandt, L., 2002. Property rights, labor markets, and efficiency in a transition economy: the case of rural China. Canadian Journal of Economics 35 (4), 689–716.

Berry, R.A., Cline, W.R., 1979. Agrarian Structure and Productivity in Developing Countries. Johns Hopkins University Press, Baltimore.

Bhalla, S.S., Roy, P., 1988. Mis-specification in farm productivity analysis: the role of land quality. Oxford Economic Papers 40, 55–73.

Binswanger, H.P., Deininger, K., Feder, G., 1995. Power distortions revolt and reform in agricultural land relations. In: Behrman, J., Srinivasan, T.N. (Eds.), Handbook of Development Economics, vol. III. Elsevier Science B.V., Amsterdam, The Netherlands.

Bogaert, P., Delincé, J., Kay, S., 2005. Assessing the error of polygonal area measurements: a general formulation with applications to agriculture. Measurement Science and Technology 16, 1170–1178.

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

Collier, P., Dercon, S., 2009. African agriculture in 50 years: smallholders in a rapidly changing world? Paper presented at the Expert Meeting on How to Feed the World in 2050 Food and Agriculture Organization of the United Nations Economic and Social Development Department, Rome, June 24–26.

De Groote, H., Traoré, O., 2005. The cost of accuracy in crop area estimation. Agricultural Systems 84, 21–38.

Deininger, K., Carletto, G., Savastano, S., Muwonge, J., 2012. Can diaries help improving crop production statistics? Evidence from Uganda. Journal of Development Economics 98 (1), 1–148 (May 2012).

Eastwood, R., Lipton, M., Newell, A., 2010. Farm size. In: Evenson, Robert, Pingali, Prabhu (Eds.), Handbook of Agricultural Economics, vol. 4. Elsevier.

Escobal, J., Laszlo, S., 2008. Measurement error in access to markets. Oxford Bulletin of Economics and Statistics 70 (2), 209–243 (April).

Eswaran, M., Kotwal, A., 1985. A theory of contractual structure in agriculture. The American Economic Review 75, 352–367.

Eswaran, M., Kotwal, A., 1986. Access to capital and agrarian production organization. The Economic Journal 96, 482–498.

Feder, G., 1985. The relation between farm size and farm productivity: the role of family labor, supervision and credit constraints. Journal of Development Economics 18 (2–3), 297–313 (August).

Gibson, J., McKenzie, D., 2007. Using the global positioning system in household surveys for better economics and better policy. Policy Research Working Paper Series, 4195. The World Bank.

Goldstein, M., Udry C., 1999. Agricultural innovation and risk management in Ghana. Unpublished, Final report to IFPRI.

Hill, P., 1972. Rural Hausa: A Village and a Setting. Cambridge University Press, Cambridge.

Keita, N., Carfagna, E., 2009. Use of modern geo-positioning devices in agricultural censuses and surveys. Bulletin of the International Statistical Institute, the 57th Session, 2009: Proceedings, Special Topics Contributed Paper Meetings (STCPM22), Durban, August 16–22.

Kelly, V., Diagana, B., Reardon, T., Gaye, M., Crawford, E., 1995. Cash Crop and Foodgrain Productivity in Senegal: Historical View, New Survey Evidence, and Policy Implications. MSU Staff Paper No. 95-05. Michigan State University, East Lansing.

Kevane, M., 1996. Agrarian structure and agricultural practice. Typology and application to western Sudan. American Journal of Agricultural Economics 78 (1), 236–245.

Kutcher, G.P., Scandizzo, P.L., 1981. The Agricultural Economy of Northeast Brazil. The Johns Hopkins University Press.

Lamb, R.L., 2003. Inverse productivity: land quality, labor markets, and measurement error. Journal of Development Economics 71 (1), 71–95.

Lau, L.J., Yotopoulos, P.A., 1971. A test for relative efficiency and application to Indian agriculture. The American Economic Review 61, 92–109.

Roberts, John M., Brewer, Devon D., 2001. Measures and tests of heaping in discrete quantitative distributions. Journal of Applied Statistics 28 (7), 887–896.

Sen, A.K., 1962. An aspect of Indian agriculture. Economic Weekly 14, 243–266.

Sen, A.K., 1966. Peasants and dualism with or without surplus labor. Journal of Political Economy 74 (5), 425–450.

UBOS, 2009. Uganda National Household Survey 2005/2006, Study Documentation.

Udry, C., 1996. Gender, Agricultural Production, and the Theory of the Household. Journal of Political Economy, vol. 104(5). University of Chicago Press, pp. 1010–1046 (October).

Walker, T.S., Ryan, J.G., 1990. Village and Household Economies in India's Semi-arid Tropics. Johns Hopkins Univ. Press, Baltimore.

Zaibet, L.T., Dunn, E.G., 1998. Land tenure, farm size, and rural market participation in developing countries: the case of the Tunisian olive sector. Economic Development and Cultural Change 46.