Poverty and Inequality in Malawi: Trends, Prospects, and Policy Simulations

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Abstract

Using data from the third integrated household survey the paper has performs forward-looking conditional and unconditional policy simulations. Results from the unconditional simulations reveal that Malawi's exclusive focus on growth while ignoring inequality would have little or no impact on poverty reduction by 2020. Massive but unlikely levels of growth would be required to reduce poverty. The results further indicate that a modest combination of consumption growth of 10% and a reduction in inequality to 2004 levels would be associated with a projected poverty incidence of 38% in 2020, which is substantially below the level of poverty in 2011 of 51%. Results from the conditional simulations which condition on determinants of poverty reveal that the impact of changes in years of education on projected poverty levels is gender-differentiated. Precisely, if the years of schooling for females were to rise by one year by 2020, then 39% of the population would be poor. In stark contrast, 40% of the population would be poor as a result of an identical change in the years of schooling of males. Thus, going forward education gender-sensitive policy interventions which target women's education would have far reaching consequences on poverty alleviation in Malawi.

1 Introduction

Poverty reduction is the *sine qua non* of development policy. As argued by Ravallion (2016), antipoverty policies are essentially premised on three things: (a) poverty is a social bad, (b) poverty can be eliminated, and (c) public policies can help do that. Broadly speaking, antipoverty policies take two forms; protection and promotion. Protection policies focus on short-term palliatives, and ensure that current consumptions do not fall below some crucial level, even though poor people remain a wealth poverty trap. On the other hand, promotion policies lift poor people out of the poverty trap, through a sufficiently large wealth gain, to put them on a path to eventually reach their own (higher and stable) steady state level of wealth (Ravallion, 2016). A good antipoverty policy aims at both promotion and protection.

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Historically, in Malawi like in other low income countries, the mixture of these two components has not always been balanced. From independence, the focus has primarily been on protection rather promotion. It is only from the 1990s that explicit promotion policies have gained prominence. This evolution in thinking about how to deal with poverty has led to two important products. First, data collection through integrated household surveys to measure poverty has now been regularised. Second, in an attempt to reduce poverty in Malawi, the government has since the 1990s put in place various strategies emphasizing both promotion and protection. These strategies include the Poverty Alleviation Program (1994); the Malawi Poverty Reduction Strategy (2002-2005); and, more recently, the Malawi Growth and Development Strategy (MGDS) (2006-2011 and 2011-2016) (GOM, 1994,2002, 2012).

Whereas poverty has gained prominence in both the political and policy discourse, inequality is still on the periphery. As a matter of fact, a notable characteristic of all the above poverty strategies is that they do not recognise the role of inequality in increasing poverty and reducing economic growth. The implicit assumption in the strategies is that poverty reduction will come through growth i.e. growth will trickle down to poverty. However, growth is necessary but not sufficient for poverty reduction; levels of inequality also matter (Ravallion, 2001; Bourguignon, 2004; Fosu 2009). Interestingly, Vision 2020 for Malawi identified inequality as a challenge, but, this has not filtered through to the development strategies implemented so far. According to the Vision "Malawians aspire to have a fair and equitable distribution of income and wealth. To this effect, they endeavour to reduce disparities in access to land, education, employment and business opportunities between urban and rural people, men and women, people with and without disabilities" (GOM,1998).

The objectives of this paper are twofold. First, it looks at the levels and trends in poverty and inequality in Malawi. This is essentially a backward-looking analysis. The second objective of the paper is to look to the future by conducting unconditional and conditional simulation exercises. Both sets of simulations are relevant for policy. For the analysis to be tractable and meaningful, the paper limits itself to projected poverty levels in 2020.

The unconditional simulations analyse the relationship between poverty, inequality, and growth while assuming exogenously given inequality and growth levels. The unconditional simulations do not take into account the fact that households face significant binding constraints to reducing poverty. By conditioning on determinants of poverty, the conditional analysis allows an examination of the effects that policy interventions can have on projected poverty.

The rest of the paper is structured as follows. Section 2 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 has experienced a strong economic growth performance in the recent past, however, the impact of this growth on poverty and consumption inequality has been mixed. 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. Table 1 shows trends in the poverty headcount, poverty gap, and poverty intensity over the period 2004-2011. Nationally, the trends show marginal declines in the poverty headcount, poverty gap, and poverty intensity. For instance, the percentage of poor people in Malawi was 52.4% in 2004, and declined slightly to 50.7% in 2011. This national picture however hides the contrasting pattern in rural-urban poverty trends. The poverty headcount in rural areas minimally increased from 55.9% to 56.6% while urban poverty declined from 25.4% to 17.3%. Over the same period, the poverty gap and intensity worsened in rural areas, but improved in urban areas.

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). Could it be that the decline in poverty is possibly underestimated? Some recent empirical evidence points to this possibility. A re-examination of these poverty figures by Pauw et al. (2016) shows that the decrease in poverty was much larger than officially estimated. Their results show a more substantial decline in poverty between 2004 and 2011 of 8.4 percentage points. Furthermore, unlike the official figures, they also find that poverty declined by 7.5 percentage points in rural areas over that period.

The nature of economic growth in Malawi provides a good example of the warning contained in the 1996 edition of the human development report. The report warns that "Policy-makers are often mesmerized by the quantity of growth. They need to be more concerned with its structure and quality" (UNDP, 1996). Economic growth in Malawi can be classified as "ruthless": this is growth that only benefits the rich, and leaves the poor in their poverty (see UNDP (1996) for different types of negative or uneconomic growth). The ruthlessness of Malawi's growth is depicted in Table 2. Nationally, in 2004/5, the richest 10% of the population accounted for 46% of total consumption while the bottom 40% accounted for 15% of total consumption. The share of consumption attributable to the top 10% increased to 53% in 2011, and that for the bottom 40% declined to 13%. This means that over the period 2004-2011, the consumption of the top 10% rose from being about three times higher to being about four times higher than that of the poorest 40%.

All this points to the worsening of consumption inequality in Malawi. Furthermore, a comparison of the richest and the poorest 10% of the population indicates that the consumption of richest 10% was about twenty two times higher than that of the bottom 10% in 2004. This number jumped to thirty four times in 2011. This national picture hides a lot of spatial inequalities. In contrast to the pattern of lower incidence of poverty in the urban areas noted earlier, the level of inequality in consumption is considerably higher in the urban areas than in the rural areas. The difference between the share of total consumption taken by the richest 10% in urban and rural areas is quite staggering.

Between 2004 and 2011, the top 10% in urban areas experienced an increase in their share of consumption from 79% to 86%. Over the same time, the richest 10% in rural areas saw their share of consumption decrease from 33% to 29%. Looking at 2011 for example, the share of consumption of the top 10% in urban areas, was about 960 times higher than that of the bottom 10%. In contrast, the share of consumption of the richest 10% in rural areas was only about 12 times higher than that of the poorest 10%.

Using the Gini coefficient as an alternative measure of inequality, Table 2 shows that nationally, the Gini coefficient increased from 0.39 in 2004 to 0.45 in 2011. The table also shows that magnitude of the disequalising effect of growth varies with location. It was more pronounced in rural areas which saw the Gini coefficient increase from 0.34 in 2004 to 0.38 in 2011 while the urban Gini coefficient rose from 0.48 to 0.49 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.

Do official inequality figures understate the inequality problem in Malawi? A recent re-examination of consumption inequality by Mussa (2014a) using the consumption aggregates developed by Pauw et al. (2016) shows that indeed official inequality statistics grossly underestimate inequality. Specifically, Mussa (2014a) finds that measured inequality based on the new consumption aggregate is much higher than that based on the official consumption aggregate. For instance, at the national level, inequality as measured by the

Gini coefficient is underestimated by 11.3% for 2004, and by 5.5% for 2011. Further to this, he finds that the underestimation is more evident for rural areas than for urban areas. In 2011 for instance, official inequality figures underestimated rural inequality by 10.5%, in contrast, urban inequality was understated by 5.8%.

3 Empirical Strategy

3.1 An Unconditional Poverty-Inequality-Growth Relationship

Poverty changes can either be due to changes in mean income or changes in the distribution of relative incomes (see e.g. Bourguignon, 2003; Datt and Ravallion, 1992). Consequently, any change in the poverty headcount, a measure of the incidence of poverty, can be decomposed into a) a "growth effect" that is the result of a proportional change in all incomes that leaves the distribution of relative incomes unaffected and b) a "distributional effect" that is only due to a change in the distribution of relative incomes leaving the mean income constant.

Use is made of the fact that under the assumption that consumption is lognormally distributed, the total distribution of individual consumption is not needed for one to calculate the headcount poverty (Bourguignon, 2003; Klasen and Misselhorn, 2008). One only needs the mean consumption $\bar{y}$, the constant poverty line z, and the standard deviation of the lognormal distribution. The poverty headcount under lognormality of consumption is

$$H = \Phi\left(\frac{\ln z - \ln \bar{y}}{\sqrt{2}\Phi^{-1}\left(\frac{(G+1)}{2}\right)} + \frac{\sqrt{2}\Phi^{-1}\left(\frac{(G+1)}{2}\right)}{2}\right) \tag{1}$$

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 equation makes it explicit that the poverty headcount not only depends on average consumption but also depends on the extent of inequality as measured by the Gini coefficient. Hence, multiplying H with the population for Malawi would give the number of poor people in Malawi.

I then use equation (1) to analyse the relationship between poverty, inequality, and growth. This is done through scenarios analysis whereupon I perform simulated and hypothetical changes in the mean of consumption and the Gini coefficient. These are then used to compute projected poverty levels in terms of the number of poor people in 2020. Under each scenario, I experiment with different but plausible changes in the Gini coefficient and the mean of consumption. These scenarios are by no means exhaustive, other configurations are possible. Their utility is in showing how the different trajectories of inequality and mean consumption would affect poverty, and hence provide guidance on which path would be the most effective in reducing poverty in Malawi.

3.2 Conditional Poverty-Inequality-Growth Relationship

The above simulation procedure is unconditional, it therefore represents a black box way of looking at the poverty-inequality-growth nexus. More specifically, it fails to account for the fact that households face significant binding constraints to reducing poverty. Government policies and programs are often put in place to remove or relax these constraints. By making it conditional on a vector correlates of poverty, the simulation method can be used to demonstrate the effects that various deliberate policy interventions can have on the projected prevalence of poverty.

The conditional simulation method used in this study is an improvement over the simulation method used by Datt and Jollife (2005) and Mukherjee and Benson (2003) in that it accommodates the hierarchical nature of the data by allowing for community level random effects. In order to make equation (1) conditional, a poverty regression is first specified. The log of per capita annualized household consumption expenditure is used as a dependent variable. I use a linear multilevel model to analyse the determinants of poverty. 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

$$\ln y_{ij} = \beta' x_{ij} + \delta' z_j + u_j + \varepsilon_{ij} \tag{2}$$

where; β and δ are coefficients, x_{ij} and z_j are observed household level and community level characteristics respectively, $u_j \sim N(0, \sigma_u^2)$ are community-level spatial effects (random intercepts), assumed to be uncorrelated across communities, and uncorrelated with covariates, and $\varepsilon_{ij} \sim N(0, \sigma_\varepsilon^2)$ is a household-specific idiosycratic 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 $\sigma_\zeta^2 = \sigma_u^2 + \sigma_\varepsilon^2$.

The set up and assumptions of equation (2) imply that $\ln y_{ij} \sim N\left(x'_{ij}\beta, \sigma_\zeta^2\right)$, and this further means that per capita consumption is lognormally distributed. Using this, the headcount (equation (1)) can be respecified to get

$$H = \frac{\sum_{ij}^{N} w_{ij}\Phi\left(\frac{\ln z-(\beta' x_{ij}+\delta' z_j)}{\sigma_\varsigma}\right)}{\sum_{ij}^{N} w_{ij}} \tag{3}$$

Where w_{ij} is the weight of each household, defined as the product of the survey sampling weight of the household, and the number of members in the household, and $N = M_j * J_l$ is the total number of households in the sample. This reformulation shows that the incidence of poverty not only depends on household and community characteristics but also depends on the extent of inequality.

In performing the conditional policy 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.

3.3 Data description, poverty lines, and variables used

The data used in the study 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 services.

[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.

The unit of analysis is an individual, and this is achieved by using sampling weights which are multiplied by household size. I adopt the national level official annualised poverty line of 37002 Malawi Kwacha (MK). For the conditional simulations, 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) 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.

4 Results

4.1 Unconditional Policy Simulations

Beyond the aggregated national level analysis, and in order to allow for possible spatial differences, the analysis also looks at rural and urban areas separately. Four scenarios are considered, and it is assumed that consumption grows at 10%, 20%, and 30% under each setup. The scenarios are as follows:

1. SCENARIO 1: The Gini stays at the level it was in 2011. This means the Gini is 0.45 for Malawi, 0.38 for rural areas, and 0.49 for urban areas.

2. SCENARIO 2: A 6 point Gini increase from the 2011 level. In this case, the new Gini is 0.51 for Malawi, 0.44 for rural areas, and 0.55 for urban areas.

3. SCENARIO 3: A 10 point Gini increase from the 2011 level. The new Gini is 0.55 for Malawi, 0.48 for rural areas, and 0.59 for urban areas.

4. SCENARIO 4: The Gini stays at the level it was in 2004. Thus, the Gini is 0.39 for Malawi, 0.34 for rural areas, and 0.48 for urban areas.

The unconditional simulation results for Malawi as whole and for rural and urban areas are reported in Table 3. The NSO projects Malawi's population in 2020 to be at 19.1 million. For rural and urban areas, the projected populations in 2020 are 17 million and 3 million respectively. Assuming a consumption growth of 10%, and that inequality stays at the level it was in 2011 (i.e. the Gini remains at 0.45, 0.39, 0.45 for Malawi, for rural areas, and for urban areas respectively) then the projected number of poor people in 2020 would be about 8.4 million, 8.3 million, and 0.5 million in Malawi, in rural areas, and in urban areas respectively. This means that half of rural population would be poor in 2020 while only one in five of the urban population would be poor.

As would be expected, when these levels of inequality are associated with higher consumption growth rates, the projected number of poor in 2020 is much lower. Specifically, the projected number of people in 2020 in Malawi would be 7.7 million (representing 40% of the population) if consumption grew at 20%, and it would be 7 million (representing 36% of the population) if consumption growth was at 30%. Similar declines corresponding to higher consumption growth rates are observed for rural and urban areas. For instance, at 20% consumption growth, the projected prevalence of poverty in rural areas is 45%, and this drops to 41% when consumption growth is pegged at 30%.

I now turn to a scenario where the Gini increases by 6 points. This increase in inequality amounts to saying that at the national level inequality increases at the same pace as it did between 2004 and 2011 (i.e. the Gini increased from the current level of 0.45 to 0.51). If consumption is projected to grow by 10%, then the projected number of poor people in 2020 in Malawi would be 9.5 million (representing about 50% of the population). This means that compared to the first scenario, a worsening of inequality that is linked to a low consumption growth of 10% would lead to over a million more poor people in Malawi in 2020.

The negative impact of this increase in inequality on poverty is only offset when consumption grows at a high level of 30%; in this case the projected number of poor people of 8.2 million is lower than the number of poor people under the scenario where the Gini remains at its 2011 level but consumption grows at 10%. Interestingly, when one looks at the spatially disaggregated picture, it is observed that for urban areas, even a 30% consumption growth is not enough to push the projected number of poor people below 0.6 million, the number holding under the scenario of 10% growth with the Gini staying at its 2011 level.

What would happen for different levels of consumption growth if there was a further worsening of inequality by 10 points? In Malawi in 2020, there would be 10.2 million poor people (representing 53% of the population) if consumption grew at 10%, 9.6 million poor people (representing 50% of the population) if consumption grew at 20%, and 9 million poor people (representing 47% of the population) if consumption grew at 30%.

The last set of scenarios shows the projected levels of poverty under different consumption growth trajectories if inequality stayed at the level it was in 2004. Nationally, this amounts to a 6 point Gini decrease. Now if consumption grew at 10%, then the projected number of poor people in 2020 would be 7.2 million. This implies that there would be close to a million fewer poor people in poverty in Malawi than the 8.4 million seen when inequality stays at the 2011 level.

For all scenarios, projected rural poverty is consistently higher than projected urban poverty. This is despite the fact that in Malawi inequality is worse in urban areas than in rural areas. It is worth noting that the rural-urban poverty gaps are inversely related to the level of consumption growth. For instance, if inequality increases by 10 Gini points and consumption grows by 10% there would be 8.4 million more poor people in rural areas than in urban areas. Similarly, if inequality increases by 10 Gini points and consumption grows by 20% there would be 8 million more poor people in rural areas than in urban areas. Finally, rural areas would have 7.3 million more poor people if consumption were to grow by 30%. This suggests that the rural-urban poverty gap can be significantly reduced if rural areas experience substantial consumption growth.

The simulation results suggest that both inequality and growth are important for poverty reduction. An exclusive focus on growth as is the case in Malawi would have little or no impact on poverty reduction. In the Malawian context, this obsession with growth requires that growth must be massive to reduce poverty. Clearly, this is highly unlikely, and perhaps significantly, the results demonstrate that a modest combination of consumption growth of 10% and a reduction in inequality to 2004 levels would lead to a projected poverty incidence of 38% in 2020, which is substantially below the level of poverty in 2011 of 50.7%.

4.2 Conditional Policy Simulations

4.2.1 Regression Results

Detailed definitions and summary statistics for all the independent variables are given in Table 4. I first look at the validity of assumptions adopted in this study, and a discussion of the parameter estimates of the regression. The determinants of poverty results for rural and urban areas are reported in Table 5. Wald test results ($\chi^2 = 1828.8$) indicate the null hypothesis that poverty regression parameters between rural and urban areas are equal is not supported by the data. The rejection of parameter homogeneity suggests that estimating separate rural and urban regressions is appropriate.

In both rural and urban areas, log likelihood tests reject 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. The Wald test results further indicate the presence of significant seasonal and agro-ecological effects. Consequently, seasonal and agro-ecological dummies are included in the two regressions.

The parameter estimates for the two regressions are generally consistent with *apriori* expectations. I comment on some of the findings. Education has a statistically significant effect on poverty in both rural and urban areas. Furthermore, the magnitude of the impact of education is gender differentiated in that in both areas the coefficient on the average years of education for females is larger than that for males. For instance, in rural areas and holding other factors constant, an additional year of schooling for females in a household leads to a 4% increase in per capita consumption while for males the corresponding effect is 3%. This difference is statistically significant with a z-statistic of 3.5 (i.e. $z = 0.04 - 0.03)/((0.002\hat{\ }2 + 0.002\hat{\ }2)\hat{\ }0.5))$. Irrespective of gender, the results indicate that there are spatial differences in the size of the returns to education with urban areas exhibiting quantitatively larger returns than rural areas.

There are no statistically significant welfare advantages to finding employment in the primary (agriculture, fishing, mining, etc.) sector. 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, adding a household member employed in the tertiary sector increases consumption by 23% in rural areas and by 14% in urban areas. Both health and economic infrastructure in the community have a positive effect on household welfare. The effect is however statistically significant in rural areas only. In rural areas, the presence of economic infrastructure such as a perennial and passable main road, a daily market, a weekly market has a larger effect on welfare than health infrastructure such as clinics and nurses. The z-statistic for the difference is 2.8 (i.e. $z = (0.076 - 0.038)/(0.011\hat{}2 + 0.009\hat{}2)\hat{}0.5$), implying that the difference is statistically significant.

4.3 Simulation Results

Since the idea is to project the number of poor people in 2020, I simulate policy interventions which change the level of a regressor from its current level (as of 2011) to a simulated level in 2020. I then calculate the number of poor people in 2020 under each simulated intervention. The interventions focus on population, education, employment, and agriculture. Precisely, the study simulates what would happen to the incidence of poverty in 2020 if eleven interventions were to be implemented.

A reference point or base simulation is necessary in this context 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 difference is due to 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; it therefore represents a continuation of the status quo. If the determinants of poverty remain at the current levels until 2020, the projected number of poor people in Malawi is 6.1, representing 42% of the population. The projected poverty incidences are 47% and 13% for rural and urban areas respectively.

It should be noted that the size of the impact of a simulation depends on three things namely; (a) the sign and magnitude of the estimated regression coefficients, (b) the size of the simulation, and (c) the proportion of the population affected by the simulation. Simulation results for eleven policy experiments are displayed in Table 6. 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 The simulation results indicate that these changes would induce increases in poverty in 2020. Simulation 1 is a more targetted approach as it involves adding a child to households with no children, and this associated with a projected number of people of about 9 million, representing 46% of the 2020 population. This represents an increase in the number of poor of about 2.7 million over the base scenario.

Furthermore, adding a child to all households as in simulation 2 has an ever bigger impact on projected poverty. Nationally, the headcount jumps to 58% implying that

11 million people would be poor in 2020. A rural-urban comparison of the two simulations shows that rural areas would experience a larger increase in the poverty headcount. Specifically, the poverty headcount increases by 13 percentage points for rural areas while it goes up by 9 percentage points in urban areas. The finding that additional children lead to higher levels of poverty conforms to previous studies (e.g. Eastwood and Lipton, 1999; Mussa, 2014b) . All this points to the importance of population policy which seeks to reduce family sizes.

The second set of simulations 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. This means that compared to a continuation of the status quo, intervening in the education sector would lead to lower levels of projected poverty. Distinguishing the interventions by gender reveals that a uniform change in the years of schooling for females leads to a larger reduction in poverty levels than that for males.

Simulation 3 demonstrates that for Malawi as a whole, if the years of schooling for females were to rise by one year by 2020, then the number of poor people would be 7.5 million. In contrast, simulation 4, shows that a higher incidence of poverty (7.6 million) is associated with a similar change in years of schooling of males. Unsurprisingly, the effect is much higher when the uniform increase is two years of schooling. Nationally, a two-year increase in the average years of schooling for females leads to a poverty headcount of 37% while a similar increase for males is associated with a poverty prevalence of 38%.

A comparison of the induced effect of these education simulations show that location and gender are interrelated. Looking at the 2-year increase in the years of schooling for males and females, the results show that the gender-differential is more pronounced in rural areas than in urban areas. The gender-difference in the headcounts emanating from a 2-year increase in years of education is 1.1 and 0.26 percentage points for rural and urban areas respectively. This means that increasing years of education of women as opposed to men would lead to a change in the poverty incidence which is 4 times higher in rural areas than in urban areas.

As noted by Datt and Jollife (2005), there is potential for overestimating the impact of increasing education on poverty especially the two-year increase in years of education which represents a rather substantial intervention. The overestimation could emanate from two sources. First, it could be that .the increase in education could also lead to a decline in the return to education, and secondly, the returns to education may be confounded by innate abilities of household members. This notwithstanding, the finding that educating females as compared to males has a larger poverty reducing effect is relevant for gender policy as it implies that education interventions which deliberately seek to improve women's education have far reaching consequences on poverty alleviation in Malawi.

The next three simulations are concerned with employment, and they essentially consider hypothetical movements of a household member from the primary industry to secondary industry, from primary industry to a tertiary industry, and finally from secondary industry to a tertiary industry. These movements amount to changing the structure of employment between 2011 and 2020. The results suggest that compared to the baseline scenario, changing the structure of employment has a significant potential for reducing poverty in Malawi. A clear pattern in the results is evident; the ordered movement from primary to secondary to tertiary is associated with correspondingly higher reductions in projected poverty.

Overall, the movement of a household member from a primary industry occupation to a secondary occupation leads to a poverty headcount of 40%, this declines to 33% if a member moves from a primary industry to a tertiary industry. However, a movement from a secondary industry to a tertiary industry reduces the projected headcount to 34%. This implies 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 last set of simulations look at the effect of changing crop diversification on projected poverty. These simulations are done for rural areas only. The agricultural simulation considers increasing diversity of crops of agriculture households from 0 to 1. This intervention would lead to a poverty headcount of 46% in 2020. A further increase in crop diversification by agriculture households from 0 or 1 to 2 entails a drop in the headcount to 44%. These declines in poverty are lower than what holds under the baseline scenario.

5 Concluding Remarks

Using data from the third integrated household survey the paper has performed forward-looking conditional and unconditional policy simulations. Results from the unconditional simulations reveal that Malawi's exclusive focus on growth while ignoring inequality would have little or no impact on poverty reduction by 2020. Massive but unlikely levels of growth would be required to reduce poverty. The results further indicate that a modest combination of consumption growth of 10% and a reduction in inequality to 2004 levels would be associated with a projected poverty incidence of 38% in 2020, which is substantially below the level of poverty in 2011 of 51%.

Results from the conditional simulations which condition on determinants of poverty reveal that the impact of changes in years of education on projected poverty levels is gender-differentiated. Precisely, if the years of schooling for females were to rise by one year by 2020, then 39% of the population would be poor. In stark contrast, 40% of the population would be poor as a result of an identical change in the years of schooling of males. Thus, going forward education gender-sensitive policy interventions which target women's education would have far reaching consequences on poverty alleviation in Malawi.

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Table 1: Trends and levels of economic growth and poverty

Indicator/Area	2005	2011
GDP growth	6.2[a]	6.1[b]
Poverty headcount		
National	52.41	50.64
Rural	55.86	56.62
Urban	25.4	17.28
Poverty Gap		
National	17.78	18.88
Rural	19.16	21.39
Urban	7.06	4.83
Poverty Severity		
National	7.98	9.27
Rural	8.64	10.57
Urban	2.83	2.02

[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: Trends and levels of inequality

	2005				2011			
	Bottom 40%	Bottom 10%	Top 10%	Gini Coefficient	Bottom 40%	Bottom 10%	Top 10%	Gini Coefficient
National	14.71	2.09	46.03	0.39	12.59	1.55	52.85	0.45
Rural	23.29	2.64	33.27	0.34	18.49	2.34	29.04	0.38
Urban	3.32	0.30	78.80	0.48	1.67	0.09	86.40	0.49

Source: Authors' computation using IHS2 and IHS3

Table 3: Unconditional projected percentage and number of poor people in 2020

	Malawi		Rural		Urban	
	Headcount	Poor People (Millions)	Headcount	Poor People (Millions)	Headcount	Poor People (Millions)
10% Growth						
The Gini stays at the level it was in 2011	44.05	8.42	49.95	8.08	18.71	0.55
A 6 point Gini increase	49.70	9.50	54.49	8.81	27.10	0.79
A 10 points Gini increase	53.24	10.17	57.28	9.27	30.83	0.90
The Gini stays at the level it was in 2004	37.83	7.23	46.59	7.54	17.56	0.51
20% Growth						
The Gini stays at the level it was in 2011	40.03	7.65	45.01	7.28	16.30	0.48
A 6 point Gini increase	46.15	8.82	50.28	8.13	24.53	0.72
A 10 points Gini increase	49.99	9.55	53.51	8.65	28.25	0.83
The Gini stays at the level it was in 2004	33.34	6.37	41.08	6.64	15.20	0.45
30% Growth						
The Gini stays at the level it was in 2011	36.42	6.96	40.53	6.56	14.28	0.42
A 6 point Gini increase	42.91	8.20	46.42	7.51	22.28	0.65
A 10 points Gini increase	47.01	8.98	50.00	8.09	25.98	0.76
The Gini stays at the level it was in 2004	29.41	5.62	36.16	5.85	13.22	0.39

Table 4: Descriptive statistics of variables

Variable	Variable Description	Rural		Urban	
		Mean	SD	Mean	SD
sexh	Dummy (1 if household head is male, 0 otherwise)	0.75	0.43	0.82	0.39
ageh	age of household head	42.93	16.68	38.72	13.41
under 9	No. of individuals in a household aged below 9 years	1.56	1.31	1.27	1.17
10-17	No. of individuals in a household aged 10-17 years	0.95	1.11	0.86	1.08
females 18-59	No. of females in a household aged 18-59 years	0.95	0.57	1.12	0.72
males 18-59	No. of males in a household aged 18-59 years	1.84	1.00	2.25	1.15
over 60 years	No. of individuals in a household over 60 years old	0.26	0.55	0.13	0.40
edu_avghhf	Average years schooling of females in a household	3.05	2.69	5.61	3.74
edu_avghhm	Average years schooling of males in a household	3.77	3.08	6.58	3.94
prim_ind	No. of individuals in a household in primary industry occupation	0.04	0.23	0.03	0.19
second_ind	No. of individuals in a household in secondary industry occupation	0.04	0.22	0.10	0.32
tert_ind	No. of individuals in a household in tertiary industry occupation	0.10	0.33	0.56	0.69
land	land per capita in acres	0.12	0.46	-	-
crops	number of crops grown other than maize/tobacco	0.19	0.58	-	-
economic index	index of economic infrastructure	0.79	0.86	1.59	1.29
health index	index of health infrastructure	2.33	1.19	2.61	1.05
zone1	Nsanje, Chikwawa districts	0.07	0.26	-	-
zone2	Blantyre, Zomba, Thyolo, Mulanje, Chiradzulu, Phalombe districts	0.23	0.42	-	-
zone3	Mwanza, Balaka, Machinga, Mangochi districts	0.18	0.38	-	-
zone4	Dedza, Dowa, Ntchisi districts	0.11	0.31	-	-
zone5	Lilongwe, Mchinji, Kasungu districts	0.13	0.34	-	-
zone6	Ntcheu, Salima, Nkhotakota districts	0.11	0.31	-	-
zone7	Mzimba, Rumphi, Chitipa districts	0.11	0.31	-	-
zone8	Nkhatabay, Karonga districts	0.07	0.25	-	-
season1	Dummy (1 if household was interviewed in March-April, 0 otherwise): Base	0.19	0.39	0.17	0.38
season2	Dummy (1 if household was interviewed May-August, 0 otherwise)	0.27	0.45	0.26	0.44
season3	Dummy (1 if household was interviewed in September-November, 0 otherwise)	0.30	0.46	0.32	0.47
season4	Dummy (1 if household was interviewed in December-February, 0 otherwise)	0.24	0.43	0.25	0.43
Observations		10038		2233	

Table 5: Determinants of poverty in Malawi

Variable	Rural		Urban	
sexh	0.156***	(0.014)	-0.077**	(0.038)
ageh	0.013***	(0.002)	0.028***	(0.006)
ageh2	-0.000***	(0.000)	-0.000***	(0.000)
num_9	-0.320***	(0.008)	-0.330***	(0.019)
num10_17	-0.320***	(0.009)	-0.257***	(0.021)
numf18_59	-0.005	(0.015)	-0.035	(0.029)
numm18_59	-0.304***	(0.013)	-0.223***	(0.025)
num_60	-0.333***	(0.017)	-0.139**	(0.057)
hhsizesq	0.017***	(0.001)	0.013***	(0.002)
edu_avghhf	0.040***	(0.002)	0.047***	(0.004)
edu_avghhm	0.030***	(0.002)	0.042***	(0.004)
prim_ind	0.038	(0.024)	0.022	(0.068)
second_ind	0.075***	(0.024)	0.034	(0.041)
tert_ind	0.233***	(0.017)	0.144***	(0.021)
landpc	0.076***	(0.013)		
crops	0.034***	(0.012)		
econ_index	0.076***	(0.011)	0.053*	(0.027)
health_index	0.038***	(0.009)	0.034	(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 (overall significance)	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	
Observations	10038		2233	

Notes: Standard errors in parentheses. *** indicates significant at 1%; ** at 5%; and, * at 10%.

Table 6: Conditional projected percentage and number of poor people in 2020

Simulation	Description	Malawi		Rural		Urban	
		Headcount	Poor People (Millions)	Headcount	Poor People (Millions)	Headcount	Poor People (Millions)
1	Adding a child if there is no child in HH	45.78	8.75	52.46	8.49	14.91	0.44
2	Adding a child to all HHs	58.06	11.09	65.82	10.65	23.83	0.70
3	Increase average HH schooling of females by 1 year	39.17	7.48	45.08	7.29	11.94	0.35
4	Increase average HH schooling of males by 1 year	39.73	7.59	45.63	7.38	12.07	0.35
5	Increase average HH schooling of females by 2 years	36.90	7.05	42.74	6.91	10.80	0.32
6	Increase average HH schooling of males by 2 years	38.02	7.26	43.84	7.09	11.06	0.32
7	Adult moves from primary industry occupation to secondary	40.38	7.71	45.27	7.32	12.83	0.38
8	Adult moves from primary industry occupation to tertiary	33.25	6.35	36.16	5.85	10.18	0.30
9	Adult moves from secondary industry occupation to tertiary	34.28	6.55	38.24	6.18	10.45	0.31
10	Increase diversity of crops from 0 to 1	39.96	7.63	45.73	7.40		
11	Increase diversity of crops to 2, if 0 or 1	38.16	7.29	43.67	7.06		