AGRODEP
African Growth & Development Policy modeling consortium
FACILITATED BY IFPRI

AGRODEP Working Paper 0015

September 2015

Modeling the Determinants of Poverty in Zimbabwe

Carren Pindiriri

About the Author

Carren Pindiriri is a Lecturer and Ph.D. candidate at the University of Zimbabwe. He has been an AGRODEP member since April 2013.

Acknowledgments

I appreciatively acknowledge the crucial guidance provided by Dr. John Gibson as my trainer in poverty measurement and analysis. Many thanks go to AGRODEP and IFPRI for funding this project and a number of modeling training workshops which I have attended. My thanks also go to the AGRODEP staff for their invaluable assistance and support. I also extend my gratitude and thanks to Drs. Jeanette Manjengwa and Collen Matema for making the data set available for this study.

Table of Contents

Abstract

Many poverty profiles classifying the poor according to characteristics such as level of education, consumption levels, employment status, and household size have been constructed in Zimbabwe (see Malaba, 2013). However, despite their usefulness in summarizing poverty information and providing clues to possible determinants of poverty, these profiles are restricted by the bivariate nature of their clarifications (Datt and Jolliffe, 1999). This article extends Zimbabwe's poverty profiles into a poverty determinants model, with the overall objective of examining the impact of household characteristics on household poverty. The findings show that poverty measures in Zimbabwe have been understated by previous studies due to the absence of data weighting and endogeneity. Poverty in Zimbabwe is primarily caused by low household income, low educational achievement of the household head, bigger household size, and household location. The possible endogeneity of household size was controlled for in order to improve the robustness of the results. This article recommends, among other things, increasing family planning campaigns, supporting education for the poor, creating employment through implementing investment-friendly policies, and establishing land redistribution policies targeting the poor.

Résumé

De nombreux profils de pauvreté classant les pauvres en fonction de caractéristiques telles que le niveau de l'éducation, les niveaux de consommation, la situation d'emploi, et la taille du ménage ont été construites au Zimbabwe (voir Malaba, 2013). Cependant, en dépit de leur utilité dans le traitement synthétique des informations sur la pauvreté et dans la fourniture des indices sur les déterminants possibles de la pauvreté, ces profils sont limités par leur caractère bivarié (Datt et Jolliffe, 1999). Cet article étend les profils de pauvreté du Zimbabwe a un modèle des déterminants de la pauvreté, avec l'objectif global d'examiner l'impact des caractéristiques des ménages sur leur état de pauvreté. Les résultats montrent que les mesures de la pauvreté au Zimbabwe ont été sous-estimées par les études précédentes en raison de l'absence de pondération de données et du caractère endogène de certaines variables. La pauvreté au Zimbabwe est principalement causée par le faible revenu du ménage, le faible niveau d'instruction du chef de ménage, la taille du ménage et le lieu de résidence. L'endogénéité possible de la taille du ménage a été contrôlée dans le but d'améliorer la robustesse des résultats. Cet article recommande, entre autres choses, de plus en plus de campagnes de planification familiale, de soutien à l'éducation pour les pauvres, la création d'emplois grâce à la mise en œuvre des politiques favorables à l'investissement, et l'établissement de politiques de redistribution des terres en faveur des pauvres.

1. Introduction

Several poverty profiles have been created in Zimbabwe (Malaba, 2013; Sakuhuni et al., 2012 and Manjengwa et al., 2012), and the Zimbabwe Statistical Agency (Zimstat) also frequently constructs poverty profiles, the recent one in 2013. However, despite their usefulness in summarizing poverty information and providing clues to possible determinants, these profiles are restricted by the bivariate nature of their clarifications (Datt and Jolliffe, 1999). Poverty profiles are based on a comparison of households' consumption levels, education, income, or other qualities with some defined threshold (Coudouel et al., 2002). While these comparisons provide valuable leads for policymakers, they do not provide quantifiable effects of poverty determinants, which are crucial for true policy change.

The poverty profiles constructed by Manjengwa et al. (2012) and Malaba (2013) indicate that poverty remains very high in Zimbabwe, with over 70 percent of the population classified as poor. These profiles show higher poverty levels for rural households than for urban households and indicate further divergence of poverty levels from the millennium development goals (MDGs). In addition, poverty has continued to increase despite the country's increased rates and levels of literacy; Zimbabwe's literacy rate is currently over 80 percent (World Bank, 2014). Thus, questions arise as to which factors actually explain poverty in Zimbabwe. Increased knowledge regarding poverty determinants is crucial for the establishment of effective poverty reduction strategies and the achievement of the Millennium Development Goal of poverty elimination. Measuring regional poverty deficits can help capture the amount of resources required in each region to lift the poor out of poverty. It is also important to measure poverty intensity using the poverty gap and its square, which captures poverty severity, in addition to modeling the determinants of poverty.

Many studies on poverty determinants have been carried out in different countries; most of these apply the Ordinary Least Squares (Sakuhuni et al., 2011; Manjengwa et al., 2012; Benson et al., 2005; Okwi et al., 2006; and Datt and Jolliffe, 1999). The recent Zimbabwe poverty determinants regressions conducted by Sakuhuni et al. (2011) and Manjengwa et al. (2012) did not use person weights, making it likely that they understated the level of poverty in Zimbabwe since poor households are larger than non-poor households.

Other studies have applied binary-dependent variable models such as probit, logit, and Tobit models (see Bogale et al., 2005). The main weakness of these models is that they lump poor households as a single uniform group and rich households as another single uniform group; this results in the loss of useful information when transforming expenditures by households into dichotomous variables. Consider a country with a poverty line of US$500 per month. In binary models, a household with per capita expenditures equal to $400 is treated the same as one with per capita expenditures equal to $100. Such treatment is unfair since there are huge differences in these households' poverty gaps. Probit models also require stronger assumptions about the distribution of errors, such as the normality assumption (Gibson and Rozelle, 2003).

The real poverty measure is a continuous variable measured as household consumption expenditure levels; thus, this article measures poverty as such a continuous variable. The overall objective of the article is to examine the determinants of poverty in Zimbabwe using the consumption model and to further refine the results obtained by previous researchers through the use of recent and weighted data.

The rest of this article is structured as follows: Section 2 surveys existing literature on poverty. Section 3 presents and discusses the approach to measuring poverty determinants. Section 4 describes data, presents the poverty determinants model as a consumption model, and discusses estimated results and compute different poverty measures in Zimbabwe. Section 5 concludes.

2. Literature Survey

Several theories have been put forward to explain the causes of poverty. Theoretical literature categorizes poverty as caused by individual deficiencies, cultural belief system, economic, social, and political distortions, geographical disparities, and cumulative and cyclical interdependencies (Bradshaw, 2006). Individual deficiency theorists blame poverty on the poor, claiming that poor people are poor because they are lazy. This idea is also supported by the classical economic theory which argues that with perfect information, individuals seek to maximize their welfare by making choices regarding investment and consumption. Some individuals may choose short-term decisions with low payoff returns, while others may choose long-term decisions with high payoff returns. Hence, individuals are largely responsible for their poverty status. However, more recent welfare economic theory argues that the poor lack incentives to improve their own welfare.

Another theory related to the individual deficiency theory, called the "culture of poverty" theory, advocates that poverty is inherited from generation to generation. According to Lewis (1970), the culture of poverty institutes a design for living that is inherited from one generation to the next. This theory is more important when studying poverty dynamics.

Progressive social theorists have pointed to economic, political, and social distortions as the major cause of poverty. Economic and political distortions reduce individuals' opportunities to increase incomes, assets, and wellbeing. It must be remembered, however, this school of thought looks at the causes of poverty only at a macro level. Marx showed how a capitalist economic system created the "reserve unemployed" to supress wages, and Durkheim later showed how even suicide was mediated by social distortions. When looking at poverty at the macro level, economic, political, and social factors could in fact be key determinants of poverty.

In addition to political, social, economic, cultural, and individual factors, geographical disparities have also been identified as a major theoretical cause of poverty. Terms such as rural poverty, urban poverty, and third world poverty have generally been used to indicate the spatial distribution of poverty according to geographical location. There are five major natural regions with different ecological

characteristics in Zimbabwe. Hence, when modeling poverty determinants in the country, these regional differences have to be taken into consideration.

Myrdal (1957) originated an economic theory of "interlocking, circular, interdependence within a process of cumulative causation" in which individual and community wellbeing are regarded as closely connected. For example, the closure of a company can cause an individual to become unemployed, leading to household poverty and a lack of income for children's education. When children are uneducated, their future employment opportunities dwindle. This type of poverty is caused by cumulative and cyclical interdependencies (Sher, 1977). If such interdependencies exist in poverty modelling, then the robustness of the results generated by the ordinary least squares (OLS) technique could be questionable. Under such circumstances, historical events can be used as instrumental variables for the educational attainment of adults. For example, Hoddinott (2006) demonstrates the long-term effects of being a school-age child during a severe drought in Zimbabwe.

The two most recent studies on the determinants of poverty in Zimbabwe are Sakuhuni et. al (2011) and Manjengwa et al. (2012). Sakuhuni et al. find primary education to be a significant determinant of poverty, while higher education was insignificant. On the other hand, Manjengwa et al. established that primary education was not a significant determinant of poverty in Zimbabwe; rather, they found higher education to be statistically significant. Such diverging results call for further investigation into the determinants of poverty using a different approach.

The main determinants of poverty identified by both of these studies include demographic factors such as age and household size, geographical location, education, employment, environmental factors such as drought (Hoddinott, 2006), remittances, and asset ownership, among others. Kinsey et al. (1998) identified drought as one of the major factors affecting livelihoods in Zimbabwe. Rainfall is highly variable between different regions of the country.

However, these two studies of poverty determinants in Zimbabwe do not apply weighting, despite the recognition that poor households are larger than non-poor ones. Poverty measures could be understated if such differences are not taken into consideration.

Studies applying binary dependent variable models (logit, probit, and Tobit) in other developing countries include Asogwa et al. (2012), Bogale et al. (2005), Osowole et al. (2012), and Ranathunga (2010). The Nigerian poverty determinant studies by Asogwa et al. and Osowole et al. identify education, household size, sex, economic efficiency, farm size, dependency ratio, and market access as key determinants of poverty among rural households. Asset holdings, sex, land ownership, and oxen ownership are among the determinants identified by Bogale et al. in rural Ethiopia and by Ranathunga in Sri Lanka. Other studies on poverty determinants apply the OLS method and establish similar poverty determinants (Benson et al., (2005) in rural Malawi; Datt and Jolliffe (1999) in Egypt; Gibson and Rozelle (2003) in Papua New Guinea). Gibson and Rozelle apply an instrumental variable (IV) approach to remedy the problem of endogeneity. Education, dependency ratio, household size,

inequality, access to roads, and asset holdings are also identified as key determinants of poverty in OLS models.

Despite the existence of an extensive literature on poverty, there still exists a huge gap in knowledge regarding how to model poverty determinants in Zimbabwe. Most models overlook regressions weighting, while other studies fail to observe that poverty is not a dichotomous but rather a continuous variable. It is in this regard that this article considers measuring poverty as a continuous variable and applies person weight to avoid an understatement of poverty measures.

3. Measuring Poverty Determinants

According to Datt and Jolliffe (1999), poverty determinants can be generally modelled using either consumption or poverty models. In this article, we use a consumption model rather than a poverty model as in Datt and Jolliffe (1999), Sakuhuni et. Al (2011), and Manjengwa et al. (2012). The advantages of using a consumption model over a poverty model, as explained by Datt and Jolliffe, are: 1) one can use a consumption model to derive a poverty measure, but a poverty measure cannot be used to derive household consumption; 2) in poverty models, poverty measures are associated with a loss of information since information regarding households living above the poverty line is stifled; 3) unlike poverty models in which different poverty lines imply censoring of consumption data at different levels, estimates in consumption models are independent of the poverty line, and 4) consumption models do not require strong distributional assumptions like binary poverty models do (also see Gibson and Rozelle, 2003).

The commonly used household-level consumption model was applied in this article. The model is expressed as follows:

$$In\, c_i = \mathrm{X}_i\beta + \varepsilon_i \qquad (3.1)$$

where c_i is consumption per capita of household i defined as total household consumption divided by household size, X_i is a vector of determinants of household consumption, and ε_i is an error term. The error term ε_i is treated as uncorrelated with X_i. The augmented Keynesian consumption function was used in this article. Hence household income was considered to be the central explanatory variable, although additional variables were considered. The supplementary explanatory variables included household assets, employment, household size, educational attainment of head of household, gender, location, and age. We augmented the Keynesian consumption function in order to establish the impact of household characteristics on poverty. Table 3.1 summarizes explanatory variables in the consumption function.

Table 3.1: Variable definition in the consumption function

Explanatory variable	Variable definition
Tcons_ex_pc	Per capita household consumption
Average_income	Household income
Total_assets	Asset holdings of the household
Gender_head	Gender of household head
Years_schooling_head	Education attainment of the head of household
HHsize	Household size
Employment_head	Employment status of household head
Agric_region	Regional location of the household (ecological)
Age_head	Age of the household head
Marital_head	Marital status of head of household
Rural	Location of household either rural or urban

Household income was measured as average household income in US$ per month. All household members' take-home income was added and divided by the size of the household. Household income also encompasses the imputed value of own production. Gender is a dummy variable, taking a value of 1 for a male-headed household and zero for a female-headed household. Education was measured as the educational attainment of the household head. Household size was measured as the total number of members in a household, and age was measured in number of years at the last birthday of the household head. Employment status took a value of one if the household head was employed and if the household head was a paid employee. Location was defined in terms of the ecological region in which the household is located. Zimbabwe has five ecological regions; the first three regions (i, ii and iii) have a climate suitable for agriculture, while the other two (iv and v) are dry regions not suitable for agriculture. The location variable took a value of one if the household was located in an ecological region suitable for agriculture and zero otherwise. However, dummies for each region were also used to define location. Assets in this article have been defined in terms of total assets (both machinery and livestock). The rural variable was used to separate rural households from urban households; it takes a value of one for rural households and zero otherwise.

The second stage involved the computation of poverty measures - in this case, the poverty gap index and its square. The Foster, Greer, and Thorbecke (1984) class of poverty measures was computed in this article. In this class, the poverty measure for household i is expressed as:

$$p_{\alpha,i} = \left[\max\left(1 - \frac{c_i}{z}\right), 0 \right]^{\alpha}, \quad \alpha \geq 0 \qquad (3.2)$$

where z represents the poverty line associated with household i. Different poverty lines were use, one for each of the ten provinces. The parameter α is positive and is 0, 1, and 2 for headcount index, poverty gap index, and squared poverty gap index, respectively. Since we also wanted to compute poverty measures from the consumption function, all values of α are applied in this article. Note that the aggregate poverty severity for the n households weighted by household size (h_i) is given as:

$$P_2 = \left(\sum_{i=1}^{n} h_i p_{2,i} \right) \div \left(\sum_{i=1}^{n} h_i \right) \qquad (3.3)$$

The main source of data used in this article is the 2011 Moving Zimbabwe Forward (MZF) Survey conducted by the Institute of Environmental Studies at the University of Zimbabwe. A total of 3448 households were interviewed. The article also made use of the Poverty, Income, Consumption and Expenditure Survey (PICES) conducted by Zimstat in 2011-2012 for the purpose of comparing general household characteristics. Both surveys covered all ten provinces of Zimbabwe using the Zimbabwe Master Sample (ZMS) generated from the 2002 census. These datasets tally well with the 2012 Census results in terms of gender proportions, average household size, education of household heads, employment status, and other variables. These similarities show a reasonable degree of reliability. However, despite the relatively high quality of the data, seasonal effects may affect the results, particularly for rural households, since seasonality is not accounted for in cross-sectional analysis.

The other problem with the MZF dataset is that it is not self-weighting. Hence measuring poverty and its determinants without weighting the regressions is likely to understate the poverty estimates. In order to deal with this problem, the article uses person weighting since poor households are larger than non-poor ones. Probable outliers were eliminated from the data in order to avoid problems resulting from measurement errors.

Zimbabwe has five different ecological geographical areas and ten provinces. Food poverty lines differ from province to province. In this article, food poverty lines were determined through the method used by Zimbabwe National Statistical Agency (Zimstat). Monthly food consumption requirements, which fulfill the biological minimum of 2250 calories required per adult per day, are valued. In 2011, Zimstat computed this food poverty line for the country's ten provinces. The poverty line was higher in drier provinces, namely Matebeleland South, North, and Masvingo, as indicated in Table 3.2. Since the inflation level has remained lower than two percent since the country's dollarization, the food poverty line has remained fairly constant since 2011.

The major problem in the determination of the total consumption poverty line is the complexities involved when determining a non-food poverty line. Although poverty datasets capture both food and non-food consumption expenditures, there is no clear criteria for determining the upper poverty line based on the food poverty line. In this article, it is assumed that households are rational, implying that they seek to maximize utility and thus distribute their expenditures accordingly. A household which survives on exactly a food poverty line is expected to also survive on exactly a non-food poverty line. Consider a household with income *m* to be spent on both food and non-food items, λm of this income being spent on food items and $(1-\lambda)m$ on non-food items. If λm is exactly equal to the food poverty line, then for a rational consumer, $(1-\lambda)m$ must be equal to the non-food poverty line. If this is not the case, then income must be redistributed to maximize utility.

The upper poverty line was then computed as the average non-food consumption per adult-equivalent of the households on the food poverty line. However, neighborhood households in the range -10 percent and +10 percent of the food poverty line were also considered. The findings show a consumption poverty line which is very different from the one used by previous Zimbabwean studies, which assumed the same values for both the food poverty line and the total consumption poverty line. For the food poverty line, the minimum was US$28.91 and the maximum was US$34.26, while the upper poverty line indicates huge variations, with a minimum of US$4.29 and a maximum of US$131.58.

Unlike the food poverty line, which has smaller variations across provinces, the upper poverty and the total consumption poverty lines show huge variations across provinces. The results show US$1.79, US$36.61, and US$35.86 standard deviations of food, non-food, and total consumption poverty lines, respectively. The huge variations in the non-food poverty line across provinces show that regional consumption preferences for non-food items are very different. Upper poverty lines are higher in provinces with the largest cities (Bulawayo, Harare, Midlands, and Masvingo) and are very low in rural provinces. In urban areas, the upper poverty line is higher because of expenses such as rentals and transport costs; these are not a factor in rural areas. The huge differences in upper poverty lines across provinces indicate that non-food poverty is relative in contrast with food poverty. What can be defined as poor in Harare is not the same as poverty in rural Matebeleland. The importance of items considered to be part of the non-food basket differs from one province to the other.

Table 3.2: Provincial Poverty Lines

Province	Food Poverty Line	Upper Poverty Line	Total Consumption Poverty Line
Bulawayo	29.43	131.58	161.01
Manicaland	29.43	63.19	92.62
Mashonaland Central	29.69	18.11	47.80
Mashonaland East	29.45	57.99	87.44
Mashonaland West	30.22	51.67	81.89
Matebeleland North	34.26	4.29	38.55
Matebeleland South	32.5	53.98	86.48
Midlands	29.88	80.62	110.50
Masvingo	32.41	92.35	124.76
Harare	28.91	85.30	114.21

Source: Study Data

4. Results and Discussion

This section describes the data and presents and discusses the research findings. A sample of 3448 households, of which 58.4 percent are rural, is used. The sample is based on a master sample, developed by Zimstat, which covers the whole country. A total of 58.8 percent of the sampled households are in regions suitable for agriculture (that is, regions i, ii, and iii), while the remainder are in regions iv and

v, which are not conducive for agriculture. Out of these households, 71 percent are male-headed and only 29 per cent are female-headed. Most household heads (68 percent) have attained at least a secondary education. However, only 43 percent of household heads are employed, and only 39 percent are paid employees. Table 4.1 illustrates household heads' characteristics.

Table 4.1: Characteristics of Households' Heads

Characteristic	Proportion (%)
Males	71
Married	69
At least secondary education	68
Employed	43

Source: Study Data

The findings show that an average household in Zimbabwe spends about US$15.80 on food items and about US$41.35 on non-food items per month. The average household size is 4.65, while average income per household is about US$79.18. The average number of assets owned by a household is 11.37. On the one hand, the results show huge variations across households in terms of expenditures on non-food items, income, and total consumption. On the other hand, variations in food expenditures, asset holdings, and household size are very small across households. This is an indication that food preferences are almost uniform across provinces, while non-food preferences are very different. Table 4.2 provides descriptive statistics of some of the variables used in this article.

Table 4.2: Descriptive Statistics

Variable	Sample	Mean	Std. Dev.	Min	Max
Food expenditure pc	2888	15.80	26.22	0.11	576.75
Non-food expenditure pc	3174	41.35	110.74	0.02	4071
Total consumption pc	3323	53.23	116.28	0.02	4117
Household size	3401	4.65	2.14	1	18
Total household income	1590	299.43	613.8	2	12000
Average household income	1590	79.18	173.3	0.25	3075
Total household assets	3448	11.37	17.43	0	332

Source: Study Data

Household expenditures differ from one province to the other. Households in Harare and Bulawayo have the highest average expenditures on both food and non-food items; the lowest average consumption expenditures are in Mashonaland East and Matebeleland North provinces. Bulawayo has the highest average expenditure on non-food items, while Harare has the highest on food items. Provinces which are largely rural, such as Mashonaland East and Matebeleland North, have the lowest expenditures on non-food and food items, respectively. These provincial variations are presented in Table 4.3.

The average expenditures on food items are far below the food poverty lines in all provinces, an indication that, on average, all provinces are food-poor. Similarly, average expenditures on non-food items in most provinces are generally lower than the non-food poverty line; the exceptions are Harare, Matebeleland North, and Mashonaland Central. Thus, on average, most provinces have households which are also non-food-poor. The question is, what factors determine these variations in household expenditures?

Table 4.3: Average Provincial Consumption Expenditures

Province	Mean food expenditure per capita (US$)	Mean non-food expenditure per capita (US$)	Mean total consumption expenditure per capita (US$)
Bulawayo	17.66	73.27	90.93
Harare	21.47	72.50	93.97
Manicaland	14.63	41.31	55.94
Mash central	10.56	21.05	31.58
Mash east	5.05	5.43	10.48
Mash west	15.56	29.72	45.28
Masvingo	6.02	8.44	14.46
Mat north	4.19	7.05	11.24
Mat south	12.90	30.99	43.89
Midlands	10.73	39.86	50.59

Source: Study Data

A person-weighted linear regression was used to estimate the log of per capita consumption function (see Appendix A). The results of the basic model of consumption ignoring endogeneity of household size are presented in Table 4.4 column (2). In column (1), the results of the consumption model with instrumented household size are presented. Since rural households are bigger than urban households, the rural variable could be a plausible instrument for household size. In this paper, household size was instrumented by rural location, age of household head, marital status, and gender of household head. Generally, both models (instrumented and non-instrumented) fit well; the fit, as measured by R-squared, is 37.34 percent in the instrumented consumption model and 47.25 percent in the non-instrumented basic consumption model. However, the R-squared value is not useful in IV technique. Furthermore, all coefficients have the expected signs, except the square of age in the instrumented model.

These results tally very well with the theory which states consumption is a function of household income; they also tally with the findings by Manjengwa et al. (2012), Datt and Jolliffe (2005), and Gibson and Rozelle (2003), which say that the educational attainment of the household head significantly influences household consumption expenditures in Zimbabwe. In both models presented in Table 4.4, the findings show that the major determinants of household consumption in Zimbabwe are household income, household size, household assets, employment status, and head of household's education attainment.

Table 4.4: Estimated Log of Per Capita Consumption Function

Variable	Household size instrumented (1)	Non-instrumented model (2)
Household size	-0.165 (4.68)*	-0.141 (13.46)*
Household Income	0.002 (9.21)*	0.001 (8.52)*
Household assets	0.011 (7.79)*	0.009 (7.50)*
Gender of household head		-0.098 (1.90)***
Age of household head		0.022 (3.22)*
Marital status of head		0.102 (2.16)**
Agricultural region	0.567 (12.10)*	0.071 (1.57)
Education attainment of head	0.112 (16.73)*	0.067 (10.99)*
Employment status	0.598 (12.85)*	0.353 (8.23)*
Rural		-1.364 (28.12)*
Age of head squared	0.00004 (2.88)*	-0.0002 (2.71)*
Intercept	1.953 (10.81)*	2.951 (15.89)*
	$R^2 = 37.34$ Observations = 2,757	$R^2 = 47.25$ Observations =2,339

(*), (**) and (***) imply significant at the 1 percent, 5 percent, and 10 percent, respectively. The absolute values of *t*-statistic in parenthesis are corrected for clustering, stratification and weights using the Jack-knife standard errors (see Appendix).

Results of the basic consumption model (2) show that rural households' log of consumption is 136 percent less than that of urban households. In addition to the detrimental consumption effects of being in a rural location, the results indicate a significant substantial loss of consumption from increased household size. Increasing household size by one member reduces log of consumption by about 14 percent. However, this is an understatement of the impact of household size because of its endogeneity (see instrumented model). The age factor in the basic consumption model shows diminishing effects of the household head's age on consumption. The negative sign of the coefficient of the age square shows that the consumption-age relationship follows a converted 'U' shape. In other words, consumption increases as the age of the household head increases, until a certain age level at which any further increase in age starts to decrease household consumption. The consumption function is therefore concave in the age of the household head; it reaches a maximum[1] at 55 years.

[1] The optimal age, or the age (55 years) associated with the turning point of the consumption curve, is obtained by maximizing the basic consumption function (2) with respect to age and equates first derivative to zero.

Many determinants of consumption presented in the basic consumption model (2) indicate a positive association with the log of consumption. There are significant consumption gains from employment, marriage, and increased education of the household head. The log of per capita consumption is higher for employed and married household heads than unemployed and unmarried household heads (35 percent and 10 percent higher, respectively). Increases in household per capita income and assets marginally increase log of per capita consumption. The basic consumption model, however, does appear to understate the impact of these determinants on consumption. This could be a result of some variables which might be endogenous in the model, such as the size of the household. To remedy this, we also apply the instrumental variable approach.

All coefficients of variables in the instrumented model are larger than those in the basic log of consumption model. The findings presented in the instrumented log of consumption model (1) indicate that there are significant losses in household consumption due to extra gains in household size. Household consumption per capita declines by around 16.5 percent as the household size increases by one member. Population increases exert pressure on resources; hence, households increase in size, each household gets less and less of the national or community pie. Similar findings have been established by Bogale et al. (2005) in Ethiopia and Gibson and Rozelle (2003) in Papua New Guinea. However, there are significant gains in consumption from additional years of education, increased income and assets, employment, and wet weather conditions. These results tally well with those found in the basic consumption model, except that the coefficients are larger. Log of consumption per capita by households in dry regions is lower than that of those households located in wet regions (about 57 percent lower).

The predicted or fitted values of the log of per capita consumption function in Table 4.4 has a mean of 3.12 and a standard deviation of 0.92. The minimum fitted value is 0.03 and the maximum is 10.37. The fitted values are then used to generate the poverty gap variable, as in equation 3.2 (see commands in Appendix A). The results show an average poverty gap of 31.4 percent in Zimbabwe. Household consumption in the country is below the poverty line by 31.4 percent. Therefore, resources equivalent to 31.4 percent of the total consumption poverty line are required to push household consumption to at least the poverty line. Harare has the lowest poverty gap (21.8 percent), while Masvingo has the highest (53.3). Poverty could be greatly reduced if Zimbabwe distributed resources according to poverty gap proportions, with Masvingo given the most resources, followed by Mashonaland East, Matebeleland South, and others (see Appendix A).

Although the poverty gap index provides a useful assessment of the amount of resources required to push households to at least the poverty line, it does not provide information regarding how resources should be distributed within a given region or province. In this regard, the study also estimates computed poverty severity using the squared poverty gap index. The findings show an aggregate poverty severity of 53.7 percent, using equation 3.3 in the methodology section. It is critical for Zimbabwe to implement

policies that will reduce this large value of poverty severity. Harare fares well in terms of household consumption distribution compared to other provinces; the mean poverty severity is only 6.5 percent in this province, while it is about 31 percent in Masvingo (see Appendix A). Poverty is more severe among rural households, with average poverty severity of over 18 percent; urban households show an average poverty severity of 7 percent.

5. Conclusion and Policy Implications

This article has attempted to derive the provincial upper poverty line for Zimbabwe and to compute the poverty severity index at the household level in order to explore household-level determinants of poverty in the country. The instrumental variable technique, specifically the two-stage least squares method, was employed using the MZF data set. The findings generally indicate that at the household level, poverty is worsened by increased household size but could be reduced through increased education, assets accumulation, employment, and relocation to better agricultural regions. Although many policy implications could be drawn from the estimated results, we derive the following specific poverty modeling and policy implications:

First, household size is an endogenous variable in poverty regressions. Hence it is crucial to apply techniques such as the instrumental variable technique when modeling the determinants of poverty. In cases in which such techniques are not applied, coefficients of poverty determinants are likely to be understated. It is also worth noting from the derivation of the upper poverty line that poverty researchers should not use the food poverty line as a proxy for the total consumption poverty line because there is great divergence between the two lines.

Second, according to the instrumented model, low consumption is more severe in drier areas not suitable for agriculture and in rural provinces. Being located in regions with a suitable agricultural climate reduces poverty by over five percent. Thus, relocating households through land reform is key to the reduction of poverty, particularly in drier rural regions. This land reform is an ongoing process in Zimbabwe, but thus far, land distribution has been independent of households' poverty status. It is our view that the government of Zimbabwe should consider giving first priority to the most poverty severe provinces and households when redistributing land.

Third, households headed by employed members have higher consumption levels than those headed by unemployed members. Lack of employment accounts for over 35 percent of the difference in poverty between households headed by unemployed members and those headed by employed members. Employment creation is therefore critical to reducing consumption poverty. In addition, the government to start providing safety nets such as unemployment benefits. However, limited resources will likely hamper the provision of social insurance; hence the government's best option is to create employment through attracting investment (both foreign and domestic).

Fourth, households headed by uneducated members have less consumption compared to those headed by members with at least a secondary education. The main implication of this finding is that making secondary education compulsory will go a long way toward reducing poverty and inequality among the poor. In order to improve educational attainment by future generations, government expenditures on education should target poor households and districts. More support should also be provided for the Basic Education Assistance Module (BEAM) which provides free primary education to all.

Fifth, asset accumulation is crucial in poverty reduction. In rural provinces where drought shocks are more prevalent, accumulating assets can be a good form of consumption insurance. To aid this, the government could provide equipment or machinery to poor households in order to start businesses. This assistance should, however, be biased toward female-headed households, since the findings show that female-headed households experience higher consumption levels than male-headed households.

Last, household size is negatively associated with per capita consumption. Family planning is therefore crucial in poverty reduction. Rural households are still bearing many children despite their deep state of poverty; therefore, awareness campaigns to reduce the number of children per household should be central in rural provinces.

Future studies should consider the time-series dimension of poverty modeling in order to capture seasonality, political changes, and some macroeconomic variables such as inflation and investment flows.

References

Asogwa, B.C., V.A. Okwoche, and J.C. Umeh. 2012. "Analysing the Determinants of Poverty Severity in Nigeria: A Censored Regression Model Approach." *American International Journal of Contemporary Research* 2(5): 166-176.

Benson, T., J. Chamberlin, and I. Rhinehart. 2005. "An Investigation of the Spatial Determinants of Local Prevalence of Poverty in Rural Malawi." *Food Policy* 30: 532-550.

Bogale, A., K. Hagedorn, and B. Korf. 2005. "Determinants of Poverty in Rural Ethiopia." *Quarterly Journal on International Agriculture* 44(2): 101-120.

Bradshaw, K.T. 2006. "Theories of Poverty and Anti-Poverty Programs in Community Development." Rural Poverty Research Center Working Paper No. 06-05. Iowa City, IA: Rural Poverty Research Center.

Bruck, T., A.M. Danzer, A. Muravyev, and N. Weibhaar. 2007. "Determinants of Poverty during Transition: Household Survey Evidence from Ukraine." PRUS Working Paper No. 40. Sussex: Poverty Research Unit, Sussex University.

Coudouel, A., J.S. Hentschel, and T.Q. Wodon. 2002. "Poverty Measurement and Analysis." In *A Sourcebook for Poverty Reduction Strategies,* edited by Jeni Klugman. Washington DC: The World Bank.

Datt, G. and D. Jolliffe. 1999. "Determinants of Poverty in Egypt: 1997." FCND Discussion Paper No. 75. Washington DC: IFPRI.

_____. 2005. "Poverty in Egypt: Modeling and Policy Simulations." *Economic Development and Cultural Change* 53(2): 327–346.

Foster, J., J. Greer, and E. Thorbecke. 1984. "A Class of Decomposable Poverty Measures." *Econometrica* 52(3): 761-765.

Gibson, J. and S. Rozelle. 2003. "Poverty and Access to Roads in Papua Guinea." *Economic Development and Cultural Change* 52(1): 159-185.

Hoddinott, J. 2006. "Shocks and their Consequences Across and Within Households in Rural Zimbabwe." *Journal of Development Studies 42(2)*: 301-321.

Kinsey, B.H., J.W. Gunning, and K. Burger. 1998. "Coping with Drought in Zimbabwe: Survey Evidence on Responses of Rural Households to Risk." *World Development Report* 26(1): 89-110.

Lewis, O. 1970. *Anthropological Essays'* New York: Random House.

Malaba, J. 2013. "Poverty and Poverty Datum Line Analysis in Zimbabwe 2011/12." Harare, Zimbabwe: Zimbabwe Statistical Agency.

Manjengwa, J., I. Kasirye, and C. Matema. 2012. "Understanding Poverty in Zimbabwe: A Sample Survey in 16 Districts". Paper Presented at the Centre for the Study of African Economies Conference 2012. Oxford, United Kingdom.

Myrdal, G. 1957. *Economic Theory and Underdeveloped Regions*. London: Gerald Duckworth and Co.

Osowole, O.I., R. Ugbechie, and U. Ezenwanyi. 2012. "On the Identification of Core Determinants of Poverty: A Logistic Regression Approach." *Mathematical Theory and Modeling* 2(10): 45-52.

Ranathunga, S.P.B. 2007. "The Determinants of Household poverty in Sri Lanka: 2006/2007." Paper Presented for the 14th Annual Student Research Conference, October 18, 2010. New Zealand: Waikato Management School, University of Waikato.

Sakuhuni, R.C., C. Chidoko, N.L. Dhoro, and C. Gwaendepi. 2011. "Economic Determinants of Poverty in Zimbabwe." *International Journal of Economic Research* 2(6): 1-12.

Sher, J.P. 1977. *Education in Rural America*. Westview, Boulder.

World Bank. 2014. "Country Statistics, Zimbabwe." Available at www.worldbank.org.

APPENDIX A

```
. svyset A1_EA [pweight=HHSIZE], strata(A1_PROVINCE) fpc(A1_PROVINCE) vce(linea
> rized) singleunit(missing) || A1_HOUSEHOLD, strata(HHSIZE) fpc(HHSIZE)

      pweight: HHSIZE
          VCE: linearized
  Single unit: missing
     Strata 1: A1_PROVINCE
         SU 1: A1_EA
        FPC 1: A1_PROVINCE
     Strata 2: HHSIZE
         SU 2: A1_HOUSEHOLD
        FPC 2: HHSIZE
```

```
. tabulate a1_province, summarize(povgap2)
```

A1_PROVINCE	Summary of povgap2 Mean	Std. Dev.	Freq.
Bulawayo	.27380189	.14074119	232
Harare	.21774295	.13168642	499
Manicaland	.30085938	.16587206	468
Mash centr	.25124226	.19367338	302
Mash east	.39790759	.15604622	153
Mash west	.33275512	.14041835	325
Masvingo	.53257564	.1547835	172
Mat north	.34142167	.16367944	117
Mat south	.38100263	.17720556	182
Midlands	.3393577	.21608866	387
Total	.3137475	.18320134	2837

```
. tabulate rural, summarize(povgap2)
```

Rural	Summary of povgap2 Mean	Std. Dev.	Freq.
0	.23162873	.14102448	1305
1	.38369854	.18597724	1532
Total	.3137475	.18320134	2837

```
. tabulate a1_province, summarize (povgapsq)
```

A1_PROVINCE	Summary of povgapsq Mean	Std. Dev.	Freq.
Bulawayo	.09469018	.08300536	232
Harare	.06471855	.06916684	499
Manicaland	.11797112	.10975436	468
Mash centr	.10050785	.12001572	302
Mash east	.18252172	.13289681	153
Mash west	.13038262	.1044939	325
Masvingo	.30745546	.16635711	172
Mat north	.14313073	.13213922	117
Mat south	.17639228	.14645239	182
Midlands	.1617373	.16560302	387
Total	.13198839	.1337828	2837

```
. tabulate rural, summarize (povgapsq)
```

Rural	Summary of povgapsq Mean	Std. Dev.	Freq.
0	.07352454	.07936098	1305
1	.18178952	.14964654	1532
Total	.13198839	.1337828	2837

```
.
```

Poverty determinants model with instrumented household size

```
. ivregress 2sls logtcons_ex_pc average_hincome total_assets employment_head ag
> ric_region years_schooling_head agesq (hhsize = gender_head age_head marital_
> head rural)

Instrumental variables (2SLS) regression          Number of obs =    2757
                                                  Wald chi2(7)  = 1507.53
                                                  Prob > chi2   =  0.0000
                                                  R-squared     =  0.3734
                                                  Root MSE      =  1.1602
```

logtcons_e~c	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
hhsize	-.1646652	.0351753	-4.68	0.000	-.2336075	-.0957229
average_hi~e	.0016514	.0001794	9.21	0.000	.0012998	.002003
total_assets	.0110228	.0014148	7.79	0.000	.0082498	.0137959
employment~d	.5978763	.0465451	12.85	0.000	.5066497	.689103
agric_region	.5873634	.0485244	12.10	0.000	.4922574	.6824695
years_scho~d	.1115276	.0066655	16.73	0.000	.0984634	.1245918
agesq	.0000436	.0000151	2.88	0.004	.000014	.0000732
_cons	1.952667	.1807064	10.81	0.000	1.598489	2.306845

```
Instrumented:  hhsize
Instruments:   average_hincome total_assets employment_head agric_region
               years_schooling_head agesq gender_head age_head marital_head
               rural
```

Correlations among instruments

```
. correlate AVERAGE_HINCOME TOTAL_HASSETS EMPLOYMENT_STATUS AGRIC_REGION years_
> schooling_head MARITAL_HHEAD AGE_HHEAD AGE_HHEAD GENDER_HHEAD rural
(obs=2826)
```

	AVERAG~E	TOTAL_~S	EMPLOY~S	AGRIC_~N	years_~d	MARITA~D	AGE_HH~D
AVERAGE_HI~E	1.0000						
TOTAL_HASS~S	0.1424	1.0000					
EMPLOYMENT~S	0.2133	0.0082	1.0000				
AGRIC_REGION	0.1112	0.0050	0.1597	1.0000			
years_scho~d	0.1203	0.0692	0.2304	0.1965	1.0000		
MARITAL_HH~D	0.0072	0.0131	0.1174	-0.0387	0.0735	1.0000	
AGE_HHEAD	-0.0401	0.1151	-0.0794	0.0005	-0.1647	-0.1675	1.0000
AGE_HHEAD	-0.0401	0.1151	-0.0794	0.0005	-0.1647	-0.1675	1.0000
GENDER_HHEAD	0.0774	0.0204	0.2231	-0.0423	0.1170	0.4676	-0.1307
rural	0.0113	-0.0124	0.0243	0.4315	0.0650	-0.0154	0.0792

	AGE_HH~D	GENDER~D	rural
AGE_HHEAD	1.0000		
GENDER_HHEAD	-0.1307	1.0000	
rural	0.0792	-0.0674	1.0000

Poverty determinants model with non-instrumented variables

```
. regress logtcons_ex_pc rural hhsize average_hincome total_assets gender_head
> age_head marital_head agric_region secondary_educ_head years_schooling_head e
> mployment_head agesq [pweight = poor], vce(jackknife, cluster(a1_province)) b
> eta
(running regress on estimation sample)

Jackknife replications (10)
----+--- 1 ---+--- 2 ---+--- 3 ---+--- 4 ---+--- 5
..........

Linear regression                               Number of obs     =       2339
                                                Replications      =         10
                                                F(  9,     9)     =          .
                                                Prob > F          =          .
                                                R-squared         =     0.4725
                                                Adj R-squared     =     0.4698
                                                Root MSE          =     0.9288

                                (Replications based on 10 clusters in a1_province)
------------------------------------------------------------------------------
             |             Jackknife
logtcons_e~c |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
```

See results in Table 4.4

AGRODEP Working Paper Series

0001. Poverty, Growth, and Income Distribution in Kenya: A SAM Perspective. Wachira Rhoda Gakuru and Naomi Muthoni Mathenge. 2012.

0002. Trade Reform and Quality Upgrading in South Africa: A Product-Level Analysis. Marko Kwaramba. 2013.

0003. Investigating the Impact of Climate Change on Agricultural Production in Eastern and Southern African Countries. Mounir Belloumi. 2014.

0004. Investigating the Linkage between Climate Variables and Food Security in ESA Countries. Mounir Belloumi. 2014.

0005. Post-Liberalization Markets, Export Firm Concentration, and Price Transmission along Nigerian Cocoa Supply Chains. Joshua Olusegun Ajetomobi. 2014.

0006. Impact of Agricultural Foreign Aid on Agricultural Growth in Sub-Saharan Africa. A Dynamic Specification. Reuben Adeolu Alabi. 2014.

0007. Implications of High Commodity Prices on Poverty Reduction in Ethiopia and Policy Options under an Agriculture-Led Development Strategy. Lulit Mitik Beyene. 2014.

0008. Rainfall and Economic Growth and Poverty: Evidence from Senegal and Burkina Faso. FrançoisJoseph Cabral. 2014.

0009. Product Standards and Africa's Agricultural Exports. Olayinka Idowu Kareem. 2014.

0010. Welfare Effects of Policy-Induced Rising Food Prices on Farm Households in Nigeria. Adebayo M. Shittu, Oluwakemi A. Obayelu, and Kabir K. Salman. 2015.

0011. The Impact of Foreign Large-scale Land Acquisitions on Smallholder Productivity: Evidence from Zambia. Kacana Sipangule and Jann Lay. 2015.

0012. Analysis of Impact of Climate Change on Growth and Yield of Yam and Cassava and Adaptation Strategies by the Crop Farmers in Southern Nigeria. Nnaemeka Chukwuone. 2015.

0013. How Aid Helps Achieve MDGs in Africa: The Case of Primary Education. Thierry Urbain Yogo. 2015.

0014. Is More Chocolate Bad For Poverty? An Evaluation of Cocoa Pricing Options for Ghana's Industrialization and Poverty Reduction. Francis Mulangu, Mario Miranda and Eugenie Maiga. 2015.