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EXPLAINING THE RURAL-URBAN DIFFERENCES IN POVERTY IN MALAWI: A QUANTILE REGRESSION APPROACH

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Abstract

The study uses the most recent Integrated Household Survey (2010 IHS) data to explain the rural-urban differences in poverty in Malawi. In analysis, a welfare model is adopted from the other studies on poverty, where the per capita consumption expenditure is used as the welfare indicator. The paper further adopts the Machado-Mata decomposition technique to attribute the rural-urban welfare gap into the 'characteristics effect' and the 'returns effect'. In addition, Dinardo, Fortin and Lemiueux (DFL) approach is employed to give a detailed decomposition of the 'characteristics effect'. The results show that significance of the rural-urban differences of variables of the welfare model varies across the welfare distribution. This entails that the differences are significant in some quantiles and insignificant in the others. Secondly, the Machado-Mata decomposition technique found that both the differences in characteristics and differences in returns to those characteristics significantly contribute to the urban-rural welfare gap. Specifically it was found that the 'returns effects' were dominant across the whole distribution. Thirdly, through the DFL technique, it shows the specific variables that contribute to the 'characteristic effects'.

Keywords: Per capita consumption; Macado-Mata decomposition; DFL technique; poverty; decomposition

INTRODUCTION

Malawi is categorized as one of the poorest countries in southern Africa and in the world in general. With a population of approximately 14 million,50.7% live below the poverty line as of 2014. This is just slightly below the 52.5% as established in the 2005 Integrated Household

Survey (IHS).Malawi can be demarcated into two sectors, thus; urban areas and rural areas (NSO, 2005; MEPD, 2009). Despite the slight decrease in the national poverty rates there is a significant difference between the urban and rural poverty rates. The rural areas are experiencing high poverty rates than the urban areas despite several governments' interventions to reduce poverty. However, it can be suggested that the recent drop in poverty is due to a favorable combination of human controlled and non-controlled factors, such as weather conditions, rather than more profound changes in the country's economic structure (MEPD, 2009). With the implementation of programmes like Agriculture subsidy, irrigation initiatives, development funds and support to orphans and other vulnerable children, it is expected that the 2015 target will not be fully met. The distribution in poverty rates is summarized below;

Table 1. Distribution in poverty rates

	IHS1 (%)	IHS2 (%)	WMS (%)	WMS (%)	WMS (%)	IHS3 (%)
	1998	2004	2005	2007	2009	2011
National	54	52	50	40	39	50.7
Urban	19	25	24	11	14	17.3
Rural	58	56	53	44	43	56.6

Source: NSO, 2005, NSO, MEPD 2009, NSO 2010

There have been several approaches to deal with poverty the earliest ones focused on strategies aimed at accelerating economic development, rather than poverty reduction. These policies were aimed at translating the achieved growth into poverty reduction, improved income distribution and reduction of ignorance and diseases(GoM and UNDP,1993). These were followed by Poverty Alleviation Policy(PAP) framework in 1994, aiming at raising the productivity of the poor through a sustainable and participatory socio-economic process. Later in 1998 long-term goals namely Malawi Vision 2020 were launched and the long-run development goals identified in the policy document are in line with the Millennium Development Goals(MDGs).To operationalise the vision, the government launched the Poverty Reduction Strategy(MPRS) in April,2002 with the overall goal of achieving 'sustainable poverty reduction through empowerment of the poor'. The Ministry of Economic Planning introduced the Malawi Economic Growth Strategy(MEGS) in order to ensure that the pillar of 'sustained pro-poor economic growth' is achieved. It is thus evident that the government of Malawi has put measures to try to reduce poverty in Malawi and in addition to these, studies by Murkhejee and Benson (2003), Muhome (2008), and NSO (2005) have contributed to the study of the extent of poverty in Malawi.

Problem Statement and Significance of the Study

In studying poverty determinants in Malawi, the previous studies focused on the use of the Ordinary least squares (OLS) technique which assumes that the marginal effects of variables are the same across the whole distribution. It can however be argued that an individual at the lowest percentile in a distribution cannot benefit from ‘Education’ in alleviating poverty, in the same way an individual from the top percentile would(Nguyen et al, 2006). This study therefore introduced the use of quantile regressions to allow covariates to have marginal effects that vary with households’ position on the welfare distribution. In addition, the use of quantile regression technique is more able in handling the common problem of heteroskedasticity since it automatically produces robust estimates.

Not much literature in Malawi has used the decomposition methods to explain the extent of poverty. Muhome(2008) in a study on the rural-urban welfare inequalities in Malawi, used decompositions to provide quantitative assessment of the sources of the rural-urban welfare differential. Through the use of Machado and Mata (2005) hereafter “M-M” technique, she attributed the gap to differences in characteristics and differences in returns to those characteristics. However, she did not go ahead to identify the specific characteristics that drive the rural-urban welfare differential. This study therefore introduced the use of the technique by DiNardo, Fortin and Lemieux (1996; hereafter “DFL”) in examining the rural-urban gap, in order to identify the specific characteristics that affect different parts of the whole welfare distribution.

This study therefore stands out from the already existing literature in three interesting ways. Firstly, the study tests for the significance of the differences in the contribution of variables to welfare between the urban and rural areas. Determining whether at all these variables differ between the urban and rural areas. Secondly, the study uses the M-M decomposition technique to determine the relative contribution of the ‘returns effect’ and the ‘characteristics effect’ to the welfare gap across the quantiles. Thirdly, the study takes a further step in using the DFL technique to obtain the detailed decomposition which shows how the ‘characteristics effect’ can be attributed to each variable of the welfare model.

Objectives of the Study

The main objective of this study is to explain the rural-urban differences in poverty in Malawi, using a quantile regression approach. In pursuing the main objective the following specific objectives will be examined;

- To see if the determinants of poverty significantly differ across the quantiles between the urban and rural areas.

- To determine the relative contribution of the 'returns effect' and the 'characteristics effect' to the urban-rural welfare gap at each quantile.
- To see how the 'characteristics effect' is attributed to each factor of the welfare model.

THEORETICAL REVIEW

Measurement of Welfare

There are a number of conceptual approaches to the measurement of well being. The most common approaches are to measure economic welfare based on household consumption expenditure and household income. When divided by the number of household members, this gives a per capita measure of consumption expenditure and income respectively. There are also non-monetary measures of individual welfare, which include indicators such as infant mortality rates in the region, life expectancy, the proportion of spending devoted to food, housing conditions, and child schooling (World Bank,2005). If consumption is used as a measurement of welfare, there are several advantages and disadvantages that are incurred(Deaton and Zaidi, 2002). An alternative approach to measuring welfare is the use of income. As any other approach, it has several strengths and weaknesses. Despite the arguments supporting income approach, most developing countries use the consumption approach to measure welfare in their studies. As stipulated by World Bank (2005), most rich countries measure poverty using income, while most poor countries use consumption expenditure. This is because, for rich countries, income is comparatively easy to measure (much of it comes from wages and salaries) while their expenditure is hard to quantify. On the other hand, in less developed countries income is hard to measure (much of it comes from self employment), while expenditure is straight forward and hence easier to estimate. Thus to say, most developing countries opt for consumption expenditure measurement of welfare as the best measurement.

Decomposition Methods

One of the important limitations of summary measures such as the variance, the Gini coefficient or the Theil coefficient is that they provide little information regarding what happens where in the distribution (Fortin, Lemieux and Firpo, 2010).This is a crucial shortcoming in the literature of poverty and poverty changes where many important explanations of the observed changes have specific implications for specific points of the distribution. As a result, it is imperative to go beyond the summary measures such as the variance to better understand the sources of growing inequality. To solve this it is suggested that a decomposition of various quantiles of the distribution be done. While ordinary least squares(OLS) technique estimates the conditional mean of the dependent variable or the function that describes how the mean of the dependent variable varies conditional on the regressors, the quantile regression is a method to model conditional quantiles for any choice of quantile $\tau \in (0-1)$,Koenker and Basset(1978) .

A common approach used in the decomposition literature consists of imposing functional form restrictions to identify the various elements of a detailed decomposition(Fortin et al, 2010). For instance, detailed decompositions can be readily computed in the case of the mean using the assumptions implicit in Oaxaca (1973) and Blinder (1973).The goal of the method is to decompose differences in mean across two groups into a component of differences in average characteristics and a second part of the residual component. There has been a surge of methodologies extending the Oaxaca (1973) and Blinder (1973)

(O-B) decomposition of differences at the mean to decomposition of the whole distribution. The M-M approach is one of the approaches that goes beyond the O-B decomposition. This method requires estimation of quantile regressions and is advantageous because it allows for covariates to have marginal effects (returns) that vary across the whole distribution. The mean regression methods described above cannot reveal such variations (Nguyen *et al,* 2006). In other words, the Oaxaca-Blinder decomposition is disadvantageous because it only concentrates on the mean level when it is also important to focus on the entire distribution. The M-M decomposes gaps of the distribution into two components: one due to differences in distribution of characteristics and another due to differences in returns to those characteristics. The work of Machado and Mata in dealing with issues in the labour market in Portugal is particularly notable since it introduces a useful way to extend the counterfactual wage decomposition approach by Oaxaca(1973) to quantile regression and provides a general strategy for simulating marginal distributions from the quantile regression process(koenker & Hallock, 2001).

The other approach is the weighted-kernel density estimator introduced by DiNardo, Fortin and Lemieux (1996).This is a semi-parametric density estimation technique that allows us to visualize the impacts of the explanatory factors on the whole distribution. The DFL method has several advantages over the other methods. Firstly, unlike other methods, the DFL does not rely on a specific measure of inequality which sometimes may lead to varying results depending on the measure used (Cameron, 2000). Secondly, with DFL the analyst is able to determine how different factors affect different parts of a distribution of interest as opposed to use of summary measures (Dinardo, Fortin, & Lemieux, 1996). Thirdly, the analysis does not rely on the imposition of any functional form, thus allowing the data to speak for itself. One major disadvantage of the DFL is that the analyst should have a parsimonious model thereby limiting the number of explanatory factors that can be analyzed individually.

EMPIRICAL REVIEW

Several studies have been carried out in Malawi to assess the extent of poverty in Malawi. Murkherjee and Benson(2003) looked at the determinants of poverty, Bokosi(2006) looked at the household dynamics of poverty in Malawi while Muhome (2008) looked at the rural-urban welfare inequalities in Malawi. Using data from the 1997–98 Malawi Integrated Household Survey, Mukherjee and Benson (2003) conducted an empirical multivariate analysis of household welfare. The model was used to simulate the effects of changes in key household characteristics and assess the likely impact on poverty of a number of poverty reduction policy interventions. The results show that higher levels of educational attainment, especially for women, and the reallocation of household labor away from agriculture and into the trade and services sector of the economy would be effective in reducing poverty in Malawi (Muhome,2008).

The current study therefore contributes to the literature in Malawi by combining all the three methods in order to give a more detailed explanation on the concept of poverty in Malawi and attempts to fill in the missing empirical gap on Malawian literature on poverty.

In a similar approach to this study, Nguyen et al (2006) carried out a study in Vietnam using the Vietnam Living Standards Surveys from 1993 and 1998 to examine the inequality in welfare between urban and rural areas. The study used the M-M decomposition technique and found that household characteristics explained the welfare gap at the lowest quantiles while the differences in returns to these characteristics explained the welfare gap at the top percentiles of the distribution. There is a rapidly expanding empirical quantile regression literature in economics that, taken as a whole, makes a persuasive case for the value of “going beyond models for the conditional mean” in empirical economics. Deaton (1997) studied an application of quantile regression for demand analysis. In a study of Engel curves for food expenditure in Pakistan, he finds that although the median Engel elasticity of 0.906 is similar to the ordinary least squares estimate of 0.909, the coefficient at the tenth quantile is 0.879 and the estimate at the 90^{th} percentile is 0.946, indicating a pattern of heteroskedasticity and justification of estimating quantile regressions than just the ordinary least square estimations. Other empirical studies have focused on the wage gap between men and women. Albrecht *et al* (2006) used a quantile regression decomposition method to analyze the gender gap between men and women who work full time in the Netherlands. They used the M-M decomposition technique to analyze their gender log wage gap and it showed that the majority of the gap was due to differences between men and women in returns to labor market characteristics rather than to differences in the characteristics.

There is also considerable empirical literature that uses the DFL approach to analyze the effects of several factors on the presence and changes in inequality. DiNardo, Fortin and Lemieux(1996) used this semi parametric approach to analyze the effects of institutional and labour market factors on the changes in the United States' distribution of wages. Daly and Valletta (2006) also used this technique to analyze the contribution of rising dispersion of men's earnings and related changes in family behavior to increasing inequality in the distribution of family income in the United States.

METHODOLOGY

Model Specification and Estimation Techniques

In line with previous papers, we use an augmented welfare model inspired by Murkhejee and Benson (2006). The welfare model relates consumption of a household (as a proxy of welfare) to its determinants (such as age of household head, gender of household head) available in data set of 2010 IHS. The variables used are explained in a table in the appendix. The equation can be written as

$$\ln C = \alpha + u.\gamma + X\beta + u.X\lambda + \varepsilon \quad (2.2)$$

where X is a matrix of covariates that represent the determinants of poverty; α is the intercept depicting the coefficient of the base category which is the rural area in this case; u is the dummy variable (to test for regional hetereogeneity), taking the value 1 if urban area, 0 if rural area; γ is the differential intercept between the urban and rural areas; λ is the differential coefficient of the corresponding variable. Quantile regression, a technique for estimating the θth quantile of a random variable y (log consumption in our application) conditional on covariates ,is of special interest when there is reason to believe that the marginal effects are heterogeneous (as is our case) (Koenker & Hallock). The quantile regression model assumes that the conditional quantile of y , q_θ, is linear in x; that is, $q_\theta = x\beta(\theta)$. The coefficient vector $\beta(\theta)$ is estimated as the solution to

$$\min_{\beta(\theta)}\left\{\sum_{i:y_i \geq x_i\beta(\theta)}\theta \mid y_i - x_i\beta(\theta)\mid + \sum_{i:y_i \leq x_i\beta(\theta)}(1-\theta)\mid y_i - x_i\beta(\theta)\mid\right\}. \quad (2.3)$$

In log consumption quantile regressions, the coefficient estimates, $b(\theta)$, are interpreted as the estimated returns to the covariates at the θth quantile of the log consumption distribution.

We therefore estimate the following quantile regression,

$$Q_\theta[y \mid X, u] = \beta_\theta^o + X\beta_\theta + u.X\lambda_\theta + \varepsilon \quad (2.4)$$

Thirdly, the study calculates the M-M decomposition for each quantile and gets the two components depicting differences due to characteristics and differences due to different returns to those characteristics. The M-M technique involves estimating equations for rural and urban households, and constructing a counterfactual distribution of rural ln C using urban distribution covariates. The contribution of the differences in distribution of covariates to the urban-rural gap is estimated by comparing the counterfactual and original rural distribution and the remaining gap is attributed to the combined differences in the returns to the covariates.

The counterfactual distribution can be denoted as $F(y^* \mid Z^U, \beta^R)$, where Z is distribution of covariates and β is the collection of vector of quantile regression coefficients(returns) at the various quantiles. $F(y^* \mid Z^U, \beta^R)$ is constructed using the Machado-Mata algorithms as follows:

- For each quantile θ = 0.01, 0.02,…, 0.99, estimate regression coefficients $\beta^R(\theta)$ using the rural data.
- Using urban data generate fitted values $y^*(\theta) = Z^U \beta^R(\theta)$. For each θ this generates N^U fitted values, where N^U is the size of the urban sub sample.
- Select randomly s = 100 of the elements of y^* (θ) for each θ and stack these into a 99*100 element vector y^*. The empirical cumulative distribution function (CDF) of these values is the estimated counterfactual distribution.

The decomposition compares the counterfactual distribution with the empirical urban and rural ln C distributions, defined as $y^*(\theta), y^U$ and $y^R(\theta)$ respectively. The difference between the θ th quantile of the urban and rural distributions is given as:

$$y^u(\theta) - y^R(\theta) = \{y^u(\theta) - y^*(\theta)\} + \{y^*(\theta) - y^R(\theta)\} \quad (2.5)$$

Where $y^*(\theta)$ is the counterfactual distribution of rural log capita consumption which is the distribution of y $(\ln C)$ that would have prevailed if rural households had been endowed with urban characteristics but retained rural returns to those characteristics. The first term on the right-hand side is the returns effect: it measures the contribution of the difference in returns to the urban-rural gap at the θth quantile. The second term on the right-hand side is the covariate effect: it measures the contribution of the different covariate values to the urban-rural gap at the θth quantile (Nguyen et al,2006).

Fourthly, the study uses the semi parametric method of Dinardo et al(1996) to evaluate possible factors behind the urban-rural welfare inequalities across the welfare distribution. The study constructs counterfactual distributions where unlike before, individuals in the rural area adapt characteristics of those in rural areas but adapt the returns of the urban area (Dinardo et al, 1996).

The distribution of rural areas can be depicted as,

$$f(consumption : t_{returns} = rural, t_z = rural) = \int f(c \mid z, t_{returns} = rural) dF(z \mid t_z = rural) \quad (2.6)$$

where z represents the 'characteristics'.

The distribution of urban areas can be depicted as,

$$f(C; t_{returns} = urban, t_z = urban) = \int f(c \mid z, t_{returns} = urban) dF(z \mid t_z = urban) \quad (2.7)$$

Whereas the counterfactual distribution can be depicted as,

$$= \int f(c \mid z, t_{returns} = urban) \psi(z) dF(z \mid t_z = urban) \quad (2.8)$$

where $\psi(z) = \frac{dF(z \mid t_z = rural)}{dF(z \mid t_z = urban)}$.

Thus these densities can be used to estimate counterfactual densities by weighted kernel methods and these can be depicted as,

$$f(C; t_{returns} = urban, t_z = rural) = \sum \frac{\theta_i}{h} \psi(z_i) K\left(\frac{w - W_i}{h}\right) \quad (2.9)$$

where the actual densities are calculated by omitting the reweighting function $\psi(z)$.

ANALYSIS AND RESULTS

Descriptive Statistics for the Variables in the Welfare Model

Table 2 presents the descriptive statistics for the variables that are hypothesized to differ between urban and rural areas in determining household welfare. The statistics show a slight but statistically significant difference in the mean log per capita consumption between urban and rural households at MK11.433 and MK 10.563, respectively.

Table 2: Descriptive statistics for variables used in Econometric analysis

Variable	urban		Rural	
	mean	sd	Mean	Sd
Log of per capita consumption	11.43315	0.85405	10.56308	0.6831
Household head age	38.69548	13.41392	42.91622	16.69034
Square of age of household head	1677.193	1277.081	2120.342	1683.82
Education	2.282706	1.07508	1.36002	0.72537
Sex of household head	1.183162	0.3869	1.2533	0.4349
Household size	4.452306	2.2249	4.5881	2.2029
Household size squared	24.7712	24.344	25.9039	24.2395
Marital status	1.5249	0.9729	1.4425	0.7976

OLS Regression Results

The study firstly estimates the welfare model using the OLS estimation technique and summarises its results in the table below. This was done to show how the two techniques in question differ by producing different results to the same variables. Table 2 below presents regression results for the welfare model that was estimated through the OLS estimation technique to find the significance of the difference of the determinants of poverty between the urban and rural areas.

Table 3: OLS Estimation Results of the Welfare Model

VARIABLES	Coefficient	Se
household size	-0.338***	(0.00958)
u*household size	-0.0453**	(0.0215)
household size squared	0.0191***	(0.000836)
u*household size squared	0.00403**	(0.00186)
household head age	0.0226***	(0.00199)
u* household head age	0.00368	(0.00353)
household head age squared	-0.000229***	(2.00e-05)
u* household head age squared	6.71e-06	(3.89e-05)
household head gender	-0.181***	(0.0188)
u*household head gender	0.194***	(0.0418)
education level	0.268***	(0.00829)
u*education level	0.125***	(0.0143)
household head marital status	0.0298***	(0.0110)
u*household head marital status	0.0123	(0.0195)
Constant	10.95***	(0.0488)

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

After estimating the model with the use of the OLS technique in which the economic significance of the differences of the determinants of poverty between urban and rural areas was determined, the study's main focus was to find out if the variables significantly differ across the quantiles through the use of quantile regression technique. This was attempted because the OLS makes a weak assumption that the effects of the variables are constant across the whole distribution, which is corrected by the quantile regression approach.

Quantile Regression Results

Unlike the OLS estimation, the quantile regression approach taken in this study is able to show that the dominance of a variable between the urban and rural areas interchanges within the welfare distribution. The output of the quantile regression is summarized below.

Table 4: Quantile regression output

Variable	5^{th} Percentile		25^{th} Percentile		50^{th} Percentile		75^{th} Percentile		95^{th} Percentile	
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Household size	-0.30***	-10.98	-0.34***	-30.07	-0.36***	-31.11	-0.36***	-28.12	-0.35***	-16.22
u*Household size	-0.12*	-1.76	-0.08***	-2.86	-0.02	-0.89	-0.003	-0.08	-0.02	-0.26
Household size sq	0.02***	6.60	0.02***	18.17	0.02***	19.97	0.02***	15.63	0.02***	11.19
u*Household size sq	0.01**	2.06	0.007***	3.36	0.002	0.89	0.001	0.26	0.0005	0.06
Household head age	0.01***	3.31	0.02***	7.47	0.02***	15.09	0.03***	10.63	0.021***	4.26
u*household head age	0.02***	2.58	0.008*	1.86	-0.002	-0.71	-0.004	-0.67	0.009	0.90
household head age sq	-0.0001***	-3.50	-0.0002***	-8.23	-0.0002***	-15.42	-0.0003***	-10.06	-0.0002***	-4.12
u*household head age sq	-0.0002***	-2.86	-6.22e-05	-1.17	6.37e-05	1.63	0.0001*	1.65	-9.37e-06	-0.08
Household head gender	-0.197***	-5.27	-0.19***	-6.09	-0.17***	-7.21	-0.16***	-5.51	-0.24***	-6.62
u*Household head gender	0.18	1.22	0.20***	4.54	0.25***	6.65	0.18***	3.24	0.21**	2.48
Education level hh head	0.22***	12.02	0.25***	21.62	0.27***	26.79	0.27***	25.42	0.31***	11.40
u*education level hh head	0.09***	3.34	0.10***	5.90	0.10***	6.88	0.14***	6.56	0.16***	4.69
Marital status hh head	0.04	1.28	0.03*	1.89	0.01	1.25	0.02	0.998	0.06**	2.35
u*Marital status hh head	0.02	0.33	0.034*	1.69	0.04	1.55	0.021	0.54	-0.13*	-1.92

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

u* 'variable' represents interaction term of variable with reside dummy(urban) (urban; urban =1,rural; urban=0)

The study used the interaction term of a variable and the urban dummy (u*variable) to determine if the variable significantly differs between urban and rural areas across quantiles. The study therefore used the interaction term of household size and the urban dummy to determine if household size significantly differs between urban and rural areas across quantiles. It can therefore be observed that the variable 'u*household size' is significant at the 5^{th} and 25^{th} percentiles only from the whole distribution. The same result is observed for the interaction terms of the variables 'quadratic terms of house hold size' and 'age of household head', with the urban dummy respectively. This implies that the impact of these variables(household size, quadratic term of household size, and age of household head) on consumption per capita significantly differs between urban and rural areas only in the 5th and 25th percentiles only.

The study observed that the interaction term of quadratic term of the age of household head and the urban dummy, ‘u*household head squared’, is significant at the 5th and 75th percentiles only from the whole distribution. This implies that the impact of the quadratic term of age of household head on consumption per capita significantly differs between urban and rural areas only in the 5th and 75th percentiles.

The study observed that the interaction term of gender of household head and the urban dummy ,’u*household head gender’ is significant at the 25th ,50th ,75th ,and 95th percentiles and is insignificant only at the 5th percentile. This implies that the impact of the gender of household head on consumption per capita significantly differs between urban and rural areas in the 5th , 50th ,75th ,and 95th and 75th percentiles.

The study observed that the interaction term of level of education of household head and the urban dummy is significant across the whole welfare distribution. This implies that the impact of the level of education of household head on consumption per capita significantly differs between urban and rural areas across the whole distribution.

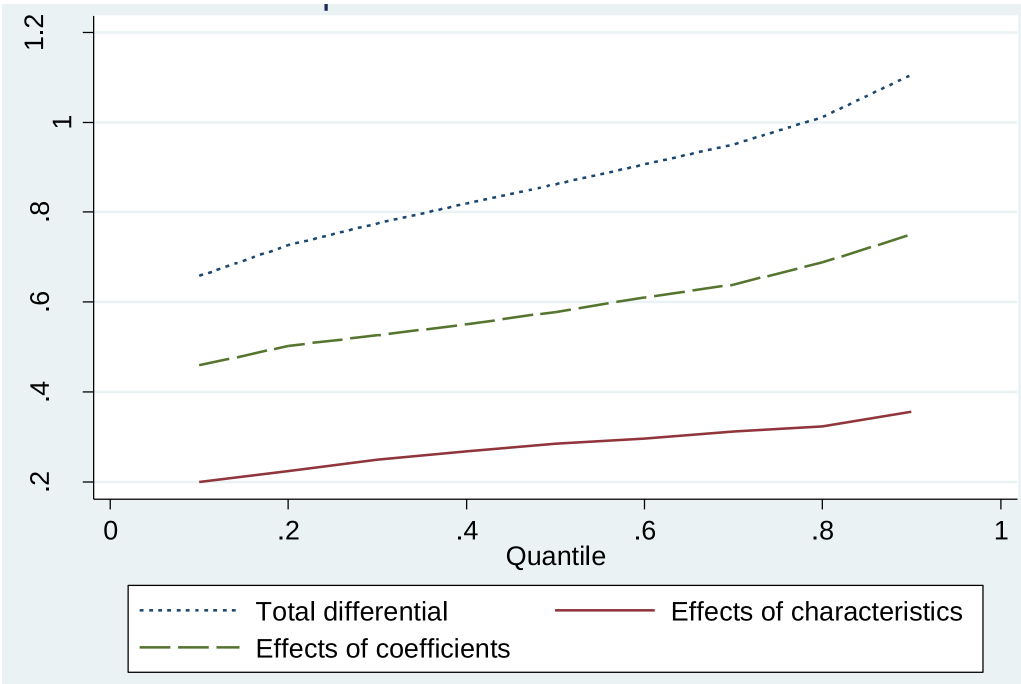
The study observed that the interaction term of marital status of household head and the urban dummy, ‘u*marital status hh head’, is significant at the 25th and 95th percentiles only from the whole distribution. This implies that the impact of the marital status of household head on consumption per capita significantly differs between urban and rural areas only in the 25th and 95th percentiles.

Machado-Mata Decomposition Results

The study uses the Machado-Mata technique to decompose the welfare gap into components due to differences in the covariates and another component due to differences in returns to those covariates for the whole distribution. In order to see the results over the whole distribution, it is best to view them graphically.

Figure 1 below shows the returns and covariates effects for all quantiles and how they vary across the whole distribution. The total differential gap is increasing steadily as we move up to higher levels of welfare levels. Furthermore, it can be seen that both effects are larger at higher quantiles, resulting in a larger rural-urban gap at higher quantiles. In the figure below, the returns effects dominated throughout the whole welfare distribution and this implies that the differences in returns to characteristics matter more than differences household characteristics in Malawi.

Figure 1: Decomposition of Differences in Distribution of lnC



In contrast to these results, Nguyen et *al* (2006) found that characteristics effects and returns effects dominated at the bottom and top of the log consumption distribution in Vietnam, respectively. Arguably, this reflected the fact that the poor typically work in jobs that pay little above the subsistence level; hence rural-urban variation in market returns is not important among the poor.

The "DFL" Approach results

The study further looks into the various covariates to determine which covariates matter most in bringing about inequality between the urban and rural areas. The study therefore uses a semi parametric kernel density reweighting method developed by Dinardo, Lemieux and Fortin to achieve the analysis.

The study analyses the variables to determine how they contribute to the inequality between urban and rural areas by comparing the rural area density (dotted line) and the counterfactual density(solid line).The study analyses how the highest qualification of education contributes to the inequality between the urban and rural areas. According to the figures 2a and 2b below, it is apparent that the impact of the differences in education variable is significant in the middle section of the welfare distribution and insignificant in the lower and higher quantiles of the distribution.

Figure 2a: Comparing the impact of education on rural-urban inequality

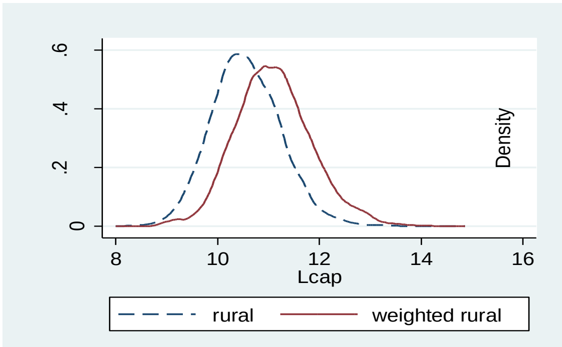
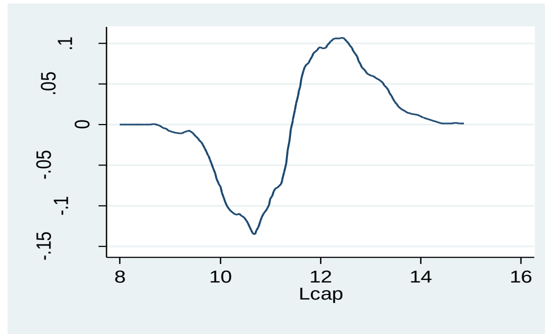


Figure 2b: Impact of differences in education on rural-urban inequality



The study secondly analyses how the gender of the household head contributes to the inequality between the urban and rural areas. According to the figures 2a and 2b below, it shows that the impact of the differences in gender variable is significant in the middle section of the welfare distribution and insignificant in the lower and higher quantiles of the distribution.

Figure 3a: Comparing the impact of gender of household head on rural-urban inequality

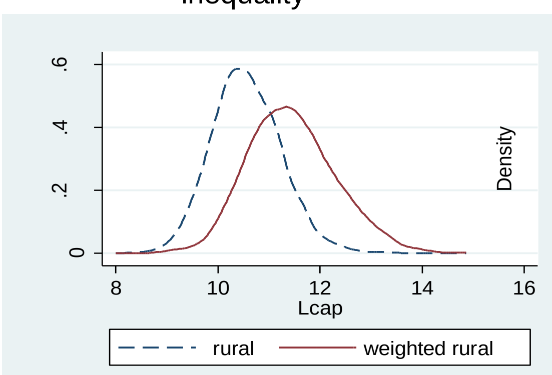
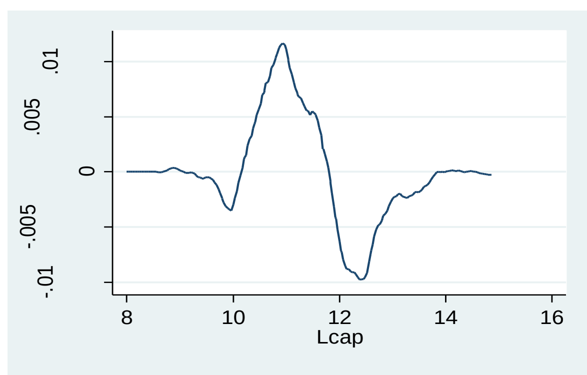


Figure 3b: Impact of differences in gender of household head on rural-urban inequality



The study thirdly analyses how the age of the household head contributes to the inequality between the urban and rural areas. According to the figures 4a and 4b below, it shows that the impact of the differences in age variable is significant in the lower and middle section of the welfare distribution and insignificant in the higher quantiles of the welfare distribution.

Figure 4a: Comparing the impact of age of household head on rural-urban inequality

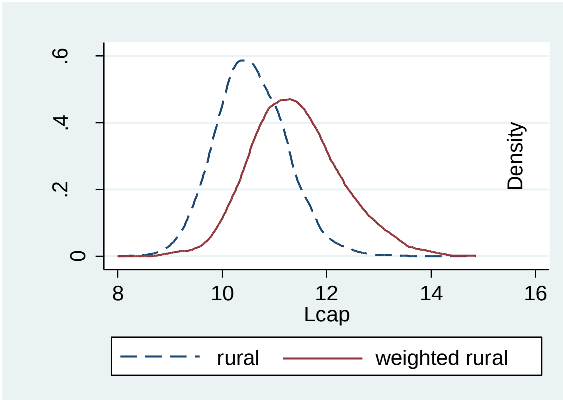
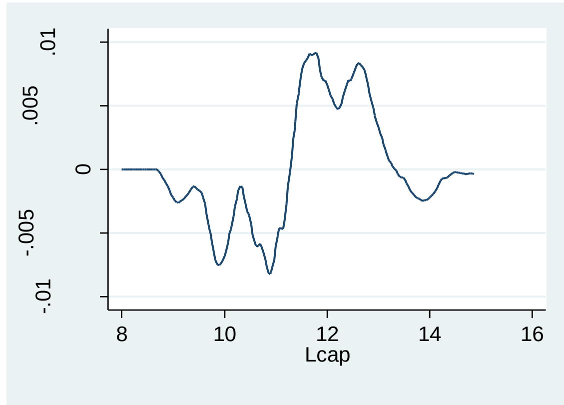


Figure 4b: Impact of differences in age of household head on rural-urban inequality



The study analyses how household size contributes to the inequality between the urban and rural areas. The figures 5a and 5b below show that the impact of the differences in household size variable is significant in the middle section of the welfare distribution and insignificant in the lower and higher quantiles of the welfare distribution.

Figure 5a: Comparing the impact of household size on rural-urban inequality

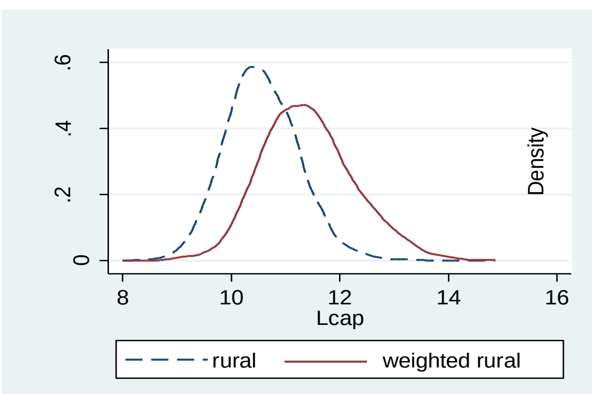
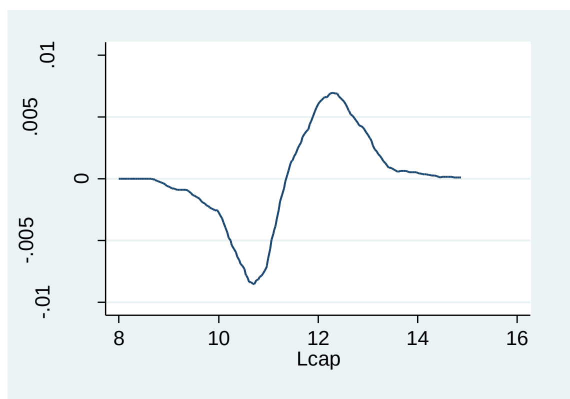


Figure 5b: Impact of differences in household size on rural-urban inequality



The study analyses how marital status of household head contributes to the inequality between the urban and rural areas. The figures 6a and 6b below show that the impact of the differences in marital status of household head variable is significant in the middle section of the welfare distribution and insignificant in the lower and higher quantiles of the welfare distribution.

Figure 6a: Comparing the impact of marital status of household head on rural-urban inequality

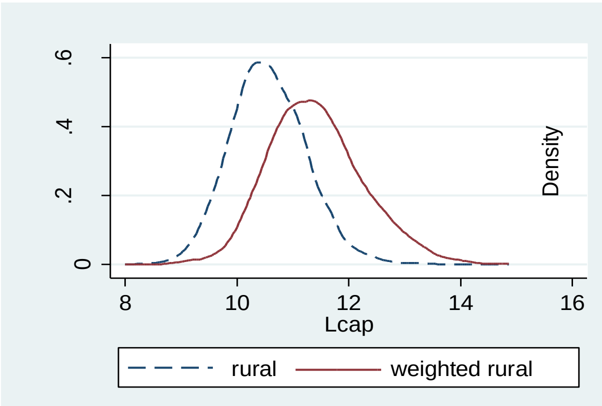
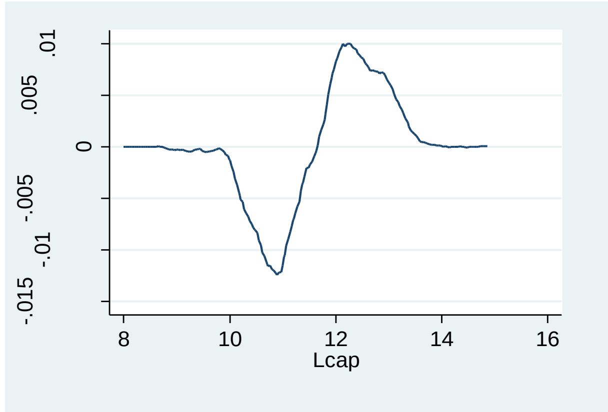


Figure 6b: Impact of differences in marital status of household head on rural-urban inequality



DISCUSSION

The study has attempted to explain the rural-urban differences in poverty in Malawi based on the Integrated Household survey of 2010-2011 .This was done by: 1) examining the differences of the determinants of poverty between urban and rural areas using both OLS estimation and quantile regression techniques; 2) by decomposing the urban-rural welfare gap across the whole distribution into relative contribution of differences in returns to characteristics and differences in the characteristics using the Machado-Mata(2005) decomposition methods; 3) identifying the covariates that contribute to the urban-rural welfare inequality across the whole welfare distribution.

In an objective to see if the determinants of poverty significantly differ across the quantiles between the urban and rural areas, the study hypothesized that the variables do not significantly differ across the quantiles between the urban and rural areas. To show the significance of estimating a quantile regression, the study also estimated the model using OLS estimation technique. It was therefore found that using the OLS estimation technique, only marital status and the quadratic term of age of household head variables were significantly different between the urban and rural areas. However, with the use of quantile regressions it was found that the impact of the two variables on consumption per capita significantly differed between urban and rural areas at particular quantiles across the welfare distribution.

In an objective to determine the relative contribution of returns and covariates to the urban-rural welfare gap in each quantile, the study hypothesized that there is no welfare gap between rural and urban areas resulting from either differences in characteristics or differences in returns to those characteristics. The Machado-Mata decomposition however found that both the differences in characteristics and differences in returns to those characteristics significantly contribute to the urban-rural welfare gap. Specifically it was found that the returns effects were dominant across the whole distribution.

In support of the Machado-Mata decomposition, the study used the “DFL” technique to identify the specific covariates that contribute to the urban-rural welfare inequality across the whole welfare distribution. From all the determinants of poverty, the study identified covariates that clearly showed their contribution to the welfare inequality across the whole distribution. The study found that the variables contributed to the urban-rural welfare gap differently across the whole distribution.

FURTHER RESEARCH

Due to the fact that National Statistics Office (NSO) releases the IHS after every 5 years, the data from the year 2011 to 2016 is still unavailable. Thus this study does not include data covering the past four years. Future studies can therefore use the IHS 4 when it becomes available to explain the rural-urban differences in poverty in Malawi. Comparisons can then be made between this study and subsequent studies.

REFERENCES

Albrecht, J., A. van Vuuren and S. Vroman. (2006). “Counterfactual Distributions with Sample Selection Adjustments: Econometric Theory and an application to the Netherlands”, Georgetown University, Department of Economics, Working Paper # gueconwpa~07-07-06.

Blinder, A.S. (1973). “Wage Discrimination: Reduced form and Structural estimates”, *The Journal of Human Resources*, 8(4), pp. 436-455

Bokosi, F.K. (2006). “Household poverty dynamics in Malawi”, Muchin Personal RePEc Archive (MPRA), Paper No. 1222.

Cameron, L. A. (2000). Poverty and Inequality in Java: Examining the impact of the changing age, educational and industrial structure. *Jouranl of Development Economics, 62*, 149-180.

Daly, M. C., & Valletta, R. G. (2006). Inequality and Poverty in the United States: The Effects of Rising Dispersion of Men's Earnings and Changing Family Behaviour. *Economica, 73*, 75-98.

Deaton, A., and S. Zaidi. (2002). “Guidelines for Constructing Consumption Aggregates for Welfare Analysis”, Living Standards Measurement Study (LSMS), Working Paper # 135, World Bank, Washington DC.

Deaton, A. (1997). “The Analysis of Household Surveys: A Micro econometric Approach to Development Policy”,The John Hopkins University Press, Baltimore.

DiNardo, John, Nicole M. Fortin, and Thomas Lemieux. (1996), .Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semi-parametric Approach,.*Econometrica*64: 1001-1044.

Fallavier, P., C. Mulenga and H. Jere.(2005). “Livelihoods, Poverty and Vulnerability in UrbanZambia: Assessment of situations, coping mechanisms and constraints”. UPAZDraft Document

Firpo,S., Fortin,N.M., and T. Lemieux. (2010) .“Decomposition methods in Economics.”

Government of Malawi and UNDP (1993). "Situation Analysis of Poverty in Malawi", Zomba Government Print.

Greene,W.(2002). "Econometric analysis." Prentice Hall: USA

Kalemba, E. (1997). "Anti-poverty Policies in Malawi: a critique", *Bwalo,* Issue 1, pp. 11-19, University of Malawi, Centre for Social Research.

Koenker, Roger and G. Bassett. (1978). "Regression Quantiles," .*Econometrica*, 46, 33-50.

Koenker, R. and K. Hallock(2001). "Quantile Regressions", *Journal of economic perspectives,* 15(4), pp. 143-156.

Machado, J.A.F. and J. Mata. (2005). "Counterfactual decomposition of changes in wage distributions using quantile regression". *Journal of Applied Econometrics*, 20, 445-465

Muhome,M.(2008). "Rural-Urban welfare inequalities in Malawi: Evidence from a decomposition." MA Thesis,University of Malawi,Zomba,Malawi.

Mukherjee, S. and T. Benson .(2003). "The Determinants of Poverty in Malawi 1998", *World Development*, 31(2), pp. 339-358.

National Economic Council. (2000). "Profile of Poverty in Malawi, 1998: Poverty Analysis of the Malawi integrated Household Survey (1997–98)",Mimeo,(http://www.nso.malawi.net/data_on_line/economics/ihs/poverty_profile. pdf).

National Statistical Office. (2005). "Integrated Household Survey 2004-2005", Zomba.

Nguyen, B.T., Albrecht, J. W., S. B. Vroman and M. D. Westbrook. (2006). "A Quantile RegressionDecomposition of Urban-Rural Inequality in Vietnam", Department of Economics.Georgetown University and Economics and Research Department of the Asian Development Bank.

Oaxaca,R. (1973). "Male-Female Wage Differentials in Urban Labor Markets," International*Economic Review*,14,693-709.

NSO. (2012a). Integrated Household Survey 3. Household Socio-economic Characteristics Report ; National Statistics Office: Zomba, Malawi.

NSO. (2005). Integrated Household Survey (IHS2), 2004. Zomba, Malawi: NSO.

M E P D. (2009). Poverty Trends for Malawi: 2009 Report. Lilongwe: Monitoring and Evaluation Division Ministry of Development Planning and Cooperation

NSO. (2010). Welfare and Monitoring Survey 2009. Zomba: NSO:

APPENDIX: Key determinants

Independent Variable	Meaning and Significance of Variable
Demographic characteristics	-These include *age of household head* , *sex of household head* and *number of individuals in household;* quadratic terms of the variables to capture non linear relationships.
Education variables	-Captures effect of education level attainment on welfare. -Maximum education level attained by individual in household is used. -The education categories include : primary education, secondary education, and tertiary education dummies. -Hypothesized to have positive impact on welfare
Employment and Occupation Variables	-Captures the effects of distribution of different sorts of occupation. -A member is defined as in formal employment if he has main occupation as: professional; technical ; administrative ; managerial; clerical; service occupation - Hypothesized to have a positive impact on welfare
Credit access	-Captures the effect of amount of credit obtained by household on welfare -Hypothesized to have a positive impact on welfare