Measurement Error and Farm Size: Do Nationally Representative Surveys Provide Reliable Estimates?

By

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Abstract

We assess the reliability of measured farm sizes (ownership holdings) in the Living Standard Measurement Study – Integrated Surveys on Agriculture (LSMS-ISA) in Ethiopia and Malawi based on three survey rounds (2012, 2014, 2016) in Ethiopia and four rounds (2010, 2013, 2016, 2019) in Malawi. By using the balanced panel of households that participated in all the rounds, we utilized the within-household variation in reported and measured ownership holdings that were mostly measured with GPSs and/or with rope and compass. While this gives reliable measures of reported holdings, we detect substantial under-reporting of parcels over time within households that largely have been overlooked in previous studies. The problem may cause until now unrecognized biases in agricultural statistics. We find that the estimated farm sizes within survey rounds are substantially downward biased due to systematic and stochastic under-reporting of parcels. Such biases are substantial in the data from both countries, in all survey rounds, and in all regions of each country. We estimate models with alternative estimators for the ownership holding share of maximum within-household holding to examine factors associated with variation in reported farm sizes. Based on the analyses, we propose that the maximum within-household reported farm sizes over several survey rounds provide a more reliable proxy for the real farm size, as these maximum sizes are less likely to be biased due to parcel attrition. The ignorance of this non-classical measurement error is associated with a downward bias in *the range of 23-41% in average and median farm sizes and an upward bias in the gini-coefficients for farm size distributions. We propose ideas for follow-up research and improvements in collecting these data types and draw relevant policy implications.*

Key words: Farm size measurement, measurement error, plot attrition, LSMS-ISA, Ethiopia, Malawi.

JEL codes: C81, C83, Q12, Q15.

1. Introduction

Good agricultural statistics are essential for planning and dealing with many global challenges associated with climate change and global, national, and local food security (Carletto 2021). Carletto et al. (2021) argue for the importance of renewed attention to data quality issues for advancing the research frontier in agricultural economics and designing better agricultural policy. Developing countries that rely on agriculture as a primary source of livelihood for a large share of their population are among the most vulnerable to climate change (Lowder et al. 2016). Recent conflicts have further contributed to instability in global prices for food and energy and have enhanced global food insecurity. Rural transformation, rural-urban, and international migration are putting more pressure on areas on the receiving end. While economic development creates new opportunities in rural transformation processes, climate shocks and social unrest are among the push factors associated with more desperate migration. Agricultural development and intensification are essential to reduce the extent of desperate migration and enhance food security. Good agricultural policies are crucial, and good agricultural statistics are relied on to tackle these challenges and promote sustainable agricultural intensification (World Bank 2021).

The 2008 World Development Report on Agriculture for Development became a vital driver in generating better agricultural statistics as a basis for a new push for agricultural development. One outcome was nationally representative household farm surveys such as the Living Standard Measurement Study - Integrated Surveys on Agriculture (LSMS-ISA). They provided essential data for analyzing important policy issues in developing countries. Modern technologies such as handheld GPSs and preprogrammed tablets linked to cloud servers have reduced costs and improved the quality of such survey data. Accompanied by improved methods for area measurement, the role of potential measurement error and its implications for various types of estimation purposes and data reliability has become a new area of research (Carletto et al. 2013; 2017; Abay et al. 2019; 2021; 2023a: 2023b; Burke et al. 2019; Gourlay et al. 2019; Kilic et al. 2017a; b; Wossen et al. 2022). Handheld GPSs provide much more reliable estimates of farm parcel sizes than farmers' estimates of parcel and farm sizes, which were often used in the past (Carletto et al. 2013; 2017). Self-reported area data include systematic biases that depend on the parcel size, rounding errors, and influences from local measurement units (Abay et al. 2019; Carletto et al. 2017; Holden and Fisher 2013). Such systematic errors could affect yield estimates and explain the frequently found phenomenon of an inverse relationship between parcel yield and parcel size, as the parcel size is used to construct the yield variable. Such measurement errors could also systematically affect measures aggregated to the farm level, where a farm may contain a varying number of parcels (Holden and Fisher 2013). Kilic et al. (2017a) used multiple imputations (MI) methods to predict more accurate area measures of unmeasured parcels. In a follow-up study, Kilic et al. (2017b) did a more comprehensive test of the MI approach with the 2013/2014 Ethiopia Socioeconomic Survey Wave II data from Ethiopia and the Integrated Household Survey 2010/2011 (IHS3) for Malawi where they had more complete parcel-level data measured with GPS and farmers' own estimated areas[i]. They found that the MI approach, to a large extent, could correct biases associated with incomplete coverage with GPS-measurement of parcels when farmers' estimated parcel sizes were available. Our study focuses on the same two countries, Ethiopia and Malawi, where the GPS-measured parcel coverage has been high. However, our study focuses on a different missingness problem that we elaborate on below, which is revealed only when multiple survey rounds for the same households (balanced panel) are combined.

Areas measured with handheld GPS are also measured with error; the relative error size is inversely related to parcel size. However, unlike self-reported area sizes, GPS-based parcel size estimates are not found to be biased even for tiny parcels (Carletto et al. 2017). Farm sizes aggregated from several parcels estimated by GPS are therefore also not likely to have a systematic bias given that GPS estimated all the parcels before aggregation (assuming the error is uncorrelated across parcels).

In this study, we focus on farm size measurement and its reliability in the LSMS-ISA data from two countries, Ethiopia and Malawi. We aim to assess the farm sizes and potential measurement errors in these data over time, where GPSs are the primary device in measuring farm parcels. We ask the question: Can these extensive surveys provide reliable estimates of farm size changes over time? If yes, the data may also be used to provide reasonably reliable estimates of farm size distributions such as Gini-coefficients and cumulative farm size graphs and how these measures change over time within the smallholder sector in these countries[ii]. To assess the reliability of such estimates, we utilize only households that are repeatedly surveyed in each country for three panel rounds in Ethiopia and four panel rounds in Malawi. We propose that there is a high probability of under-reporting of land parcels due to the drudgery of reporting data from and measuring plots. In this study, we assess the extent of such potential plot attrition and separate it from real within-household farm size change over time that can occur due to inheritance and bequeath, land purchases and sales, administrative redistributions, and land grabs. We use censored Tobit models to estimate the reported farm sizes as shares of maximum within-household farm sizes across survey rounds. We also test alternative estimators. These models provide insights about possible real farm size changes but, more importantly, strong indications of widespread stochastic under-reporting of plots. To our knowledge this is the first study to provide such comprehensive evidence. This is the main contribution of our study. We demonstrate that such under-reporting leads to substantial under-estimation of farm sizes and over-estimation of farm size distribution Gini-coefficients, if ignored. These biases in estimated farm sizes due to the wicked plot attrition problem cannot easily be overcome with econometric estimators that attempt to control for real farm size changes and plot attrition with plot count indicators, although the models help to scrutinize the evidence.

We conclude that the maximum reported within-household farm size over repeated survey rounds represents the most reliable measure of household farm size and is the least likely to suffer from downward bias due to plot attrition. We compare the farm size distributions based on these reported maximum within-household farm sizes with the reported farm sizes in each survey round in Ethiopia and Malawi. We thereby get ballpark indications of the degree of bias associated with the under-reporting of plots. This is the second major contribution of this paper. We demonstrate substantial downward biases in the range of 23-31% for mean farm sizes and in the range of 26-35% for median farm sizes in Ethiopia, and in the range of 30-39% in mean and of 30-41% in median farm sizes in Malawi. Our study reveals a type of measurement error that largely has gone under the radar and has received too little focus until now. Any studies that have attempted to study land productivity and associated it with farm size based on these data should be revisited with these new insights in mind. It is highly likely that this plot attrition is also associated with under-reporting of plot output reporting and possibly input use if such reporting is done at the plot level and not at the parcel or household level.

In part 2, we outline a theoretical framework for the study, followed by a description of the data management strategy in part 3. In part 4, we present the main findings for Ethiopia and Malawi. In part 5, we discuss the results before we conclude.

2. Theoretical framework: Explaining observed farm size variation due to real changes and measurement error

2.1. Theories to explain real farm size variation

We outline a set of theories that may explain real changes in farm sizes over time within households. The standard theories that attempt to explain the within-household changes in farm sizes over time are due to the following;

a) *Inheritance and bequeath of land within families.* Young household heads are more likely to inherit land, and old household heads with adult children are likelier to bequeath their land to the next generation. Changes in heads of households may also be associated with such changes in ownership holding size, e.g., related to divorce or marriage and takeover of farms.
b) *Purchases or sales of land.* In countries with active land sales markets, farms may change owners, but there could also be changes in farm sizes associated with sales or purchases of parcels of land.

Such markets tend to be thin in developing countries and are not likely to influence farm size changes from a large share of a random sample of household farms.

c) *Administrative expropriations and land redistributions.* Depending on national land policies, such administrative redistributions are more common in some countries than others. Such redistributions may also be more common during rapid urban expansion and transformation in peri-urban areas.

d) *Private land takings and losses.* The extent to which such processes are common depends on land abundance, national policies, and enforcement capacity/tenure security. Such events as sudden shocks may affect rural households.

2.2. Theories to explain errors in farm size measurement

We need theories to explain potential non-classical measurement errors that can lead to systematic biases in reported and estimated farm sizes. These theories should help explain the under-reporting of ownership holdings and possible mistakes in reported holdings. Recent literature distinguished measurement errors due to mis-reporting and mis-perceptions (Abay et al. (2021; 2023a: 2023b: Wossen et al. 2022). Our basic assumption is that the introduction of GPS or other high quality measurement of farm parcels/plots eliminates most errors associated with misperceptions that can lead to errors in measured plot, parcel, and farm sizes. However, this important quality improvement does not prevent errors due to misreporting of plots/parcels.

Conditional on finding such an unexplained gap that the standard theories above cannot explain, we suggest a set of propositions based on theories in new institutional economics, such as imperfect information and transaction cost theories. Information asymmetries and the high costs of obtaining information may contribute to explaining that a substantial nonclassical measurement error due to misreporting exists in household ownership holdings. These propositions are as follows:

Prop.1: *Farmers have incentives to hide some of their parcels to reduce the burden of answering all questions in the survey*.

Prop.2. *Enumerators also have incentives to reduce the number of parcels recorded for each household to reduce their work burden*. Prop. 1 and 2 may also imply that farmers and enumerators collude to reduce their joint burden associated with the data collection. The extent of enumerators' supervision, transparency, and motivation may vary over survey rounds and possibly across data collection teams, which may cause spatial and intertemporal variations in data quality.

Prop.3. *Surveys tend to focus only on the main (large)nearby parcels of a farm and leave out small parcels of less significance and parcels that are located far away*. Survey budgets and standards may be set that cause less than complete parcel measurement.

Prop.4. *Rented-out parcels are more likely to be left out from the survey as such parcels are not managed by the household included in the survey*. The owner may be unable to provide much production data from rented-out parcels.

Prop.5. *Improvements in the data collection technologies and methods have reduced information asymmetries and transaction costs over time.* The new CAPI tools have also made it easier to monitor enumerators, and the information and transaction costs associated with data collection have been substantially reduced. These technological improvements may imply that parcel attrition has been reduced over time. Over time, such a reduction in parcel attrition may have led to an artificial increase in farm sizes in balanced household farm panels.

We are unable to test each of these theoretical propositions explicitly. In this study, we only aim to assess the size of the measurement error problem by estimating farm size variation and controlling for real farm size changes to the extent that suitable control variables exist in the publicly available data. A challenge we face is that we do not know the true farm size for each household in the LSMS-ISA data. It is, therefore, difficult to identify a proper benchmark to get a reliable estimate of the measurement error. Consequently, we attempt a second-best approach to assessing the significance of such errors. We use the largest ownership holding size identified over the three or four survey rounds as the benchmark. We do this as we believe that the main problem in the data may be omitted parcels/plots, and the largest within-household estimate of the farm size (ownership holding) is, therefore, least likely to suffer from this omitted parcel problem. This theoretical framework is the basis for our data management and estimation strategy, which we outline in the next section.

3. Data management and estimation strategy

We create the three (Ethiopia) and four (Malawi) rounds of balanced household (households for which there are data for all these rounds) LSMS data with all land size relevant variables such as the size of all parcels (GPS and self-reported parcels), number of parcels, number of owned parcels, number of operated parcels, number of rented out parcels, number of rented in parcels, number of borrowed in/out parcels, inherited and bequeathed parcels between survey rounds, expropriated parcels, and parcels received through redistribution. One challenge is to match parcels from survey round to survey round within households. Parcels should be stable over time and easier to match than plots, which could be sub-units of parcels that may change with crop planting patterns.

Between survey rounds, we make the following within-household identity for ownership holding based on GPS-measured parcels (as far as possible) based on data from survey rounds *t*1 and *t*2:

(1) $A_{t2}^{o} = A_{t1}^{o} + A_{t1-t2}^{p} + A_{t1-t2}^{i} - A_{t1-t2}^{s} - A_{t1-t2}^{b} - A_{t1-t2}^{e} + \Delta A_{t1-t2}^{M}$

where superscripts *o* represents ownership holding measured at times *t*1 and *t*2, *p* represents purchased holding, *i* inherited holding, *s* sold holding, *b* bequeathed holding, and *e* expropriated holding, where these changes had happened between period *t*1 and *t*2 when ownership holdings were measured. The identified discrepancy ΔA_{t1-t2}^{M} represents the unexplained changes due to measurement error/data gap. A similar identity can be set up for *t*2 versus *t*3 to identify a similar household-level discrepancy in farm size determination.

It is also possible that the operational holding (area being farmed by the household in a specific year) deviates from the ownership holding because the household rents in or rents out land and because all the owned land may not be farmed but is left fallow, and some land may be lent out or lent in.

Unfortunately, the LSMS survey data do not provide complete information regarding the components in the identity in equation (1). In the survey, there is a question about the origin of each parcel of land but not when it has been received such that it is possible to verify with certainty whether it has changed since the previous survey rounds, which typically took place two to three years earlier (in rounds two, three and four of the three- and four-rounds balanced household panels).

While GPS-records exist for the parcels, these are not publicly available because of the need to protect the anonymity of the households. We recommend that those with access to these GPS records do a parcel-level matching of the data for the balanced panel to verify parcel attrition over time more accurately based on exact location records. However, such parcel matching is beyond what we can do based on the publicly available data. We hope our study draws more attention to the importance of such across-round data verification to reduce parcel attrition and improve data quality.

Based on the data, we have attempted to approximate the ownership holding of households by survey round. Based on the measured areas, we have subtracted rented and borrowed land from the declared parcels to approximate the ownership holding sizes. We acknowledge that this may represent an underestimation of ownership holding as it is possible that some owned parcels have not been reported, e.g., because they are rented out or, for other reasons, have not been declared. Such attrition is more likely to be detected with repeated survey rounds of the same households. We have constructed two new within-household variables for ownership holdings to assess the extent of such possible attrition. The first is the time-invariant maximum within-household ownership holding. The second is the time-variant ownership holding as a share of the maximum within-household ownership holding.

Our study is exploratory in the sense that we want to get a measure of the relative size and variation in this measurement gap. The reference point is the maximum within-household measured ownership holding observed over the three or four rounds.

We then measure each household's ownership holding in each survey round as a share of its' maximum measured ownership holdings over the three (Ethiopia) and four (Malawi) survey rounds. We then explore the variation in this ownership share of the maximum size across households and survey rounds. We estimate how much of the share of the maximum holding size is influenced by the real changes in farm sizes by including control variables associated with such real changes in the form of inheritances, bequeaths, sales and purchases, and administrative redistributions and land takings. We attribute the residual deviation from maximum farm size to the imperfection information theories that explain parcel attrition. We use several available control variables for this. First, we include variables associated with land being rented out as such land is more likely to have been unreported. Second, we use parcel counts in each survey round and within-household deviation in parcel counts over survey rounds. As the division into sub-parcels may change from survey round to survey round and depend on the cropping pattern, using such sub-parcel counts is not a waterproof measure of parcel attrition. Still, it can nevertheless be a good indicator. We expect that a higher parcel count, on average, is associated with a larger and more complete measure of the farm size.

We take the maximum ownership holding over time as the reference point as this area is the least likely to suffer from attrition, as proposed by our theoretical framework.

We tailor the approach to the specific contextual and policy situations and survey instruments used in the two countries.

Hypothesis: *Parcel (plot) attrition varies stochastically across survey rounds and causes substantial within-household measurement error and downward bias in measured within-round average farm sizes.* We construct the dependent variable as a share of the within-household maximum farm size across survey rounds as the benchmark.

We need complementary strategies to investigate the reasons for the within-household farm size variation over time. In addition to the real area changes that we introduce controls for, we add the following variables as tests and controls for within-household stochastic attrition:

a. Total number of (sub-)parcels reported in the survey round
b. Deviation in the maximum number of (sub-)parcels reported in the survey round compared to the round with the highest number of (sub-)parcels reported.
c. Number of unmeasured (sub-)parcels in the survey round.

Given that this attrition is stochastic, we assume that a larger parcel count positively correlates with the measured farm size and the ownership share of maximum holding in a given survey round. Furthermore, we think a larger deviation from the maximum within-household number of (sub-)parcels is associated with a smaller farm size estimate relative to the maximum within-household farm size (lower ownership share).

The larger number of unmeasured (sub-)parcels, the smaller the measured farm size is assumed to be. The number of unmeasured but reported parcels was low in the Ethiopia and Malawi balanced panel data. We did not use MI to fill this gap but control for it in our estimation of relative farm sizes in the form of ownership holding shares of max within-household ownership holdings.

We remove possible outlier errors in the estimated data by winsorizing the measured farm sizes at a 1% level at each distribution end. We also assessed the effect of varying degrees of winsorizing the data. We found that doing this at a 1% level was sufficient to remove random noise that could affect the tails in the distribution and make maximum and minimum area measurements unreliable.

There is also a small share of the households that have dropped out after the initial survey round. To correct for possible attrition bias due to dropout of households, we ran models for the data from the first survey round with the attrition dummy as a dependent variable and with household/farm characteristics as expanatory variables. We constructed attrition weights based on the ratio between the predicted attrition rates with all variables included and a model where only insignificant variables were included. We use these inverse probability weights in weighted regressions to test for and correct this type possible attrition bias in the data.

We estimate the ownership shares using censored Tobit models censored from above at one for each survey round and jointly as a panel for all rounds within each country. These models allow us to assess and separate the relative farm size changes associated with the variables that control for real changes in ownership holding shares over time from changes related to incomplete reporting of areas.

Censored Tobit models are sensitive to non-normality and heteroskedasticity. As a robustness check, we therefore also estimated alternative models in form of fractional probit models, symmetrically censored least squares estimator (SCLS), and panel stochastic frontier models for the ownership holding shares of max holding share as these are all in the zero-one range. We compare the parameters across models and also the cumulative predicted outcome distributions and error distributions across models.

Furthermore, we compare the predicted and actual distributions of ownership shares across alternative models. We compute the farm size distributions in each survey round against the across-years maximum household farm size distribution as indicators of the potential bias in ownership holding sizes based on data from each round, to assess the extent of bias in the farm size in each survey round caused by within-household stochastic parcel/plot attrition bias. We also assess the spatial and inter-temporal variation in ownership holding shares to evaluate whether that can provide insights about variation in the survey quality in terms of reducing the extent of this type of measurement error. Finally, we also generate Gini-coefficients for the measured ownership holdings and the maximum holdings to assess whether parcel attrition is associated with bias in such distributional skewness estimates.

Parcel-level GPS coordinates are not publicly available, which makes it impossible to generate balanced household-parcel-level panel data to scrutinize the (sub-)parcel attrition in more detail. GPS-based parcel matching over time could be an interesting exercise to investigate further the parcel attrition in the data for those with such data access.

4. Results

Below, we outline the detailed data analysis for each country by first looking at some basic descriptive results, then by running regression models for ownership holding shares with alternative estimators to investigate alternative explanations for the within-household farm size variation across survey rounds, and to assess the severity of stochastic plot attrition, its implications for estimated farm sizes, and cumulative farm size distributions. We demonstrate that stochastic plot attrition results in large nonclassical measurement errors in farm sizes that are severely downward biased in each survey round.

4.1. Ethiopia

We have used the 2012, 2014, and 2016 survey rounds for Ethiopia. Table 1 presents the balanced household sample by region in Ethiopia.

The size of the deviation from the maximum holding (measured as a share of the maximum holding) is an indicator of the extent of within-household reported change in ownership holding over time. It may be due to inheritance, bequeath, administrative allocation, purchase and sale (rare in Ethiopia), or plot attrition. Over the short period from 2012 to 2016, the extent of inheritances, bequeaths, administrative allocations, and purchases are expected to be pretty small. A large deviation may indicate substantial attrition (parcels omitted in surveys). Based on our theoretical framework, we have included land renting for several reasons: a) households are more likely to report parcels they cultivate themselves, b) the land rental market (including sharecropping) is very active in Ethiopia, c) households in Ethiopia may not perceive sharecropping as a form of renting, d) rented (sharecropped) out plots are less likely to be reported. If we, in the sample, find a deviation in the aggregate area rented out as being substantially smaller than the aggregate area rented in. this may indicate substantial under-reporting of rented-out areas.

Table 1. The balanced panel for Ethiopia, distribution of households by region and year

	Year of survey			
Region	2012	2014	2016	Total
Tigray	252	252	252	756
Afar	35	35	35	105
Amhara	498	498	498	1,494
Oromiya	471	471	471	1,413
Somalie	127	127	127	381
Benishangul Gumuz	72	72	72	216
snnp	665	665	665	1,995
Gambella	50	50	50	150
Harari	73	73	73	219
Dire Dawa	96	96	96	288
Total	2,339	2,339	2,339	7,017

Detailed descriptive data at household and parcel levels are provided in the Appendix 3, Tables A3.1 (aggregated from the parcel level to the household level by survey rounds) and A3.2 (aggregated from sub-parcel (plot) to parcel level by survey round). Table A3.1 gives a basis for a first examination of the estimated ownership and operational holdings for the balanced household panel over the three survey rounds. The table shows that the number of reported parcels per household has increased from 2012 to 2014, and this may indicate that the survey coverage in terms of number of parcels reported has improved. Inheritance and population growth should have the opposite effect, with the number of farms growing and average farm size shrinking over time, as shown based on complete land registry data, e.g., in the Tigray region (Holden and Tilahun 2020)[iii]. We see a similar tendency in the data from 2014 to

2016. The average ownership holding measured with GPS or rope and compass increased from 1.12 to 1.34 ha from 2012 to 2014 and then declined to 1.21 ha in 2016. These changes may indicate that the data from 2014 are the most complete. The average operational holding in 2014 was 1.52 ha, substantially higher than the average ownership holding this year. Suppose we assume that ownership holding in this year suffers from attrition of rented/sharecropped out plots. In that case, the average operational holding may represent a more reliable estimate of this year's average ownership holding. The average operational holding increased to 1.59 ha in 2016 after the explicit recording of sharecropped and purchased parcels was added to the survey instrument. These changes may indicate that there was also a problem with the attrition of parcels in 2014. We can further explore this by inspecting the average maximum within-household ownership holding over the survey years.

There may be a downward bias due to attrition even in the year with the largest recorded ownership holding because of unrecorded rented/sharecropped-out parcels or distant and/or small parcels that were inconvenient to include in the survey. There could also be measurement errors in GPS or rope and compass measurements, causing random noise in the data that could lead to an upward bias in the maximum ownership holding. We tried to control for this latter possible effect by winsorizing 1-5% of the outliers on each side of the distribution.[iv] With removal of 1% of the outliers of each side of the maximum ownership holding, we obtained a mean maximum ownership holding of 1.57 ha which is close to the average operational holding of 1.59 in 2016. We suggest that this average maximum within-household ownership holding is a good proxy for the ownership holdings of sample households.

Table 2 presents basic statistics for reported and measured ownership holding sizes by survey round where these estimates are un-winsorized or winsorized at the 1% level. These estimates are then compared with winsorized maximum within-household ownership holding sizes over the three survey rounds, where we alternatively have winsorized the maximum ownership holdings at 1, 2, and 5% levels. We see an astonishing gap between the estimates for each survey round and the maximum holding sizes over all three survey rounds. Winsorizing the annual data at 1% creates a downward trend over the years in mean and median ownership holding sizes, as would be expected due to population growth and bequeaths of land from parents to children. We, therefore, think the data quality may have been improved with this adjustment of outlier observations.

Table 2. Estimated average ownership holdings in ha based on 3 rounds of household-parcel panel data from Ethiopia

	Unwinsorized Ownership holdings, ha			1% winsorized Ownership holdings, ha			Max ownership holdings 2012-2014 in ha, winsorized at:		
	2012	2014	2016	2012	2014	2016	1%	2%	5%
Mean	1.140	1.338	1.208	1.066	1.162	1.132	1.572	1.510	1.390
Median	0.702	0.791	0.753	0.702	0.791	0.753	1.117	1.117	1.117
P25	0.278	0.331	0.307	0.278	0.331	0.307	0.560	0.560	0.560
P75	1.408	1.523	1.434	1.408	1.523	1.434	2.009	2.009	2.009
P90	2.397	2.550	2.560	2.397	2.550	2.560	3.344	3.344	3.344
sdev	2.023	3.950	2.128	1.193	1.267	1.271	1.525	1.322	1.033
n	2345	2345	2345	2345	2345	2345	2345	2345	2345
Gini	0.539	0.57	0.545	0.507	0.506	0.515	0.473	0.453	0.413

To better understand the potential upper bound of the attrition frequency across the three survey rounds within households, we construct a new variable, which is the household and year-specific ownership holding divided by the maximum within-household ownership holding over the three survey rounds. We graph the ownership share distributions of maximum within-household ownership holding distribution for each survey round, and we know that one of the three rounds is represented with the maximum ownership holding in the three panel-years. To better understand whether random measurement errors cause outliers, especially in maximum ownership holding, we compare the completed data with alternative winsorized data at 1, 2, and 5% on each side of the distributions. We present cumulative density distributions for each survey round with the winsorized data as overlays in each panel year in Figure 1.

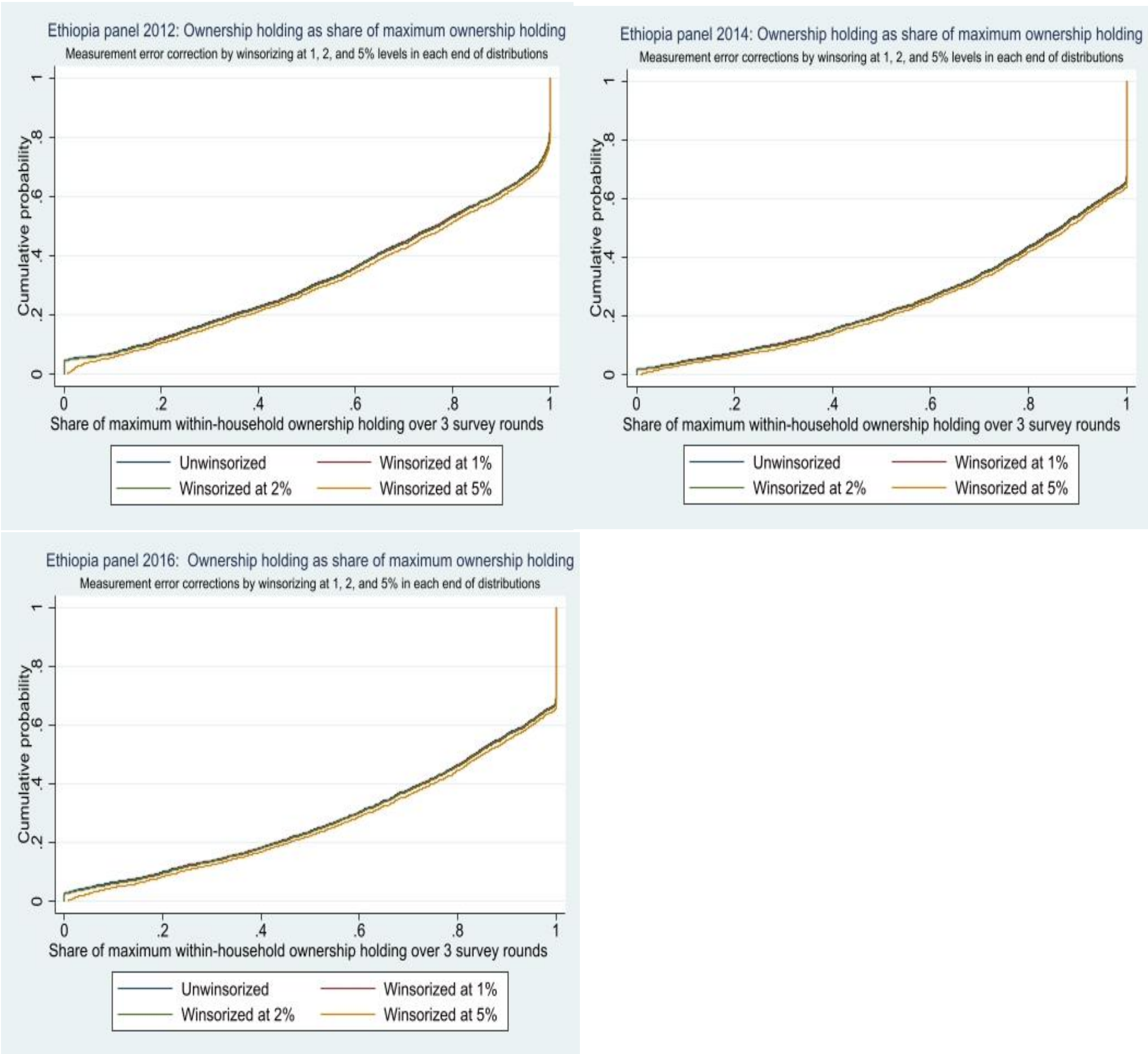
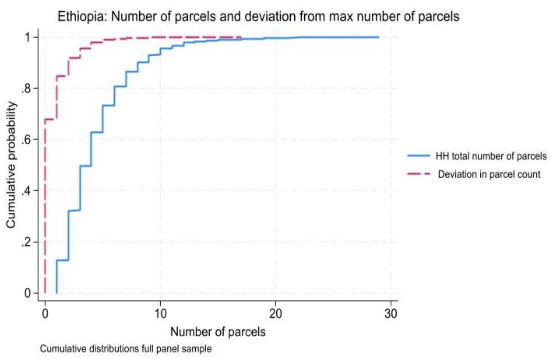


Figure 1. Within-household ownership holding shares of maximum household ownership holdings over three survey rounds in Ethiopia with alternative levels of winsorizing.

Figure 1 shows that a larger share of the households are at the maximum farm size in 2014 and 2016 than in 2012. This may indicate a higher level of parcel attrition in 2012, which is also consistent with the fact that the total number of reported parcels/plots was lower in 2012. Another important insight from Figure 1 is that the measurement error corrections by winsorizing data at 1, 2, and 5% levels had a minimal effect on the cumulative ownership share distributions. This minimal effect on the distributions indicates that only a tiny part of the variation in within-household ownership shares is due to random measurement errors. However, the graphs do not tell how much of the deviations from one in ownership shares are due to changes over time in inheritances, bequeaths, purchases, sales, or administrative redistributions, and within-survey round attrition of parcels. We use econometric methods to explore these deviations. While we have data on the origin of the parcels, we do not know when the parcels were received or whether parcel transfers occurred within the panel period (2012-2016). Figure 1 indicates surprisingly large changes in ownership holding sizes compared to the maximum holding size over this fairly limited period from 2012 to 2016. For example, we see in 2012 that 20% of the sample households had an ownership holding that was less than 40% of the maximum ownership holding size within the 2012-2016 period. For 2014 and 2016, about 20% of the sample had ownership holding sizes below 50% of the maximum holding size over the 2012-2016 period. Knowing that land sales are illegal in Ethiopia and that administrative redistributions have become much less common than before, makes it hard to understand that inheritances and bequeaths have resulted in such large changes in farm sizes over such a limited period.

To inspect the importance of parcel attrition, we include the number of (sub-)parcels (plots) measured in each survey round and the within-household deviation in number of parcels from the maximum number across survey rounds, see Figure 2a and 2b.



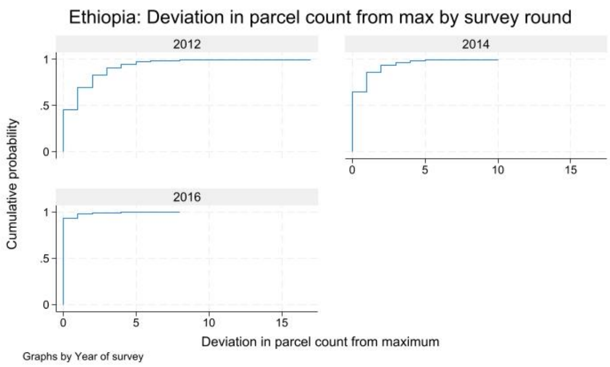


Figure 2a and Figure 2b. Ethiopia: Parcel count and deviation from max parcel count (total and by survey round) for households

Figure 2a shows that more than 30% of the households have reported a varying number of sub-parcels (plots) across survey rounds. This represents no absolute evidence of parcel attrition, as parcels may have been divided into variable plots depending on changing cropping patterns over the years. However, Figure 2b shows that the number of reported parcels was systematically lower in 2012 than in the two following rounds. This may be associated with the smaller average farm size in 2012 in the un-winsorized data in Table 2.

To test our hypotheses about the within-household observed variation in ownership holding shares over time, we have estimated censored Tobit models separately for each survey round and jointly with a panel Tobit model. The complete model results are presented in Table 3. For robustness assessment we estimated fractional probit, symmetrically censored least squares estimator (SCLS), and panel stochastic frontier models as well, and the results are summarized in Appendix A2. These models provide similar results, and the choice of estimator did not give reasons to change any of our interpretations of the main results.

For the 2012 survey round, the intercept share for a male-headed household with more than two oxen, less than 31 years old, and located in the Tigray region is about 0.61 of the maximum own holding size. For household heads that are above 60 years the holding size is 9.7 percentage points higher. This change may represent the effect of bequeath on ownership holding and indicate that the youngest household head group aged <31 years may have, *ceteris paribus*, gained this nine percentage points in relative farm size compared to the oldest group. This change only captures a 9.7/38.8 share of the gap in the average ownership holding share of maximum holding. The logic behind this is that the oldest household heads were closer to their maximum holding in 2012 than the youngest household heads, who were more likely to inherit land during the 2012-2016 period. Surprisingly, the variables associated with a higher likelihood of renting out land (female-headed households, households having no oxen, or only one ox for land cultivation) did not have significantly smaller ownership holding shares than other households. The administrative redistributions or land-taking indicators were also insignificant and had high standard errors. The total plot count was highly significant (at 0.1% level) and positively correlated with the ownership holding share, indicating that higher counts are associated with less likelihood of attrition. The deviation from the maximum plot count was highly significant and had a negative sign. We interpret this as evidence of plot attrition explaining low ownership shares. One less sub-parcel (plot) counted in 2012 than the maximum count is significantly (at 0.1% level) associated with a 3.5 percentage point lower ownership share measured.

Furthermore, one unmeasured plot/parcel is significantly (at a 5% level) associated with a 2.7 percentage point smaller ownership share measured. The ownership share was also significantly (at

Table 3. Ethiopia censored Tobit models for ownership shares of maximum holdings split by survey round and pooled panel censored Tobit model

	Tobit12	Tobit14	Tobit16	Tobit1216
Year(s)→	2012	2014	2016	2012-2016
Female-headed hh	-0.023	-0.027	-0.057**	-0.040***
	(0.03)	(0.02)	(0.02)	(0.01)
Threeplusoxen(base)	0.000	0.000	0.000	0.000
No ox	0.013	-0.028	-0.151****	-0.054***
	-0.03	-0.04	-0.03	-0.02
One ox	(0.00)	0.02	-0.081**	(0.02)
	-0.040	-0.040	-0.040	-0.020
Two oxen	0.01	(0.03)	(0.06)	(0.02)
	-0.03	-0.04	-0.03	-0.02
Household size	-0.017	0.007	0.004	0.005
	(0.01)	(0.01)	(0.01)	(0.00)
Tot. Labor units	0.017	-0.003	0.007	-0.004
	(0.02)	(0.01)	(0.01)	(0.01)
Age oldest child	0.004**	0.004*	0.00	0.003****
	(0.00)	(0.00)	(0.00)	(0.00)
Base: Age hhh 20-30	0.000	0.000	0.000	0.000
Age hhh 31-40	0.041	-0.040	0.033	0.013
	(0.03)	(0.03)	(0.04)	(0.01)
Age hhh 41-50	0.064**	-0.035	-0.002	0.011
	(0.03)	(0.03)	(0.04)	(0.02)
Age hhh 51-60	0.077**	-0.057	-0.002	0.012
	(0.03)	(0.04)	(0.04)	(0.02)
Age hhh >60	0.097***	-0.010	-0.045	0.016
	(0.03)	(0.04)	(0.04)	(0.02)
Involunatry loss of farm	0.012	-0.016	-0.141	-0.044
	(0.14)	(0.15)	(0.11)	(0.07)
Displacement by Gov.	0.043	-0.072	0.228	0.132
	(0.15)	(0.09)	(0.26)	(0.11)
Local unrest shock	-0.210**	0.303	0.094	0.004
	(0.10)	(0.34)	(0.07)	(0.06)
Sqrt(Distance to admin center)	-0.007***	0.001	-0.008***	-0.005****
	(0.00)	(0.00)	(0.00)	(0.00)
Total plot count	0.016****	0.016****	0.009***	0.014****
	(0.00)	(0.00)	(0.00)	(0.00)
Deviation from max plotcount	-0.035****	-0.045****	-0.041**	-0.041****
	(0.00)	(0.01)	(0.02)	(0.00)
Number unmeasured parcels	-0.027**	-0.066****	0.011	-0.050****
	(0.01)	(0.01)	(0.02)	(0.01)
Tigray region (base)	0.000	0.000	0.000	0.000
Afar	-0.006	-0.114	-0.176**	-0.094**
	(0.09)	(0.09)	(0.09)	(0.04)
Amhara	0.052	-0.002	-0.017	0.011
	(0.03)	(0.03)	(0.04)	(0.02)

Oromiya	0.108***	0.016	0.022	0.051***
	(0.04)	(0.04)	(0.04)	(0.02)
Somalie	0.000	-0.064	0.092*	0.008
	(0.05)	(0.05)	(0.05)	(0.02)
Beninshangul Gumuz	0.094	-0.048	-0.033	0.009
	(0.06)	(0.06)	(0.06)	(0.03)
SNNP	0.111****	0.031	0.000	0.051***
	(0.03)	(0.03)	(0.04)	(0.02)
Gambella	-0.156**	-0.027	-0.015	-0.065**
	(0.06)	(0.08)	(0.08)	(0.03)
Harari	0.030	-0.013	0.161***	0.052*
	(0.05)	(0.05)	(0.06)	(0.03)
Dire Dawa	0.184****	-0.007	0.009	0.065**
	(0.05)	(0.05)	(0.05)	(0.03)
2012.panel year				0.000
2014.panel year				0.092****
				(0.01)
2016.panel year				-0.004
				(0.01)
Constant	0.612****	0.758****	0.878****	0.717****
	(0.06)	(0.06)	(0.06)	(0.03)
var(e.own~1)	0.127****	0.136****	0.149****	
	(0.00)	(0.00)	(0.00)	
sigma_u				0.000
				(0.01)
sigma_e				0.375****
				(0.00)
Prob > chi2	0.0000	0.0000	0.0000	0.0000
Number of observations	2339	2339	2339	7017

*Note:*Models corrected for attrition bias with IPW. Robust standard errors in parentheses. Signficance levels: *: 10% level, **: 5% level, ***: 1% level, ****: 0.1% level.

0.1%) negatively associated with the distance to the nearest administrative center. Finally, there were some regional differences, with ownership shares being significantly higher in the Oromiya, SNNP, and Dire Dawa regions and significantly lower in the Gambella region compared to the Tigray region used as a base.

In the 2016 model, we find strong evidence of under-reporting of rented-out plots. We know that female-headed households and households without oxen or owning only one ox are likelier to rent out land. Female-headed households report ownership shares that are 5.7 percentage points smaller (significant at 5% level) than male-headed households. Households without oxen in the 2016 survey round reported ownership holding shares that were 15.1 percentage points lower (significant at 0.1% level), and households with one ox reported ownership holding shares that were 8.1 percentage points lower than households with more than two oxen. The other indicators of parcel attrition, the total number of plots/parcels, and deviation from the maximum within-household plot count show similar results as in the 2012 model. Still, there was less problem with unmeasured parcels than in the previous rounds. The constant term in the 2016 model was much higher, at 0.9, compared to the 0.62 level in 2012, which indicates a general improvement in the data quality from 2012 to 2016. Still, the results above clearly suggest that parcel/plot attrition, in general, and related to the land being rented out still leads to substantial underestimation of ownership holding sizes.

Finally, the pooled censored Tobit model results for all three survey rounds are presented in Figure 3, and as the last model in Table 3. This model allowed us to test for differences across survey rounds with panel-round fixed effects. The dummy for the 2014 survey round is highly significant (at 0.1% level) and indicates that the ownership share is 9.2% higher in this year. The pooled model indicates that land renting contributes significantly to under-reporting, but parcel/plot attrition is the leading cause of the low ownership shares while inheritance and administrative redistributions play only minor and insignificant roles.

As a next step, we want to assess how well these censored Tobit models of ownership holding shares predict the actual ownership shares, given that the models have been constructed to take into account real changes in ownership holding shares and parcel/plot attrition. The reported and measured versus the predicted ownership holding shares are shown in Figure 4 as cumulative distributions of the actual and predicted ownership shares by survey round and for the panel.

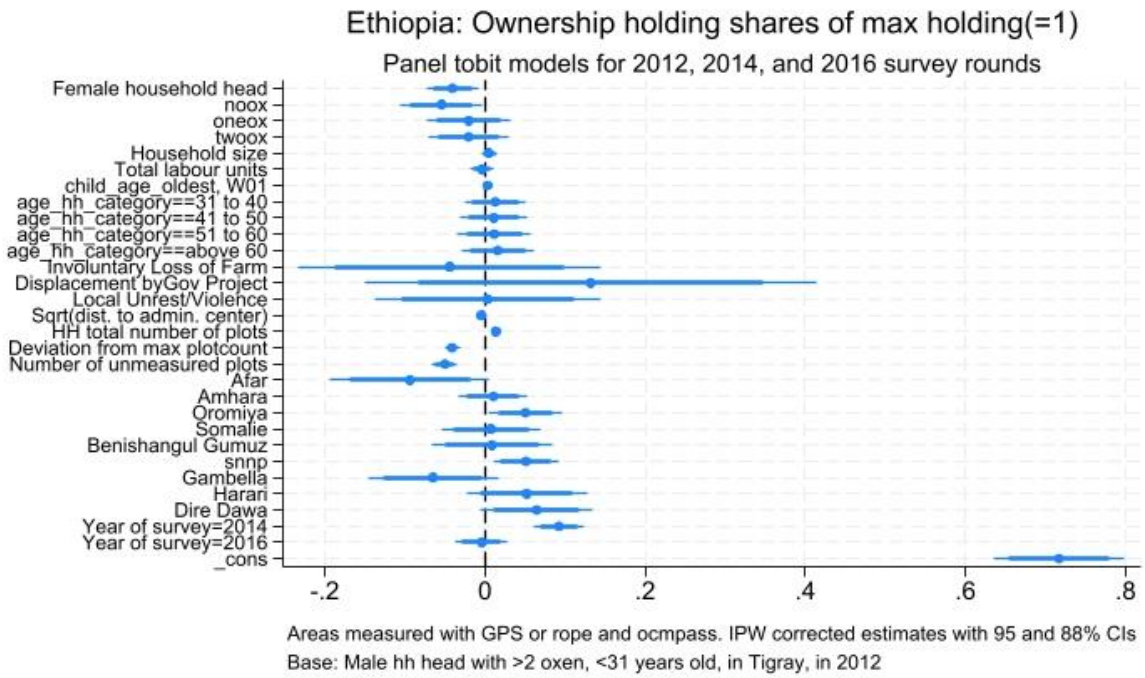


Figure 3. Panel Tobit models for ownership holding shares of maximum own ownership holding size over three survey rounds in Ethiopia

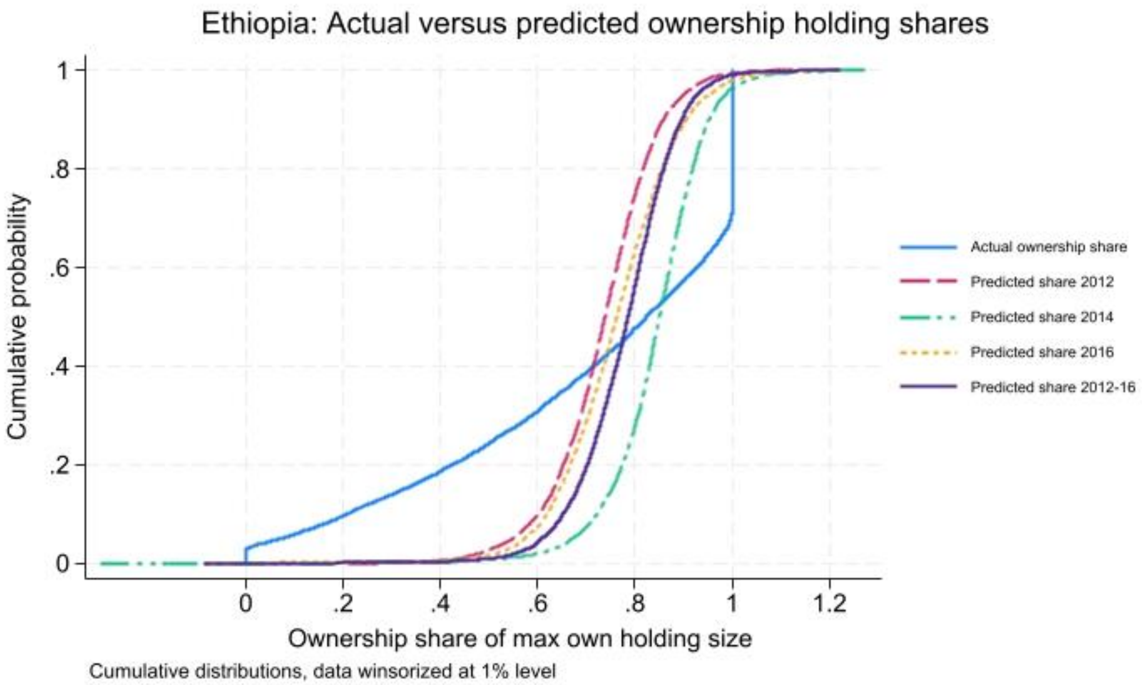


Figure 4. Ethiopia: Actual versus predicted ownership shares of max own holding sizes

The first and most fundamental problem is that the Tobit models, censored from the top, poorly predict the actual ownership holding share distribution. The model for the first 2012 survey round predicts lower ownership shares than the later survey rounds, and we found that this could partially be explained by inheritance and bequeath transfers. However, the models for 2014 and 2016 also predict poorly.

One may then ask whether the censored Tobit models are the problem, as they may be sensitive to non-normality and heteroskedasticity. We therefore tested alternative estimators including fractional probit, symmetrically censored least squares estimator (SCLS), and panel stochastic frontier models. The results of these are presented in Appendix 2. We found, however, that all these estimators give poor predictions of the ownership holding shares.

Based on this evidence, we conclude that the best proxy of households' actual holding sizes over the three survey rounds is their maximum reported and measured ownership holding size across survey rounds. This measure is the measure that is least likely to suffer from plot attrition. While it is not a perfect estimator it is the best we have. We proceed by inspecting the distributions of these maximum within-household ownership holding sizes versus the actual reported and measured (with GPS or rope and compass) ownership holding sizes in the three survey rounds to get a better picture of the bias in ownership holding distributions associated with such parcel/plot attrition, see Figure 5.

Figure 5 compares the cumulative ownership holding distributions in 2012, 2014, and 2016 in ha with the cumulative within-household maximum ownership holding distribution across the three survey rounds in 2012, 2014, and 2016. Based on the previous analyses, we notice a substantial gap in all three survey rounds and suggest that this gap is primarily explained by parcel attrition that varies over time within households. The annual ownership distributions point towards about 60% of farms being one ha or smaller, against only about 45% of the holdings being smaller than one ha according to the maximum holding distributions. We believe that the latter estimate is closer to the truth.

Figure 6 shows the distributions disaggregated to the regional level, where we compare the maximum holding size with the ownership holding distributions in 2014, which may have been the year with the most complete parcel measurements. We see that there is also a significant gap between the 2014 and maximum holdings in all regions, indicating that such parcel attrition was also a significant problem, leading to bias in ownership holding distributions this year.

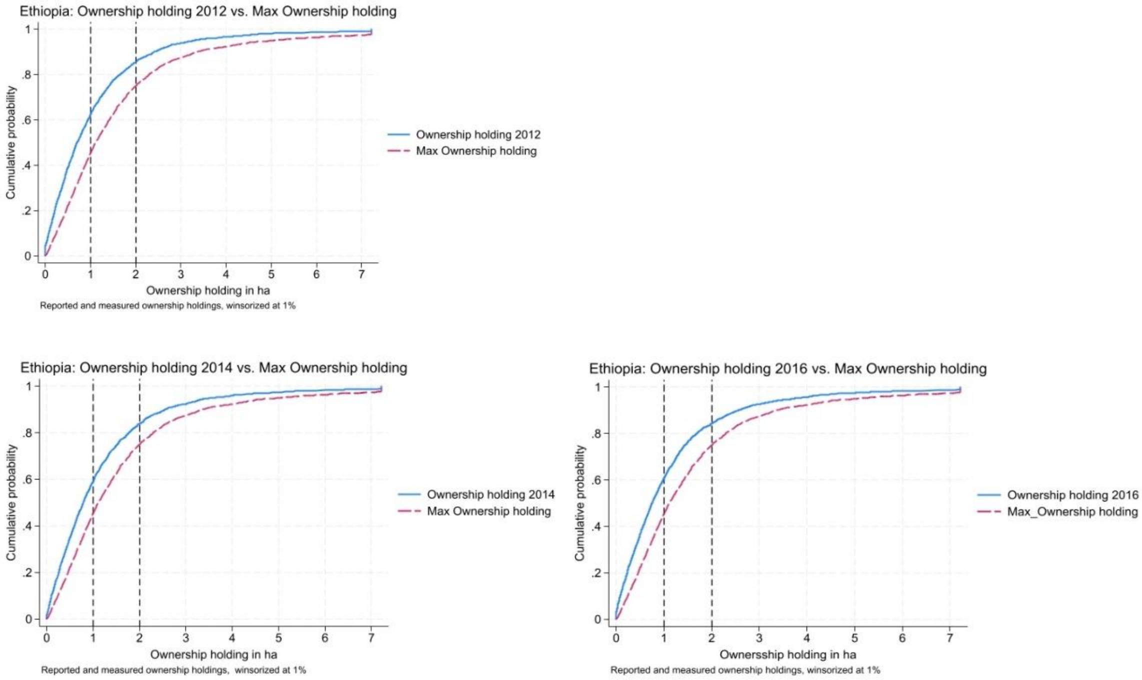


Figure 5. Ownership holding size distributions in ha in 2012, 2014, and 2016 versus maximum size distributions 2012-2016.

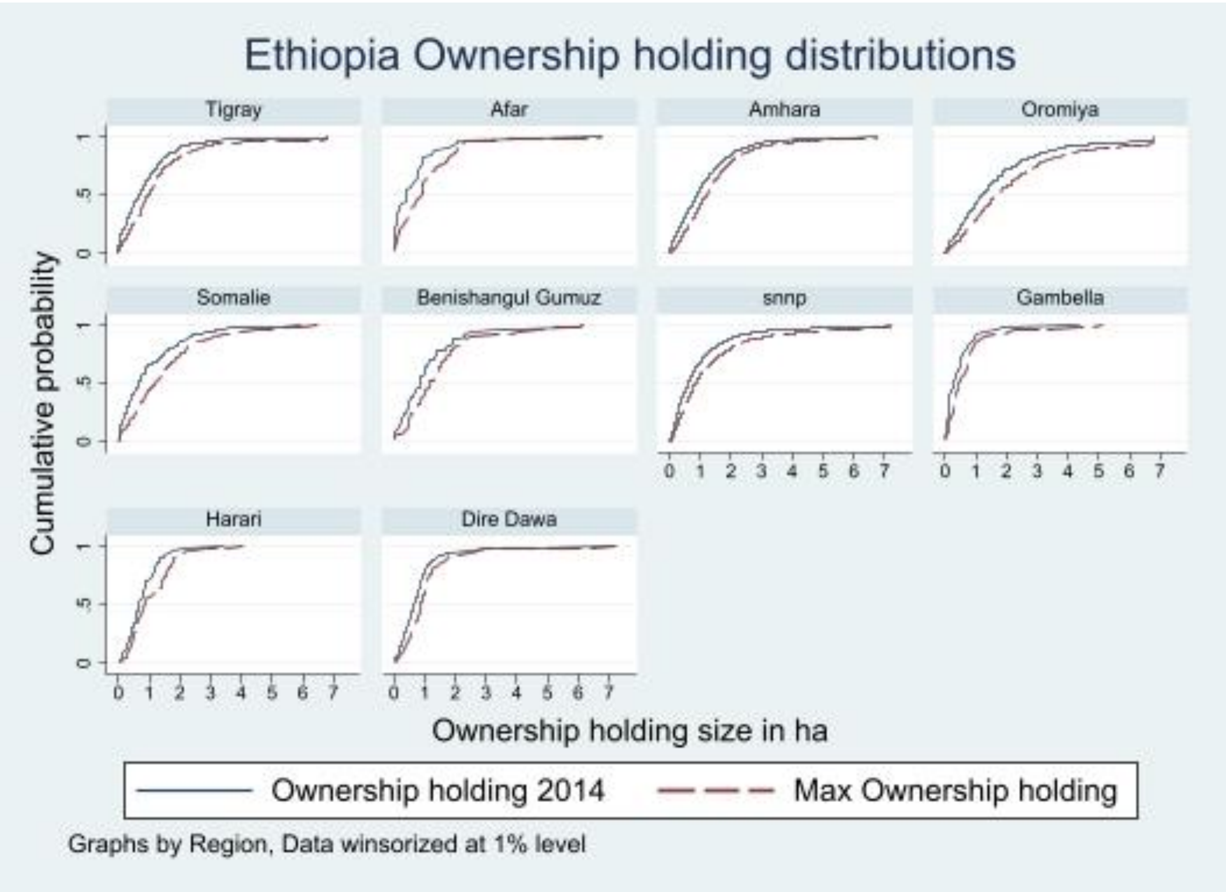


Figure 6. Ownership holding size distributions in ha in 2014 versus maximum size distributions 2012-2016, dis-aggregated by region.

Next, we assess the implications for the gini-coefficients for measured ownership holding distributions that we control for random and non-random measurement errors. Table 4 provides estimates at the regional level.

Table 4. Gini-coefficients for ownership holding size distribution by region without and with measurement error corrections

	Unvinsorized Ownership holdings	1% winsorized Ownership holdings	1% winsorized max Ownership	2% winsorized max Ownership	5% winsorized max Ownership
Tigray	0.603	0.511	0.461	0.44	0.416
Afar	0.575	0.573	0.483	0.459	0.434
Amhara	0.479	0.453	0.408	0.397	0.368
Oromiya	0.539	0.472	0.433	0.4	0.34
Somalie	0.505	0.504	0.448	0.437	0.402
Benishangul	0.457	0.457	0.415	0.403	0.36
SNNP	0.571	0.536	0.514	0.494	0.455
Gambella	0.544	0.544	0.522	0.522	0.489
Harari	0.39	0.39	0.349	0.349	0.344
Dire Dawa	0.409	0.404	0.375	0.363	0.345

It makes sense to adjust outlier observation values in the data as these may be driven by random measurement and aggregation errors. Table 4 illustrates that when ownership holdings are winsorized at a 1% level, the Gini coefficients for regional land distributions are substantially reduced in regions such as Tigray and Oromiya. If we compare these estimates with the within-household maximum ownership holding winsorized at 1%, we see a further substantial reduction in the regional Gini coefficients. We suggest this is because of nonclassical measurement errors due to parcel attrition. Winsorizing the maximum areas further from 1 to 2 or 5% on each side of the distributions may go too far in adjusting the tails of the maximum farm sizes (ownership holdings). Gini-coefficients at district and community levels based on land registry data in the Tigray region of Ethiopia in 2016 varied from 0.40 to 0.56 for comparison (Holden and Tilahun 2020).

4.2. Malawi

Table 5 presents the overview of the distribution of households across regions in the balanced LSMS-ISA data from Malawi. It shows that the number of households in the less densely populated Northern region is much lower than in the two more populous Central and Southern regions.

Table 5. Malawi: Distribution of the LSMS-ISA balanced household panel

Region	2010	2013	2016	2019	Total
North	86	86	86	86	344
Central	416	416	416	416	1,664
Southern	484	484	484	484	1,936
Total	986	986	986	986	3,944

Figure 7 presents the ownership holding share distributions of maximum ownership holdings for each survey round. We see a distributional pattern quite similar across survey rounds and minimal effects of winsorizing the data at 1, 2, and 5% levels. The shapes of the ownership share distributions are also astonishingly similar to those for the Ethiopian sample. This is a first indication that the parcel attrition problem we detected in the Ethiopian data also appears to be there in the Malawian data.

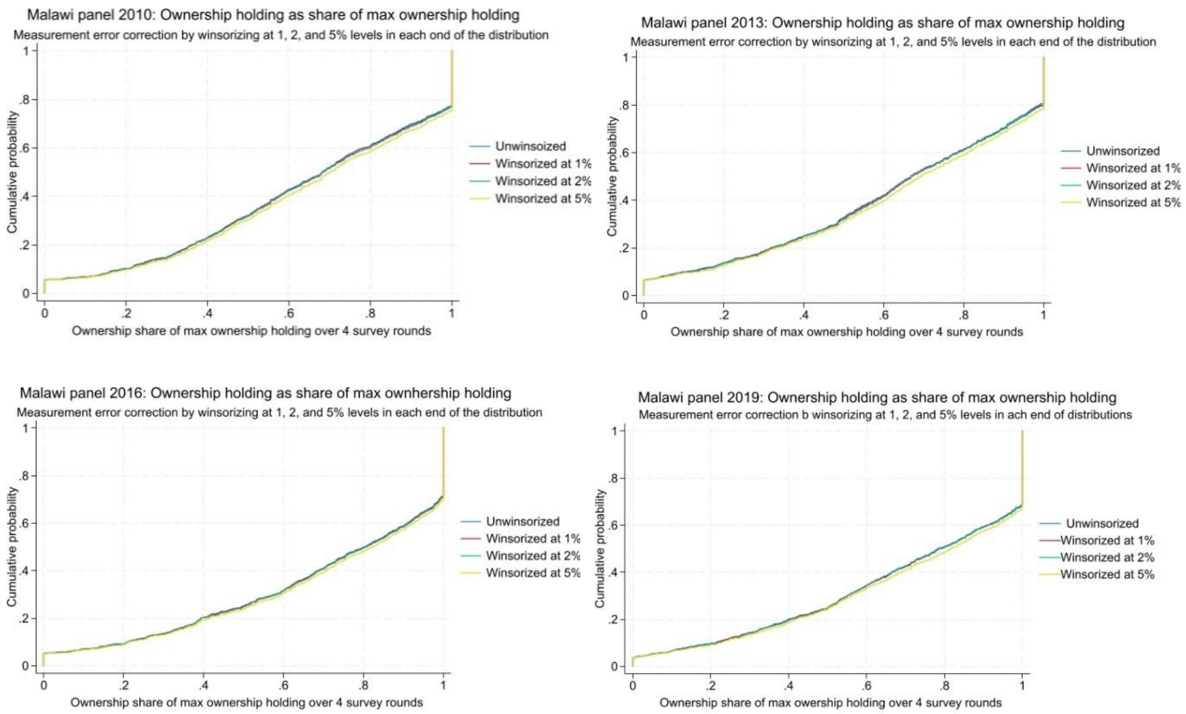


Figure 7. Within-household ownership holding shares of maximum household ownership holdings over four survey rounds in Malawi.

To scrutinize the possible parcel attrition problem, we also graph the total parcel/plot counts, the deviation from the within-household maximum parcel/plot counts in Figure 8a, and the deviation from the maximum parcel/plot count by survey round in Figure 8b. We see a deviation in parcel counts for more than 50% of the households in Figure 8a and similarly in each survey round in Figure 8b, with some indications that the problem is smaller in 2019.

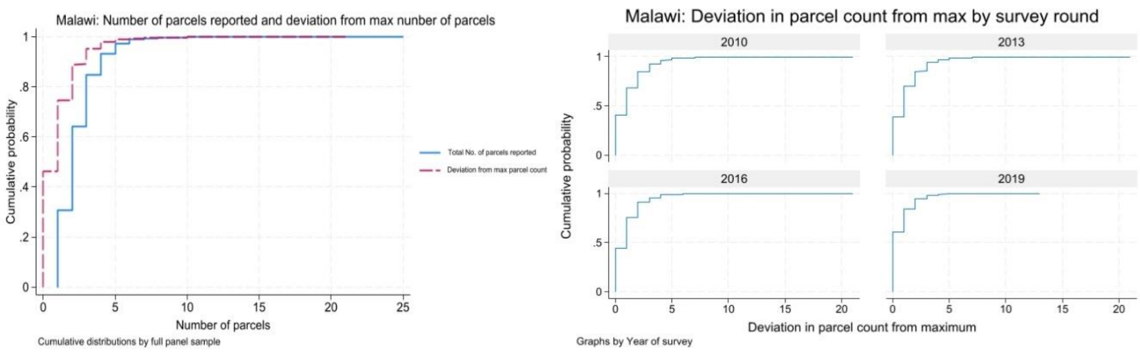


Figure 8a and 8b. Malawi: Parcel count and deviation from max parcel count (total and by survey round) for households

Based on this, we used that same estimation approach (censored Tobit models by survey round and as a four-round panel) to detect factors associated with real changes in within-household ownership holding shares over time and factors associated with varying degrees of parcel/plot attrition. The results for all models are found in Table 6.

Table 6 shows results similar to those for the first survey round in Ethiopia, with the oldest household heads having significantly higher ownership shares than the youngest. We interpret this in the same way as being evidence of the ownership holdings of the most senior heads declining in size relative to the youngest due to inheritances and bequeaths of land between the generations. Therefore, the holdings of the youngest heads are likely to grow more over the panel years, causing them to have smaller shares on average in the first survey round. This difference between the youngest and oldest heads is about 9 percentage points over the nine years between the first and last survey rounds in the Malawi data and is about the same as that in the Ethiopian panel covering a shorter period. The constant term (0.595) for the ownership holding shares was also similar to that for Ethiopia (0.622) and illustrates a sizeable average gap up to the maximum holding size. This gap can only partially be explained by inheritances and bequeaths. The variables, which are potential indicators of land being rented out (female head, total labor force, drought power dummy), were only significant in the 2019 model and the full panel. On the other hand, the variables potentially indicating parcel/plot attrition (total plot number reported, deviation from maximum parcel/plot count) causing low ownership holding shares were highly significant and with positive and negative signs, in line with these variables signaling significant under-reporting of parcels/plots for some households compared to the year they reported the most complete parcel/plot counts.

Table 6. Malawi: Tobit models for ownership holding shares of max holding shares by year

	t1	t2	t3	t4	t14
	b/se	b/se	b/se	b/se	b/se
Year→	2010	2013	2016	2019	2010-2019
Female headed, dummy	0.004	0.031	0.000	0.007	0.013
	(0.03)	(0.03)	(0.03)	(0.03)	(0.01)
Total labor units	-0.024**	0.015	0.014	0.040****	0.013**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Livestock endowment	-0.001	0.004	-0.001	-0.005***	-0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Draught_power, dummy	0.074	-0.005	0.044	0.121**	0.054*
	(0.06)	(0.06)	(0.05)	(0.06)	(0.03)
Oldest child age	0.001	-0.002	-0.001	-0.004**	-0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age hhh <31 (Base)					
Age hhh 31-40	0.002	-0.002	0.033	0.113*	0.027
	(0.03)	(0.04)	(0.05)	(0.06)	(0.02)
Age hhh 41-50	0.072*	0.026	-0.057	0.065	0.014
	(0.04)	(0.04)	(0.05)	(0.06)	(0.02)
Age hhh 51-60	0.094**	0.029	-0.037	0.000	0.009
	(0.04)	(0.05)	(0.06)	(0.07)	(0.02)
Age hhh >60	0.087**	0.083*	0.033	0.092	0.059**
	(0.04)	(0.05)	(0.06)	(0.06)	(0.02)
Distance pop.center	-0.001	-0.001	-0.001	0.002**	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Parcel count	0.066****	0.065****	0.078****	0.069****	0.072****
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Deviation max parcel count	-0.046****	-0.044****	-0.061****	-0.077****	-0.055****
	(0.01)	(0.01)	(0.02)	(0.01)	(0.00)
Parcels not measured, dummy		-0.462****	-0.11	-0.286***	-0.316****
		(0.08)	(0.12)	(0.09)	(0.05)
Urban_rural, dummy	0.024	0.053	0.020	0.085	0.049*
	(0.06)	(0.06)	(0.07)	(0.06)	(0.03)
Northern region (base)	0.000	0.000	0.000	0.000	0.000
Central region	-0.025	-0.03	0.123***	0.012	0.024
	(0.04)	(0.05)	(0.04)	(0.05)	(0.02)

Southern region	0.008	0.047	0.144***	0.061	0.071***
	(0.04)	(0.05)	(0.04)	(0.05)	(0.02)
2010.panel year(base)					0.000
2013.panel year					-0.028*
					(0.02)
2016.panel year					0.042**
					(0.02)
2019.panel year					0.002
					(0.02)
Constant	0.595****	0.454****	0.479****	0.263*	0.428****
	(0.11)	(0.11)	(0.13)	(0.14)	(0.05)
var(e.own~1)	0.126****	0.124****	0.134****	0.133****	
	(0.01)	(0.01)	(0.01)	(0.01)	
sigma_u					0.000
					(0.01)
sigma_e					0.363****
					(0.00)
Prob > chi2	0.0000	0.0000	0.0000	0.0000	0.0000
Number of observations	982	982	982	982	3928

*Note:*Models corrected for attrition with inverse probability weighting (IPW). Standard errors in parentheses. Signficance levels: *: 10% level, **: 5% level, ***: 1% level, ****: 0.1% level.

In the 2019 model, a one-unit deviation in plot count from the maximum within-household plot count is associated with a 7.7 percentage point smaller ownership holding share. For this model, we also included a dummy for households with unmeasured parcels/plots, which were not included in the aggregate household ownership holding measure. We did not attempt to create proxy measures for these households; we just used a dummy variable to control for this. As expected, this dummy was associated with a large and significant (at 1% level) negative effect on the ownership holding share. Very few households reported such unmeasured parcels/plots, however, and this explains the much larger confidence intervals for this variable in Figure 9 than that for the plot count variables that varied for much larger shares of the sample. These findings indicate that under-reporting of parcels/plots is a bigger problem than the lack of measurement of reported parcels in the data that Kilic et al. (2016; 2017) have demonstrated can be overcome with MI methods. The under-reporting of parcel/plot data may also imply the under-reporting of production data from the unreported parcels/plots.

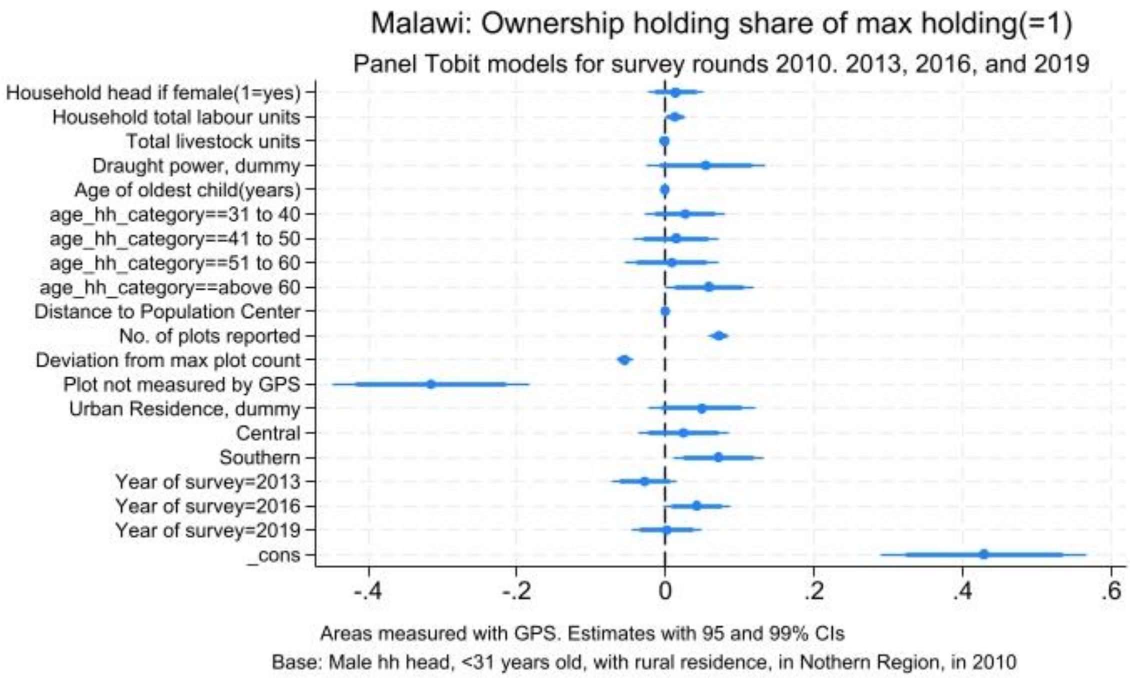


Figure 9. Malawi: Panel Tobit model estimates for ownership holding shares in 2010-2019 panel

Figure 9 presents the results for the censored panel Tobit model, which confirm that variation in parcel/plot reporting is the main reason for the variation in ownership holdings. The variations over survey rounds were small, indicating that the problem persists. We finally predicted the ownership holding shares based on the censored Tobit models for each survey round and based on the panel Tobit model. We compare the cumulate probability distributions for the predicted ownership holding shares with the actual ownership shares in Figure 10. The figure shows the same poorly predicted fits to the actual data as we saw for the Ethiopian data. Alternative estimators do not perform much better (Appendix 2). This illustrates the stochastic, although not entirely random, nature of parcel/plot attrition. We come to the same conclusion as for the Ethiopian data that the maximum within-household farm size over survey rounds is a better proxy for the average ownership holding size than the measures for each survey round as this maximum holding size is the least likely to suffer from parcel attrition for one reason or other.

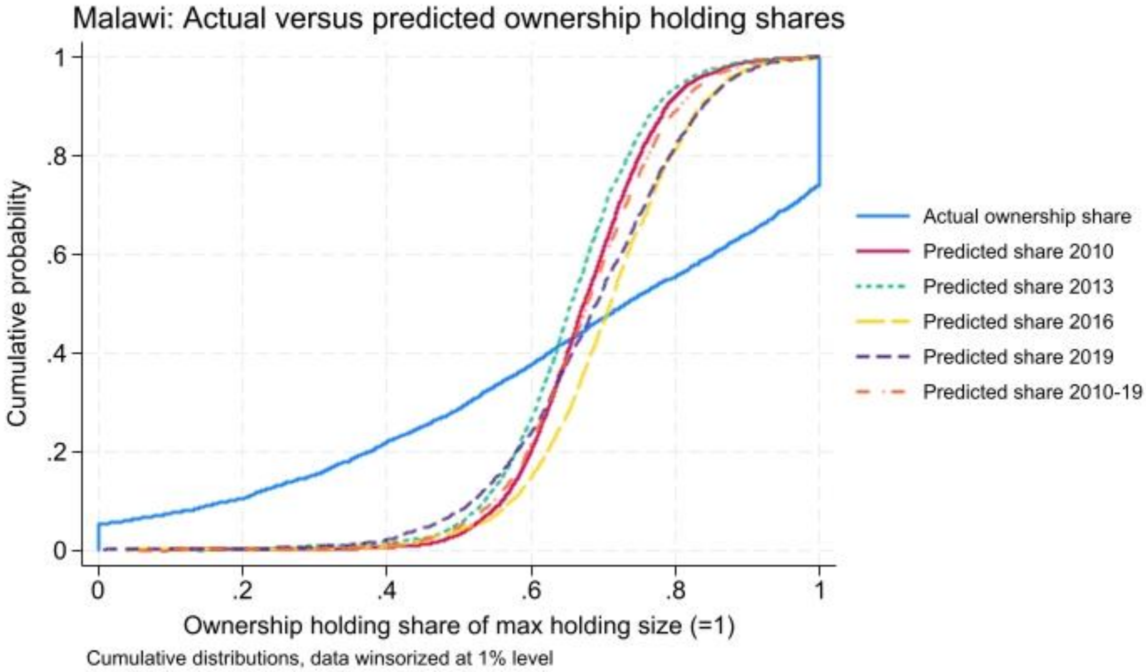


Figure 10. Malawi: Actual versus predicted owner ownership shares from Tobit models

Based on this assessment, we proceed as we did with the Ethiopian data by comparing the maximum holding sizes measured in ha with the actual holding sizes in each survey round. We complement the analyses by alternatively winsorizing the reported and measured farm sizes at a 1% level at each distribution end. We use 1, 2, and 5% winsorizing for the maximum holding sizes, see Table 7. We see that the maximum holding sizes give ownership holding sizes substantially larger than the average reported and measured holding sizes in each survey round, whether winsorized or not. The reported and measured ownership holding size distributions in each survey round and the maximum holding size distribution, winsorized at 1% level, are presented in Figure 11. We claim that these graphs give a good picture of the downward bias in farm sizes caused by the stochastic attrition in the reporting of parcels/plots in these surveys in the case of Malawi.

Figure 12 illustrates the regional variation in these reported and measured farm size distributions versus the maximum ownership holding size distribution over the panel years. We see that the gap is largest in the Northern region where the sample is the smallest and the population densities are the lowest (making fallowing more likely as an additional reason for under-reporting of parcels/plots).

Table 7. Estimated ownership holding sizes in ha based on 4 rounds of household-parcel panel data from Malawi, without and with outlier corrections.

	Ownership holding, unwinsorized				Ownership holding, winsorized 1%				Max ownership holding, winsorized at		
Year	2010	2013	2016	2019	2010	2013	2016	2019	1%	2%	5%
Mean	0.738	0.697	0.803	0.788	0.713	0.690	0.793	0.781	1.133	1.102	1.025
Median	0.567	0.532	0.631	0.599	0.567	0.532	0.631	0.599	0.902	0.902	0.902
P25	0.308	0.291	0.336	0.332	0.308	0.291	0.336	0.332	0.587	0.587	0.587
P75	0.902	0.890	1.036	1.036	0.902	0.890	1.036	1.036	1.449	1.449	1.449
P90	1.425	1.392	1.639	1.619	1.425	1.392	1.639	1.619	2.125	2.125	1.947
St.dev.	0.837	0.652	0.741	0.718	0.626	0.609	0.688	0.680	0.790	0.702	0.543
St.err.	0.027	0.021	0.024	0.023	0.020	0.019	0.022	0.022	0.025	0.022	0.017
N	986	986	986	986	986	986	986	986	986	986	986
Gini	0.416	0.407	0.415	0.420	0.396	0.401	0.407	0.415	0.358	0.341	0.298

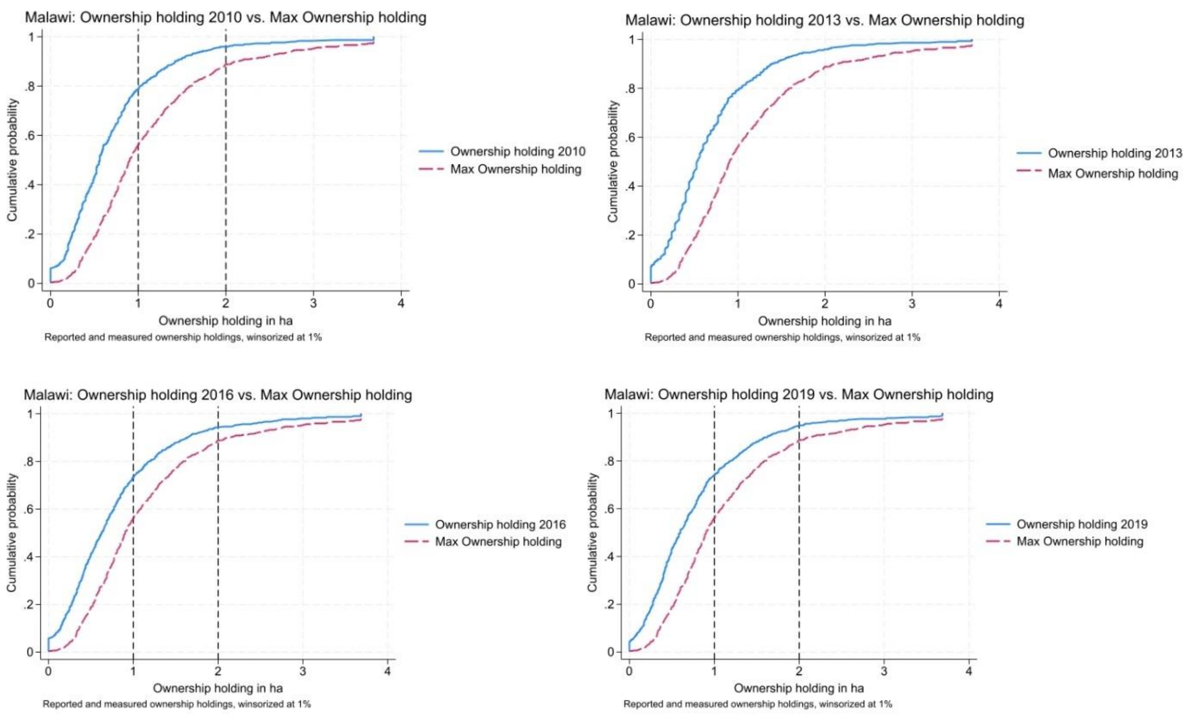


Figure 11. Ownership holding distributions by survey year versus maximum within-household ownership holdings across the four survey rounds.

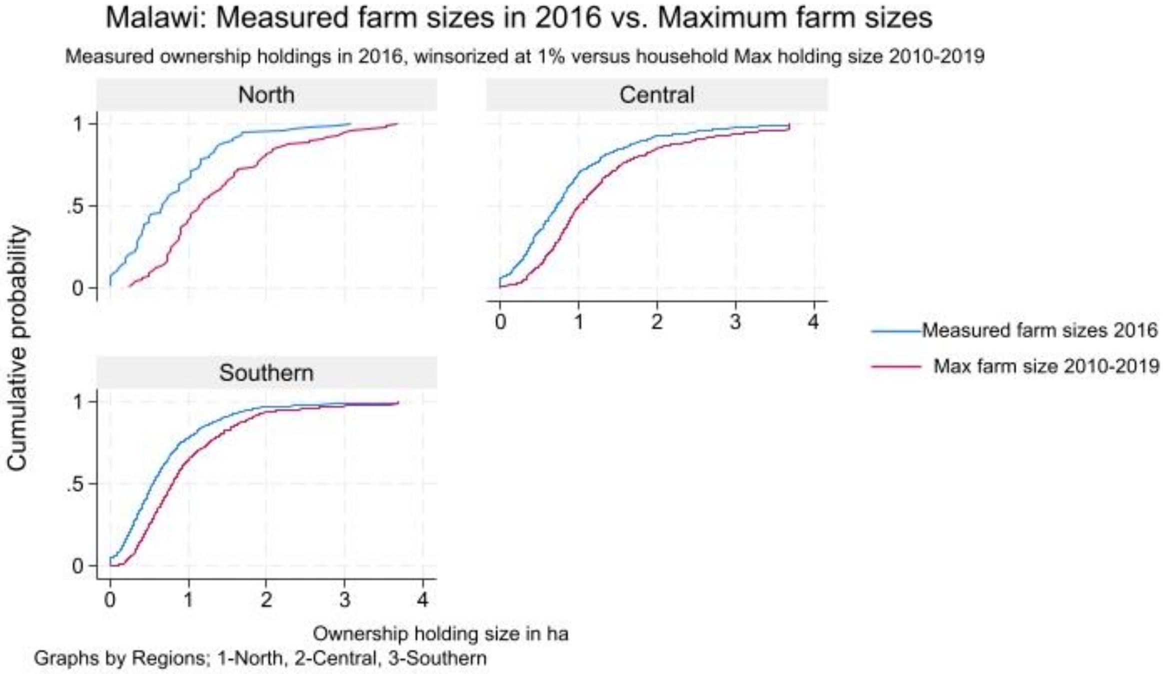


Figure 12. Measured farm sizes in 2014 versus max farm size 2012-16 by region

Finally, we assess the Gini distributions for the actual and maximum ownership holding sizes in Table 8. The table indicates that the parcel/plot attrition also leads to an upward bias in the estimated gini-coefficients for the farm size distributions, like we found in Ethiopia.

Table 8. Malawi: Gini-coefficients by region, without and with winsorized variables

Region	Ownership holdings Unwinsorized	Ownership holdings Winsorized at 1%	Max Ownership holding Winsorized at 1%	Max Ownership holding Winsorized at 2%	Max Ownership holding Winsorized at 5%
North	0.400	0.399	0.313	0.297	0.242
Central	0.409	0.395	0.351	0.330	0.278
Southern	0.413	0.406	0.358	0.345	0.314
Total	0.416	0.406	0.358	0.341	0.298

5. Discussion

It is very demanding to collect reliable farm size data in field surveys, whether measured with handheld GPSs or rope and compass. Such data collection may be unnecessary in countries where reliable land registries are linked to digital maps. While such a digital and administrative revolution is underway in an increasing number of developing countries, reliable agricultural statistics are vital in countries without such land registry data. We have investigated the reliability of the measured farm sizes in the nationally representative LSMS-ISA surveys in Ethiopia and Malawi and have found substantial downward bias in the estimated farm sizes, caused mainly by systematic and stochastic under-reporting of parcels/plots. We were able to detect this type of error by combining multiple survey rounds from the same balanced sample of farm households. Earlier studies aiming to enhance the reliability of the measurement of farm and parcel sizes have utilized data from single survey rounds and compared alternative techniques of measuring parcel sizes. However, the phenomenon we studied was not detectable with that approach.

We have benefitted from access to data from three survey rounds in Ethiopia and four in Malawi. We find that the extent of the problem is substantial in both countries. We provided some theoretical propositions for why we thought this might be an essential problem, and we believe that those propositions may explain the problem and the large biases in farm size estimates that we have detected. Our findings have important implications for policy analyses based on these data and for developing better ways to generate reliable measures of farm sizes in these countries.

For policy analysis purposes, it implies that these surveys do not provide reliable measures of ownership holding sizes in each survey round, even if all parcels have been measured with GPS. The under-reporting of parcels/plots leads to the under-reporting of farm sizes. Further work is needed to assess how this affect the reporting of outputs from and input use on unreported parcels. If such data are also collected at the plot/parcel level, plot/parcel attrition will also lead to similar bias in output and input data at the household level. The bias may be less if input and output data are collected at a more aggregated level or have been through quality and consistency checks across plot, parcel, and household levels.

The benefit of the balanced household panels is that we may use the maximum holding sizes over survey rounds to get more reliable measures of actual farm sizes. One may also combine these maximum holding sizes with real identified changes in farm sizes associated with inheritances and bequeaths, purchases and sales of land, and administrative redistributions to get more exact farm size distributions. Such refinements go beyond this paper's scope, which was to assess the importance of this type of measurement error. It is also evident that with this type of measurement error, it becomes even more tricky to study the famous relationship between farm size and land productivity as the under-reporting of areas and possibly the related input use and outputs for unreported parcels cannot be assumed to represent white noise in the data.

Researchers within the World Bank or the Statistical Offices within Ethiopia and Malawi may have access to the detailed GPS data coordinates at the parcel level. These data could be used to dig deeper and create parcel panel data to study further the parcel/plot attrition and how parcels have, in different ways, been split into different sub-parcel/plot structures over the years within households.

Another obvious way forward could be to explicitly link the survey households to the land registry data likely to exist for a large share of the households in the Ethiopian sample. Ethiopia has undergone two land registration processes during the last 20-25 years, and a large share of the rural households, therefore, have land certificates for their ownership holdings. The Second-Stage land certification process, which took place around the time of the Ethiopian surveys (2014-16), should provide reliable farm size data for a large share of the sample households. This would require access to household IDs and the land registry data and could be an interesting control of the findings in our study.

In smaller surveys in various locations in Ethiopia, the first author trained the enumerators to ask to see the land certificates of the households and to record the parcel and farm-level data from these certificates. Unfortunately, the same was not done in the LSMS-ISA survey in Ethiopia.

Another way to get more reliable parcel and farm size data is to use a more comprehensive land tenure module as part of the LSMS-ISA survey instrument (Holden et al. 2016). While this has been proposed, it has not been implemented to any extent due to the already huge survey instrument used in these multipurpose surveys. This represents a heavy burden to get through for the responding households and trained enumerators. Unsurprisingly, they have incentives to under-report in collecting parcel/plot level data that also require visits to the field for parcel/plot measurement. An easier way to enhance the reliability of the parcel-level data would have been to have the tablets preprogrammed with the parcel data from the previous survey round. A potential danger could then be that an initial parcel attrition type of error could be carried over from the previous round, and the balanced panel could become less suitable for detecting this type of error.

Protecting respondents' anonymity is a crucial issue to handle carefully related to this type of balanced panel household survey. However, a core group of persons must manage the household, person, and GPS coordinate data. They should also be trained to deal more effectively with these types of measurement errors to help generate more reliable agricultural statistics.

6. Conclusions

We have used three rounds and four survey rounds of balanced household-farm data from the LSMS-ISA from Ethiopia and Malawi, respectively, to assess the reliability of the estimated ownership holding sizes of these households. Almost all the recorded parcels and sub-parcels/plots have been measured with reliable tools such as handheld GPSs and/or rope and compass, giving reliable estimates of the recorded areas. Our contribution to the literature is to use the balanced panel to investigate the within-household variation in reported parcels and, thereby ownership holding sizes over several survey rounds and to investigate the possible reasons for such a variation over time. This variation could be either real and caused by inheritances and bequeaths, purchases and sales, administrative redistributions, or private land grabs. However, it could also be due to a varying degree of under-reporting of parcels/plots over time, which could be due to a lower likelihood of reporting land that is rented out and thereby being farmed by somebody else. It could also be due to other reasons for convenience for hiding areas related to the drudgery of reporting all relevant data associated with the reported parcels, including going to the field and measuring the parcels/plots. To assess the extent of changes in reported farm sizes over time, we used the maximum within-household ownership holding size as the reference holding, and computed the ownership holding shares of this maximum holding in each survey round.

We detected large variations in these ownership shares and found that only a limited part of this variation could be explained as being due to real changes. We found a strong tendency of under-reporting parcels/plots beyond the fact that the survey teams may not have been able to measure all the reported parcels. This under-reporting of parcels/plots was found to be quite stochastic and not easy to predict, although we developed econometric models that provided strong evidence of this being a substantial problem. While we tried to use our theoretical framework to predict ownership holding shares, we remained with large unexplained residuals. We conclude that the best and easiest proxy variable for the real farm size of households is the maximum reported and measured ownership holding size over the survey rounds. This maximum holding could also be biased downward due to under-reporting but much less so than the GPS-measured ownership holding sizes in each survey round. We demonstrate the degree of bias by comparing actual reported and measured holding size distributions versus the distribution of the maximum within-household holdings. These discrepancies are substantial in all survey rounds and across all regions in both Ethiopia and Malawi. The ignorance of the biases due to such parcel/plot attrition may cause average and median ownership holdings to be underestimated by about 25-30% and Gini coefficients for ownership holding distributions to be substantially over-estimated.

Here are important policy implications regarding the need to take these substantial nonclassical measurement errors into account when using these data for policy analyses to generate aggregate data at the national level. It is likewise important that the statistical authorities responsible for these surveys and future data collection consider this measurement error problem. Our clear perspective is that these errors have largely gone under the radar as they are easy to overlook when focusing on the data from a single survey round. We have provided recommendations for alternative ways to reduce the problem in future surveys and to further scrutinize the errors we detected in the already collected data. The similarity in the findings in these two LSMS-ISA countries makes us reasonably confident that this problem also exists in other LSMS-ISA and similar surveys in other countries. Investigating this should be an essential area for future research to generate more reliable agricultural statistics that are important for improving and developing future agricultural policies.

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[i] Both these surveys are part of the Livings Standards Measurement Study – Integrated Surveys on Agriculture (LSMS-ISA) program.

[ii] These surveys are population-based and may therefore not adequately capture medium- and large-sized farms (Jayne et al. 2019).

[iii] The splitting of farms into smaller farms may or may not be captured in the balanced panel, depending on the instructions given to the survey teams.

[iv] We experimented with alternative levels of winsorizing outliers from 1% to 5%. Adjustment of 5% on each side of the distribution may be a too conservative way to avoid bias in maximum farm sizes due to random measurement error. With adjustment of 1% of the outliers, the maximum farm size is 7.2 ha, with 2% removal the maximum ownership holding is 5.3 ha, and with 5% removal the maximum farm size is 3.48 ha. We decided to stop at 1% in our follow-up analyses based on detailed inspections of the distributions.