Land Inequality, Gender Land Disparity and Poverty in Rural Zimbabwe

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Working Paper GIZ-002

Bringing Rigour and Evidence to Economic Policy Making in Africa

AFRICAN ECONOMIC RESEARCH CONSORTIUM
CONSORTIUM POUR LA RECHERCHE ÉCONOMIQUE EN AFRIQUE

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AERC Working Paper GIZ-002
African Economic Research Consortium, Nairobi
June 2022

THIS RESEARCH STUDY was supported by a grant from the African Economic Research Consortium. The findings, opinions and recommendations are those of the author, however, and do not necessarily reflect the views of the Consortium, its individual members or the AERC Secretariat.

Published by: The African Economic Research Consortium
P.O. Box 62882 - City Square
Nairobi 00200, Kenya

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Abstract

Zimbabwe has redistributed vast quantities of arable land to the landless, women and poor communal farmers in order to reduce inequality, yet poverty and gender disparity in land ownership is still discernible. This paper explores the relationship between poverty, gender disparity and land inequality using a combination of descriptive statistics, regression discontinuity and a simple regression. The results reveal a gender gap in land ownership and larger land inequality among female-headed households. In female-headed households, the proportion of poor is smaller and per capita consumption is higher than in male-headed households. The results further reveal that the transfer of arable land to women will only reduce poverty and promote equality if it targets women without land and those at the lower end of land distribution. Spatially, poverty can be reduced by increasing the share of women who own arable land in regional districts. The main policy implication is that there are substantial spillover benefits from addressing gender inequality in land ownership if land redistribution policy targets women at the lower end of plot size distribution.

Acknowledgements

We are grateful to the African Economic Research Consortium (AERC) for their unwavering support, in particular, for providing coordination, funding and leadership support. We thank Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ) for awarding a grant to the AERC, which provided the necessary resources for us to undertake rigorous research on land inequality, gender land disparity and poverty in rural Zimbabwe for informed policy development, programme design and improved gender equality outcomes.

Key words: *Agriculture policy; land distribution; gender gap; poverty; developing country*

JEL classification: *D63; J16; O55; Q15*

1. Introduction

Access to arable land is regarded as a crucial avenue for reducing poverty and hunger in poor countries (Erickson and Vollrath, 2016; Birdsall and Londoño, 1997). Although land inequality has been identified as one of the main drivers of income inequality, hence poverty in many poor countries (Deininger et al., 2018; Cipollina et al., 2018; Barrett et al., 2006; Carter, 2003; Baulch and Hoddinott, 2000; Besley and Burgess, 2000), the debate on the relationship between land inequality and poverty has remained unsettled. For example, Cipollina et al. (2018) demonstrate that land inequality can negatively influence economic growth and increase poverty in the long run through credit constraints, but in the short run they found a lower positive association between land inequality and economic growth. Other scholars argue that commercial agriculture contributes to equity, efficiency, agricultural growth and a reduction in rural poverty (Etuk and Ayuk, 2021; Mao, 1971). Adhikari and Bjørndal (2014) argue that land redistribution wastes resources, does not make everyone richer and does not abolish poverty, which can only be achieved through economic development. In this view, land inequality does not matter for production, growth and poverty alleviation.

While Griffin et al. (2002) argue in favour of land redistribution rather than tenure reforms, countries such as Zimbabwe have continued to implement land reforms. Poverty levels and gender disparities in land ownership continue to be unpleasantly high (ZIMSTAT, 2017) despite several land reforms. There has been no study on the impact of land redistribution on land inequality and gender disparities in Zimbabwe. Although a substantial body of literature exists on gender disparity, land inequality and poverty (Fonjong, 2016; Doss et al., 2015; Holden et al., 2013; Behrman et al., 2012; FAO, 2011; Agarwal, 2003), the inconclusive findings call for further research in this area, as rightly pointed out by Carter (2003). For example, many of these studies investigated the extent of inequalities in land rights between women and men in poor countries without looking at how these inequalities translate into rural poverty. In many African countries such as Zimbabwe, women play a critical role in agriculture. Despite acknowledging the strategic role of rural women in reducing poverty, hunger and malnutrition and their reduced rights to agricultural land (see FAO, 2011 and Allendorf, 2007), little work has been done to examine the impact of improving rural women's access to land on poverty alleviation. Doss et al. (2015) point out that a lack of clarity on the measurement and interpretation of statistics on gender and land is the main cause of government failure to articulate suitable policy responses to the inequalities faced by women. It is against this background that this paper investigated the impact of gender disparity in land ownership and land inequality on rural poverty. In many African countries, poverty is concentrated in the rural areas where most women are deprived of their land rights (FAO, 2011). It is therefore crucial to examine the interaction between gender inequalities in land ownership and poverty.

Reducing inequalities in both the economic and social spheres through inclusive growth is recognized as central to the improved wellbeing of societies and, therefore, an obligation for the country's 2030 development Agenda of reducing poverty and achieve inclusive growth. Studies on gender and macroeconomics argue that improving equality in the economic sphere, such as equality in the means of production such as land, will not only promote gender equality but will also significantly promote inclusive growth and reduce poverty (Terkoğlu et al., 2017; Rosche, 2016; Razavi, 2016). Similarly, reducing inequality in the social sphere, such as gender inequality and poverty among women, can empower women to acquire economic resources, thereby reducing inequality in the economic sphere (Terkoğlu et al., 2017). The complementarity and complex interactions of the Sustainable Development Goals (SDGs) on gender inequality, economic inequality, poverty and inclusive growth require an investigation in order to inform countries about the implications of addressing inequality on the achievement of SDG 1 on poverty elimination, and SDGs 5, 8 and 10 on gender equality, inclusive growth, and decent work and inequality reduction, respectively. It is important to understand the current state of land inequality and its impact on poverty so as to inform the SDG targets in developing countries. In this regard, the research raised the following questions:

1. What are the levels of land and gender disparities in land ownership across the rural regions of Zimbabwe?

2. Does an increase in arable land for female-headed households improve household consumption, income and reduce poverty?

3. How much poverty would be alleviated if land redistribution policies reduced the level of land ownership inequality within regions (regional inequality and gender disparities in land holding)?

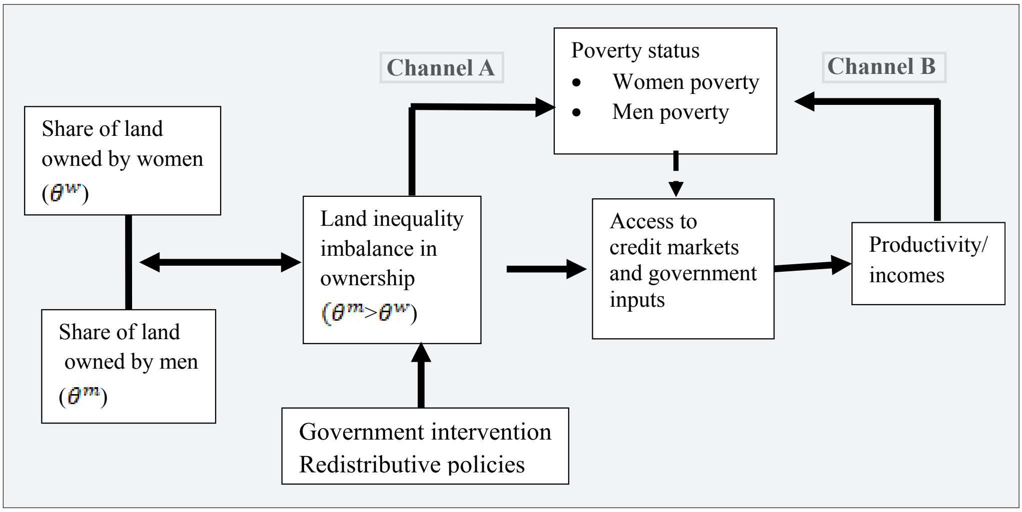
The importance of land redistribution as a strategy for poverty alleviation and socioeconomic development is extensively discussed in Keswell and Carter (2014), Deininger et al. (2009), Griffin et al. (2002) and Binswanger et al. (1995). Jayne et al. (2003) further highlight that realistic discussions on poverty alleviation strategies in Africa need to be grounded in the context of land distribution patterns. However, many studies about Africa on land inequality have largely concentrated on how land inequality influences economic growth (see Cipollina et al., 2018 and Besley and Burgess, 2000). This paper adds a gender dimension to the investigation of how land ownership relates to poverty among rural households. In support of the 2030 Agenda, which identifies a radical transformation in policy making as the solution to the achievement of SDGs this paper, unlike others, applies the theory of radical transformation in land policy. The paper evaluates the poverty reduction benefits of a radical land redistribution policy that transfers parts of arable land from men to women and from a smaller group of large land holdings to a bigger group of small land holdings.

2. Theoretical concept and literature review

Theoretically, poverty is linked to land access through credit markets and as a wealth asset for rural households. With competitive rural factor markets, high land prices exclude the poor from the market. Therefore, the vulnerable population such as women will have limited access to land (Adhikari and Bjørndal, 2014). However, market imperfections are common in developing countries and they worsen the situation of the poor. Household production models with imperfect markets formalize the role of land market imperfections by introducing credit markets (see Carter and Olinto, 2003; Carter and Mesbah, 1993 and Eswaran and Kotwal, 1986). Finan et al. (2005) demonstrate the non-linear relationship between marginal returns of land and farm size and how such a pattern gives rise to a powerful association between poverty and land distribution under land market imperfections. The size of land owned determines the availability of credit for farmers, hence productivity, income and consumption are associated with land holdings. The gender implication of this theory is that policies that improve women's access to arable land have a positive impact on their access to credit and therefore increase their productivity and incomes while reducing poverty. In developing countries such as Zimbabwe, some potential farmers (women and men) are excluded from input programmes such as contract farming because of limited access to land. These farmers may become poor because of their limited access to inputs provided by credit markets simply because of their lack of land ownership.

One of the major weaknesses of the dominant traditional economic theory that emphasizes efficiency is its failure to promote fairness in resource distribution. However, the global 2030 Agenda for sustainable growth places inclusive growth or "leaving no one behind" at the centre of the world development process. This requires governments to address inequalities in both the economic and social spheres. Markets must not be left alone to achieve inclusive growth. The theory of change or radical transformation of the traditional economic theory takes precedence in addressing the global developmental goals. The presence of market failure in land allocation requires governments to intervene to ensure optimal outcomes or inclusive growth. Therefore, the theory of change considers the government as an agency of transformation whose aim is to redistribute resources to promote inclusive growth and achieve equality in the economic, social and environmental spheres. The theory of change starts when a government realizes that there is an imbalance in land ownership between men and women. From there, a policy may be implemented (an intervention) to correct the imbalances to promote inclusive growth and reduce poverty (see Figure 1). Previous land reforms in Zimbabwe, such as the Fast Track Land Redistribution (FTLR) policy that set aside a quota of 20% for women beneficiaries failed to correct gender land disparities (Tekwa and Adesina, 2018).

Figure 1: Land, gender inequality and poverty linkages



Source: Authors' illustration based on reviewed literature.

An imbalance in land ownership occurs when women are disadvantaged in land ownership, that is, when they own less land on average than men. When government identifies and addresses land imbalances between men and women, there are two channels through which this intervention will influence poverty. First, land is part of a household's assets and is directly associated with the household's wealth and poverty, as in channel A of Figure 1 (see Ali et al., 2014 and Carter, 2003). Therefore, giving women more land implies an addition to their wealth or physical assets. Second, increasing land ownership for women improves their access to credit in well-functioning credit markets (Holden et al., 2013) and their access to agricultural support schemes and services in the case of Zimbabwe, thereby promoting productivity and incomes which, in turn, influence the poverty status of rural households. Land is an important asset used as collateral when borrowing (Akinyemi and Mushunje, 2019; Carter and Olinto, 2003). So, when women are disadvantaged relative to men in terms of land ownership, the imbalance may translate into credit markets where those with collateral are more advantaged. Even in the absence of competitive credit markets, women in Zimbabwe will be deprived of free input opportunities by the government, given to those with land. In the theory of change, the government intervenes to eliminate the gender gap between women and men in land ownership. It is crucial to understand whether the elimination of the gender gap in land ownership translates into reduced household poverty and the wellbeing of women. The reverse causality, where poverty influences land ownership, presents an endogeneity problem. However, this only holds in areas where there are competitive land markets.

There is a substantial body of empirical literature focussing on the relationship between the distribution of rural assets, economic growth and poverty (Cipollina et al., 2018; Brockington et al., 2018; Holden et al., 2013; Barrett et al., 2006; Carter, 2003; Ravallion and Datt, 2002; Baulch and Hoddinott, 2000; Besley and Burgess, 2000; Deininger and Squire, 1998). Using a meta-analysis (MA) and focussing on land instead of income inequality, Cipollina et al. (2018) established that the negative impact of land inequality on growth is only a long-run phenomenon, with a lower or positive short-run association. Cipollina et al. (2018) indicate that the advantage of focussing on land inequality is that it allows contributing to the debate on the role of agrarian structures and smallholder agriculture in development. Other studies that focussed on the relationship between land inequality and growth include Adamopoulos (2008), Ravallion and Datt (2002); Besley and Burgess (2000); and Deininger and Squire (1998), among others.

Many studies established a positive association between land inequality and poverty and recommend improved access to land for the rural poor through land reform (Keswell and Carter, 2014; Deininger et al., 2009; Carter, 2003; Jayne et al., 2003; Deininger, 2003; Ravallion and Datt, 2002; Baulch and Hoddinott, 2000). Although the importance of access to land in poverty alleviation is discussed in the literature, findings continue to vary among researchers. For example, Griffin et al. (2002) argue that land tenure reforms may have no significant impact on production and poverty among rural households, while others established otherwise (see Bezabih et al., 2016; Fonjong, 2016; Fisher and Naidoo, 2016; Doss et al., 2015; Behrman et al., 2012; FAO, 2011; and Agarwal, 2003). Fonjong (2016) argues that in cases where large land acquisitions are carried out for plantation agriculture, women's access to land will be reduced, making them more vulnerable to poverty and poor working conditions. Generally, there are conflicting schools of thought. On the one hand, land inequality in large commercial agriculture is regarded to contribute to equity, efficiency, agricultural growth and a reduction in rural poverty (Etuk and Ayuk, 2021; Okun, 1975; Mao, 1971; Boulding, 1968). On the other hand, distributive policies that reduce land inequality are considered to have a direct impact on the incomes of the poor who benefit from these transfers (see Deininger et al., 2018; Jayne et al., 2003; Deininger, 2003; Ravallion and Datt, 2002; and Baulch and Hoddinott, 2000).

Studies on gender inequalities in land ownership and control have generally ended up evaluating the extent of gender inequalities and the violation of women's rights in land ownership (Fonjong, 2016; Doss et al., 2015; Behrman et al., 2012; FAO, 2011; Agarwal, 2003). For example, Fisher and Naidoo (2016) analyzed global data from demographic health surveys and established that male-headed households have, on average, 13% more asset wealth and 303% more land for agriculture than female-headed households. They found gender inequality in land ownership not to be correlated with poverty, development and income inequality. Although rural women play a crucial role in household food production, land ownership in rural Africa is heavily skewed towards men (FAO, 2017). But does a transfer of land from men to women have any implications for household expenditures and poverty?

3. Data and empirical strategy

The data used in this paper are household level data collected by ZIMSTAT in conjunction with The World Bank in 2017. Poverty, assets and agricultural production modules for the 2017 Poverty, Income, Consumption and Expenditure Survey (PICES) data were applied. PICES is a periodic household survey by ZIMSTAT, which collects household data on poverty, consumption, incomes, expenditures and other demographic characteristics. In 2017, the survey was extended to cover agriculture (production, inputs, input support, crops, farm size, area planted and other agricultural attributes). The sampling frame for the PICES 2017 was based on the complete framework of Enumeration Areas (EAs) from the 2012 Zimbabwe Census. A stratified two-stage sample design was used for the survey, with EAs selected at the first sampling stage and households selected from a new listing of EAs at the second sampling stage. The first level of stratification corresponded to the 93 administrative districts of Zimbabwe, which are the geographic domains of analysis defined for the PICES. The rural and urban areas are domains at the national level. EAs were also stratified as urban or rural. However, a sample of 26,298 rural households from 60 administrative rural districts was considered in this paper because agriculture is mostly practiced in the rural areas of the country. At the national level, a sample of 2,232 EAs with 31,248 households was selected, with more than 50% from rural districts. Both the poverty and assets modules are based on the whole PICES sample.

Contrary to the PICES modules such as poverty and assets modules, the agricultural productivity module (APM) is a sub-sample of the PICES that surveyed only 2,528 smallholder rural households randomly selected from PICES 2017. A total of 2,338 households were successfully interviewed giving a 92.5% response rate. However, 2,259 households effectively gave responses on land ownership. The survey covered four smallholder farming sectors, namely, communal lands (CL), small-scale commercial farms (SSCF), old resettlement areas (ORA) and smallholder farms created during the fast track land reform (A1 farms). The APM data were collected in two rounds, that is, post-planting and post-harvest, designed to coincide with the major periods of the main agricultural season in the country. The post-planting data collection was conducted between April and June 2017, while the post-harvest data collection took place between September and November 2017. The sizes of all farm plots were measured using a global positioning system (GPS). The three modules (poverty, assets and APM) provide adequate information to study the associations between land inequality, gender inequality and poverty.

Land inequality and income inequality can only be measured for a group of households. Using provinces significantly reduces the number of observations in the PICES data set as there are only 8 rural provinces. However, there are enough observations if the aggregation ends at the district level. There are variations across districts in Zimbabwe, hence a district can be used as the sampling unit. Inequality measures were then computed at the district level. In addition to the district-level aggregated data, disaggregated data at household level were also used for the first two questions.

With regards to empirical strategy, the first research question on the level of inequalities was answered through descriptive statistics. Land inequalities, income inequalities and gender disparity in land ownership were computed for each rural district. The Gini coefficients for land size inequality and income were computed for each district. Comprehensive descriptive statistics were applied to assess the spatial distribution of land ownership structure, gender disparities and poverty in all rural districts of Zimbabwe. Hypothesis tests were also applied to assess differences in average land ownership and poverty between men and women, and across districts. Specifically, a test for the difference in means was applied.

For the second question on the impact of land transfer to women on household income, consumption and poverty, a regression discontinuity design (RDD) was applied. While causal inference in nonexperimental designs requires a strong assumption that no unobserved factors muddle the relationship between the assignment of treatment and the outcome, RDD does not require that assumption for causal inference (Bor et al., 2014). RDD is a quasi-experimental study design that can be implemented when the exposure of interest is assigned by the value of a continuously measured random variable and whether that variable lies above (or below) some cutoff value. In this paper, the variable of interest is farm size of female-headed farming households. The objective was to establish the impact of giving more land to female-headed farming households with land sizes falling below some threshold of land holding on household income and consumption. Although RDD has been usually applied in the ex-post evaluation of an intervention, one of the innovations in this paper was to apply it in an ex-ante evaluation of a policy. It was used to examine the potential effect of a government intervention that would increase the mean land holding of women.

As the aim of the paper was to establish the impact of reducing the gender gap in land ownership on some outcome variables, the threshold or the cutoff of land size was derived from the gender gap in land sizes. There are basically three types of gendered land ownership in rural Zimbabwe, that is, land owned by men, land owned by women and land jointly owned by men and women. In joint ownership, which is common among married couples, ownership is generally considered to be with the male head. As a result, in the determination of the gender gap in land ownership, land ownership was generally considered to be male owned as the culture defines male heads to be the owners. If the average land size owned by households headed by males is $\bar{L}_m$ and that owned by female-headed households is $\bar{L}_w$, then the average gender gap in land holding is:

$$\bar{L}_m - \bar{L}_w = \bar{G} > 0 \tag{1}$$

Land size can equally be applied in terms of per capita land size. The gap is greater than zero because male-headed households have larger average land sizes than female-headed households in Zimbabwe. This positive gap also exists globally; women own less land than men (Doss et al., 2015). A gender-equitable land redistribution policy will transfer a women's representative proportion of $\bar{G}$ from a total of n_m male-headed households to a total of n_w female-headed households. Hence, under conditions of equality, each female-headed household must have the following land holding:

$$\bar{L}_w + \frac{n_w}{n_m + n_w}\bar{G} \tag{2}$$

where n_w and n_m are the sample sizes of female-headed and male-headed households, respectively, and $\frac{n_w}{n_m + n_w}$ is the share of female-headed households in the combined sample.

A radical land redistribution policy intended to reduce gender inequality in land ownership must transfer land to female-headed households whose land sizes are less than the quantity given in Equation 2. Equation 2 therefore defines the farm size per average female head under conditions of gender equality. A radical transformation of land ownership intending to achieve gender equality will attempt to push the existing average land holding of female-headed households ($\bar{L}_w$) towards the quantity presented in Equation 2. The issue is then to investigate the household income, consumption and the poverty implications of increasing the land holding of female-headed households from the existing sizes. The paper therefore considered $\bar{L}_w$ as the threshold of the running variable (land size). Female-headed households with land sizes greater than $\bar{L}_w$ were regarded as treated, as they portray the obtainable situation of a policy that deliberately attempts to increase the land holding of women. Hence, they were assigned a value of 1, and those with land sizes less than or equal to $\bar{L}_w$ were regarded as untreated and assigned a value of zero. The key characteristic of this design is that the probability of being treated conditional on land size, L_{wi}, jumps discontinuously at the cutoff point, prompting variation in treatment assignment that is assumed to be unrelated to potential confounders (Calonico et al., 2014).

The land size variable used to determine treatment is subject to random variability due to the nature of ZIMSTAT's sampling procedure and measurement errors. Hence, female-headed households that are immediately above and below the cutoff point must be the same, in expectation, on all observed and unobserved pre-treatment characteristics such as education, age and household size, among other things, exactly as in a randomized controlled trial (Calonico et al., 2014; Wooldridge, 2009). A robustness test in RDD involves testing this assertion. Causal effect can be estimated by simply comparing outcomes of female-headed households immediately above the cutoff and those immediately below the cutoff point. However, it is important to note that the causal effect estimates need to be complemented with descriptive statistics as these estimates may be far from accurate (Lawry et al., 2017).

As in Imbens and Lemieux (2008) and Wooldridge (2002), this paper adopted a potential-outcomes framework commonly used in impact evaluation literature. The paper defines treatment ( ) as:

$$T_i = \begin{cases} 1 \; if \; L_{wi} > \bar{L}_w \\ 0 \; if \; L_{wi} \leq \bar{L}_w \end{cases} \tag{3}$$

By letting Y be the outcome variable representing consumption, income and poverty, we have a PICES random sample $[Y_i(0), Y_i(1), L_{wi}]$ for $i = 1, \cdots, n$ from a population $[Y(0), Y(1), L_w]$, where $Y(0)$ and $Y(1)$ are potential outcomes with land size less than or equal to the threshold and greater than the threshold, respectively. Poverty in this section was measured using consumption and income. Hence, only two outcomes were evaluated. The observed outcome, Y_i, can be expressed as:

$$Y_i = \begin{cases} Y_i(0) \quad if \; T_i = 0 \\ Y_i(1) \quad if \; T_i = 1 \end{cases} \tag{4}$$

To measure the impact of improved gender equality in land ownership on the outcome variables, we require the potential outcome of the female-headed household without additional arable land (observed outcome) and the potential outcome of the same female-headed household if given additional land (counterfactual outcome). The inference is therefore counterfactual, an outcome that would have happened if the female-headed household were given additional land. In other words, the impact of increased land holding for female-headed household on income, consumption and poverty on the same household cannot be measured; a condition referred to as the problem of missing data (Dimara and Skuras, 2003). However, individual causal effect can be extended to measure the causal effect of all female-headed households, known as the average treatment effect (ATE). From the sample, we can identify the average treatment effect (β) at the cutoff, which is non-parametrically estimated under mild continuity conditions (Hahn et al., 2001) as:

$$\beta = E[Y_i(1) - Y_i(0) | L_{wi} = \bar{L}_w] = \lim_{l \downarrow \bar{L}_w} E[Y_i | L_{wi} = l] - \lim_{l \uparrow \bar{L}_w} E[Y_i | L_{wi} = l] \quad (5)$$

The parameter β is computed from non-parametric kernel polynomial functions from either side of the cutoff point. β measures the impact of a marginal increase of the mean land holding of female-headed households on the outcome variables. One of the approaches to estimating β would be to compare means in a range of L_{wi} above and below the cutoff. However, these averages will be biased estimates of the true averages at the limit, as $L_{wi} \rightarrow \bar{L}_w$, if $E[Y_i | L_{wi}]$ is non-zero on either side of the threshold. This paper estimated a local linear polynomial regression model to alleviate the biases inherent in the β generated from comparing the means of the treated and untreated groups. The paper estimated the following linear polynomial with two parts, one regression for the treated and the other for the non-treated:

$$\begin{array}{ll} Y_i = \pi_- + \gamma_-(L_{wi} - \bar{L}_w) + \varepsilon_{-,i} & | Y_i = \pi_+ + \gamma_+(L_{wi} - \bar{L}_w) + \varepsilon_{+,i} \\ for\ L_{wi}^{min} \leq L_{wi} \leq \bar{L}_w & | for\ \bar{L}_w < L_{wi} \leq L_{wi}^{max} \end{array} \quad (6)$$

where min and max are minimum and maximum values, respectively. π_- and π_+ are intercepts of the control and treated regressions, respectively, while γ_- and γ_+ are slope parameters of the control and treated regressions, respectively. $\varepsilon_{-,i}$ and $\varepsilon_{+,i}$ are, respectively, the error terms of the control and treated regressions assumed to be uncorrelated with $L_{wi} - \bar{L}_w$. The optimal bandwidth, L_{wi}^{min} and L_{wi}^{max}, was selected using the optimal plug-in developed by Imbens and Kalyanaraman (2012) and later refined by Calonico et al. (2014). The estimated unbiased average treatment effect at the threshold, also known as the local average treatment effect (LATE), is therefore given by:

$$\hat{\beta} = \hat{\pi}_+ - \hat{\pi}_- \quad (7)$$

As the probability of being treated conditional on land size, L_{wi}, jumps discontinuously at the cutoff point and that the nature of the running variable leads to non-compliers, a sharp RD model was applied in this paper. Model stability was therefore tested using the treatment effect derivative (TED) instead of the compliers' probability discontinuity (CPD), which is more appropriate for fuzzy RD models. The TED command allows for the estimation of LATE and TED in sharp RD models and CPD in fuzzy RD models. If TED is significantly different from zero then the LATE estimate will be considered unstable (Cerulli et al., 2016).

The third question was answered through a simple regression technique. For this question, the paper followed the methodology applied by Adhikari and Bjørndal (2014) and Jayne et al. (2003). After generating district level variables from the PICES data, we regressed district-level poverty measures (income inequality, assets inequality, headcount) on land inequality, gender disparity in land ownership, and other control variables. A simple ordinary least squares (OLS) model with robust standard errors was estimated. The estimated model is:

$$pov_i = \beta_0 + \beta_1 LEQ_i + \beta_2 WOM_i + \boldsymbol{X\varphi} + \varepsilon_i \quad (8)$$

where pov_i is a poverty measure at district level, LEQ_i is a measure of land inequality at District level, WOM_i is the share of women owning agricultural land in district i, $\boldsymbol{X}$ is a vector of control variables which include, among other things, the percentage of household heads who have completed secondary and tertiary education in a district, average household size in a district, percentage of resettled households, and average farm size in a district. β and $\boldsymbol{\varphi}$ are the estimated vectors of parameters. The term ε is the error term assumed to be independent and identically distributed with a mean of zero and a constant variance. Robust and clustered standard errors were applied to correct problems arising from the nature of the data (district clustering).

Three measures were applied for the dependent variable (pov), namely, pov_lower, pov_upper and $pov\_extreme$. Three poverty lines, lower equals \$45.61, upper equals \$66.13 and extreme equals \$29.76, were applied by ZIMSTAT in PICES 2017 to estimate the three poverty measures. In this paper, the proportion of the poor in each district was estimated for each poverty measure using the PICES household data. Similarly, the independent variables were estimated for each district using household level data. Land ownership inequality (LEQ) was estimated for each district using the $adgini$ command in STATA that produces a Gini coefficient for each district. The share of women owning land (WOM) was also computed for each district. The other variables used in the paper are the share of household heads who completed secondary education (Sec_edu), the share of household heads who completed tertiary education ($Tert\_edu$), the share of resettled farmers ($Reset$), average farm size in a district ($farm\_size$) and the average household size ($hhsize$) in each district. Land was measured in acres, household size in numbers, land inequality as a Gini coefficient and the rest were measured as shares. In this paper, farm size refers to the size of the overall farm owned while a parcel is a specific geographical unit that contains plots. So, within the same farm there may be several parcels or several plots within a parcel.

In a market system where land is purchased from the market, land inequality may be endogenous in the poverty model. However, in Zimbabwe rural land is not purchased from the market but is rather provided through inheritance and community leaders. Hence, there is no need to be concerned about the endogeneity of the land inequality variable. The paper notes that although employment has been established as a key determinant of poverty by previous studies, rural households have similar activity. As a result, there is no significant variation in the type of activity among rural households. The PICES data support this assertion. There were less than 7% household heads with a wage employment. Therefore, activity was not considered in the poverty model.

4. Findings and discussion

Descriptive statistics

Households who responded to the questions on plot sizes and area under cultivation in the APM module were matched to a total of 2,259 rural households in the poverty module. Of these 2,259 households, 2,206 households answered the question on sex of the household head. About 38% of household heads were female and 62% were male. A larger number of households (52%) were from communal areas, 44.3% were from resettlement areas and the remainder (3.7%) were from large-scale and small-scale commercial farming areas. A majority of the 927 respondents from resettlement areas were from old resettlements (471) and A1 (450). Only 6 were from A2 farms. Distributions of some variables in female-headed households are presented in Appendix A.

The overall average plot size for both male and female-headed households was 10.02 acres while the average planted area as measured by GPS was 2.6 acres. The findings demonstrate that, on average, female-headed households own smaller plot sizes than male-headed households. The average gender gap in land ownership as defined in Equation 1 in the previous section is about 2.1 acres. On average, male-headed households own 2.1 acres more than female-headed households, which translates to 0.6 acres per capita. This mean difference is statistically significant at the 1% level (see Table 1). This confirms the assertion that women own smaller portions of arable land than men in Zimbabwe. In addition, land ownership inequality is higher for female-headed households than male-headed households. The plot size Gini coefficient for female-headed households (0.756) is larger than that of male-headed households (0.733). Similarly, the Gini coefficient for per capita farm size is larger for female-headed households than male-headed households. These statistics are further buttressed by the nature of land tenure systems. Of the 2,199 households who responded to the question on tenure, 607 female-headed households indicated that they own their plots against 990 male-headed households. Table 2 presents ownership statistics by sex of household head.

Table 1: Mean differences between male and female-headed households

Characteristic (mean)	Male-headed (n_m=1,374)	Female-headed (n_w=832)	Total (n=2,206)	Difference
Farm size (acres)	10.8	8.7	10.02	2.1***
Farm size Gini	0.733	0.756	0.738	-0.023**
Per capita farm size Gini	0.698	0.804	0.728	-0.106**
Monthly income ($)	188.5	163.0	178.9	25.5***
Household size	4	4	4	0
Per capita farm size (acres)	2.8	2.2	2.5	0.6***
Per capita income ($)	47.1	40.8	45.6	6.3***
Per capita consumption	36.3	37.9	36.8	-1.6***

***, ** and * indicate that the difference between the means of male-headed and female-headed households is statistically significant at the 1%, 5% and 10% level, respectively. Difference in means was tested using z-tests for equality of means.

Table 2: Number of households owning land by sex of household head

Head sex	Arable land ownership or access			
	Owned	Free access[1]	None	Total
Female-headed households	607	108	114	829
Male-headed households	990	210	170	1370
Total	1597	318	284	2199

Source: Authors' computation.

Despite having smaller plots, on average, $25.5 less real monthly income and $6.3 less per capita income than male-headed households, the results demonstrate that female-headed households have a larger real consumption per capita. Monthly real per capita consumption is $1.6 larger for female-headed households than male-headed households. This points to the importance of women in poverty alleviation. Women utilize the available resources more effectively than men in poverty alleviation. In other words, women prioritize household consumption more than men. The results in Table 3 reinforce the importance of women in poverty alleviation as they demonstrate that the percentage of poor female-headed households is smaller than that of poor male-headed households despite the skewed distribution of land and income resources favouring male-headed households. About 46.4% of female-headed households are non-poor compared to only 38.5% of male-headed households. A poor household is one with a monthly income below the poverty datum line (PDL); a lower PDL of $45.6 in PICES was applied in this paper.

Table 3: Proportion of poor households by sex of household head

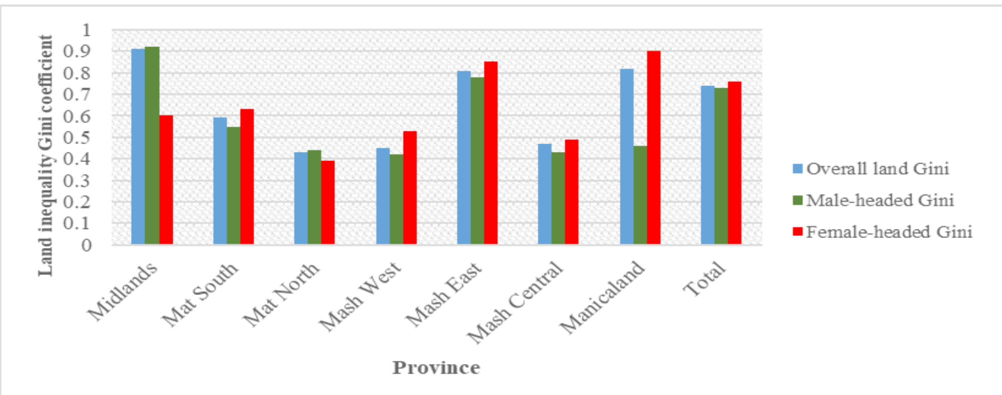
	Observations	Percentage of poor	Percentage of non-poor
Male-headed	1,374	61.5	38.5
Female-headed	832	53.6	46.4
Total	**2,206**		

Source: Authors' computation.

Inequality in plot sizes as measured by the Gini coefficient shows that a larger part of arable land in the hands of female-headed households is owned by a minority. Among the eight largely rural provinces of Zimbabwe, the land inequality Gini coefficient for female-headed households is larger than that of male-headed households, except in Mat North and the Midlands. Despite being smaller than that of male-headed households, the land inequality Gini coefficient for female-headed households in the Midlands is still substantially large (0.60). Only Mat North, Masvingo and Mash Central have land inequality Gini coefficients below 0.5. Figure 2 illustrates provincial inequalities in plot sizes as measured by the Gini coefficient. In some provinces, such as the Midlands, the Gini coefficient is largely driven by men, while in others such as Manicaland it is driven by women. These differentials may be a result of differences in traditional or cultural practices. For example, the patriarchy system is stronger in Manicaland than in the Midlands, hence fewer women are likely to own land in Manicaland, thereby driving inequality. This finding suggests that radical agricultural policies for inclusive growth may require the annihilation of some cultural practices.

The descriptive findings generally agree with the previous findings that rural women own less arable land than men and that inequality in land ownership among women is substantially higher in developing countries (Doss et al., 2015; FAO, 2011; Allendorf, 2007). However, what is fascinating about the descriptive statistics is that besides having a larger inequality in land distribution, female-headed households have smaller arable land sizes and lower monthly incomes, but larger real per capita consumption and a smaller proportion of poor than male-headed households. This kind of a paradox makes it even more crucial to investigate the impact of a policy that attempts to address rural poverty through correcting gender inequality in land ownership.

Figure 2: Provincial inequality in arable land size



Source: Authors' illustration using computations from APM.

Regression discontinuity design

Building on the work by Cippolina et al. (2018) and Lawry et al. (2017), which shows that causality measurement is a complex process, we present our causality findings as a complement to the descriptive statistics presented earlier. We take caution and rely more on descriptive statistics and relate them to the causality findings. As with any other study, a statistical measurement of causality is never accurate as there are multiple other factors that make it difficult to accurately apportion the change in a variable to a specific factor. In this regard, all causality findings must be read in conjunction with descriptive statistics.

The running variable, land size, was corrected for outliers or data points that differ significantly from other observations. For example, the maximum farm size was 3,207.6 acres and the average farm size was only 10.02 acres, suggesting the presence of outliers. The outliers were a result of the few households from the commercial farming sector who own large farms. Around 95.1% of households had farm sizes or plot sizes smaller than 15 acres. Only 4.9% of the observations on farm size, largely from the commercial farming sector with more than 100 acres, were identified as outliers. However, this was not a problem in this section as only female-headed households were considered in the analysis. A total of 798 female-headed households remained after some cleaning. The maximum land holding for female-headed households was 14.8 acres. The threshold as defined in Chapter 3 was established to be =8.7 acres, which translates into 2.2 acres per capita. The findings from the use of per capita land holding were not significantly different from the ones applying land holding because of the similarities in household size between female-headed and male-headed households. The two outcome variables are real per capita consumption and monthly income. These variables are also used to measure poverty. Real consumption per capita is a good measure of welfare and an indicator of a household's poverty. Income is regarded as a measure of welfare opportunity, while consumption is a measure of welfare achievement (Appleton, 2001). Both the outcome variables were logged to improve their distributional characteristics.

The bandwidth estimators for the RD local polynomial regression are presented in Table 4, while the LATE and TED estimators are presented in Table 5 for the two outcomes. However, the paper made use of the CCT method of selecting the optimal bandwidth. Graphical findings are provided in Figure 3.

Table 4: Bandwidth estimators for the two outcome variables

Outcome variable	Method	h	b	rho
Consumption per capita	CCT	3.57665	4.343398	0.8234681
	IK	5.363546	5.978249	0.8971766
	CV	5.892492	NA	NA
Monthly income	CCT	1.945873	2.81595	0.6910185
	IK	4.815681	3.895824	1.236114
	CV	5.8263	NA	NA

Calonico et al. (2014) proposed the CCT method, Imbens and Kalyanaraman (2012) the IK method and the CV (cross validation) method was proposed by Ludwig and Miller (2007).

Table 5: Local average treatment effect (LATE) and treatment effect derivative (TED)

Outcome = consumption	Coefficient	Std. Err	z-statistic	p-value
LATE	-0.408	0.317	-1.28	0.199
TED	-0.176	0.417	-0.42	0.673
Outcome = monthly income	**Coefficient**	**Std. Err**	**z-statistic**	**p-value**
LATE	-0.668	0.715	-0.93	0.350
TED	-0.258	1.123	-0.23	0.818

***, ** and * indicate that the coefficient is statistically significant at a 1%, 5% and 10% level, respectively. The main regressions and other statistics generating these estimators are presented in Appendixes B and C.

The findings presented in Table 5 show that the coefficient of TED is statistically insignificant in both models. In other words, the coefficient is not statistically different from zero. This indicates that the RD models are both stable. The RD model with either consumption or income as outcome variable is stable. Robust checks using graphs also indicate that female-headed households closer to the cutoff from below and above have similar characteristics and, for this small group, the RDD line shows some form of continuity. However, the findings show that a policy that deliberately increases the mean farm size of female-headed households will not yield any income and poverty-reduction benefits among female-headed households. In other words, there are no positive returns in household consumption and income among female-headed households from an increase in farm size above the cutoff 8.7 acres. These findings are in line with the descriptive statistics which indicate that despite having larger farms, male-headed households have a smaller consumption per capita and are poorer than female-headed households. The findings suggest that in communal areas, women average farm sizes smaller than 8.7 acres may be beneficial for poverty alleviation.

Figure 3: Regression discontinuity graphs

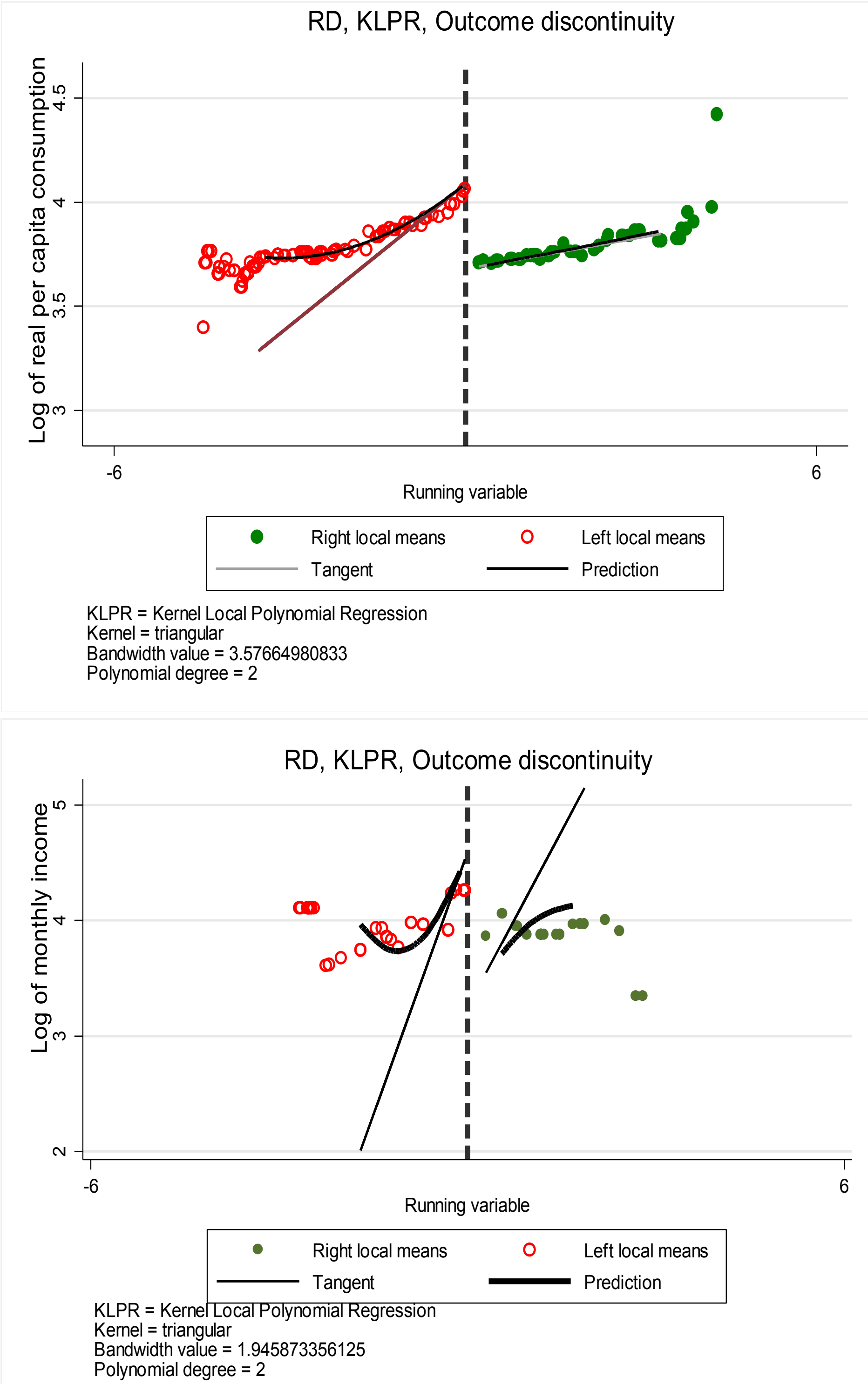


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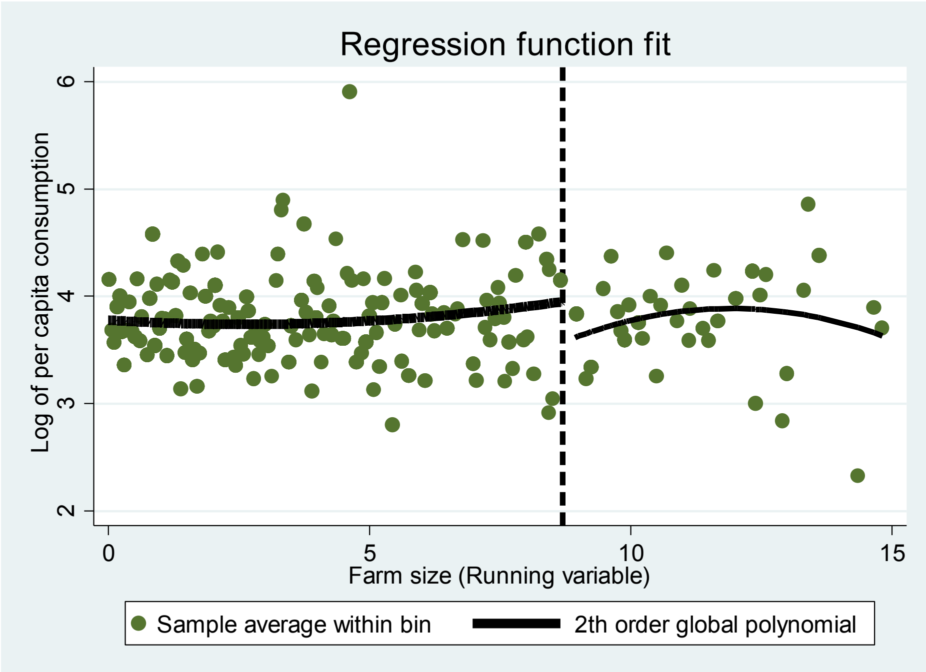
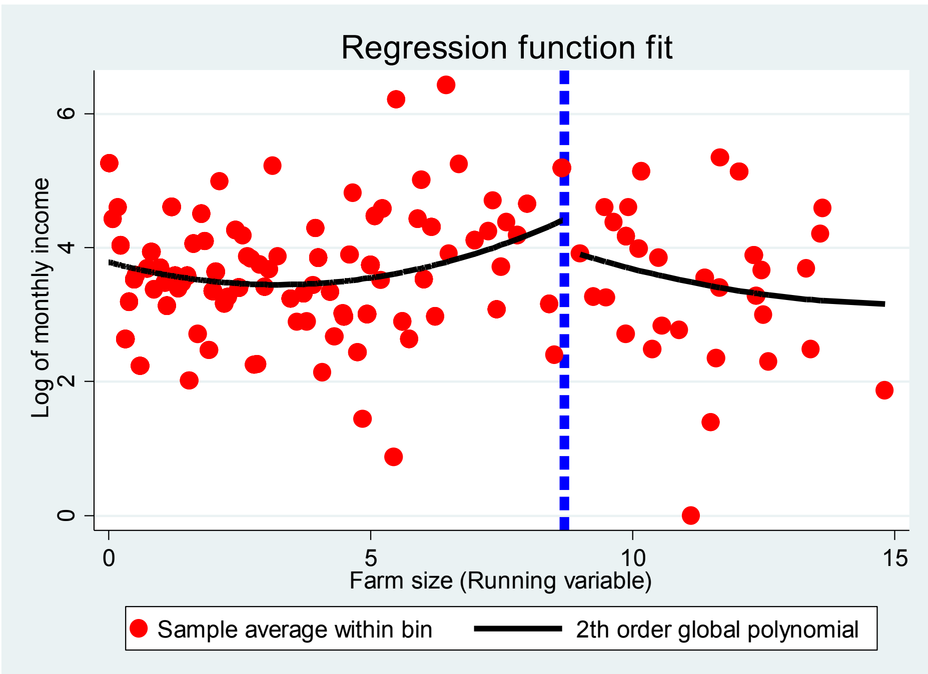
Figure 3 Continued





The graphs in Figure 3 demonstrate that female-headed households with larger farm sizes exceeding 8.7 acres have lower per capita household consumption and income despite this impact being statistically insignificant. The findings suggest an optimal farm size effective for poverty alleviation to be smaller than 8.7 acres in communal and resettlement areas. But a majority of the 798 female-headed households (55%) have farm sizes smaller than 3 acres and about 37% are at the lower end with less than 2 acres, which is less than the per capita average of 2.2 acres. This is the reason why the RDD findings are not significant at high cutoff points. However, increasing the farm size of the 55% of households with smaller land sizes by a marginal unit can significantly improve their incomes. The RDD-based simulation findings presented in Table 6 demonstrate that increasing land holding for this group is beneficial.

Table 6: LATE estimators from varying lower cutoff points with income as outcome

Cutoff (acres)	% of female-headed households with farm sizes smaller than or equal to cutoff	LATE coefficient	Std. Err	z-statistic
2	37	2.314	0.847	2.73***
3	55	0.890	0.457	1.95*
4	65	-0.261	0.431	-0.60

***, ** and * indicate that the coefficient is statistically significant at a 1%, 5% and 10% level, respectively.

The LATE for female-headed households with land sizes smaller than 3 acres is positive and statistically significant. For example, using a cutoff of 2 acres, we establish the coefficient of LATE to be 2.314 and statistically significant at the one-per-cent level. Similarly, with a cutoff of 3 acres the coefficient is still positive but weakly significant at the 10-per-cent level. Larger land sizes, exceeding 4 acres, are not beneficial to poverty alleviation in the rural areas of Zimbabwe. A land policy designed to reduce gender inequality will only have positive spillover effects in poverty alleviation if it targets women at the lower end of land distribution. In other words, land distribution policy must target a majority of women (55%) with less than 3 acres of arable land in order to improve household income and consumption. Hence, land redistribution policies aimed at reducing poverty among rural women must aim at reducing land inequality among rural households rather than increasing the average land holding of women. Increasing farm sizes for women at the lower end is crucial for reducing inequality and improving the households' poverty status. These findings tally with those of Jayne et al. (2003), Deininger (2003), and Ravallion and Datt (2002) who argue that reducing land inequality will have a direct impact on the incomes of the poor who benefit from the transfers.

Figure 4: RDD with different cutoff points

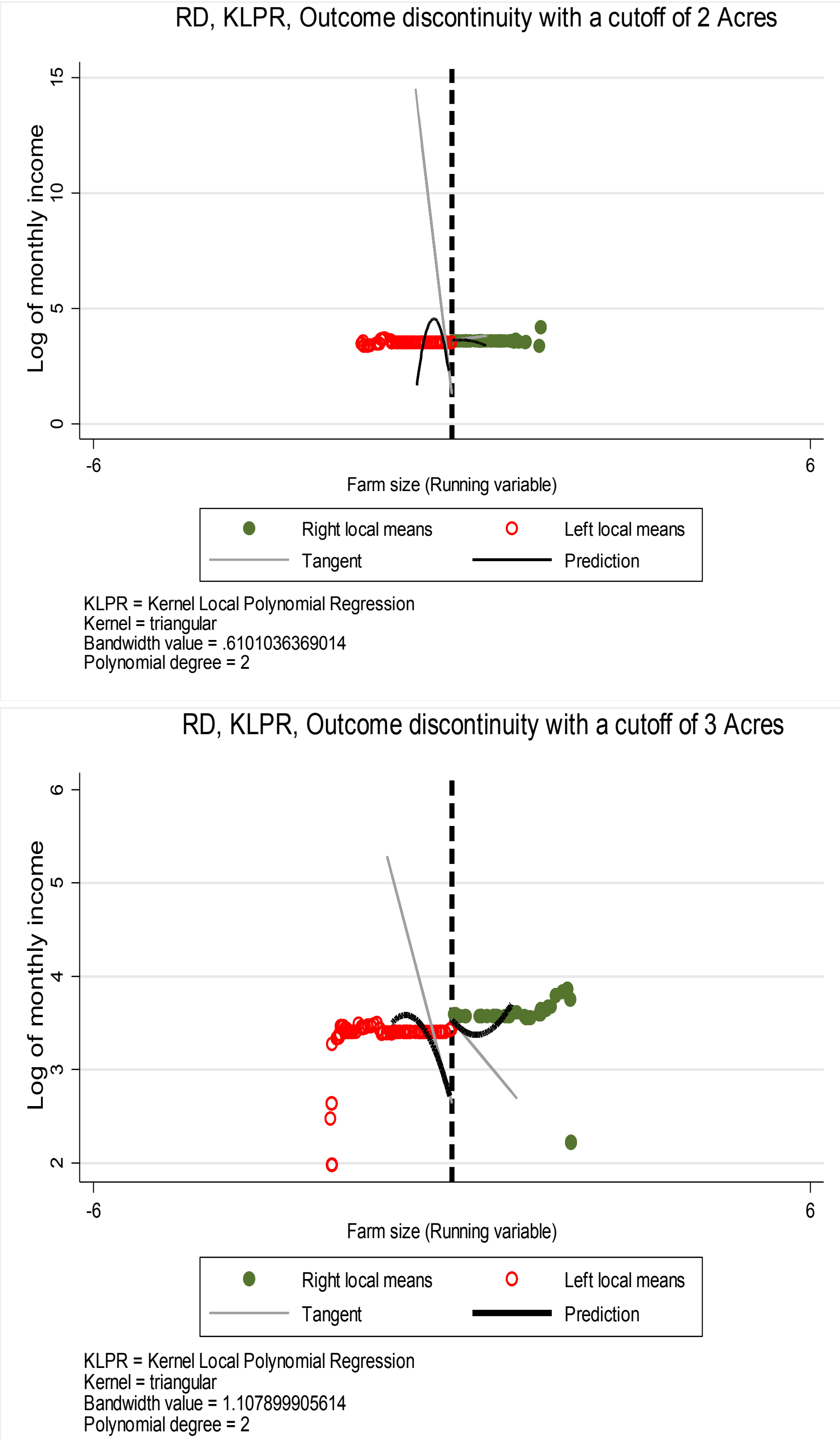


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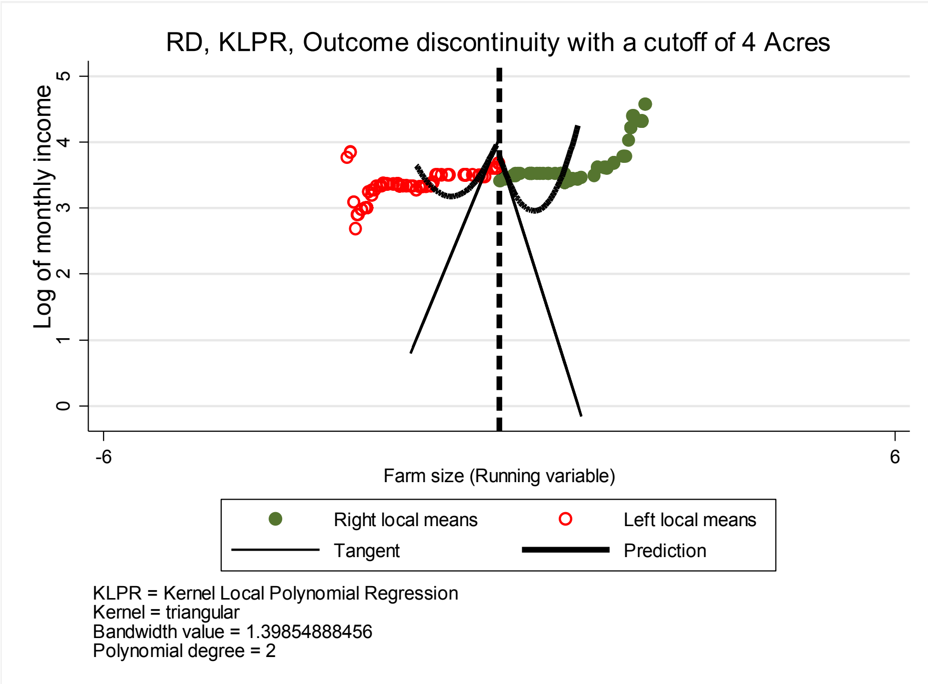
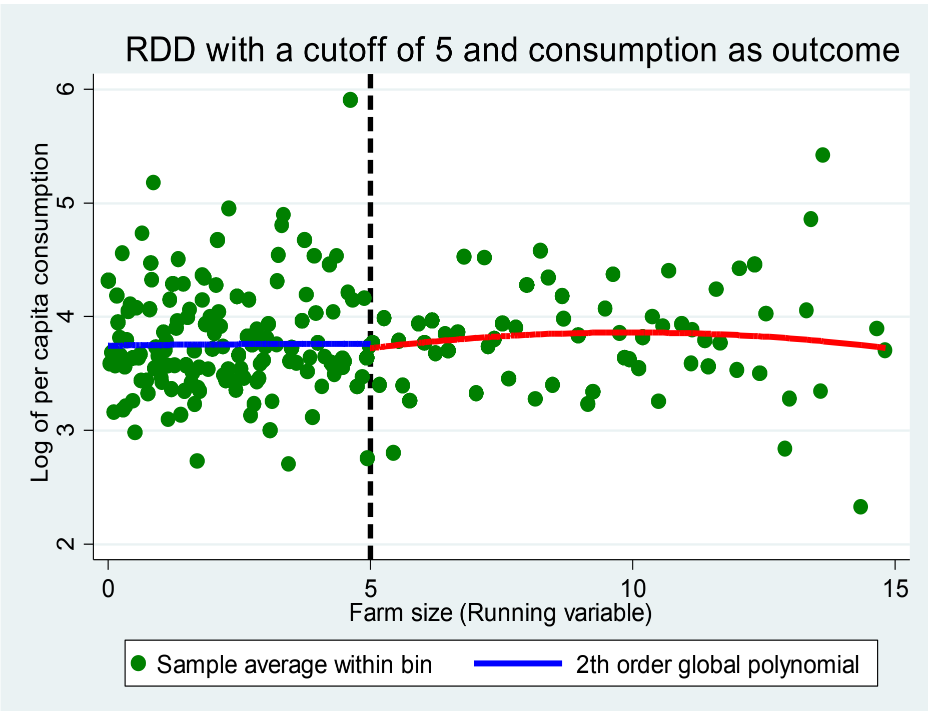
Figure 4 Continued





Regional (District) gender disparity in land ownership and poverty association

A total of 60 rural districts with a total of 2,206 households were considered in this part of the analysis. Continuous household level variables were collapsed to provide district averages, and proportions were also provided at district level. The mean number of households in each district was 37 with a minimum of 6 and a maximum of 67 households. Table 7 presents the descriptive statistics of the variables applied in the poverty, land inequality and gender disparity model.

Table 7: Descriptive statistics

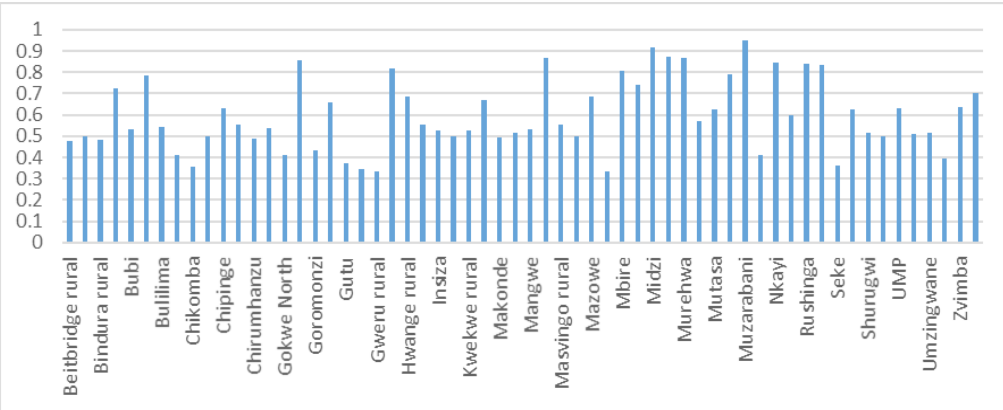
Variable	Observations	Mean	Std.Dev.	Min	Max
pov_lower	60	0.596	0.166	0.333	0.952
pov_upper	60	0.802	0.097	0.576	1
$pov\_extreme$	60	0.306	0.155	0.056	0.667
LEQ	60	0.520	0.184	0.257	0.950
WOM	60	0.376	0.130	0.043	0.656
Sec_edu	60	0.397	0.130	0.091	0.750
$Tert\_edu$	60	0.047	0.048	0	0.231
$hhsize$	60	4.857	0.484	3.969	5.969
$farm\_size$	60	9.342	13.261	1.348	78.706
$Reset$	60	0.330	0.299	0	1

pov_lower is proportion of poor using lower poverty line, pov_upper is proportion of poor using upper poverty line, $pov\_extreme$ is proportion of poor using food extreme poverty line, LEQ is measure of land inequality, WOM is share of women owning arable land, Sec_edu is share of household heads with completed secondary education, $Tert\_edu$ is share of household heads with completed tertiary education, $hhsize$ is household size, $farm\_size$ is farm size and $Reset$ is share of resettled farmers. All variables are measured at district level. For detailed definitions refer to Chapter 3 of the methodology.

Mean district level poverty is 59.9% if a lower poverty line is applied, 80.2% for an upper poverty line and 30.6% for extreme poverty. Households in some districts are all poor when using the upper poverty line. There is a high variability of poverty across districts, as shown in Figure 5. The mean inequality in land ownership is 0.52

as measured by the Gini coefficient, while the district average share of female-headed household owning land is 37.6%. Some districts have less than a 10-per-cent share of women owning arable land, while others exceed 50%. The district with the minimum share has only 4.3% female-headed households owning arable land while the district with the maximum has 65.6%. The average farm size in a district is 9.3 acres, with a minimum of 1.3 acres and a maximum of 78.7 acres. There are very few household heads with a tertiary education. The number is significantly very small and is zero in some districts. It was therefore not appropriate to use tertiary education in the regressions. Instead, secondary education was used. The mean share of household heads who completed secondary education in a district is 39.7% with a maximum of 75%.

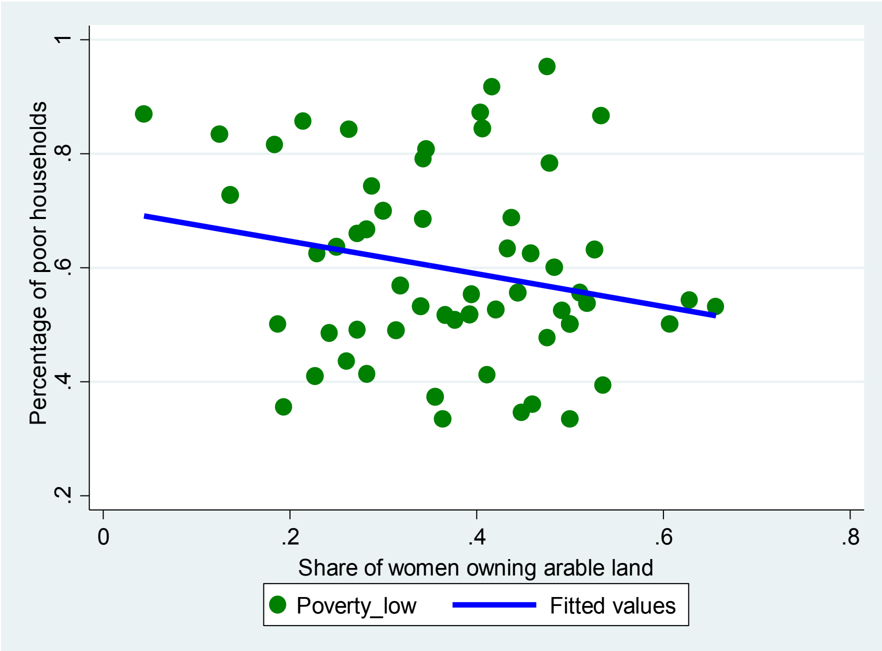
Figure 5: Proportion of poor households



Source: Authors' illustration.

The scatter graphs in Figure 6 reveal that districts with a larger share of women owning land are associated with smaller proportions of poor households. There is a negative correlation between the proportion of poor households and the share of women who own arable land. However, this is not the case with land size inequality. There is no clear association between poverty and inequality in land ownership. The scatter graphs show the nature of correlation between variables, but cannot provide the impact of a change in one variable on the other. It is therefore crucial to support the results from the scatter graphs with regressions. Regressions with robust standard errors are presented in Table 8.

Figure 6: Scatter plots of poverty against gender and land inequality



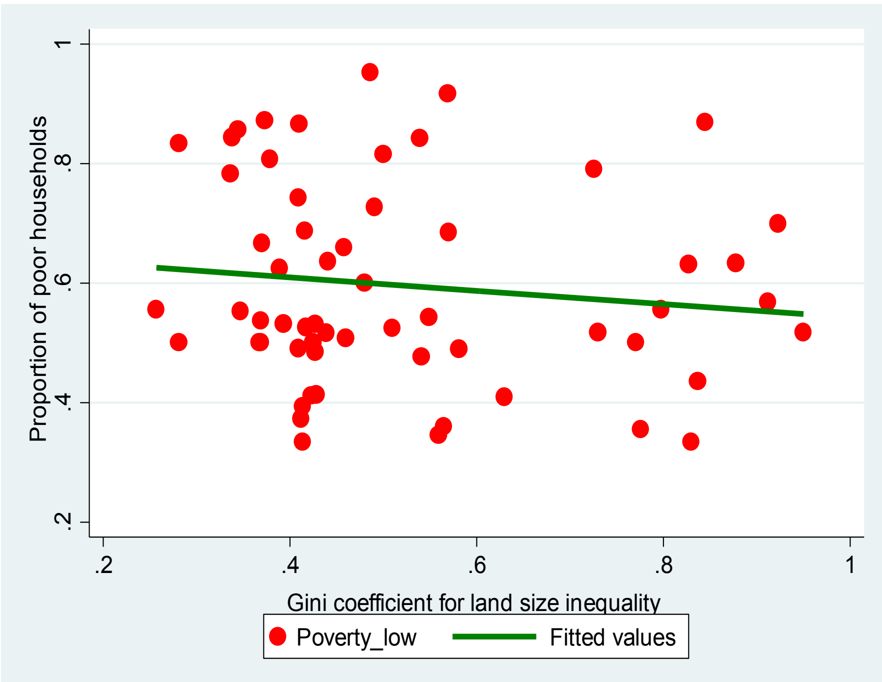


Table 8: Regression results

Variables	(1) *pov_lower*	(2) *pov_upper*	(3) *pov_extreme*	(4) *pov_lower*	(5) *pov_lower*
LEQ	-0.177	-0.0918	-0.0682	-0.108	
	(0.147)	(0.0784)	(0.138)	(0.0999)	
WOM	-0.327*	-0.199**	-0.402**	-0.339*	-0.334*
	(0.181)	(0.0929)	(0.161)	(0.178)	(0.177)
Sec_edu	-0.110	-0.109	-0.00474	-0.118	-0.146
	(0.190)	(0.102)	(0.184)	(0.186)	(0.178)
hhsize	0.0271	0.0281	0.0108	0.0331	0.0356
	(0.0448)	(0.0232)	(0.0385)	(0.0434)	(0.0443)
farm_size	0.00138	0.000874	0.000981		-0.000317
	(0.00156)	(0.000723)	(0.00123)		(0.000873)
Reset	-0.0436	-0.0696*	-0.0632	-0.0392	-0.0367
	(0.0723)	(0.0411)	(0.0682)	(0.0722)	(0.0717)
Constant	0.725**	0.846***	0.454*	0.679**	0.622**
	(0.293)	(0.148)	(0.257)	(0.282)	(0.279)
Observations	60	60	60	60	60
Ramsey RESET F	0.51	0.11	0.80	0.83	0.90
Ramsey Prob>F	0.68	0.95	0.50	0.48	0.45
R-squared	0.106	0.176	0.122	0.100	0.087

Robust standard errors are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Although the R-squared values are very low for the five models in Table 8, the Ramsey regression equation specification error test (RESET) for specification indicates correctly specified models; this test is also supported by the absence of heteroscedasticity. The p-values of the Ramsey test are greater than 5% in all five models. In this case, the hypothesis that the models are correctly specified cannot be rejected. Furthermore, in the absence of robust standard error, the findings in Appendix D support the absence of heteroscedasticity. A low R-squared value in models with cross-sectional data is not an unusual scenario. It is common to have such values. Robustness can be shown by the consistency of significant coefficients despite changing and dropping some variables. For example, the coefficient of *WOM* remains negative and statistically significant in all models despite a change in the measurement of poverty and dropping the land size variable or land inequality variable in models 4 and 5.

The findings demonstrate that women play a major role in poverty alleviation. The coefficient of the share of female-headed households is negative and statistically significant at 10% in models 1, 4 and 5, but significant at 5% in models 2 and 3. Using the lower poverty line, a unit increase in the share of women owning land in a district will reduce the proportion of poor households in a district by about 0.3 units (see models 1, 4 and 5). This finding is in line with the previous finding that resolving gender inequality in land ownership is key for poverty alleviation. Increasing the share of women owning arable land in a district implies reducing gender inequality in the economic sphere. However, the findings suggest that land policies that attempt to improve equality in land ownership without paying attention to women will likely fail to improve the wellbeing of communities. This is demonstrated by the statistically insignificant coefficient of land inequality. Similar findings were established by Fisher and Naidoo (2016) and Cipollina et al. (2018) who argue that the negative impact of land inequality on growth and production is only a long-run phenomenon. In cases where poverty is measured using the upper poverty line, as in model 2, the resettlement of rural households can also help in reducing poverty.

5. Conclusion and policy implications

First, we began this study by investigating the level of inequality and gender disparity in land ownership among rural households. It turns out that the results support the view that women own less arable land than men, as established by Doss et al. (2015), FAO (2011) and Allendorf (2007). The average gender gap in land ownership is about 2.1 acres. On average, male-headed households own 2.1 acres and 0.6 acres per capita more than female-headed households. Land inequality is also larger for female-headed households. Furthermore, male-headed households have higher average incomes than female-headed households. However, what is interesting about the findings is that despite having smaller arable land sizes and lower monthly incomes than male-headed households, female-headed households have a larger real per capita consumption and a smaller proportion of poor households. It seems that women spend a larger proportion of their incomes on household consumption, and they better utilize agricultural land compared to men. The major implication of this finding is that women play a major role in poverty alleviation. Hence, empowering women will not only improve gender equality but will also have positive spillover effects on poverty alleviation and food security.

Second, we asked whether there is an association between farm size of female-headed households and household consumption and income. The answer to this question from the RDD approach turns out to support policy interventions that can increase arable land size for women owning less than 3 acres. The findings show that the current average of 8.7 acres for women owning land is inflated by very few women owning large farms. Hence, increasing this overall mean will not have any returns in poverty alleviation and gender equality. Over 55% of female-headed households own an average of less than 3 acres, and more than the first quartile own less than 2 acres. The key implication of the findings is that policies that only look at increasing arable land for women but pay less attention to the bottom group, or those owning less than 3 acres, will be ineffective in poverty alleviation. A good example of such policies or interventions is that of Zimbabwe during the FTLRP, which set aside 20% of redistributed land for women. But the question is, what if the 20% is given to only one or a few women or even taken by women with already large farms? The policy will not bear any fruit in poverty alleviation under such circumstances. The results imply that effective redistributive land policies in poor countries are those targeting the bottom group of women without or with very few acres of arable land.

Third, we asked whether land inequality and gender disparity influence the spatial distribution of poor households. The answer turns out to support previous studies that indicated that increasing the proportion of women owning land in a district can substantially reduce the number of poor households in that district (Fonjong, 2016; Doss et al., 2015; Behrman et al., 2012). Similar to the RDD findings, the findings for this question point to the importance of correcting regional gender disparity in land ownership. However, the results suggest that policies that are targeted at correcting land inequality without paying attention to increasing the share of women owning arable land are likely to be ineffective in poverty alleviation. The implication of the findings is that land policies must be gender sensitive to be effective in poverty alleviation. The spatial distribution of poor households in districts is significantly explained by variations in gender disparity in land ownership. Areas with larger shares of women owning land are associated with smaller proportions of poor households.

Generally, the results reveal a gender gap in land ownership and a higher level of land inequality among female-headed households. Despite this gender gap in plot sizes, the proportion of poor female-headed households is smaller than that of male-headed households. Therefore, the government can take substantial strides towards simultaneous achievement of Goal 5 on gender equality, Goal 8 on inclusive growth and Goal 1 on poverty elimination if land policies are designed to provide arable land to women without it and to increase plot sizes for over 30% of women owning less than 2 acres. The major policy implication of the findings is that any land redistribution policy aimed at achieving gender equality in land ownership and reducing poverty must pay attention to women at the lower end of plot size distribution. Intervention must not only target women, but must be designed to include disadvantaged women without arable land in rural areas.

Notes

1. Free access means having access to the land at any time despite not owning it. This is basically communally owned land.

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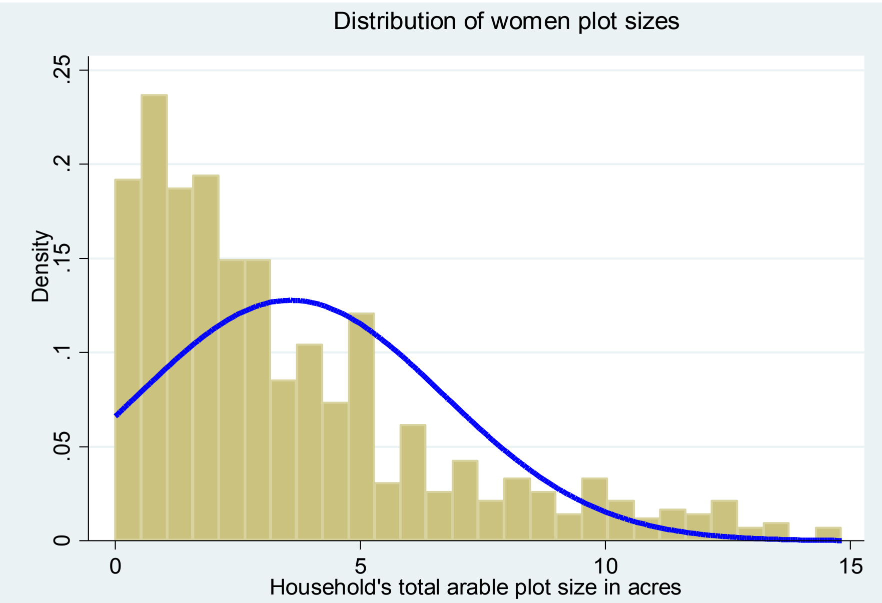
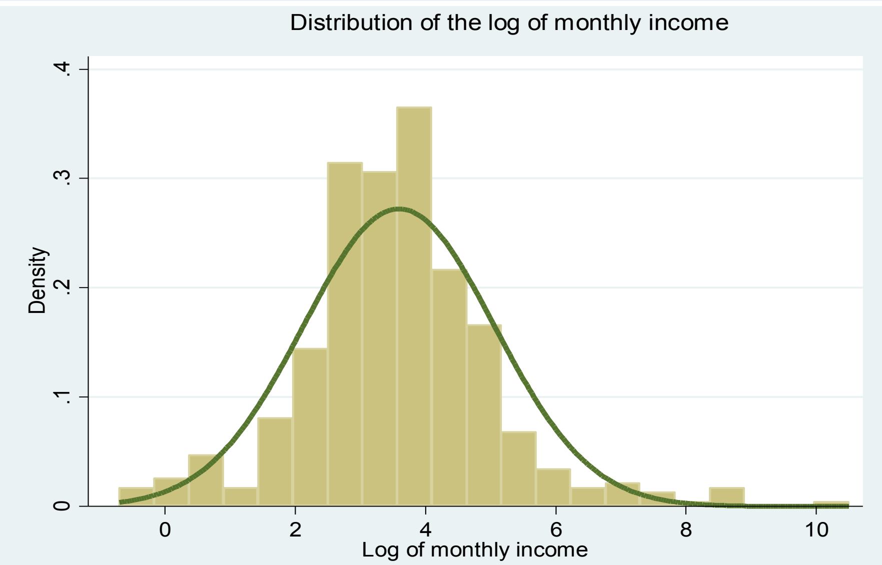
Appendices

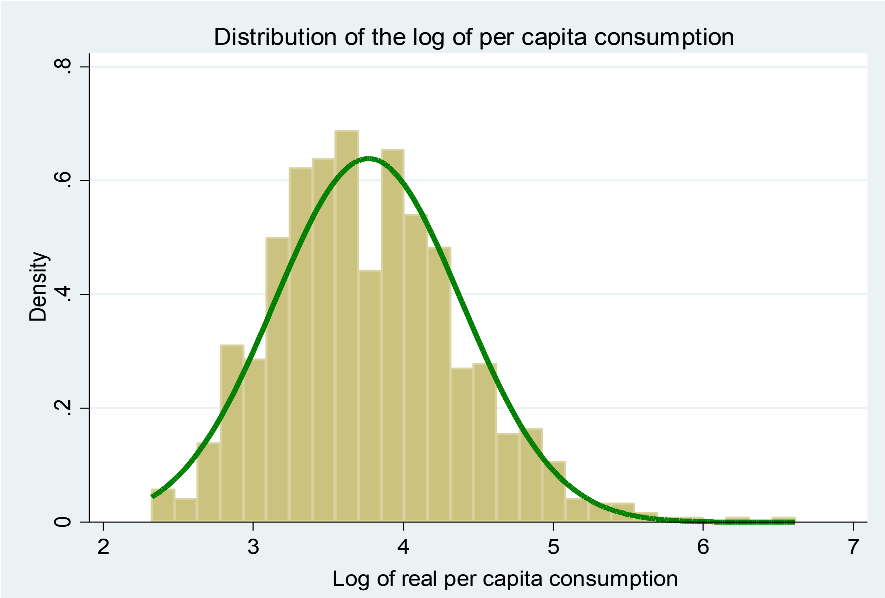
Appendix A: Distribution of selected variables in female-headed households

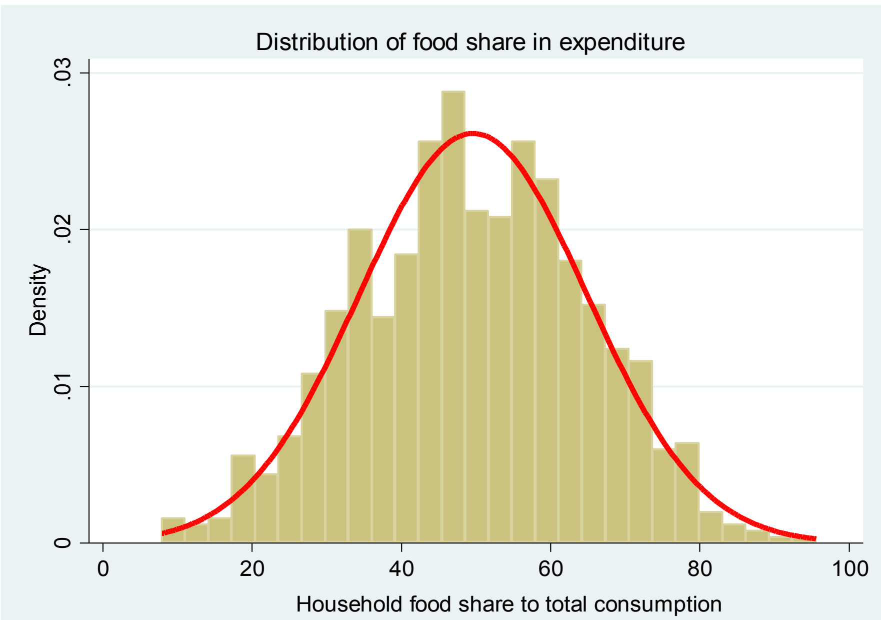




continued next page

Appendix A Continued





APPENDIX B: Regression on Real Per Capita Consumption

```
. ted y1 r treat, model(sharp) h($band) c($r_star) m($M) l($L) k($kernel) graph vce(robust)
(157 real changes made)

------------------------------------------------------------------------------------------------
*******************************************************************************
*********************** DISCONTINUITY IN THE OUTCOME ***********************
*******************************************************************************
(sum of wgt is   1.0000e+00)

Linear regression                               Number of obs     =        157
                                                F(5, 151)         =       0.93
                                                Prob > F          =     0.4645
                                                R-squared         =     0.0540
                                                Root MSE          =     .49871

------------------------------------------------------------------------------
             |               Robust
          y1 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         _x_1 |   .2267002   .2395512     0.95   0.345    -.2466049    .7000052
         _x_2 |   .0360682   .0700353     0.52   0.607    -.1023075    .1744439
           _T |  -.4077768   .3173907    -1.28   0.201    -1.034877    .2193234
       _T_x_1 |  -.1759755   .4167305    -0.42   0.673    -.9993512    .6474002
       _T_x_2 |  -.0349785   .1194179    -0.29   0.770    -.2709241    .2009672
        _cons |   4.087655   .1780437    22.96   0.000     3.735876    4.439433
------------------------------------------------------------------------------
(728 missing values generated)
(70 missing values generated)
(0 real changes made)
------------------------------------------------------------------------------------------------
*********************** Test of significance for LATE **********************

        LATE:  _b[_T]

------------------------------------------------------------------------------
          y1 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        LATE |  -.4077768   .3173907    -1.28   0.199    -1.029851    .2142975
------------------------------------------------------------------------------
------------------------------------------------------------------------------------------------
*********************** Test of significance for TED ***********************

         TED:  _b[_T_x_1]

------------------------------------------------------------------------------
          y1 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         TED |  -.1759755   .4167305    -0.42   0.673    -.9927523    .6408013
```

APPENDIX C: Regression on Monthly Income

```
. ted y2 r treat, model(sharp) h($band) c($r_star) m($M) l($L) k($kernel) graph vce(robust)
(157 real changes made)

------------------------------------------------------------------------------------------------

******************************************************************************
*********************** DISCONTINUITY IN THE OUTCOME ***********************
******************************************************************************
(sum of wgt is   5.4176e-01)

Linear regression                               Number of obs     =         90
                                                F(5, 84)          =       0.87
                                                Prob > F          =     0.5050
                                                R-squared         =     0.0690
                                                Root MSE          =     1.1578

------------------------------------------------------------------------------
             |               Robust
          y2 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         _x_1 |   .6365959     .642261     0.99   0.324    -.6406106    1.913802
         _x_2 |   .1632493    .1911898     0.85   0.396    -.2169527    .5434512
           _T |  -.6683477    .7152901    -0.93   0.353     -2.09078    .7540851
       _T_x_1 |  -.2580097    1.123296    -0.23   0.819    -2.491807    1.975787
       _T_x_2 |  -.4081905    .3531593    -1.16   0.251    -1.110487    .2941055
        _cons |   4.403913    .4486456     9.82   0.000     3.511732    5.296094
------------------------------------------------------------------------------
(728 missing values generated)
(70 missing values generated)
(0 real changes made)

*********************** Test of significance for LATE **********************

        LATE:  _b[_T]

------------------------------------------------------------------------------
          y2 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        LATE |  -.6683477    .7152901    -0.93   0.350     -2.07029    .7335951
------------------------------------------------------------------------------
------------------------------------------------------------------------------------------------
*********************** Test of significance for TED ***********************

         TED:  _b[_T_x_1]

------------------------------------------------------------------------------
          y2 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         TED |  -.2580097    1.123296    -0.23   0.818    -2.459629     1.94361
------------------------------------------------------------------------------

.
end of do-file
```

APPENDIX D: Pre-robust Heteroscedasticity Tests for Regressions in Table 8

Model 1

```
. hettest

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of Poverty_low

         chi2(1)      =     0.61
         Prob > chi2  =   0.4366
```

Model 2

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of Poverty_upp

         chi2(1)      =     0.07
         Prob > chi2  =   0.7941
```

Model 3

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of Poverty_ext

         chi2(1)      =     1.73
         Prob > chi2  =   0.1881
```

Model 4

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of Poverty_low

         chi2(1)      =     1.09
         Prob > chi2  =   0.2961
```

Model 5

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of Poverty_low

         chi2(1)      =     1.53
         Prob > chi2  =   0.2165
```

Mission

To strengthen local capacity for conducting independent, rigorous inquiry into the problems facing the management of economies in sub-Saharan Africa.

The mission rests on two basic premises: that development is more likely to occur where there is sustained sound management of the economy, and that such management is more likely to happen where there is an active, well-informed group of locally based professional economists to conduct policy-relevant research.

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