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Wealth-related inequalities in adoption of drought-tolerant maize and conservation agriculture in Zimbabwe

Running title: **Wealth related disparities in adoption of climate smart technologies.**

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Abstract

This paper concerns Drought-Tolerant Maize (DTM) and Conservation Agriculture (CA), practices introduced to enhance maize productivity and food security in smallholder maize-based farming systems under a changing climate in Zimbabwe. While these technologies are technically appropriate, there are difficulties with their use by smallholder farmers of relatively lower socio-economic status, as measured through ownership of farm or household assets or endowments. Thus, in this article we sought to quantify and explain wealth-related inequalities in the adoption of DTM and CA in smallholder farming communities and discuss their implications to food security. The analysis used cross-sectional household-level data gathered from 601 smallholder farmers from four districts in Zimbabwe. We found evidence of a pro-rich distribution of inequalities in the adoption of DTM and CA that were mostly explained by differences in household wealth, access to agricultural extension services and size of farm land. No meaningful differences in DTM adoption disparities were found across districts. Significant gender differences were observed for CA, and meaningful differences by district were noted. The results suggest the need for decision makers to consider implementing policies that focus on the poorer segments of the farming society to alleviate any differences in the adoption of such agriculture technologies. For instance, subsidizing the uptake of improved maize varieties including DTM and prioritizing equitable land distribution coupled with specialised extension services for the poor in a cereal-based CA farming system could reduce the observed gap between rich and poor in the uptake of these innovations and consequently improve food security.

Keywords: Climate-smart agriculture · Food security · Socioeconomic inequalities · Smallholder farmers · Concentration index · Zimbabwe

1. Introduction

Significant investment in agricultural production practices (technologies and methods) that improve farmers' food security and resilience against weather-related shocks such as droughts, is one key strategy that can mitigate the associated adverse impacts (Cairns et al. 2013; Davies et al. 2009; Katengeza et al. 2016; Makate et al. 2017; Pangapanga et al. 2012). Maize is one significant value chain in sub-Saharan Africa (SSA), including Zimbabwe, that has been targeted by programs aiming to enhance climate resilience and food security in smallholder farming systems (Fisher et al. 2015; Fisher and Carr 2015; Makate et al. 2017). In Zimbabwe, maize is the most important cereal crop, vital for food security, with average per capita per day consumption estimated to be 248 g (Ranum et al. 2014). The maize crop is at risk due to persistent weather shocks that are evident in some parts of SSA (Fisher and Carr 2015; CIMMYT 2013), yet it is the most important food security staple crop in the region (Mango et al. 2017; Mango et al. 2014; Nyikahadzoi et al. 2012). For instance, Zimbabwe recorded at least twenty drought episodes as measured by the standardized precipitation index between 1900 and 2013 (Masih et al. 2014) which highlights the level of climate risk exposure of the maize crop.

Drought-Tolerant Maize (DTM) – a 'climate-smart' agricultural technology now widely available in Africa, is expected to improve resilience of maize-based farming systems in Zimbabwe, thereby enhancing food security and nutrition (Fisher et al. 2015; Makate et al. 2017) as well as alleviate poverty (Abdoulaye et al. 2018; Jaleta et al. 2018; Lunduka et al. 2017; Wossen et al. 2017). Evidence from Zimbabwe suggests that smallholder farmers that adopt DTM varieties are not only more likely to be food secure for an extended period of time, but also expected to have additional income to boost their food security prospects (Lunduka et al. 2017). A recent study in Ethiopia also showed that in the absence of DTM adoption, the food consumption expenditure of an ordinary household was expected to decline by an estimated US$119 per year while food insecurity increased by about 2.5 percentage points (Jaleta et al. 2018). In addition, DTM varieties exhibit high protein content and stronger resistance to major diseases (Fisher et al. 2015). The proliferation of DTM in Africa was enhanced significantly in the last decade through the Drought Tolerant Maize for Africa (DTMA) project, launched in 2006 and implemented in 13 countries across SSA. The primary purpose of this project was to increase household food security and income of smallholder farmers through the development and dissemination of drought tolerant, well-adapted maize varieties. The project was jointly implemented with National Agricultural Research Services by the International Maize and Wheat Improvement Center (CIMMYT) in eastern and Southern Africa and the International Institute for Tropical Agriculture (IITA) in western Africa (Lybbert and Carter 2015) and was concluded in 2015 (Lunduka et al. 2017). Zimbabwe is one of the countries where successful trials on selected farms were conducted followed by widespread adoption programs (Kassie et al. 2012).

Conservation Agriculture (CA) is another 'climate-smart' agricultural practice strongly promoted to improve climate resilience and productivity of the maize crop (Baudron et al. 2012; Thierfelder et al. 2017; Thierfelder and Wall 2010) while conserving the environment in SSA countries including Zimbabwe (Mango et al. 2017). CA can also improve crop diversification and soil quality – important factors associated with food security. CA was promoted after observing that frequent droughts severely threaten the food security situation of many smallholder agriculture-based communities in southern Africa, which are characterised by low crop productivity, food insecurity, hunger and malnutrition (Mango et al. 2017; Nyikahadzoi et al. 2012). These communities experience problems of inadequate farming knowledge and skills, and insufficient implements and inputs such as seeds, fertilizers, herbicides and pesticides, along with poor soils and soil fertility management. CA is underpinned by three

main tenets, namely, (i) minimum soil disturbance, (ii) permanent soil cover, and (iii) crop rotations that give rise to a suite of practices. Mulching and reduced tillage are the ones primarily targeted for SSA including Zimbabwe (Giller et al. 2009; Siziba 2008). The Food and Agricultural Organization of the United Nations (FAO), government ministries, non-governmental organizations and national and international research institutes have all been making concerted efforts to promote CA in southern Africa since the mid-1980s (FAO 2001).

There is now substantial information on the main determinants of adoption of DTM and CA. Emerging research on DTM adoption reports different socioeconomic characteristics of farmers (i.e. access to information, resource endowments and gender) to explain variation in adoption (Fisher et al. 2015; Fisher and Carr 2015; Holden and Fisher 2015; Holden and Quiggin 2016; Makate et al. 2017). Similarly, literature on CA adoption demonstrate that different socioeconomic and institutional factors are determinants of adoption. Previous research has also showed the importance of household wealth on DTM adoption (Legese et al. 2009) and found a somewhat pro-rich technology adoption gradient (DeWalt 1975; Lansing and Markiewicz 2011). These studies underline that smallholder farmers are not homogenous (Chikowo et al. 2014; Giller et al. 2011; Tittonell et al. 2010) and that different farmer socioeconomic characteristics influence adoption of farming technologies (Asfaw and Admassie 2004; Fisher and Carr 2015; Mahapatra and Mitchell 2001; Milán et al. 2006; Solano et al. 2001; Somda et al. 2005). According to Fisher and Carr (2015), ensuring that DTM seed varieties meet the diverse needs of farmers is one crucial challenge still to be critically scrutinized and considered. Also, Thierfelder et al. (2012) stressed that both farm and community-level socioeconomic constraints to the adoption of conservation farming (including rotations and intercropping) should be addressed to raise rates of uptake.

Despite the documented potential strong links to food security and nutrition of DTM and CA strategies, the adoption of such strategies is still impeded by household socioeconomic status-related differences e.g. household asset wealth endowments (Fisher et al. 2015; Fisher and Carr 2015; Holden and Fisher 2015; Holden and Quiggin 2016; Makate et al. 2017). Several factors are believed to influence the adoption of DTM and CA varieties including input acquisition costs or price (Fisher et al. 2015). In our study we focussed on the wealth endowments of the household as an important factor in the adoption of such strategies. This idea was premised on the observation that a household's wealth endowments could be an important predictor of their likelihood or ability to pay for agricultural inputs including seed of DTM varieties and that policies which incorporate individual farmer-level differences in wealth endowments should be consistent with those targeted at manipulating the pricing mechanism of improved varieties.

Against this background, our study sought to quantify and decompose observed inequalities in DTM and CA adoption into their underlying determinants using cross-sectional household-level data from selected smallholder farming communities in Zimbabwe and derive implications for food security. Specifically, we measured and explain socioeconomic status-related inequalities in the adoption of DTM and CA using rank-based techniques, including the concentration index (see O'donnell et al. (2008). A subsequent decomposition of the observed disparities in adoption was performed to establish the underlying drivers of such inequalities. To the best of our knowledge, no study in low-income nations such as Zimbabwe has attempted to explain the inequalities related to socioeconomic status in the adoption of DTM and CA.

The rest of the article is organised as follows: section 2 discusses the study methodology and underlying empirical model and analytical framework, results of the study are presented in section 3 followed by discussions of the study findings in section 4. Conclusions and recommendations are provided in section 5.

2. Methods

2.1. Data

This study used cross-sectional household-level data collected during a survey that was conducted from October to December 2011 in four districts of Zimbabwe; Goromonzi, Guruve, Mudzi, and Hwedza. Goromonzi and Guruve districts fall in natural farming region IIb while Hwedza and Mudzi are in region III and IV respectively. The study relied on data from districts with different agro-ecological zones since research has shown that DTM varieties (mainly hybrids) are important for all farmers and can even outperform conventional maize varieties in good rains (CIMMYT 2017). The four districts were selected based on agro-ecological potential and market access. Goromonzi and Guruve districts lie in high potential agro-ecological zones while Mudzi and Hwedza are in low potential zones respectively. In terms of market access, Mudzi has the lowest access compared to the other three action sites. A simple random sampling technique was used to select wards from a list obtained from the district extension office of each of the four districts. Within the selected wards, the households selected for interview were randomly chosen from lists provided by resident agricultural extension officers. Using figures from the 2002 Zimbabwe population census, Goromonzi, Mudzi, Hwedza, and Guruve had populations of 154,262, 128,174, 70,677 and 111,398 persons respectively (Zimbabwe National Statistics Agency 2017). The population proportions generated from the district populations were used to generate the total study population. This stratification based on agro-ecological potential and market access generated a large sample from which 601 households were extracted for the survey; 175 from Goromonzi, 187 from Guruve, 120 from Mudzi and 119 from Hwedza.

Data collection was in the form of face-to-face administration of structured questionnaires with the farmers. The surveys collected information on several household characteristics including ownership and number of assets kept by the household, crop and animal production, access to agricultural extension services, agricultural inputs and technologies and the use of farming methods such as CA adoption. Extensive data on asset holdings was collected which included information on ownership of livestock, household goods (e.g. television, radio, bicycle), farm implements and other intermediate technologies (e.g. oxcart, planter, wheelbarrow, tractor, plough), household dwelling characteristics (such as floor, roof and wall material) and other common assets (such as mobile phones). The study used the information to generate a wealth index variable for the household using Principal Components Analysis (PCA). Crop production data included information on several crops including maize. Detailed maize production information was collected and included input use in production, land area for growing maize, hybrid maize seed varieties sown, crop management, harvesting, and post-harvest handling of the maize crop. Data on maize hybrid varieties also captured the adoption and use of DTM varieties. Specific questions were asked on whether farmer planted any DTM variety, the amount of DTM seed sown, total output, and amount of output sold and consumed.

2.2. Outcome variables

This study used two binary measures of 'adoption' of climate-smart agricultural practices: DTM and CA[1] adoption. DTM[2] adoption was measured as a binary variable indicator taking 1, if the smallholder farmer had planted at least one of the released DTM varieties and 0 otherwise. Several DTM varieties had been released at the time of the survey (see Abate et al. (2015)). CA was also measured as a binary indicator variable taking 1 if the farmer was practising at least one of the several practices that fall under CA and 0 otherwise.

2.3. Explanatory variables

Several explanatory variables that are believed to possibly explain adoption and contributions to observed inequalities in adoption of DTM and CA were included in the survey. These variables were age of household head, gender of household head, marital status of household head, labour, education of household head, extension, distance to the nearest main market, land size, asset wealth and region. The choice of these variables was guided by the empirical literature on CA and DTM adoption. This work included (Feder et al. 1985; Fisher et al. 2015; Fisher and Carr 2015; Fisher and Kandiwa 2014; Legese et al. 2009; Makate et al. 2017) for DTM adoption and (Mazvimavi and Twomlow 2009; Nkala et al. 2011; Siziba 2008) for CA adoption. Household head characteristics such as age, gender, marital status and education can influence the level of risk that can be tolerated, decision-making on the farm, access to resources, technology adoption, and the capacity to evaluate technologies and hence, they can explain wealth related disparities in the adoption of CA and DTM. The availability of labour also influences adoption of innovations on-farm (Murray et al. 2016) and access to extension affects access to information (Makate et al. 2018). Such variables can influence capital and resources accumulation and hence can explain wealth related disparities in technology adoption on-farm. In addition, distance to the nearest market can influence market access and rewards from the market (Fischer and Qaim 2014), while land size can influence technology adoption and hence rewards from farming (Bidogeza et al. 2009). Therefore land size and distance to market can influence the wealth gradient in technology adoption on the farm. Regional variables capture variation in several characteristics intrinsic to a particular location which can also explain a wealth gradient in technology adoption. Also, wealth itself is a known determinant of adoption of innovative technologies including CA and DTM (Legese et al. 2009; Makate et al. 2017; Mazvimavi and Twomlow 2009; Nkala et al. 2011) which means wealth can be an important factor to explain inequalities in technology adoption on the farm. Specific details on measurement of all the explanatory variables, including their descriptive statistics, are shown in Tables 1 and 2.

2.4. Measuring socioeconomic status using an asset-based index

Studies in low-income countries are increasingly using asset-based indices as measures of the socioeconomic status of the family given the difficulty associated with acquiring data on household income or consumption (O'donnell et al. 2008). Our study followed this trend to compute the asset index as a proxy for household wealth using PCA (Filmer and Pritchett 2001). Several studies focusing on explaining disparities in health outcomes in low-income countries have used the asset index as a measure of socioeconomic status (Makate and Makate 2017;

[1] A farmer was considered a CA adopter if he or she had practiced any of reduced tillage, mulching, crop residue retention or crop rotations (in isolation or in combinations) consistently in the last two seasons.
[2] A farmer was considered a DTM adopter if he/she had planted at least one DTM variety consistently in two preceding seasons.

Gwatkin et al. 2007; Hajizadeh et al. 2014). This asset index is based on the household's ownership of key items of household property, livestock, and housing quality characteristics and is summarized in Table 1. For brevity, the outputs from PCA are omitted and only the means of the variables are considered. The means of variables considered are shown by wealth category (Table 1).

[Insert Table 1 here]

2.5. Enumerating socioeconomic status related disparities in DTM and CA adoption

The concept of quantifying socioeconomic related disparities in an outcome variable has received increased consideration in the economics, especially health economics, literature (Wagstaff et al. 2003; van Doorslaer et al. 1997; Kakwani et al. 1997; Wagstaff et al. 1991). Many studies relied on inequality measures such as the Gini coefficient, relative index of inequality, relative index of dissimilarity and the concentration index (Wagstaff et al. 1991). Our study followed recent studies in health economics that employ concentration indices to measure disparities in health outcome variables. The outcome variables considered are binary and measure adoption of DTM and CA. Following Wagstaff et al. (2003), the standard concentration index can be specified as follows:

$$CI = \frac{2}{N\mu}\sum_{i=1}^{n} Y_i R_i - 1 - \frac{1}{N} \qquad (1)$$

where Y_i represents the outcome variables for DTM and CA adoption for the ith smallholder farmer, μ represents the mean for the dependent variables, and $R_i = 1/N$ is the rank of the smallholder farmer in the socioeconomic status distribution, with $i = 1$ representing the lowest ranked farmer (i.e. the poorest) and $i = N$ for the highly-ranked smallholder farmer (i.e. wealthiest). The CI is often written in a more convenient way as follows:

$$CI(Y) = \frac{2}{\mu} Cov(Y, R) \qquad (2)$$

Note that equation (2) shows that the $CI(Y)$ depends only on the covariance between the outcome variable and the smallholder farmer's rank in the SES distribution and not on the measure of SES itself. The sign of $CI(Y)$ represents the direction of concentration of the index with index itself ranging from -1 to $+1$. The index takes a value of zero if DTM and CA adoption rates are equally distributed in the population (i.e. no socioeconomic status related disparities). A value of -1 implies that disparities in DTM or CA adoption are concentrated in the poor farmers (i.e. pro-poor) while a $+1$ indicates that DTM and CA adoption is all concentrated among the richest smallholder farmers (i.e. pro-rich).

As noted in Wagstaff (2005), in the case of a binary outcome variable, the computed concentration index might not only exceed the -1 and $+1$ boundaries, but also violate key properties like the "mirror property". In the case of this study, the mirror property states that inequalities in adoption should mirror those in no adoption. In other words, we should expect to get the same magnitudes when our outcome variable is either measuring adoption of DTM or non-DTM with the only difference being in the sign. Thus, we used the corrected concentration index as suggested by Erreygers (2009) which addresses some of the shortcomings of the standard concentration. The Erreygers (2009) corrected CI can thus be expressed algebraically as follows:

$$E(Y_i) = \frac{4\bar{Y}}{(Y^{max} - Y^{min})} \times CI(Y_i) \quad (3)$$

where Y_i is as mentioned earlier, Y^{min} and Y^{max} are the lower and upper values of the dependent variables (i.e. DTM and CA), $E(Y_i)$ is the corrected concentration index, and $CI(Y_i)$ is as defined in equation (2). Since the chosen outcome variables in this study are all binary (1/0) and substituting equation (2) into equation (3), some small algebraic manipulations give us the following:

$$E(Y_i) = 8 \times Cov(Y, R) \quad (4)$$

To better appreciate the factors influencing socioeconomic status-related disparities in DTM and CA adoption, the study employed a decomposition strategy recommended by Wagstaff et al. (2003), who showed that the standard concentration index, $CI(Y)$ with outcome variable Ycan be expressed in terms of its underlying characteristics using a linear model specified as follows:

$$Y_i = \beta_0 + \sum_{k=1}^{K} \beta_k X_{ik} + \epsilon_i \quad (5)$$

where X_{ik} is a vector of explanatory variables linked to adoption of DTM and CA, ϵ_i is an idiosyncratic error term, β_0 and β_k are regression coefficients. Even though chosen outcome variables are all binary, our study followed the previous literature and estimated equation (5) using an ordinary least squares (OLS) approach (O'donnell et al. 2008) with robust standard errors. The OLS approach is preferable despite the binary-nature of the outcome variables, since it generates a unique decomposition of the observed disparities (O'donnell et al. 2008). As postulated by Wagstaff et al. (2003) and Erreygers (2009), equation (4) is rewritten as follows

$$E(Y_i) = 4\left[\sum_{k=1}^{K} \beta_k \bar{X}_k \times CI(Y_i)_k + GC_\epsilon\right] \quad (6)$$

where $\bar{X}_k$ represents the mean of the kth explanatory variable, $CI(Y_i)_k$ is the concentration index of the kth covariate, and GC_ϵ is the residual component that captures all the unobservable features. The analysis was conducted using Stata version 13 (Stata 2013). The corrected concentration index was calculated using a user-written command, $conindex$ (O'donnell et al. 2008) while the decomposition of the concentration index was completed using the estimation guidelines provided in O'donnell et al. (2008).

3. Results

3.1. Descriptive statistics

Descriptive statistics for the variables used in this study and stratified by district of residence are in Table 2. Mean DTM adoption rate ranged from 55.5% in Wedza to about 89.2% in Mudzi. CA adoption at the survey date ranged from 28.3% in Guruve to 33.3% in Mudzi. Generally, Mudzi had higher rates of CA and DTM adoption as at survey date. Fig. 1 shows how DTM and CA adoption rates compared in the studied districts as observed at the survey date.

[Insert Figure 1 Here]

In terms of socioeconomic variables, the mean age of sampled household heads ranged from 48.5 years in Guruve to 55.5 years in Wedza. Mean representation of male household headship ranged from 71.4% in Wedza to 78.6% in Guruve. The majority of the farmers were married with percentages ranging from 67.2% in Wedza to 77.5% in Mudzi. Average family labour endowment was almost uniform across districts as it ranged from 3.1 persons per household in Goromonzi to 3.4 persons in Guruve. Close to 50% of farmers in all sampled districts had attained at least secondary education. The sample was dominated by full-time farmers with mean proportions of farmers who reported farming as their major economic activity ranging between 79.4% in Goromonzi and 96.7% in Mudzi. In addition, at least 90% of sampled farmers in Goromonzi, Guruve and Mudzi reported maize to be one of their major cash crops grown whilst only 16.8% farmers reported the same in Wedza. Contact with agricultural extension varied from 53.7% in Goromonzi to 71.4% in Wedza. The average distance to the nearest main maize market was lowest for Goromonzi (43.5 km away), with Guruve, Mudzi and Wedza having average distances of 125.5, 132.3 and 104 km respectively. Average arable land sizes owned by the household varied by district with the lowest average of 1.4 ha in Goromonzi to about 3.0 ha in Mudzi. Concerning household wealth, Guruve had the largest representation of farmers (54.5%) in the poorest wealth categories (asset quintile 1 and 2) and the least representation of farmers (27.2%) in the highest wealth categories (asset quintiles 4 and 5). At the other extreme, Wedza had the largest concentration of farmers in the richest wealth group with about 68% representation in the top three richest asset quintiles combined (3, 4 and 5) and only 31.9% in the lowest two asset quintiles. Mudzi and Goromonzi had almost similar proportions with 64.1% and 66.8% mean proportions in the top three asset wealth categories respectively.

[Insert Table 2 Here]

3.2. Wealth-related inequalities in DTM and CA adoption

Table 3 provides the concentration indices (and their respective standard errors shown in parentheses) for the binary outcome variables of DTM and CA adoption. The reported estimates are the indices based on the Erreygers (2009) corrected concentration index. The concentration indices (Table 3) all show that wealth-related inequalities in DTM (0.123) and CA (0.125) adoption are all statistically significant at the 5% level and mostly pro-rich. Thus the results reveal that observed inequalities in adoption of both DTM and CA exist and that use of these technologies are highly concentrated among the more affluent farming households.

[Insert Table 3 Here]

To improve understanding on the factors that explain the observed inequalities in DTM and CA adoption, a decomposition analysis was performed of which results are provided in the next sub-section. A decomposition analysis splits the corrected concentration index (inequalities) into its determining factors using the methods described earlier and using equation (6).

3.3. Decomposition of observed inequalities in DTM and CA adoption

Table 4 summarises the decomposition of each 'climate-smart' agricultural practice’s adoption inequalities into the percentage contributions of the explanatory variables. A positive (negative) x% contribution of variable X is to be interpreted as follows: wealth-related adoption inequality would, *ceteris paribus*, be x% lower (higher) if variable X were equally distributed across the wealth range (population), or if variable X had a zero-adoption elasticity.

From Table 4, the farmer's age, maize grown as a cash crop, asset wealth (measured by the asset quintile) and district the farmer belongs to, contributed significantly to the observed inequalities in DTM adoption. These results revealed that these parameters explained 13.5%, -23.7%, 63.7% and 22.0% of the observed inequalities in DTM adoption. Also, land size though not significant explained close to 16.9% of the observed inequalities in DTM adoption. Asset wealth therefore, forms the largest contribution to the observed disparities in the adoption of DTM. The positive sign on the asset wealth variable implies that if household wealth was distributed equally across the smallholder farming population, then the observed inequalities in the adoption of DTM would be lower by about 63.7%. The observed contribution of household wealth was large. The positive sign on the age of household also signifies that if the age distribution of farmers was about the same in the sample, observed inequalities would be lower by the respective percentage (i.e. 13.5%). The negative sign of the variable grow maize, indicates that if all the farmers grew maize as one of their major cash crops, the observed inequalities would be greater by nearly 23.7%. However, inequalities in DTM adoption would have been lower by about 22% if farmers were from the same district (i.e. Mudzi, the reference category). Furthermore, if land was distributed equally among sampled farmers, observed inequalities would have been less by approximately 16.9%.

[Insert Table 4 Here]

For CA, growing maize as the main cash crop, contact with agricultural extension officers, land size holding and district of residence explained 7.5%, 30.3%, 41.9% and 19.5% respectively of the observed inequalities in CA adoption (Table 4). In this case, household wealth was not amongst the notable and significant contributing factors to the observed disparities in CA adoption. Instead, the results show that if all farmers grew maize as the major cash crop, had equal access to extension services, equal land sizes and all came from Mudzi district, the observed inequalities in CA adoption would have been lower by 7.8%, 31.5%, 42.8% and 19.4% respectively. These results point to the overall importance of growing maize as one of the main cash crops, equal access to extension services, equal distribution of land and equal distribution of other district level parameters (measured in the district dummy variable) in explaining the observed inequalities in the adoption of CA.

For further scrutiny of the observed inequalities in CA and DTM adoption, we analysed how the inequalities compare by district and gender (Table 5).

3.4. Heterogeneities in DTM and CA adoption inequalities

3.4.1. Heterogeneities by geographical location (district)

Results on wealth-related inequalities in CA and DTM adoption by district of residence of the farmer are shown in Table 5. The joint significance tests in Table 5 assess the hypothesis that: observed wealth-related disparities in DTM and CA adoption are not statistically different across all the districts whilst the alternative hypothesis suggests otherwise. The joint significance test results on DTM adoption showed an insignificant outcome (F-statistic=1.2198; and P-value=0.3017) indicating that the observed inequalities were not considerably different by farmer's district of residence. However, the significant concentration index with a magnitude of 0.210 indicated that inequalities in DTM adoption were pro rich, and significant in Guruve district. In other words, DTM adoption inequalities concentrated in the more affluent population are significant and more pronounced in Guruve district. On the other hand, the joint significance test (all districts) results on CA adoption reveal significant differences in wealth-

related inequalities of CA adoption. Results point to the overall significance of geographical location and associated characteristics in explaining the observed disparities in CA adoption. The significant concentration index (0.327) for Goromonzi district reveals a more pronounced pro-rich distribution of inequalities in CA adoption in the district when compared to other districts.

[Insert Table 5 here]

3.4.2. Heterogeneities by gender

We also scrutinised the inequalities in CA and DTM adoption by the farmer's gender. The results shown in Table 6 reveal a significant joint test (F-statistic=2.9177; p-value=0.0881) by gender on inequalities in DTM adoption and an insignificant joint result on CA adoption (F-statistics=0.1807; p-value=0.6709). There was a significant and mostly pro-rich disparity in DTM adoption observed by gender. The magnitude of the concentration index for male farmer (0.169) reveal that inequalities in DTM adoption in the male sample were overwhelmingly pro-rich and significant at the 1% level. Also, the negative concentration index (-0.004) of the female sub-sample, although not significant, revealed that DTM adoption inequalities are pro-poor in the female sub-sample.

[Insert Table 6 Here]

The joint test results in Table 6 also revealed that the observed pro-rich distribution in CA adoption did not significantly differ by gender of farmer as indicated by the F-statistic and p-value reported earlier. However, taking results from the male sub-sample, results show that inequalities in CA adoption were significant and mostly pro-rich (concentration index=0.126, significant at the 1% level). Although not statistically different from the male-sub-sample, the inequalities in CA adoption within the female sub-sample were mostly pro-rich (concentration index=0.083). Overall, the results point to a pro-rich distribution of both DTM and CA adoption which was more pronounced in the sub-sample of male smallholder farmers.

3.4.3. Potential links to food security

To explore the potential links between the adoption of DTM and CA with food security, we plotted local polynomial regressions of CA adoption and DTM adoption separately (Fig. 2). The results are reported in graphs a) to d) of figs 2. In graph a) of figs 2, the dependent variable is a dummy variable for CA adoption and the explanatory variables were each of the livelihood outcomes. The results in figs 2a) suggest that higher rates of CA adoption are linked to increasing maize yield, including maize set aside for consumption and for sales. Figs 2b plots local regressions in which the concentration index (measuring wealth-related inequality in CA adoption at the district level) is the dependent variable. Here, we observed that districts within which household wealth was unequally distributed and where CA adoption was highly concentrated in richer or wealthier households, livelihood outcomes are also expected to be better or much higher. A similar pattern was observed for DTM (i.e. in figs 2c and d). Overall, the results of figs 2 appear to suggest that higher levels of DTM and CA adoption are expected to be associated with better livelihood outcomes and hence improved food security.

[Insert Figure 2 here]

4. Discussion

The results showed an overall pro-rich distribution of inequalities in DTM and CA adoption in the studied smallholder farming areas of Zimbabwe. This outcome could be explained by the fact that the more affluent population of smallholder farmers could be having an advantage in uptake of technologies as they can afford the initial investments and capital often required to adopt new technologies (Doss 2006; Legese et al. 2009; Mahapatra and Mitchell 2001; Nkala et al. 2011). In the Zimbabwean context, improved maize varieties including DTM fetch high prices on the market which makes it difficult for the poorer farmers to buy and use them. The same with CA, adoption of the practice is often associated with huge additional costs for the smallholder farmer (Rusinamhodzi 2015) including labor costs, costs of equipment (e.g. reduced tillage equipment, sprayers etc.), cost of complementary inputs (herbicides) which explains the pro-rich distribution of inequalities in CA adoption. Besides several studies have also reported wealth and or poverty as important determinants of sustainable agriculture practices (technologies and methods) adoption in smallholder farming (Feder et al. 1985; Makate et al. 2016; Makate et al. 2017; Mazvimavi and Twomlow 2009; Nkala et al. 2011) which is in-line with findings from this study. The results could imply that the poorer smallholder farmers continue to be sidelined by the DTM and CA technology adoption process as it favors the rich which can have negative consequences in efforts towards reducing poverty and income/wealth inequalities in Zimbabwean rural societies. This also has negative implications for food security. Improved technology adoption in agriculture can positively impact on food security (Brüssow et al. 2017; Dibba et al. 2017; Magrini and Vigani 2016) which implies that if CA and DTM continue to be pro-rich, they may not significantly improve food security and welfare in poor rural societies in Zimbabwe in the long-term. Results may also imply that, for climate-resilient maize technologies such as DTM and CA to have greater impacts on maize productivity, and food security to the wider society they have to be mostly pro-poor. Deliberate policy and institutional efforts towards subsidizing access to improved maize varieties such as DTM and complementary CA inputs (e.g. reduced tillage equipment, herbicides, sprayers among other CA inputs) by the poor can help. Pro-poor institutional support, technologies and policies generally promotes pro-poor agricultural growth in poor areas (Dorward et al. 2004).

A closer look at the observed inequalities in DTM adoption by district shows no significant dissimilarities in observed pro-rich inequalities. This result points to an overall pro-rich distribution of inequalities in DTM adoption, which is common in the entire sample of smallholder farmers irrespective of geographical location. Furthermore, stratifying the sample of farmers by gender revealed significant disparities in the adoption rates. Precisely, a pro-rich distribution of inequalities in the male sub-sample is evident which points to the fact that relatively rich male farmers enjoy better adoption rates unlike their poorer counterparts. This finding is plausible since farming in Zimbabwe is still considered or arguably a predominantly male-dominated endeavor by most research and extension staff. More so, it could be the case that advertisement of DTM seed and other improved varieties by seed companies and agro-dealers responsible for seed distribution is biased towards men. Men as household heads are generally more likely to have contacts with extension agents, input suppliers and even marketers which gives then an absolute advantage. As for CA, The results reveal an overall pro-rich distribution in adoption, which is significantly different by district

of residence. For instance, a more pronounced pro-rich distribution of inequalities in CA adoption is evident in Goromonzi district. In other words, relatively big differences in CA adoption inequalities amongst farmers in the district are evident which can be explained by a steep wealth gradient among these farmers. Proximity to the capital city (Harare) offer better marketing and off-farm employment opportunities for the smallholder farmers in Goromonzi and this could explain the notable pro-rich distribution. Conversely, disparities in observed pro-rich inequalities in CA adoption are not significantly different by gender of farmer. This signifies that both affluent male and female farmers significantly enjoy CA uptake and their benefits unlike their poorer counterparts.

The study took a further step and performed a decomposition exercise of the observed inequalities in DTM and CA adoption into their contributing factors. For DTM, wealth was found to be the chief contributor of the observed inequalities as it contributed 63.7% of the observed disparities. This result points to wealth as one significant factor that accounts for the discrepancies in DTM adoption. Deepening economic crisis in Zimbabwe has tremendously reducing purchasing power of the general populace particularly those from the country side. In this regard, access to resources or wealth generally has become such an important factor to explain access and adoption of improved maize varieties from the formal market. Maize hybrids have been on the market since 1980 and were instrumental to the second small-holder farmer maize-based green revolution in Zimbabwe (Eicher 1995). However, to date access and use of maize hybrids by smallholder farmers have reduced (compared to the 1990's period) due to current economic challenges that have reduced farmer purchasing power and increased prices of seed on the market. This concurs with literature on DTM adoption that have found household wealth or rather access to resources (measured by asset wealth) to be a significant factor of adoption (Fisher et al. 2015; Legese et al. 2009; Makate et al. 2017). In another sense, the results point to the importance of wealth at household level in explaining the gradient of DTM adoption. Similarly, in the Nepalian context, Ghimire and Huang (2015) found wealth to be an important covariate explaining adoption and use intensity of improved maize varieties. Wealthier smallholder farmers may have higher propensities to adopt DTM technology and access to the needed complementary inputs, which can ultimately transform to higher productivities, incomes and food security. Growing maize as a cash crop, access to land, age of farmer and district were reported as other significant factors that contribute to the observed inequalities in DTM adoption. The results also concur with previous literature that point to age of farmer (Mugi-Ngenga et al. 2016; Ziervogel and Zermoglio 2009), and land size (Mazvimavi and Twomlow 2009; Neill and Lee 2001) as important factors with the uptake of sustainable agricultural practices. Growing maize as a cash crop is also a significant covariate contributing to the observed inequality, which is not surprising since DTM hybrid varieties being promoted recently are improved maize varieties expected to yield better returns in terms of yield, income and food security for the maize farmer. Resultantly, the decision to grow maize as a cash crop can influence adoption of an improved hybrid maize variety (DTM). Also, different geographical locations account for other unobserved location-specific factors which can explain DTM adoption decisions (Makate et al. 2016; Makate et al. 2017). For instance Makate et al. (2017) found a regional variable to be a significant determinant of DTM adoption in Zimbabwe, with farmers in drier areas having higher propensities to adopt DTM than their counterparts in less dry areas.

The decomposition analysis for CA pointed to access to agriculture extension services and land size as the top contributors to the observed inequalities with 30.3% and 41.9% contributions to the measured inequalities CA adoption, respectively. This result implies that, *ceteris paribus*, if extension access and land were equitably distributed in the sample of smallholder farmers, observed inequalities would have been lower by the respective proportions. This is plausible considering that land size and extension access are important factors that explain adoption of conservation practices (Feder et al. 1985; Mazvimavi and Twomlow 2009). Furthermore, results also point to geographical location and growing maize as important contributors to the observed inequalities. Geographic location captures a number of other factors (e.g. agro potential, market potential, and effectiveness of extension) specific to location that can influence adoption of conservation practices. For instance, Goromonzi and Guruve lie in high rainfall agro-ecological zones whilst Mudzi and Hwedza are in relatively lower rainfall agro-ecological potential zones, which expectedly can influence farming decisions. Growing maize as a cash crop can explain adoption of CA since in smallholder farming systems of Zimbabwe, maize is one of the commonly grown crops under CA (Mazvimavi and Twomlow 2009).

Additionally, we linked DTM and CA adoption and their corresponding wealth-related inequalities (as measured by the corrected concentration index calculated at the district level) to livelihood outcomes (i.e. maize yield, maize consumption, and maize sales). The evidence we found appears to suggest a positive correlation between adoption of these practices and household food security as measured by the livelihood outcomes. In addition, the local polynomial regressions suggested a positive correlation between the pro-rich distribution of inequalities in CA and DTM adoption and livelihood outcomes. This finding suggests that if household wealth was equally distributed among the smallholder farmers in our analysis sample, we would expect livelihood outcomes to be much higher for the overall population. These results are in large part consistent with the previous literature that has established that both DTM and CA strategies are all linked to improved maize productivity (Abdoulaye et al. 2018; Jaleta et al. 2018; Lunduka et al. 2017; Mango et al. 2017; Wossen et al. 2017) which in some cases translate to improved food security either through direct consumption of crop output produced or through purchasing other necessities on the market using income from crop output sales.

Overall, our results point to the existence of wealth-related inequalities in the adoption of DTM and CA in Zimbabwe, which have serious implications for food security. Important climate-resilient maize technologies such as CA and DTM may not significantly improve productivity, incomes and food security of the poor in the long run . This is worrisome given the continual increase in poverty among the rural populace which constitute approximately two thirds of the population (World Bank 2017). For instance, World Bank (2017) reported an increase in poverty levels in Zimbabwe from about 72% in 2011 to about 79% by 2017 (World Bank 2017). Given the dominance of poverty in the rural populace, interventions that deliberately serve the poorer segments of the society are likely to have greater impact on welfare (poverty reduction) see for example Gomanee et al. (2003) for the case of food aid and Anderson and Feder (2007) for the case of agricultural extension..

Our study had several limitations. We relied on cross-sectional household-level data, which might not give a clear picture with regards to the dynamics on CA and DTM adoption in Zimbabwe. We also note that even though DTM and CA are important technologies that

can improve maize productivity and food security in a changing environment they may also bring uncertainties on the farm. Since they are relatively new technologies, improper implementation of the technologies by the farmers may negatively impact on farm yields and food security. In addition, the OLS regression coefficients leading to the decomposition of the observed inequalities into their contributing components represent correlations and do not suggest causality. Despite these concerns, our study provides valuable insight on socioeconomic status related inequalities in the adoption of DTM and CA in Zimbabwe.

5. Conclusions and recommendations

In conclusion, this study points to the existence of a pro-rich distribution of inequalities in climate-smart agricultural practices (DTM and CA) adoption in Zimbabwe's smallholder farming population. Precisely, the results point to a pro-rich distribution of inequalities in DTM adoption evident in all studied locations but more pronounced within the male-farmer sub-sample. More so, a pro-rich distribution of inequalities in CA adoption is also evident and differs significantly by geographic location, with a more pronounced pro-rich distribution in Goromonzi district. However, inequalities in adoption of CA stratified by gender are not pointedly different.

More so, household asset wealth was singled out as the most important factor contributing to the observed inequalities in the adoption of drought-tolerant maize. Also, the age of the farmer, growing maize as a cash crop, district and land size were the other factors significantly contributing to observed inequalities in DTM adoption. Regarding CA, access to extension services and land size contributed largely to observed inequalities in adoption of the climate-smart practice. Growing maize as a cash crop and district were the other factors.

Our findings point to the need for decision makers to consider implementing policies that deliberately focus on the poor and mostly vulnerable segments of the society as they can reduce inequalities and ultimately promote the adoption of hybrid drought tolerant maize varieties and by the poorer segments of society. Such policies can work positively in further reducing the gap between the rich and the poor and increase household food security of the poor households who are the majority. For instance, subsidizing the price of DTM seed and associated inputs, and ensuring that seed and other complementary inputs are stocked locally to improve access in poorer segments of the farming community in Zimbabwe can be very beneficial. It can certainly improve adoption amongst poorer farmers, which can improve overall livelihood impacts of the technology (productivity, income, drought resilience, and household food security). This is plausible since in neighboring countries such as Malawi, agricultural subsidies have been found to improve adoption of improved maize (Denning et al. 2009; Fisher and Kandiwa 2014; Holden and Fisher 2015) and food security (Snapp and Fisher 2015). With regards to CA adoption, cheaper policies that improve technical knowledge on the practice or its principles can be highly beneficial. For instance, Extension services that are specialized and targeted towards the poorer farmers can improve the livelihood benefits of the practice and uplift poorer farmers. This can make farmers capital owners (through improving their household wealth from faming income) which can further reduce adoption equalities. The ultimate outcome will be enhanced livelihood benefits of improved maize farming technologies such as CA and DTM to wider society. Furthermore, equitable land distribution policies (well backed by other supportive policies) that target poorer segments of the society can also be helpful in reducing further inequalities in DTM and CA adoption. However, local level strategies need to be tailored to specific geographical

locations (agro climatic conditions, agro potential, market potential and other characteristics e.g. gender) as these may influence adoption of improved maize technologies and CA differently. Alternatively, policies that enhance economic options for farmers through diversification of economic activities or adding value to their farm produce for more income are required if food security is to be permanently improved. Some of such policy initiatives from the government are starting to resurface and they include the financial inclusion drive, value addition and beneficiation drive, and import substitution drive by the Reserve Bank of Zimbabwe.

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Conflict of interest statement

This research meets the ethical guidelines of the study country, including adherence to legal requirements.

The authors confirm that they do not have any conflict of interest.

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Table 1: Principal components and summary statistics for the variables used to compute the wealth index of the smallholder farmer

	Overall			Quintile 1		Quintile 2		Quintile 3		Quintile 4		Quintile 5	
Variables	Mean	SD	Component score	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Number of cattle	2.411	3.417	0.238	0.752	1.577	1.417	2.140	1.175	1.850	2.692	2.843	6.033	4.649
Owns draft cattle	0.496	0.500	0.219	0.132	0.340	0.475	0.501	0.350	0.479	0.625	0.486	0.900	0.301
Owns draft donkey	0.025	0.156	0.057	0.000	0.000	0.008	0.091	0.033	0.180	0.025	0.157	0.058	0.235
Owns sheep	0.188	1.053	0.068	0.041	0.271	0.092	0.485	0.033	0.222	0.225	1.205	0.550	1.896
Number of goats	2.651	3.503	0.190	1.198	1.943	1.608	1.980	2.092	2.849	3.158	3.865	5.208	4.545
Number of pigs	0.316	1.404	0.030	0.314	1.678	0.175	0.741	0.250	1.055	0.283	1.109	0.558	2.028
Number of chickens	11.819	19.730	0.162	5.926	6.460	7.967	11.135	8.967	8.383	11.283	8.696	25.000	37.640
Number of hoes	5.408	3.504	0.215	3.752	2.177	4.200	2.509	5.233	2.576	5.508	2.308	8.358	5.079
Owns a plough	0.589	0.492	0.215	0.248	0.434	0.492	0.502	0.508	0.502	0.750	0.435	0.950	0.219
Owns a tractor	0.012	0.107	0.041	0.000	0.000	0.008	0.091	0.017	0.129	0.000	0.000	0.033	0.180
Number of wheelbarrows	0.544	0.596	0.243	0.157	0.365	0.342	0.476	0.450	0.532	0.683	0.534	1.092	0.580
Owns a sprayer	0.308	0.462	0.177	0.083	0.276	0.225	0.419	0.267	0.444	0.350	0.479	0.617	0.488
Owns a planter	0.020	0.140	0.037	0.008	0.091	0.008	0.091	0.008	0.091	0.033	0.180	0.042	0.201
Owns an oxcart	0.378	0.485	0.237	0.058	0.234	0.283	0.453	0.233	0.425	0.475	0.501	0.842	0.367
Owns a hand cart	0.005	0.071	0.051	0.000	0.000	0.000	0.000	0.000	0.000	0.008	0.091	0.017	0.129
Owns a bicycle	0.378	0.485	0.172	0.107	0.311	0.333	0.473	0.358	0.482	0.392	0.490	0.700	0.460
Owns a car	0.028	0.166	0.080	0.000	0.000	0.000	0.000	0.033	0.180	0.033	0.180	0.075	0.264
Owns a truck	0.010	0.099	0.043	0.000	0.000	0.000	0.000	0.017	0.129	0.008	0.091	0.025	0.157
Owns a bike	0.008	0.091	0.032	0.000	0.000	0.000	0.000	0.025	0.157	0.000	0.000	0.017	0.129
Owns a cellphone	0.784	0.412	0.167	0.504	0.502	0.725	0.448	0.858	0.350	0.875	0.332	0.958	0.201
Owns a radio	0.594	0.491	0.159	0.339	0.475	0.542	0.500	0.575	0.496	0.675	0.470	0.842	0.367
Owns a television	0.290	0.454	0.191	0.083	0.276	0.142	0.350	0.250	0.435	0.358	0.482	0.617	0.488
Floor material type													
Mud	0.296	0.457	-0.271	0.835	0.373	0.400	0.492	0.175	0.382	0.058	0.235	0.008	0.091
Cement	0.686	0.465	0.275	0.132	0.340	0.575	0.496	0.817	0.389	0.917	0.278	0.992	0.091
Tiles	0.017	0.128	-0.025	0.033	0.180	0.017	0.129	0.008	0.091	0.025	0.157	0.000	0.000
Wall material type													
Mud	0.085	0.279	-0.077	0.149	0.357	0.133	0.341	0.092	0.290	0.025	0.157	0.025	0.157
Cement bricks	0.494	0.500	0.297	0.008	0.091	0.233	0.425	0.500	0.502	0.808	0.395	0.925	0.264
Mud bricks	0.421	0.494	-0.257	0.843	0.365	0.633	0.484	0.408	0.494	0.167	0.374	0.050	0.219
Roof material type													
Grass	0.344	0.476	-0.271	0.835	0.373	0.558	0.499	0.183	0.389	0.108	0.312	0.033	0.180
Iron sheets	0.143	0.350	-0.010	0.083	0.276	0.250	0.435	0.158	0.367	0.125	0.332	0.100	0.301
Asbestos	0.506	0.500	0.260	0.074	0.263	0.192	0.395	0.658	0.476	0.767	0.425	0.842	0.367
Observations	601			121		120		120		120		120	

Notes: SD = Standard deviation; Quintile 1= is the poorest (or lowest) wealth category; quintile 5 = highest wealth category; Component score is the overall contribution of the variable to the overall principal components score.

Table 2: Summary statistics of analysis variables for selected districts in Zimbabwe

		Goromonzi	Guruve	Mudzi	Wedza
Variables	Description and measurement	Mean	Mean	Mean	Mean
dtma_improved_maize	Binary variable =1 if farmer adopted drought tolerant maize (DTM) seed varieties; 0 otherwise	0.680	0.647	0.892	0.555
ca_farmer	Binary variable =1 if farmer practices conservation agriculture; 0 otherwise	0.320	0.283	0.333	0.303
househ_age	Age of household head in years	51.309	48.503	52.183	55.454
househ_resp_hhead	Binary variable =1 if respondent was the household head; 0 otherwise	0.514	0.551	0.608	0.630
househ_male	Binary variable =1 if gender of household head is male; 0 otherwise	0.743	0.786	0.775	0.714
househ_married	Binary variable =1 if household head is married; 0 otherwise	0.754	0.759	0.775	0.672
househ_num_workers	Number of farm workers	3.063	3.369	3.269	3.314
educ_secondary	Binary variable =1 if household head reached at least secondary school; 0 otherwise	0.480	0.503	0.458	0.454
emp_farmer	Binary variable =1 if household's main occupation is farming; 0 otherwise	0.794	0.898	0.967	0.832
grow_maize	Binary variable =1 if farmer grows maize as major cash crop; 0 otherwise	0.903	0.947	0.950	0.168
agric_extension	Binary variable =1 if farmer has had contact with agricultural extension workers; 0 otherwise	0.537	0.626	0.600	0.714
dist_market	Distance to the nearest main maize market in kilometers	43.474	125.540	132.343	103.973
Land size	Arable land size holding in hectares	1.419	2.727	2.978	2.464
log_landsize	Logarithm of arable land measured in hectares	0.760	1.193	1.271	1.113
asset_quintile1	Binary variable =1 if farmer is in asset quintile 1 (poorest); 0 otherwise	0.131	0.299	0.217	0.134
asset_quintile2	Binary variable =1 if farmer is in asset quintile 2; 0 otherwise	0.200	0.246	0.142	0.185
asset_quintile3	Binary variable =1 if farmer is in asset quintile 3; 0 otherwise	0.234	0.182	0.125	0.252
asset_quintile4	Binary variable =1 if farmer is in asset quintile 4; 0 otherwise	0.194	0.144	0.283	0.210
asset_quintile5	Binary variable =1 if farmer is in asset quintile 5 (richest); 0 otherwise	0.240	0.128	0.233	0.218
Observations		175	187	120	119

Data Source: Data for this study comes from smallholder farmers in four selected districts in Zimbabwe

Table 3: Wealth-related inequalities in the use of drought tolerant maize and conservation agriculture as sustainable agriculture practices in Zimbabwe

	Drought Tolerant Maize		Conservation agriculture	
	Coefficient	Standard error	Coefficient	Standard error
Concentration index	0.123**	(0.044)	0.125**	(0.043)
Number of observations	601		601	

Table 4: Contributions of explanatory variables to the overall concentration index for drought tolerant maize and conservation agriculture practices.

	Drought Tolerant Maize				Conservation agriculture			
Variables	Coefficient	Contribution	%	Summed (%)	Coefficient	Contribution	%	Summed (%)
Age of household	0.0044***	0.0166	13.47	13.49	-0.0012	-0.0055	-4.38	-4.38
Head of household	-0.0076	0.0000	-0.03	-0.03	-0.0681	-0.0003	-0.28	-0.28
Male	-0.0827	-0.0094	-7.63	-7.64	0.0787	0.0093	7.45	7.45
Married	0.0857	0.0129	10.48	10.5	-0.086	-0.0135	-10.76	-10.76
Number of workers	0.0014	0.0009	0.72	0.72	0.007	0.0051	4.05	4.05
Education: secondary school	0.0618	0.0090	7.34	7.35	0.0323	0.0045	3.58	3.58
Full-time farmer	0.0025	-0.0002	-0.14	-0.14	0.0345	-0.0026	-2.08	-2.08
Grow maize	0.3860***	-0.0292	-23.68	-23.72	-0.1242*	0.0097	7.75	7.75
Agricultural extension contact	0.0446	0.0094	7.66	7.67	0.1782***	0.0395	31.54	31.54
Distance to the nearest market	0.0003	0.0006	0.52	0.53	0.0975	-0.0025	-1.99	-1.99
Log land size	0.0962	0.0208	16.87	16.90	0.2415***	0.0536	42.83	42.83
Asset quintile 2	0.1744**	-0.0555	-45.07		0.018	-0.0053	-4.23	
Asset quintile 3	0.1253*	0.0002	0.14		-0.0553	-0.0001	-0.06	
Asset quintile 4	0.1474*	0.0473	38.37		-0.0225	-0.0067	-5.34	
Asset quintile 5	0.1349*	0.0864	70.14	63.69	0.02	0.0120	9.62	-0.01
District: Goromonzi	-0.1425**	-0.0142	-11.51		0.1654***	0.0168	13.46	
District: Guruve	-0.1874***	0.0433	35.15		-0.0823	0.0143	11.40	
District: Wedza	-0.0293	-0.0020	-1.65	22.02	-0.102	-0.0068	-5.44	19.42
Residual			-11.33				2.88	
Total			111.33				97.12	
Concentration index		0.1230				0.1251		
Observations		601				601		

Notes: ***Significant at 1% level; **significant at 5% level; *significant at 10% level. Reported are the marginal probability effects and robust standard errors shown in parentheses. The reference categories are as follows: Household wealth = 1 (poorest); and District = 1 (Mudzi). Coefficient is the linear regression coefficients for the models examining the factors associated with the use of drought tolerant maize and the practice of conservation agriculture in selected districts of Zimbabwe.

Table 5: Wealth-related inequalities in adoption of drought tolerant maize and conservation agriculture in selected districts of Zimbabwe

		Drought Tolerant Maize (DTMA)		Conservation Agriculture (CA)	
Districts	Counts	Concentration Index	Standard error	Concentration Index	Standard error
Goromonzi	175	0.140	(0.085)	0.327***	(0.074)
Guruve	187	0.210**	(0.081)	0.037	(0.076)
Mudzi	120	0.062	(0.058)	0.147	(0.102)
Wedza	119	-0.008	(0.106)	-0.062	(0.096)
Joint significance test (all districts): F-statistic		1.2198		3.8287***	
P-value		[0.3017]		[0.0098]	
Observations	601			601	

Notes: ***Significant at 1% level; **significant at 5% level; *significant at 10% level. Presented are the Erreygers (2009) corrected concentration indices with robust standard errors shown in parentheses. The joint significance test for checking statistically significant differences by district assumes equal variables.

Table 6: Heterogeneities in wealth-related inequalities in practice of drought tolerant maize and conservation agriculture by gender of farmer

		Drought Tolerant Maize (DTMA)		Conservation Agriculture (CA)	
	Counts	Concentration Index	Standard error	Concentration Index	Standard error
Male farmers	455	0.169***	(0.050)	0.126*	(0.051)
Female farmers	146	-0.004	(0.094)	0.083	(0.078)
Joint significance test: F- statistic		2.9177*		0.1807	
P-value		[0.0881]		[0.6709]	
Observations		601		601	

Notes: ***Significant at 1% level; **significant at 5% level; *significant at 10% level. Presented are the Erreygers (2009) corrected concentration indices with robust standard errors shown in parentheses. The joint significance test for checking statistically significant differences by gender assumes equal variables.

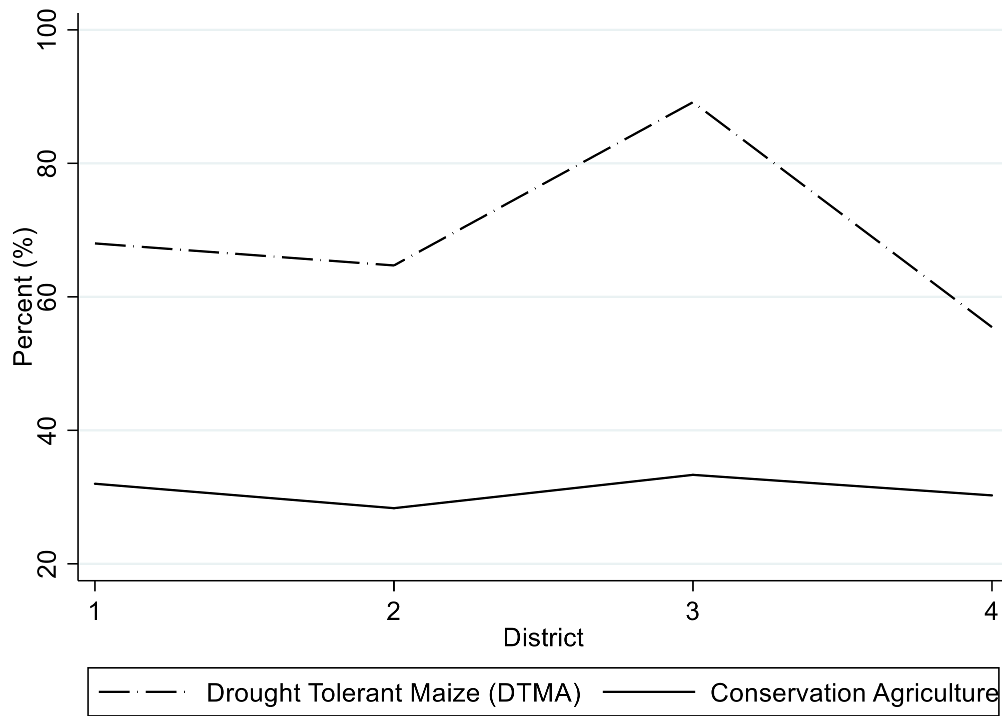

Figure 1. Drought Tolerant Maize (DTMA) and Conservation Agriculture practice adoption by district. Districts: 1 = Goromonzi; 2 = Guruve; 3 = Mudzi; 4 = Wedza.

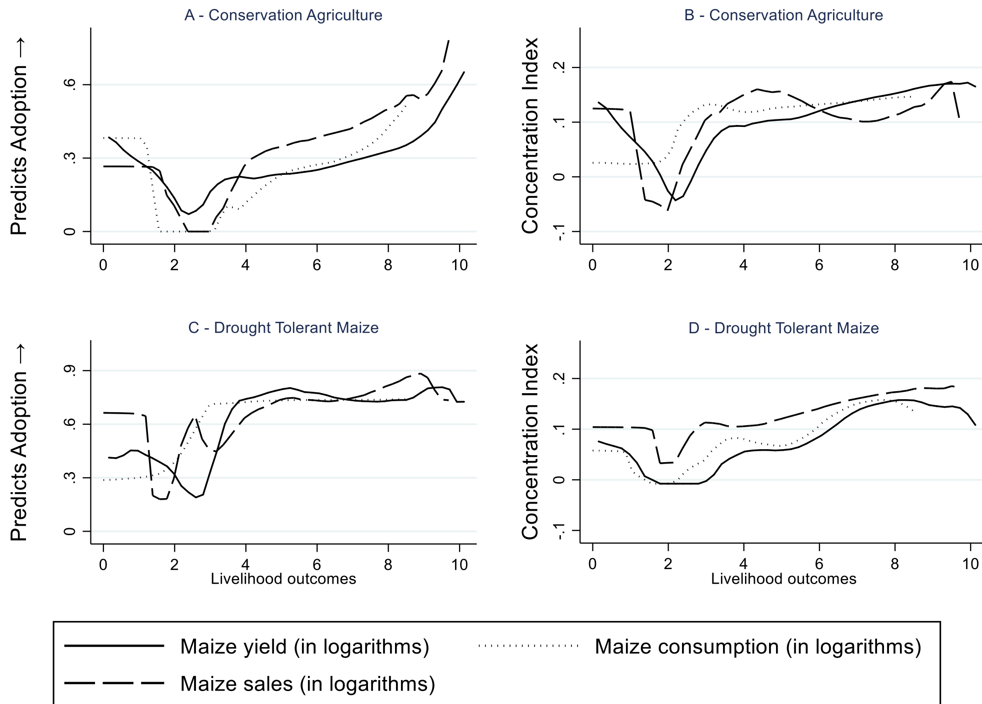

Figure 2. Higher CSA technology adoption, and an increasing pro-rich distribution in technology adoption, predicts better or more livelihood outcomes for smallholder farmers. The figure plots local regressions. The dependent variables in A and C are dummy variables for conservation agriculture and drought tolerant maize adoption (see manuscript for more elaborate definitions), respectively. In B and D, the dependent variables are the concentration index calculated for each district for Conservation Agriculture and Drought Tolerant Maize, respectively. All the dependent variables are calculated in such a way that higher values indicate higher adoption (in case of dummy variables for adoption) and positive values for concentration indices indicate a pro-rich distribution in CSA technology adoption. The explanatory variables in each case are the livelihood outcomes, all expressed in logarithms.