Poverty in Malawi: Policy Analysis with Distributional Changes

Mussa, Richard

Department of Economics, Chancellor College, University of Malawi

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Abstract

This paper addresses an issue which has hitherto been ignored in the existing studies on poverty and its correlates. Existing poverty studies ignore the fact that changes in the correlates of poverty may not only affect the average level of consumption, but may also affect the distribution of consumption. The paper develops methods for addressing this weakness. Using Malawian data from the Third Integrated Household Survey, the empirical application of the methods suggest that ignoring these distribution effects leads to mismeasurement both quantitatively and qualitatively of policy interventions on poverty. It is found that an additional year of female education for urban households without distributional changes reduces the poverty headcount by 7.6%, and the reduction almost doubles to 11.4% with distributional effects. A similar pattern is observed for the rural simulation. This in turn suggests that policy conclusions based on the existing methods might be misleading.

Keywords: Poverty; distribution; Malawi

1 Introduction

Global poverty has been declining since the 1990s; there are however disagreements about the exact magnitudes of the declines. The difference in the size of the declines is primarily explained by whether one uses national accounts data or household survey data. Studies using national accounts data (e.g..Sala-i-Martin (2002, 2006), and Pinkovskiy and Sala-i-Martin (2009, 2014, 2016)) point to much larger declines in global poverty while studies based on household survey data indicate modest declines (e.g. Chen and Ravallion (2001, 2004, 2010)). What is also evident from these studies is that Sub-saharan Africa lags behind all other regions in terms of the pace of poverty reduction.

This aggregated picture about Sub-saharan Africa hides alot of diversity in terms poverty reduction within the region. The impact of the recent impressive economic growth in Sub-saharan Africa on poverty has been mixed. Growth has led to significant poverty reduction in countries such as Ethiopia, Ghana, Uganda, and Rwanda while the same

*Department of Economics, Chancellor College, University of Malawi, Box 280, Zomba, Malawi, rimussa@yahoo.co.uk.

growth has been associated with no reduction or indeed a worsening of poverty in countries including Madagscar, Kenya, and Nigeria (Arndt et al., 2016). Another phenomenon which has characterised growth in Sub-Saharan Africa is that it has been accompanied by growing inequality in some countries such as Kenya, Uganda, and Zambia (Fosu, 2015).

Despite these positive trends in poverty reduction, understanding the drivers of poverty especially in Sub-saharan Africa is still important and relevant today as it was two decades.ago. Knowledge of what factors determine poverty is important for poverty reduction. A number of studies have identified factors which influence poverty (Grootaert, 1997; Mukherjee and Benson, 2003; Datt and Jollife, 2005; Zhang and Wan, 2006; Cruces and Wodon, 2007; Gunther and Harttgen, 2009; Echevin, 2012; Mason and Smale, 2013).

A defining weakness of the existing poverty studies is that in analysing the correlates of poverty they narrowly focus on how the changes in the mean of a particular correlate influences poverty. These studies thus ignore the fact that changes in the correlates of poverty do not only affect poverty through the direct channel of changing the average level of consumption or income, but can also affect poverty indirectly by changing the distribution of consumption or income.

In light of this research gap, the paper makes two contributions to the poverty literature. The first contribution is that this paper goes beyond this narrow focus and looks at both the direct channel (a mean effect) and the indirect channel (an inequality effect) of determinants of poverty. Precisely, it augments existing poverty simulation methods (see e.g. Datt and Jollife (2005) and Mukherjee and Benson (2003)) by more realistically accounting for both mean and inequality effects. These proposed changes to the basic linear simulation model ensure a more accurate measurement of the impact of simulated policy interventions on poverty.

The second contribution is that the paper uses the proposed methods to re-examine determinants of poverty in Malawi. The empirical application of the methods is based on data from the Third Integrated Household Survey (IHS3). The results confirm that ignoring these distribution effects leads to mismeasurement both quantitatively and qualitatively of policy interventions on poverty. This in turn implies that policy conclusions based on the existing methods might be misleading.

The rest of the paper is structured as follows. Section **??** looks at trends in poverty, inequality, and economic growth in Malawi. Section 3 presents the methodology and a description of the data and variables used. This is followed by the empirical results in Section 4. Finally, Section 5 concludes.

2 Growth, Inequality, and Poverty in Malawi

Malawi's growth, inequality, and poverty profiles mimick the pattern observed across the continent. Table 1 provides selected economic indicators for Malawi over the period 2004 and 2014. The economy grew at an average annual rate of 6.2% between 2004 and 2007, and marginally decelerated to an average growth of 6.1% between 2008 and 2014. Over the same period, the agriculture sector was by far Malawi's most important contributor to economic growth, with a contribution averaging 34.0% to overall GDP growth. Given that economic growth was primarily driven by growth in the agriculture sector, and considering that about 90% of Malawians live in farm households (Benin et al. 2012), one would expect that this impressive growth would lead to significant reductions in poverty.

Poverty statistics however indicate that the high economic growth rates could only translate into marginal poverty reduction. The poverty figures in Table 1 show that the percentage of poor people in Malawi was 52.4% in 2004, and slightly declined to 50.7% in 2011. Interestingly, the high economic growth rate had contrasting effects on rural and urban poverty. For the period 2004-2011, the poverty headcount in rural areas minimally increased from 55.9% to 56.6% while urban poverty declined from 25.4% to 17.3%. Ironically, this dismal poverty reduction performance coincided with the Farm Input Subsidy Program (FISP), which every year provides low-cost fertilizer and improved maize seeds to poor smallholders who are mostly rural based (Chirwa and Dorward, 2013). Implementation of the FISP started in the 2005/6 cropping season, and in the 2012/13 financial year, the programme represented 4.6% of GDP or 11.5% of the total national budget (World Bank, 2013).

The high economic growth rates did not only fail to lead to substantial poverty reduction but also worsened income inequality. Table 1 shows that nationally, the Gini coefficient increased from 0.390 in 2004 to 0.452 in 2011. The magnitude of the disequalising effect of growth varies with location. It was more pronounced in rural areas which saw the Gini coefficient increase from 0.339 in 2004 to 0.375 in 2011 while the urban Gini coefficient rose from 0.484 to 0.491 over the same period. It can thus be concluded that many people did not benefit from the high economic growth registered by Malawi; suggesting that growth was not inclusive. Further to this, rural households compared to their urban counterparts were the most excluded from the benefits of the high economic growth.

3 Methods

3.1 Distribution-Neutral Changes in the Poverty Headcount

The proposed poverty simulation methods are based a linear random effects regression which captures the determinants of poverty. The log of per capita annualized household consumption expenditure is used as a dependent variable. A linear multilevel model captures the fact poverty data is hierarchical in the sense that households are nested in communities, and the communities in turn are nested in districts. Households in the same cluster/community are likely to be dependent because they are exposed to a wide range of common community factors such as the same traditional norms regarding the roles of men and women. This dependency means that standard errors from a standard linear regression model are downward biased, and inferences about the effects of the covariates may lead to many spurious significant results (Hox, 2010; Cameron and Miller, 2015).

I model these common community traits as random effects. Suppose that the i^{th} household $(i = 1....M_j)$ resides in the j^{th} $(j = 1....J_l)$ community, then the determinants of consumption expenditure allowing for spatial community random effects can be modeled using the following two level linear regression

$$\ln y_{ij} = \beta' x_{ij} + \delta' q_j + u_j + \varepsilon_{ij} \tag{1}$$

where; β and δ are coefficients, x_{ij} and q_j are observed household level and community level characteristics respectively, $u_j \sim N\left(0, \sigma_u^2\right)$ are community-level spatial effects (random intercepts), assumed to be uncorrelated across communities, and uncorrelated with covariates, and $\varepsilon_{ij} \sim N\left(0, \sigma_\varepsilon^2\right)$ is a household-specific idiosyncratic error term assumed to be uncorrelated across households, and uncorrelated with covariates. u_j and ε_{ij} are assumed to be independent. The assumptions about u_j and ε_{ij} imply that $\zeta_{ij} \sim N\left(0, \sigma_\zeta^2\right)$ where $\zeta_{ij} = u_j + \varepsilon_{ij}$ and $\sigma_\zeta^2 = \sigma_u^2 + \sigma_\varepsilon^2$. Thus, the overall error variance is partitioned into two components, and this leads to an intracluster correlation coefficient (ICC), $\rho = \frac{\sigma_u^2}{\sigma_\zeta^2}$, which measures the strength of clustering within the community. If unobserved differences between communities matter more than unobserved differences within communities, the ICC approaches one, and the ICC will be close to zero if the reverse holds.

After estimating the regression, the next task in this paper is to simulate changes in the aggregate levels of poverty. The goal here is to assess how policy interventions which change the determinants of poverty would affect the proportion of poor people. A household is defined as poor if it's per capita consumption expenditure is less than a poverty line, z. Using equation (1), and noting that $\zeta_{ij} \sim N\left(0, \sigma_\zeta^2\right)$, the probability that a household is poor can be written as

$$\begin{aligned} P_{0ij} &= \text{Prob}(\zeta_{ij} < \ln z - (\beta' x_{ij} + \delta' q_j)) \\ &= \Phi\left(\frac{\ln z - (\beta' x_{ij} + \delta' q_j)}{\sigma_\zeta}\right) \end{aligned} \tag{2}$$

where $\Phi(\cdot)$ is a distribution function of the standard normal distribution. Estimated values of the parameters are used to predict the probability that a household is poor. Equation (2) shows how for given values of the estimated parameters, changes in levels of covariates lead to changes in the probability that a household is poor.

The poverty simulation methods are significant in two ways (Mukherjee and Benson, 2003; Datt and Jollife, 2005). Firstly, they can be employed to more easily illustrate the impact that changes in the levels of the determinants of poverty have on the aggregate incidence of poverty. Using regression coefficients to assess relationships between poverty and its determinants can be difficult if the determinants are intrinsically interrelated. Secondly, and most importantly, households face significant binding constraints to reducing poverty. Government policies and programs are often put in place to remove or relax these constraints. The simulation methods can be used to demonstrate the effects that various policies can have on the prevalence poverty .

A simulation model which is based on the standard linear model has been used before by Datt and Jollife (2005) in Egypt and Mukherjee and Benson (2003) in Malawi. There is however one fundamental difference between what they used, and what I have derived here. Unlike the previous modeling procedures, equation (2) takes into account the hierarchical nature of the data by allowing for community level random effects through the division by σ_ζ and not σ_ε.

The population poverty headcount, a measure of the percentage of poor people in a population, can then be computed as a weighted average of P_{0ij}; where the weight of each household is defined as the product of the survey sampling weight of the household and the number of members in the household. The weighting mechanism employed here assumes that poverty is distributed equally within the household; this assumption is obviously strong. It is however difficult to avoid it because individual-specific consumption expenditure is rarely available.

Let P_0^b be the headcount for the base scenario; this is obtained from the regressions which use the original values of the determinants of poverty, as per equation (1). Let P_0^s be the headcount for an alternative scenario arising from simulated changes in the values of the determinants of poverty, then the impact of the simulation on the incidence of poverty is simply $\Delta P_0 = P_0^s - P_0^b$. The simulated change increases poverty if $\Delta P_0 > 0$, and reduces poverty if $\Delta P_0 < 0$. To test for statistical significance of a simulated change, I use bootstrapped standard errors for the base and the simulated headcounts, and then use $\sqrt{Var(\Delta P_0)} = \sqrt{Var(P_0^s) + Var(P_0^b)}$ to get the standard error of the difference.

In performing the simulations, the paper focuses on those selected characteristics that are amenable to change through public policy. It is worth noting that these simulations assume that there are no general equilibrium effects in the sense that changes in the determinants do not affect the partial regression parameters or other exogenous variables. This assumption may be valid if the simulated changes are incremental. The interpretation of the results must therefore be looked at with this caveat in mind.

3.2 Distribution-Sensitive Changes in the Poverty Headcount

The above simulation procedure represents an improvement over the simulation methods used by Datt and Jollife (2005) and Mukherjee and Benson (2003), it nonetheless ignores the fact that changes in the correlates of poverty may not only affect the average level of consumption i.e. the numerator in equation (2), but may also affect the distribution of consumption i.e. the denominator in equation (2). A failure to account for distributional changes may therefore lead to misleading conclusions about the size of the impacts of policy interventions. To accommodate consumption inequality as measured by a Gini coefficient, equation (2) can be respecified to get

$$P_{0ij} = \Phi\left(\frac{\ln z - (\beta' x_{ij} + \delta' q_j)}{\sqrt{2}\Phi^{-1}\left(\frac{(G+1)}{2}\right)}\right) \tag{3}$$

where G is a Gini coefficient. This result uses the fact that under lognormality of a welfare indicator, a Gini coefficient is a monotone increasing function of σ_ζ, i.e. $G = 2\Phi\left(\frac{\sigma_\zeta}{\sqrt{2}}\right) - 1$ (see, e.g., Kleiber and Kotz (2003) and Cowell (2009)). This reformulation makes it more explicit that the probability that a household is poor not only depends on household and community characteristics but also depends on the extent of inequality. It further shows that increases in inequality lead to increases in poverty.

Ignoring sampling weights for expositional purposes, the Gini coefficient of consumption is expressed as (see e.g. van Doorslaer and Koolman (2004)),

$$G = \frac{2}{\bar{y}} cov(y_{ij}, R_{ij}) \tag{4}$$

where, $\bar{y} = \frac{1}{N}\sum_{ij} y_{ij}$, and $cov(.)$ is a covariance, and R_{ij} is a fractional rank of the ith household in the consumption distribution, with households ranked from the poorest to the richest. The Gini coefficient in equation (4) is a Gini coefficient for consumption y_{ij}, and not the log of consumption. I consequently, re-specify the poverty equation (1) so that the dependent variable is now linear to get

$$y_{ij} = \alpha' x_{ij} + \gamma' q_j + u'_j + \varepsilon'_{ij} \tag{5}$$

Substituting equation (5) into equation (4), yields a linear regression based Gini coefficient as (Wagstaff et al., 2003)

$$G = \sum_k \left(\alpha_k \frac{\bar{x}_k}{\bar{y}}\right) C_k + \sum_k \left(\gamma_k \frac{\bar{q}_k}{\bar{y}}\right) C_k + \dddot{C} \tag{6}$$

where, C_k is the concentration index of a regressor. The Gini coefficient is decomposed into two parts. The first part is the observed and explained component which is equal to a weighted sum of the concentration indices of the covariates, where the weight for regressor is simply the elasticity of y_{ij} with respect to a regressor. The second part, $\frac{C_{u'_j}}{\bar{y}} + \frac{C_\varepsilon}{\bar{y}} = \dddot{C}$, is the unobserved and unexplained component. If spatial effects are not accounted for, the decomposition reduces to that by Wagstaff et al. (2003).

The effect of a simulated change in a regressor on the Gini coefficient can come from two sources; a change in the mean of the regressor, and a change in the distribution of the regressor as measured by a concentration index. The corresponding total change in the Gini coefficient emanating from a change in a regressor is thus given by

$$dG = \overbrace{\frac{1}{\bar{y}}\left[\alpha_k dC_k\right]}^{mean\ effect} d\bar{x}_k + \overbrace{\frac{\bar{x}_k}{\bar{y}}\left[\pi_k dC_{bk}\right]}^{Inequality\ effect} \tag{7}$$

The first term in square brackets represents a change in the Gini following a change in the mean of a regressor. Similarly, the second term captures the inequality effect. For a community level variable, q_j the corresponding change in the Gini is computed analogously.

Effectively two possible poverty simulation exercises can be performed. First, one can assume away distributional changes in the covariates as in Datt and Jollife (2005) and Mukherjee and Benson (2003). Second, simulated changes in policy variables can rather more realistically be considered to have both mean and inequality effects. These proposed changes to the basic linear simulation model ensure a more accurate measurement of the impact of simulated policy interventions on poverty.

3.3 Data description, poverty lines, and variables used

The data used in the paper are taken from the Third Integrated Household Survey (IHS3) conducted by Malawi's National Statistical Office (NSO). It is a multi-topic survey which is statistically designed to be representative at both national, district, urban and rural levels. It was conducted from March 2010 to March 2011. A stratified two-stage sample design was used. At the first stage, enumeration areas, representing communities, as defined in the 2008 Population Census, stratified by urban/rural status were selected with probability proportional size. At the second stage, systematic random sampling was used to select households.

The survey collected information from a sample of 12271 households; 2233 (representing 18.2%) are urban households, and 10038 (representing 81.8%) are rural households. A total of 768 communities were selected from 31 districts across the country[1]. In each district, a minimum of 24 communities were interviewed while in each community a total of 16 households were interviewed. In addition to collecting household level data, the survey collected employment, education, and other socio-economic data on individuals within the households. It also collected community level information on access to basic

[1]Malawi has a total of 28 districts. However, the IHS3 treats Lilongwe City, Blantyre City, Mzuzu City, and Zomba City as separate districts. Likoma district is excluded since it only represents about 0.1% of the population of Malawi, and it was determined that the corresponding cost of enumeration would be relatively high. The total number of districts or strata covered is therefore 31.

services.

In order to capture possible locational differences, the paper distinguishes between rural and urban households, and I use the new annualized consumption aggregate for each household generated by Pauw et al. (2016) instead of the official aggregate as a welfare indicator i.e. the dependent variable. This choice is necessitated by the fact that the food component in the official aggregate is based on conversion factors which have been shown to have inconsistencies and errors (Verduzco-Gallo and Ecker, 2014). The computation of quantities of food consumed is based on conversion factors which are used to covert non-standard units of measurements such as pails, basins, and pieces into standard units such as kilograms and grams. The new aggregate uses a new set of conversion factors developed by Verduzco-Gallo and Ecker (2014) to generate the new food component. The official and the new consumption aggregates however have the same non-food component.

I also adopt two area-specific poverty lines generated by Pauw et al. (2016) instead of the national level official annualised poverty line of 37002 Malawi Kwacha (MK). The poverty lines are: MK31463 for rural areas, and MK46538 for urban areas. Three groups of independent variables are included in the regressions namely; household, community, and fixed effects variables. The choice of variables is guided by previous literature (e.g. Mukherjee and Benson, 2003; Datt and Jollife, 2005, Cruces and Wodon, 2007) on determinants of poverty. At the household level, I include a set of demographic variables: number of individuals aged below 9 years, number of individuals aged 10-17 years, number of females aged 18-59 years, number of males aged 18-59 years, the number of the elderly (above age 60) household members, the square of household size, linear and quadratic terms in the age of the household head to capture possible life cycle effects, and a dummy variable for male head of household.

I include average years of schooling in a household, and this is gender-disaggregated to measure the possibility that education can have a gender-differentiated effect on poverty. In terms of agricultural variables, I include the number of crops the household cultivated that are not maize or tobacco, a measure of the diversity of crop cultivation. These include the food crops cassava, groundnut, rice, millet, sorghum, and beans, and the cash crops cotton. Another agriculture variable included is the area of cultivated land that is owned by the household. The agriculture variables are included in the rural regressions only. The regressions also contain variables capturing the number of household members employed in the primary, secondary, and tertiary industries.

At the community level, I include community level health infrastructure and economic infrastructure indices to measure availability of and access to basic medical and economic infrastructure and services in a community. The two indices are constructed by using multiple correspondence analysis (MCA) (see e.g. Asselin (2002) and Blasius and Greenacre (2006) for more details). The health infrastructure index is constructed from information on the availability in a community of the following: a place to purchase common medicines, a health clinic, a nurse, midwife or medical assistant, and groups or programs providing insecticide-treated mosquito bed nets free or at low cost. The economic infrastructure index is based on the presence of the following in a community: a perennial and passable main road, a daily market, a weekly market, a post office, a commercial bank, and a microfinance institution.

Two sets of spatial and temporal fixed effects variables are included. I include agro-ecological zone dummies which capture zone level fixed effects. There are eight agro-ecological zones. The agro-ecological zone dummies control for differences in land productivity, climate, and market access conditions in an area. Agro-ecological zones are rural, consequently, they only appear in the rural regression. Being an agro-based economy, household welfare in Malawi may vary across the year due to possible seasonal effects. I account for these variations by including three seasonal dummies reflecting the harvest, postharvest, and preplanting periods. I use a Wald test to check for the presence of these fixed effects. Detailed definitions and summary statistics for all the independent variables are given in Table 2.

4 Results

4.1 Regression Results

The determinants of poverty results for rural and urban areas are reported in Table 3. Wald test results for the null of parameter homogeneity give $\chi^2 = 1828.8$; suggesting that estimating separate rural and urban regressions is appropriate. In both rural and urban areas, log likelihood tests reject the null hypothesis of no community random effects. This conclusion has two implications; first, even after controlling for individual characteristics, there are significant community-specific factors which affect poverty, and second, estimating a linear model as in for example Mukherjee and Benson (2003) and Datt and Jollife (2005) is invalid.

These random effects (spatial differences) in welfare could for instance reflect spatially-differentiated exposure to social policy programmes in a community or that households in these communities are subject to the same traditional norms. The results reveal that this clustering as measured by the intracluster correlation coefficients (ICC) ranges is 16% and 24% for the rural and urban models respectively. Thus, a vast majority of the variation in welfare (76% to 84%) exists within communities rather than between them, and that unobserved community level effects have a relatively smaller part to play on household welfare in Malawi. The Wald test results further point to the presence of significant seasonal and agroecological effects. Consequently, seasonal and agroecological dummies are included in the two regressions. The parameter estimates for the two regressions generally conform to *apriori* expectations. I now turn to a more detailed look at the results.

Gender of the household head emerges as a significant correlate of poverty. Holding other things constant, female headed households are poorer than male headed households in rural areas. Precisely, their per capita consumption is 17% lower than that of male headed households. A comparison with a previous study by Mukherjee and Benson (2003) reveals some differences in the relationship between gender and poverty in Malawi. Unlike the finding in this paper, they found a rather puzzling result that in rural areas of Malawi, male headed households are poorer. A negative sign on the gender dummy in urban areas suggests that this gender difference is in favour of female headed households. This rather counterintuitive finding in urban areas is however consistent with what Mukherjee and Benson (2003) also found.

The age of the household head has a significant inverted u-shaped relationship with standard of living in both areas. Precisely, I find that household living standards increase with the age of the head up to 65 years (90th percentile) in rural areas, and 74 years (99th percentile) in urban areas, and diminish thereafter. This means that there are significant life cycle effects which reflect increased earning capacity arising from greater experience and smoothing of consumption over one's lifetime. This common finding (e.g. Grootaert,1997; Datt and Jollife, 2005) is however in stark contrast to a previous study by Mukherjee and Benson (2003) who found a negative relationship between age and welfare in Malawi.

In terms of household composition, the results indicate that the coefficients are more negative for children aged 0-9 and the elderly (aged 60 above) than for the economically active category (i.e. 18-59 age category). This means that an increase in dependent household members leads to a larger welfare reduction than an increase in those in the economically active group. Moreover, in both areas, an increase in the household of female adults does not affect per capita consumption. In contrast, the effect on welfare following the addition of a male in a household is statistically significant in both areas, but, it is larger in rural areas (about 31%) than in urban areas (about 22%). Considering that economic opportunities tend to favour men, one would expect a reverse pattern.

The coefficient on the square of household size is positive and statistically significant, and this together with the finding that the household composition variables are negatively and significantly related to welfare suggests that there is a U-shaped relationship between household size and living standards. This is a common empirical finding (see e.g., Lanjouw and Ravallion, 1995; Lipton and Ravallion, 1995; Mukherjee and Benson, 2003; Datt and Jollife, 2005). The use of per capita consumption implicitly assumes away the importance of economies of scale of household size in consumption i.e. it costs less to house two people than to house two individuals separately. and the role of household composition i.e. food needs depend on age and gender. Some studies have shown that the impact of household size on poverty disappears once these two problems are addressed (e.g. Lanjouw and Ravallion, 1995; White and Masset, 2003).

To make certain that the effect of household size on consumption in Malawi is not driven by the per capita normalization, I re-estimated the poverty models by adjusting consumption for composition and economies of scale[2]. In both rural and urban models, the results show that the coefficients on the different age-sex composition variables are negative and significant, but critically, the coefficients are smaller in size compared to those from the per capita normalisation. For instance, in the rural model, the coefficient on children below 9 is -0.038 when the economies of scale parameter is 0.4, and then the coefficient rises to -0.239 for an economies of scale parameter of 1. Similarly, for urban areas, the coefficient on children below 9 is -0.029 when the economies of scale parameter is put at 0.4, it then rises to -0.226 when the parameter is 1. This means that the negative relationship between household size and welfare is not necessarily driven by the per capita normalisation but that larger households are indeed poorer than smaller ones. Besides, using the per capita measure merely leads to an overestimation of the impact of household size on poverty.

All the household education variables have statistically significant positive effects on per capita consumption; implying that the level of education in a household reduces the likelihood of poverty in Malawi. However, this effect is gender-differentiated. For instance, in rural areas and holding other factors constant, an additional year of schooling for females in a household leads to a 3.9% increase in per capita consumption while for males the corresponding effect is 2.7%. Irrespective of gender, the results further indicate that there are spatial differences in the size of the intrahousehold returns to education with urban areas exhibiting quantitatively larger returns than rural areas. For example, the marginal effect of the years of education for females in a household is 3.9% in rural areas while it jumps to 4.6% in urban areas. This rural-urban difference in the role of education perhaps reflects the paucity of remunerative economic opportunities in rural areas of Malawi (Mukherjee and Benson, 2003).

Employment as measured by the number of adults in a household employed in the primary, secondary, and tertiary economic sectors exhibit a mixed pattern. There are no statistically significant welfare advantages to finding employment in the primary (agriculture, fishing, mining, etc.) and secondary (manufacturing) sectors. However, regardless of location, employment in the tertiary sector (sales and service industries) has a statistically significant, and positive effect on welfare. Holding all else constant, having an additional household member employed in a tertiary industry occupation increases consumption by 21% in rural areas and by about 15% in urban areas. Notably, Mukherjee and Benson (2003) found a rather counterintuitive result that employment in a tertiary occupation does not influence welfare in urban areas in Malawi.

[2] Instead of normalising by household size, I normalise consumption by $\mathbf{A} = (E)^{\theta}$, where E a nutrition-based age and sex-specific adult equivalents by the WHO (1985), and $1-\theta$ is a measure of economies of scale. I experimented with the following values of economies of scale 0.4, 0.6, 0.8, and 1.0.

In terms of agriculture, the results indicate that land ownership and crop diversification have statistically significant effects on poverty. Holding other factors constant, an increase in cultivated area per capita by an acre increases per capita consumption in rural Malawi by 7.7%. Crop diversification beyond maize and tobacco leads to a rather modest *ceteris paribus* increase in living standards of 2.9%. Both health and economic infrastructure in the community have a positive effect on household welfare. Furthermore, in rural areas, improvements in economic infrastructure such as a perennial and passable main road, a daily market, a weekly market have a larger effect on welfare than health infrastructure such as clinics and nurses. However, a reverse pattern is observed in urban areas.

There are some differences in the results of this paper and a previous study by Murkherjee and Benson (2003). These differences merit some comment. There are three possible explanations for these differences. First, it could be driven by differences in the consumption aggregates used in the two studies. Due to differences in consumption information collected, the consumption aggregate used by Murkherjee and Benson (2003) which was from the first integrated household survey is not comparable to the one used in this study which is taken from the third integrated household survey. Second, it could also be that these differences reflect structural changes since this study is being done two decades after that of Mukherjee and Benson (2003). Finally, as the Wald test results have shown, estimating a linear model as was the case with Mukherjee and Benson (2003) is problematic, so the difference could be due to fact this paper is using a superior model set up. The paper does not to attempt isolate and interrogate further which explanation drives these differences by the two studies.

4.2 Simulation Results

There are ten simulations focusing on changes in population, education, employment, and agriculture. Precisely, the study simulates what would happen to the incidence of poverty under each one of the interventions. Before running these simulations a reference point or base simulation is necessary since the predicted levels of poverty are not directly comparable to the actual levels of poverty (Mukherjee and Benson, 2003; Datt and Jollife, 2005). This arises from the fact that the correlates of poverty are not perfect predictors of poverty. The base scenario is obtained from the regressions which use the original values of the determinants of poverty.

Tables 4 and 5 present simulation results for rural and urban models respectively. Each table reports simulations with and without distributional effects. The size of the impact of a simulation depends on four things namely; (a) the sign and magnitude of the estimated regression coefficients, (b) the size of the simulation, (c), the change in inequality as measured by the Gini coefficient,.and (d) the proportion of the population affected by the simulation. Broadly, accounting for distributional effects leads to more statistically significant and quantitatively larger poverty changes.

The first two simulations are essentially population related interventions, and they involve (a) adding a child if there is no child in a household, and (b) adding a child to all households. These simulations lead to statistically significant increases in the rural and urban poverty headcounts over the base scenario. Simulation 1 is a more targetted approach as it involves adding a child to households with no children, and this is associated with an increase in the rural poverty headcount of 12.3% without distribution effects. The headcount jumps by 16.4% when distribution effects are included. Similarly, the urban headcount increases by 13% without distribution effects and then rises by 21.4% when the distributional changes are accounted for.

Simulation 2 examines the impact of adding a child to all households on the incidence of poverty, and as would be expected, this leads to an even larger increase in the poverty incidence. The urban headcount for instance increases by 65.2% without distributional effects and then goes up by 80.2% after including distributional effects. The corresponding changes in the incidence of poverty for rural areas are 54.4% and 54.8% with and without distributional effects respectively. This implies that under the two simulations and regardless of whether or not one allows for distribution effects, urban areas experience a larger increase in the poverty headcount than rural areas. This positive relationship between children and poverty is consistent with previous studies (e.g. Eastwood and Lipton, 1999; Mussa, 2014).

Simulations 3 to 6 explore what would happen if there was an increase in average years of schooling in households. The results indicate that regardless of location, the four education simulations lead to lower levels of poverty as compared to the base scenario. Moreover, the sizes of the impacts increase as one moves from not controlling for distributional effects to adjusting for distributional effects. For example, under simulation 3, an additional year of female education for urban households without distributional changes reduces the headcount by 7.6%, and the reduction almost doubles to 11.4% with distributional effects. A similar pattern is replicated for the rural simulation. This means that a failure to account for distributional effects leads to a gross underestimation of the impact of potential education policy interventions.

Unsurprisingly, a doubling in the simulated change in years of schooling is associated with a doubling of the reductions in the rural and urban headcounts. The findings further suggest that the impact of the education interventions vary with gender. Simulation 5 shows that if the years of schooling for females rise by two years, then the rural headcount decreases by 13.9%. In contrast, simulation 6, shows that in rural areas a much lower reduction in the incidence of poverty of 10.2% is associated with a similar change in the years of schooling of males. This gender pattern can also be seen in urban areas, simulation 6 shows that an identical two-year increase in the schooling of males reduces the urban poverty headcount by 21.4% compared to 22.7% for females.

In addition to the gender differentials in the impacts of the interventions, all the education simulations show that the reductions in the poverty headcounts are more pronounced in urban areas than in rural areas. Notably, there is an interaction between gender and location in terms of the size of the gender difference in the impact of simulated changes in schooling on poverty. For instance, after adjusting for distributional changes, the urban gender gap in the impact of a two-year increase in male education is 1.3 percentage points higher than that of female education while the rural gap of a two-year increase in female education is 3.7 percentage points higher than of male education.

It bears mentioning that there is potential for overestimating the impact of increasing education on poverty especially the two-year increase in years of education which is quite significant in size (Datt and Jollife, 2005). Two factors could be at play and both could lead to an upward bias of the results; first, such an increase in education could also lead to a decline in the return to education through an increase in educated labour supply, and secondly, the returns to education may be confounded by innate abilities of household members. This finding is nonetheless relevant for gender policy as it indicates that education interventions which deliberately seek to improve women's education have significant potential for reducing poverty in Malawi.

Simulations 7 and 8 deal with employment, and they consider the potential poverty-reduction impacts of hypothetical movements of a household member from a primary industry to a tertiary industry, and from a secondary industry to a tertiary industry. The simulation results suggest that changing the structure of employment has a significant potential for reducing poverty in Malawi. There is a clear hierarchy, moving from primary to tertiary as compared to a movement from secondary to tertiary is associated with lower reductions in rural and urban poverty. Furthermore, this pattern is more evident when distributional changes are accounted for.

Simulation 8 demonstrates that a movement by an adult household member from a secondary industry to tertiary industry leads to reductions in rural and urban poverty headcounts of 33.7% and 26.7% respectively. However, it is interesting to note that it is the movement from a primary industry to a tertiary industry occupation which leads to more superior poverty reductions. For example, the rural headcount falls by 38.5% following an adult movement from a primary to a tertiary industry while the rural headcount decreases by 33.7% when an adult household member moves from a secondary industry to tertiary one. This means that the largest benefit in terms of poverty reduction can be achieved by a change in the structure of employment from the primary sector to the tertiary industry.

The final set of simulations look at the effect of changing crop diversification on rural poverty. Increased crop diversification beyond maize and tobacco leads to poverty reduction, the reductions though statistically significant are quantitatively small. Simulation 9 considers increasing diversity of crops of agriculture households from 0 to 1. This intervention leads to a decline in the rural poverty headcount of 3.9%. Simulation 10 represents a further increase in crop diversification by agriculture households from 0 or 1 to 2, and this doubling of crop diversification induces a drop in the rural poverty headcount by 8.4%.

5 Concluding Remarks

This paper addresses an issue which has hitherto been ignored in the existing studies on poverty and its correlates. Existing poverty studies ignore the fact that changes in the correlates of poverty may not only affect the average level of consumption, but may also affect the distribution of consumption. The paper has developed methods for addressing this weakness. Using Malawian data from the Third Integrated Household Survey, the empirical application of the methods suggest that ignoring these distribution effects leads to mismeasurement both quantitatively and qualitatively of policy interventions on poverty.

It has been found that an additional year of female education for urban households without distributional changes reduces the headcount by 7.6%, and the reduction almost doubles to 11.4% with distributional effects. A similar pattern is observed for the rural simulation. This in turn suggests that policy conclusions based on the existing methods might be misleading. Furthermore, it has been shown that an interaction exists between gender and location in terms of the size of the gender difference in the impact of simulated changes in schooling on poverty. In urban areas a two-year increase in male education leads to a reduction in the headcount which is 1.3 percentage points higher than that of female education, in contrast, for rural areas a similar increase in female education is associated with a reduction in poverty which is 3.7 percentage points higher than of male education.

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Table 1: Trends and levels of economic growth, poverty, and inequality

Indicator/Area	2005	2011
GDP growth	6.2[a]	6.1[b]
Poverty headcount		
National	52.4	50.7
Rural	55.9	56.6
Urban	25.4	17.3
Gini Coefficient		
National	0.390	0.452
Rural	0.339	0.375
Urban	0.484	0.491

[a] Average GDP growth for 2004-2007, [b] average GDP growth for 2008-2014.
Source: NSO (2005, 2012a, 2012b), RBM Annual Economic Report (various issues)

Table 2: Descriptive statistics of variables

Variable	Rural		Urban	
	Mean	SD	Mean	SD
sex of the household head (1 if head is male, 0 otherwise)	0.747	0.435	0.817	0.387
age of hh head	42.934	16.682	38.724	13.409
# of people in hh under 9 yrs	1.561	1.306	1.275	1.173
# of people in hh 10-17 yrs	0.948	1.114	0.862	1.080
# of females in hh 18-59 yrs	0.955	0.571	1.119	0.723
# of males in hh 18-59 yrs	1.838	1.000	2.249	1.145
# of people over 60 yrs	0.263	0.546	0.125	0.404
Average years schooling of females in a household	3.05	2.69	5.61	3.74
Average years schooling of males in a household	3.77	3.08	6.58	3.94
# of HH members primary industry occupation	0.041	0.226	0.033	0.186
# of HH members secondary industry occupation	0.037	0.222	0.100	0.316
# of HH members tertiary industry occupation	0.100	0.329	0.560	0.691
land per capita in acres	0.121	0.460	-	-
number of crops grown by HH other than maize/tobacco	0.189	0.576	-	-
index of economic infrastructure	-0.145	0.857	0.651	1.292
index of health infrastructure	-0.846	1.190	-0.572	1.054
zone1 (Nsanje, Chikwawa districts)	0.073	0.261	-	-
zone2 (Blantyre, Zomba, Thyolo, Mulanje, Chiradzulu, Phalombe districts)	0.226	0.418	-	-
zone3 (Mwanza, Balaka, Machinga, Mangochi districts)	0.178	0.383	-	-
zone4 (Dedza, Dowa, Ntchisi districts)	0.110	0.313	-	-
zone5 (Lilongwe, Mchinji, Kasungu districts)	0.131	0.337	-	-
zone6 (Ntcheu, Salima, Nkhotakota districts)	0.107	0.309	-	-
zone7 (Mzimba, Rumphi, Chitipa districts)	0.107	0.309	-	-
zone8 (Nkhatabay, Karonga districts)	0.068	0.252	-	-
season1 (1 if household was interviewed in March-April, 0 otherwise): Base	0.189	0.392	0.172	0.378
season2 (1 if household was interviewed May-August, 0 otherwise)	0.275	0.446	0.259	0.438
season3 (1 if household was interviewed in September-November, 0 otherwise)	0.298	0.457	0.321	0.467
season4 (1 if household was interviewed in December-February, 0 otherwise)	0.238	0.426	0.248	0.432
Observations	10038		2233	

Notes: SD is standard deviation.

Table 3: Determinants of poverty in Malawi, contextual effects (CE) and no contextual effects

Variable	Rural		Urban	
	Coefficient	SE	Coefficient	SE
sex of the household head	0.157***	(0.014)	-0.076*	(0.039)
age of hh head	0.013***	(0.002)	0.027***	(0.006)
square of age of hh head	-0.000***	(0.000)	-0.000***	(0.000)
# of people in hh under 9 yrs	-0.330***	(0.009)	-0.329***	(0.020)
# of people in hh 10-17 yrs	-0.329***	(0.010)	-0.256***	(0.022)
# of females in hh 18-59 yrs	-0.011	(0.016)	-0.035	(0.029)
# of males in hh 18-59 yrs	-0.311***	(0.013)	-0.222***	(0.025)
# of people over 60 yrs	-0.338***	(0.018)	-0.143**	(0.058)
square of hh size	0.017***	(0.001)	0.013***	(0.002)
Average years schooling of females in a household	0.039***	(0.002)	0.046***	(0.004)
Average years schooling of males in a household	0.027***	(0.002)	0.041***	(0.004)
# of HH members primary industry occupation	0.022	(0.026)	0.031	(0.070)
# of HH members secondary industry occupation	0.048*	(0.026)	0.043	(0.042)
# of HH members tertiary industry occupation	0.210***	(0.018)	0.146***	(0.021)
land per capita in acres	0.077***	(0.014)		
number of crops grown by HH other than maize/tobacco	0.029**	(0.013)		
index of economic infrastructure	0.085***	(0.014)	0.045*	(0.027)
index of health infrastructure	0.037***	(0.010)	0.042	(0.033)
zones included	Yes		No	
Chi2 (significance of agro-ecological zones)	262.79		-	
P-value of Chi2	0.00		-	
seasons included	Yes		Yes	
Chi2 (significance of seasonal effects)	7.51		6.67	
P-value of Chi2	0.06		0.08	
Chi2 (regression)	5159.71		1231.92	
P-value of Chi2	0.00		0.00	
Chi2 (random effects)	847.83		314.13	
P-value of Chi2	0.00		0.00	
intracluster correlation coefficient (ICC)	0.16		0.24	
Observations	10038		2233	

Notes: Dependent variable: ln of annualised per capita household consumption in Malawi Kwacha (MK). Standard errors in parentheses. *** indicates significant at 1%; ** at 5%; and, * at 10%.

Table 4: Poverty simulations (percent change over base simulation), rural

Simulation	Description	No Distribution Effect		Distribution Effect	
		P0	%	P0	%
0	Base	32.286		32.286	
		(0.408)		(0.408)	
1	Adding a child if there is no child in HH	36.249	12.3***	37.567	16.4***
		(0.418)		(0.383)	
2	Adding a child to all HHs	50.172	55.4***	49.964	54.8***
		(0.478)		(0.339)	
3	Increase average HH schooling of females by 1 year	30.334	-6.0***	30.068	-6.9***
		(0.396)		(0.400)	
4	Increase average HH schooling of males by 1 year	30.919	-4.2***	30.670	-5.0***
		(0.400)		(0.404)	
5	Increase average HH schooling of females by 2 years	28.434	-11.9***	27.798	-13.9***
		(0.383)		(0.391)	
6	Increase average HH schooling of males by 2 years	29.577	-8.4***	28.998	-10.2***
		(0.391)		(0.399)	
7	Adult moves from primary industry occupation to tertiary	23.376	-27.6***	19.855	-38.5***
		(0.342)		(0.364)	
8	Adult moves from secondary industry occupation to tertiary	24.529	-24.0***	21.392	-33.7***
		(0.352)		(0.376)	
9	Increase diversity of crops from 0 to 1	31.027	-3.9***	31.042	-3.9***
		(0.400)		(0.399)	
10	Increase diversity of crops to 2, if 0 or 1	29.532	-8.5***	29.566	-8.4***
		(0.390)		(0.390)	

Notes: Bootstrapped standard errors in parentheses. Statistical significance tests are based on absolute changes in the headcounts. *** indicates significant at 1%; ** at 5%; and, * at 10%.

Table 5: Poverty simulations (percent change over base simulation), urban

Simulation	Description	No Distribution Effect		Distribution Effect	
		P0	% Change	P0	% Change
0	Base	19.789		19.789	
		(0.364)		(0.364)	
1	Adding a child if there is no child in HH	22.370	13.0***	24.017	21.4
		(0.352)		(0.336)	
2	Adding a child to all HHs	32.687	65.2***	35.665	80.2
		(0.463)		(0.385)	
3	Increase average HH schooling of females by 1 year	18.276	-7.6***	17.535	-11.4
		(0.348)		(0.35–2)	
4	Increase average HH schooling of males by 1 year	18.410	-7.0***	17.670	-10.7
		(0.349)		(0.353)	
5	Increase average HH schooling of females by 2 years	16.836	-14.9***	15.295	-22.7
		(0.331)		(0.337)	
6	Increase average HH schooling of males by 2 years	17.091	-13.6***	15.556	-21.4
		(0.334)		(0.340)	
7	Adult moves from primary industry occupation to tertiary	16.099	-18.6***	13.203	-33.3
		(0.323)		(0.330)	
8	Adult moves from secondary industry occupation to tertiary	16.484	-16.7***	14.501	-26.7
		(0.327)		(0.334)	

Notes: Bootstrapped standard errors in parentheses. Statistical significance tests are based on absolute changes in the headcounts. *** indicates significant at 1%; ** at 5%; and, * at 10%.