A joint analysis of correlates of poverty intensity, incidence, and gap with application to Malawi

Mussa, Richard

Department of Economics, Chancellor College, Box 280, Zomba, Malawi

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Richard Mussa[*]

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Abstract

The paper proposes partial elasticities of the Sen-Shorrocks-Thon Index of poverty intensity which can be decomposed into elasticities of the poverty headcount and the poverty gap ratio. These partial effects are important because they can be used to jointly identify the determinants of the poverty headcount, the poverty gap ratio, and poverty intensity, which in turn can be used to suggest possible policy or behavioral responses which might be implemented to reduce poverty. The proposed partial elasticities are illustrated by analysing poverty in Malawi using data from the Third Integrated Household Survey. The empirical results indicate that the magnitudes of the elasticities for the poverty headcount are consistently larger than those for the poverty gap. This means that the dominant channel through which poverty intensity can be affected is the headcount. In terms of policy, this suggests that redistributive policy interventions that aim to reduce the incidence of poverty would significantly also reduce poverty intensity.

Keywords: Poverty intensity, Sen-Shorrocks-Thon Index, Malawi

1 Introduction

The measurement of poverty remains an active area of both theoretical and empirical research. One commonly used measure of poverty (see e.g. Osberg and Xu, 2008) is the Sen-Shorrocks-Thon Index (SST index hereinafter). The SST is a measure of poverty intensity, and it has two key attractions. First, it respects Sen's (1976) arguments which were further refined by Chakravarty (1997) and Shorrocks (1995) that poverty measures should among others satisfy the transfer axiom. Second, the SST index encompasses the poverty headcount, the average poverty gap ratio, and the Gini coefficient of poverty gaps (Xu and Osberg, 2002; Osberg and Xu, 2000). This multiplicative decomposability of the SST index is useful as it allows one to jointly examine the impacts of anti-poverty policy actions on poverty intensity as well as its three subcomponents.

Researchers are often interested in assessing the poverty reduction potential of various policy interventions through modeling determinants of poverty. For instance, microsimulation methods which rely on the log normality of income have been used (e.g. Mukherjee

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

and Benson, 2003; Datt and Jolliffe, 2005) to separately assess the effects of simulated changes of household and community level characteristics on the poverty headcount, the poverty gap ratio, and poverty intensity. Although the existing microsimulation methods can be used to assess how changes in correlates of poverty individually affect the poverty headcount, the poverty gap ratio, and poverty intensity, there is no method which provides a framework for jointly quantifying changes in the three measures.

Since the SST index nests the three poverty measures, this paper exploits this feature to develop a toolbox for assessing partial changes in its components. Precisely, this paper makes two contributions to the poverty literature. First, the paper proposes partial elasticities of the SST index which can be decomposed into elasticities of the poverty headcount and the poverty gap ratio. These partial effects are important because they can be used to jointly identify the determinants of the poverty headcount, the poverty gap ratio, and poverty intensity, which in turn can be used to suggest possible policy or behavioral responses which might be implemented to reduce poverty.

Additionally, since the SST index is multiplicatively decomposable, the magnitudes of the partial elasticities of the components of poverty intensity can further be used to pinpoint the dominant channel for reducing poverty intensity. By looking at the sizes of the elasticities, one can tell whether the effect of a particular factor on poverty intensity is largely through its effect on the incidence of poverty or the depth of poverty. The second contribution that this paper makes is that the proposed partial elasticities are illustrated by analysing poverty in Malawi using data from the Third Integrated Household Survey.

The remainder of this paper is structured as follows. Section 2 presents a parametric formulation of the Sen-Shorrocks-Thon Index. Partial elasticities of the Sen-Shorrocks-Thon Index are derived in Section 3. Section 4 provides a description of the Malawian context and data used in the empirical application. Results of the application are reported in Section 5. Finally, Section 6 concludes.

2   A Parametric Sen-Shorrocks-Thon Index

Osberg and Xu (2000) and Xu and Osberg (2002) show that the SST index $p\left(y_{ij}, z\right)$ can alternatively be written as

$$p\left(y_{ij}, z\right) = H * I * \left[1 + G\left(m_{ij}\right)\right] \tag{1}$$

where y_{ij} is per capita household consumption expenditure of household i in community j, $z > 0$ is a poverty line, H is a poverty headcount, I is the average poverty gap ratio of the poor, and $G\left(m_{ij}\right)$ is a Gini coefficient of the poverty gap ratios $m_{ij} = \frac{z - y_{ij}}{z}$ of the population. Thus, the SST Index is equal to the [headcount]×[the average poverty gap ratio of the poor]×[the inequality of poverty gap ratios of the population]. It therefore

jointly measures poverty incidence, depth and inequality.

As noted earlier, the SST index above is silent about the quantitative response of poverty intensity and its components to exogenous changes in household and community level characteristics. To accommodate this, I first specify a linear multilevel model which captures the determinants of poverty. Household data is usually clustered in nature in that households are nested in communities, and 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). An extended discussion of multilevel or hierchical models can be found in for example Rabe-Hesketh and Skrondal (2008) and McCulloch et al. (2008).

I model these common community traits as random effects. Consider household i ($i = 1....M_j$) which resides in community j ($j = 1....J_l$), then the determinants of poverty allowing for spatial community random effects can be modeled using the following two level linear regression

$$\ln y_{ij} = x'_{ij}\beta + u_j + \varepsilon_{ij} \tag{2}$$

where β is a coefficient vector, x_{ij} is a vector of observed household level and community level characteristics, $u_j \sim N\left(0, \sigma_u^2\right)$ 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 $\sigma_\zeta^2 = \sigma_u^2 + \sigma_\varepsilon^2$. 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.

I then use the lognormality of consumption to transform the SST into a parametric form. Under lognormality, the poverty headcount is given as (Datt and Jollife, 2005; Muller, 2005)

$$H = \Phi\left(\frac{\ln z - x'_{ij}\beta}{\sigma_\zeta}\right) \tag{3}$$

Noting that the average gap ratio R for the population is (Datt and Jollife, 2005; Muller, 2005)

$$
\begin{aligned}
R &= H * I \\
&= \Phi\left(\frac{\ln z - \beta' x_{ij}}{\sigma_\zeta}\right) - \frac{e^{x'_{ij}\beta_{ij} + \frac{\sigma_\zeta^2}{2}}}{z}\Phi\left(\frac{\ln z - \left(x'_{ij}\beta + \sigma_\zeta\right)}{\sigma_\zeta}\right)
\end{aligned} \tag{4}
$$

then the average poverty gap ratio of the poor is

$$I = \left[1 - \frac{1}{zH} e^{x'_{ij}\beta + \frac{\sigma_\zeta^2}{2}} \Phi\left(\frac{\ln z - \left(x'_{ij}\beta + \sigma_\zeta \right)}{\sigma_\zeta} \right) \right] \tag{5}$$

where $\Phi\left(\cdot\right)$ is a cumulative density function of a standard normal distribution. Essentially, the above poverty intensity and its subcomponents are household specific, and to get population level aggregates one simply needs to take a sample-weighted average. In this case, the weights can be defined as a household sampling weight multiplied by household size.

3 Partial Elasticities of Poverty Intensity

The above parametric specification of the sub-components of the SST index can then be utilised to measure how changes in household and community level characteristics first lead to changes in the individual components, and ultimately, how the intensity of poverty responds to the changes. Following Xu and Osberg (2000, 2002), the parametric reformulation of the SST can be rewritten by taking a natural logarithm of both sides of equation (1) to get

$$\ln p\left(y_{ij}, z \right) = \ln H + \ln I + \ln\left[1 + G\left(m_{ij} \right) \right] \tag{6}$$

I use this multiplicative decomposition of the SST to derive a partial elasticity formula which shows the percentage change in the SST associated with a percentage change in a correlate of poverty holding other things constant.

Result: The elasticity of poverty intensity with respect to regressor x_k denoted as $\eta_k^{SST} = \frac{\partial p(y_{ij},z)}{\partial x_k} \frac{x_{ijk}}{p(y_{ij},z)}$ is given by

$$\begin{aligned} \eta_k^{SST} &= \frac{\partial H}{\partial x_k} \frac{x_k}{H} + \frac{\partial I}{\partial x_k} \frac{x_k}{I} + \frac{\partial\left[1 + G\left(m_{ij} \right) \right]}{\partial x_k} \frac{x_k}{\left[1 + G\left(m_{ij} \right) \right]} \\ &= -\frac{\beta_k x_k}{\sigma_\zeta} \frac{\phi\left(Z_1 \right)}{\Phi\left(Z_1 \right)} - \frac{\beta_k x_k}{\sigma_\zeta} \left[\left(\sigma_\zeta - \frac{\phi\left(Z \right)}{\Phi\left(Z \right)} + \frac{\phi\left(Z_1 \right)}{\Phi\left(Z_1 \right)} \right) \left(\frac{1 - I}{I} \right) \right] \end{aligned} \tag{7}$$

where $Z = \frac{\ln z - \left(x'_{ij}\beta + \sigma_\zeta \right)}{\sigma_\zeta}$, $Z_1 = \frac{\ln z - \left(\beta' x_{ij} \right)}{\sigma_\zeta}$, and $\phi\left(\cdot\right)$ is a probability density function of a standard normal distribution. The first term in equation (7) corresponds to the elasticity of the headcount, η_k^H and the second term captures the elasticity of the poverty gap ratio of the poor, η_k^I, hence, the elasticity of poverty intensity with respect to regressor x_k is additively decomposable, $\eta_k^{SST} = \eta_k^H + \eta_k^I$. A proof of this result is provided in the appendix.

A number of things are noteworthy about the elasticity formula. The sign of the

elasticity of the poverty headcount is determined by whether a correlate increases the likelihood of poverty i.e. $\beta_k < 0$ or lowers it i.e. $\beta_k > 0$. The sign of the elasticity of the poverty gap ratio of the poor is ambiguous as it depends on the sign of β_k, and the sign of $\sigma_\zeta - \frac{\phi(Z)}{\Phi(Z)} + \frac{\phi(Z_1)}{\Phi(Z_1)}$. The sign of the elasticity of poverty intensity is therefore determined by the relative magnitudes of η_k^H and η_k^I. Further to this, the relative magnitudes of η_k^H and η_k^I can be used to ascertain the dominant channel through which a change in x_k affects poverty intensity. If $\left| \eta_k^H \right| > \left| \eta_k^I \right| \left(\left| \eta_k^H \right| < \left| \eta_k^I \right| \right)$, then the impact of a change in x_k mostly works through changing the headcount (the poverty gap).

The elasticity of a binary independent variable is calculated differently by replacing the partial derivative operator equation (7) with the discrete difference operator Δ. For statistical inference, standard errors for the elasticities can be computed by using either first-order mathematical approximation (see e.g. Davidson and MacKinnon (2004)), more commonly known as the delta method or by bootstrapping (Efron and Tibshirani, 1986). In the empirical application, I use bootstrapped standard errors.

4   Empirical Application to Malawi

4.1   Context

The Malawian government has pursued poverty reduction efforts through various strategies emphasizing economic growth, infrastructure development, and the provision of basic social services. 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). Although, Malawi has experienced a strong economic growth performance in the recent past, the impact of this growth on poverty has been marginal.

The economy grew at an average annual rate of 6.2% between 2004 and 2007, and surged further to an average growth of 7.5% between 2008 and 2011 (NSO, 2012a). Malawi's economy is agrobased, with the agricultural sector accounting for about 30% of GDP over the period 2004-2011. Over the same period, the agriculture sector was by far Malawi's most important contributor to economic growth, with a contribution of 34.2% to overall GDP growth (NSO, 2012b). 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.

Figure 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.

It is somewhat puzzling that this dismal poverty reduction performance especially in rural areas coincides 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. 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 (Chirwa and Dorward, 2013; World Bank, 2013).

4.2 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 with sampling probability proportional. 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.

In order to capture possible locational differences, the empirical illustration distinguishes between rural and urban households, and I adopt a new annualized consumption aggregate for each household generated by Pauw et al. (2014) 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 et al., 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

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[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.

into standard units such as kilograms and grams. The new aggregate uses a new set of conversion factors developed by Verduzco-Gallo et al. (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. (2014) instead of the national level official annualised poverty line of 37002 Malawi Kwacha (MK). The poverty lines are: MK 31573 for rural areas, and MK 46757 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; Echevin, 2012) 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 age of the household head, and a dummy variable for male head of household.

I also include a set of education variables. First, the highest education qualification attained by any adult (aged 20-59 years) in the household is included. This enters the regressions as four dummies reflecting if an adult member: completed Primary School Leaving Certificate (PSLC), completed Junior Certificate of Education (JCE) (junior secondary school qualification), completed Malawi School Certificate of Education (MSCE) (senior secondary school qualification), or completed a tertiary qualification. Second, I also include measures of the number of male and female adults with JCE and MSCE in a household. 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 1.

5 Results

5.1 Regression Results

I first look at the validity of assumptions adopted in this paper and a discussion of the results from the poverty regression. Table 2 shows parameter estimates for the poverty regressions for rural and urban households. Wald test results reject the null hypothesis that poverty regression parameters between rural and urban areas are not the same. The rejection of parameter homogeneity means that estimating one pooled national regression is invalid. The partial elasticities of the SST are based on the parametric assumption that consumption expenditure is log normally distributed. I test this assumption for both rural and urban areas by using normal probability plots of the residuals from the poverty regressions shown in Figure 2. The plots suggest that the errors indeed follow the normal distribution.

The log likelihood tests reject null hypothesis of no community random effects in both regressions. This suggests two things: (a) even after controlling for individual characteristics, there are significant community-specific factors which affect poverty, and, (b) estimating a linear model as in for example Mukherjee and Benson (2003) and Datt and Jollife (2005) is inappropriate. The intra-class correlation coefficients (ICC) for both areas range from 17% to 21%, this implies that the vast majority of the variation in welfare (79% to 83%) exists within communities rather than between them. The Wald test results support the inclusion of seasonal and agro-ecological dummies in the two regressions to control for the presence of seasonal and agro-ecological effects. With a few exceptions, the parameter estimates for the two regressions generally conform to *apriori* expectations, and their relative magnitudes are plausible.

5.2   Partial Elasticities

Elasticities of poverty intensity, poverty headcount, and poverty gap with respect to household and community characteristics for rural and urban households are reported in Tables 3 and 4 respectively. The results also show the percentage share of the two components of the elasticity of poverty intensity. The signs of the elasticities are the same for poverty intensity, poverty headcount, and poverty gap for urban households. This means that for urban households, if a factor lowers the likelihood of poverty, it also reduces the poverty intensity, poverty headcount, and poverty gap. In contrast, the picture is somewhat mixed for rural households, where the signs of elasticities of the poverty headcount, and poverty gap for some variables are not the same. The results further indicate that relative to the poverty headcount, there are fewer partial elasticities of poverty gap that are statistically significant.

The methods developed in this paper enable one to decompose changes in poverty intensity into changes in the prevalence of poverty and changes in the poverty gap. Broadly speaking, the results indicate that the magnitudes of the elasticities for the poverty headcount are consistently larger in absolute value than those for the poverty gap. Over 80% of changes in poverty intensity are attributable to changes in the poverty headcount, with the remainder arising from changes in the poverty gap of the poor. This implies that the dominant channel through which poverty intensity can be affected is the headcount. Thus, policy interventions that reduce the incidence of poverty would have a larger effect in reducing poverty intensity than policies that focus on narrowing the poverty gap of the poor.

I now turn to a more detailed discussion of the results. The effects of gender on poverty intensity, the poverty headcount, and the poverty gap are statistically significant, but, the direction of their effects vary with location. Holding other things constant, male headed households experience lower levels of poverty intensity, prevalence, and gap than female headed, in rural areas. A reverse pattern is observed for urban households. Furthermore, the gender effects across the three measures of poverty are more pronounced in absolute value terms for rural households than for urban households. Male headed households have a 26%, 3.6%, and 29% lower poverty headcount, gap, and intensity respectively as compared to female headed households in rural areas, *ceteris paribus*. In contrast, holding other things constant, male headed urban households have a 2.9%, 0.4%, and 3.4% higher poverty prevalence, gap, and intensity respectively.

Turning to household composition, the results indicate that in both rural and urban areas, elasticities are positive and statistically significant for the three measures, they are however larger for children aged 0-9 than for the economically active category (i.e. 18-59 age category). Holding all else constant, having young children increases poverty intensity, incidence, and gap by a larger magnitude in urban areas compared to rural

areas. This difference perhaps reflects the fact that the cost of raising children in urban areas might be higher. A rather surprising result is that the elasticities for male members in the economically active age group are larger than those for females; suggesting that adding a female who is in the economically active age bracket to a household as compared to adding a male leads to a smaller increase in poverty.

In both rural and urban areas, education is found to have a negative and statistically significant effect on poverty intensity and poverty incidence. The role of education in reducing the poverty gap is not conclusive, as some of the elasticities are not statistically significant. This implies that holding other factors constant, attainment of higher levels of education undoubtedly reduces the incidence and intensity of poverty. This pattern is more evident in urban areas where the poverty elasticities progressively increase in size (in absolute terms) as one moves up the qualification scales. For rural areas, having an adult with a senior secondary qualification has larger effect than having an adult with a tertiary qualification. A look at the returns to education further reveals that they are quantitatively larger in urban areas than in rural areas. This difference between rural and urban areas in the sizes of the returns to education could be explained by the fact that there are limited opportunities for regular wage employment or self-employment in rural areas.

The effect of education on poverty is not uniform across gender. Holding all else constant, and regardless of location, increases in the education of females as compared to males with a junior secondary qualification (JCE) or a senior secondary qualification (MSCE) have larger impacts on poverty intensity, poverty headcount, and poverty gap. For instance, a *ceteris paribus* 1% increase in the number of adult females and males who have completed JCE in urban areas leads to a decrease in: (a) the intensity of poverty by about 0.036% and 0.004% respectively; (b) the incidence of poverty by about 0.032% and 0.004% respectively; and (c) the poverty gap by about 0.005% and 0.001% respectively. In urban areas, the return to having females with MSCE is 2.5 times larger than the return to having females with JCE. In contrast, the sizes of the returns are reversed in rural areas; the return to having females with MSCE relative to JCE is only 0.3 times larger. As noted already, this pattern, simply reflects limited remunerative employment opportunities in rural areas that require higher education qualification.

Employment in the primary (agriculture, fishing, mining, etc.), the secondary (manufacturing), tertiary (sales and service industries) sectors significantly reduces the incidence, gap, and intensity of poverty. In both areas however, the elasticities of primary sector employment for the poverty gap are insubstantial in magnitude. Holding all else constant, increases in employment in the tertiary industry have a larger negative impact on poverty incidence, intensity, and gap than employment in the primary and secondary industries. For instance, in urban areas, holding all else constant, a 1% rise in the number of household members employed in the tertiary sector is associated with a reduction in

the poverty incidence, poverty gap, and poverty intensity of about 0.11%, 0.008%, and 0.12% respectively. The corresponding reductions in the poverty incidence, poverty gap, and poverty intensity arising from employment in manufacturing are 0.007%, 0.0007%, and 0.008% respectively

The significance of employment in the manufacturing sector in reducing the incidence, gap, and intensity of poverty is in stark contrast to a previous finding by Mukherjee and Benson (2003) who found that employment in the secondary industry does not affect poverty in Malawi. It is worth noting that the dominance of the impact of employment in the services sector over the manufacturing sector is consistent with what has been observed in other developing countries (UNCTAD, 2014). It is however markedly different from the classical pattern of structural transformation observed in developed countries where increases in income arose from a switch from agriculture to manufacturing rather than to the services sector.

Turning to agriculture, the results indicate that land ownership and crop diversification have statistically significant negative effects on the incidence and intensity of poverty but the effects are statistically insignificant on the poverty gap. A comparison of the sizes of the elasticities indicates that increases in land ownership have a larger effect in reducing in the incidence and intensity of poverty than crop diversification; the elasticity for land is about 1.8 times larger than that for crop diversification.

The availability of economic infrastructure such as a perennial and passable main road, a daily market, a weekly market has statistically insignificant effects on the incidence, gap, and intensity of poverty in rural areas but it is significant in urban areas. In contrast, the availability of health infrastructure such as clinics and nurses significantly reduces the incidence, gap, and intensity of poverty in both areas. A closer examination of the magnitudes of the elasticities on the incidence and intensity of poverty shows that the effect of both health and economic infrastructure is spatially-differentiated. Improvements in economic infrastructure in urban areas have a 2 times larger effect on the incidence and intensity of poverty than health infrastructure. However, a reverse pattern is observed in rural areas; the responsiveness of the incidence and intensity of poverty to improvements in health infrastructure is 29 times larger than that for economic infrastructure.

6 Conclusion

The paper has proposed partial elasticities of the Sen-Shorrocks-Thon Index of poverty intensity which can be decomposed into elasticities of the poverty headcount and the poverty gap ratio. These partial effects are important because they can be used to jointly identify the determinants of the poverty headcount, the poverty gap ratio, and poverty intensity, which in turn can be used to suggest possible policy or behavioral responses which might be implemented to reduce poverty. The proposed partial elasticities have

been illustrated by analysing poverty in Malawi using data from the Third Integrated Household Survey.

The empirical results indicate that the magnitudes of the elasticities for the poverty headcount are consistently larger than those for the poverty gap. This means that the dominant channel through which poverty intensity can be affected is the headcount. In terms of policy, this suggests that redistributive policy interventions that aim to reduce the incidence of poverty would significantly also reduce poverty intensity.

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7 Appendix

Proof of equation (7)

Partially differentiating equation (6) with respect to x_k yields

$$\frac{\partial p\left(y_{ij},z\right)}{\partial x_k}\frac{1}{p\left(y_{ij},z\right)}=\frac{\partial H}{\partial x_k}\frac{1}{H}+\frac{\partial I}{\partial x_k}\frac{1}{I}+\frac{\partial\left[1+G\left(m_{ij}\right)\right]}{\partial x_k}\frac{1}{\left[1+G\left(m_{ij}\right)\right]} \qquad (A1)$$

where the partial derivative for the poverty headcount is given as

$$\frac{\partial H}{\partial x_k}=-\left(\frac{\beta_k}{\sigma_\zeta}\right)\phi\left(Z_1\right) \qquad (A2)$$

for the poverty gap ratio it is expressed as

$$\frac{\partial I}{\partial x_k}=-\frac{1}{zH^2}\left[\beta_k AH\left(\Phi\left(Z\right)-\frac{1}{\sigma_\zeta}\phi\left(Z\right)\right)+\left(\frac{\beta_k}{\sigma_\zeta}\right)\phi\left(Z_1\right)\Phi\left(Z\right)A\right] \qquad (A3)$$

where $A=e^{x'_{ij}\beta_{ij}+\frac{\sigma_\zeta^2}{2}}$. Since $1-I=\frac{1}{zH}A\Phi\left(Z\right),$ equation (A3) can be rewritten as

$$\begin{aligned}\frac{\partial I}{\partial x_k} &= \left[-\beta_k\left(1-I\right)+\left(\frac{\beta_k}{\sigma_\zeta}\right)\left(1-I\right)\frac{\phi\left(Z\right)}{\Phi\left(Z\right)}-\left(\frac{\beta_k}{\sigma_\zeta}\right)\left(1-I\right)\frac{\phi\left(Z_1\right)}{\Phi\left(Z_1\right)}\right] \qquad (A4)\\ &= -\left(\frac{\beta_k}{\sigma_\zeta}\right)\left[\sigma_\zeta-\frac{\phi\left(Z\right)}{\Phi\left(Z\right)}+\frac{\phi\left(Z_1\right)}{\Phi\left(Z_1\right)}\right]\left(1-I\right)\end{aligned}$$

and finally, noting that under log normality, a Gini coefficient is a monotone increasing function of the conditional variance of the log of consumption (Kleiber and Kotz, 2003; Cowell, 2009), and does not depend on the level of x_k, the partial derivative for the Gini coefficient of the relative gap ratios is

$$\frac{\partial\left[1+G\left(m_{ij}\right)\right]}{\partial x_k}=0 \qquad (A5)$$

Substituting these derivatives into the elasticity formula of the SST as given in the first line of equation (7) produces the final result.

Table 1: Variable description and summary statistics

Variable	Variable Description	Rural		Urban	
		Mean	SD	Mean	SD
sexh	Dummy (1 if head is male, 0 otherwise)	0.747	0.435	0.817	0.387
ageh	age of HH head	42.934	16.682	38.724	13.409
under 9	No. of individuals aged below 9 years	1.561	1.306	1.275	1.173
10-17	No. of individuals aged 10-17 years	0.948	1.114	0.862	1.080
females 18-59	No. of females aged 18-59 years	0.955	0.571	1.119	0.723
males 18-59	No. of males aged 18-59 years	1.838	1.000	2.249	1.145
over 60 years	No. of individuals over 60 years old	0.263	0.546	0.125	0.404
none	Dummy (1 if adult's (20-59 years) highest qualification is none, 0 otherwise): Base	0.474	0.499	0.221	0.415
pslc	Dummy (1 if adult's (20-59 years) highest qualification is pslc, 0 otherwise)	0.116	0.320	0.126	0.332
jce	Dummy (1 if adult's highest qualification is jce, 0 otherwise)	0.099	0.299	0.189	0.392
msce	Dummy (1 if adult's highest qualification is msce, 0 otherwise)	0.057	0.232	0.262	0.440
tertiary	Dummy (1 if adult's highest qualification is tertiary qualification, 0 otherwise)	0.011	0.105	0.133	0.340
females with JCE	No. adult females (20-59 years) completed JCE	0.048	0.226	0.183	0.425
males with JCE	No. adult males (20-59 years) completed Junior Certificate of Education (JCE)	0.089	0.302	0.203	0.442
females with MSCE	No. adult females (20-59 years) completed Malawi School Certificate of Education (MSCE)	0.016	0.131	0.149	0.404
males with MSCE	No. adult males (20-59 years) completed MSCE	0.054	0.241	0.261	0.503
primary industry	No. of individuals in primary industry occupation	0.041	0.226	0.033	0.186
secondary industry	No. of individuals in secondary industry occupation	0.037	0.222	0.100	0.316
tertiary industry	No. of individuals in tertiary industry occupation	0.100	0.329	0.560	0.691
land	land per capita in acres	0.121	0.460	-	-
crops	number of crops grown other than maize/tobacco	0.189	0.576	-	-
economic index	index of economic infrastructure	-0.145	0.857	0.651	1.292
health index	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	Dummy (1 if household was interviewed in March-April, 0 otherwise): Base	0.189	0.392	0.172	0.378
season2	Dummy (1 if household was interviewed May-August, 0 otherwise)	0.275	0.446	0.259	0.438
season3	Dummy (1 if household was interviewed in September-November, 0 otherwise)	0.298	0.457	0.321	0.467
season4	Dummy (1 if household was interviewed in December-February, 0 otherwise)	0.238	0.426	0.248	0.432
Observations		10038		2233	

Table 2: Determinants of poverty in Malawi

Variable	Rural		Urban	
	Coefficient	SE	Coefficient	SE
sexh	0.1614***	(0.0147)	-0.0139	(0.0353)
ageh	0.0011**	(0.0005)	0.0015	(0.0014)
num_9	-0.1839***	(0.0047)	-0.2361***	(0.0112)
num10_17	-0.1183***	(0.0053)	-0.0885***	(0.0123)
numf18_59	-0.0024	(0.0161)	-0.0410	(0.0300)
numm18_59	-0.1103***	(0.0104)	-0.0816***	(0.0202)
num_60	-0.1617***	(0.0162)	-0.1349***	(0.0455)
plsc	0.1611***	(0.0180)	0.1049**	(0.0417)
jce	0.2102***	(0.0397)	0.1966***	(0.0536)
msce	0.3078***	(0.0626)	0.4734***	(0.0584)
tertiary	0.7263***	(0.0586)	1.0171***	(0.0508)
jcefem	0.1528***	(0.0310)	0.0611*	(0.0341)
jcemal	-0.0127	(0.0359)	0.0078	(0.0435)
mscefem	0.0852	(0.0527)	0.1320***	(0.0391)
mscemal	0.0272	(0.0556)	0.0135	(0.0447)
prim_ind	0.0351	(0.0264)	-0.0003	(0.0672)
second_ind	0.0381	(0.0267)	-0.0281	(0.0403)
tert_ind	0.1580***	(0.0193)	0.0610***	(0.0209)
landpc	0.0817***	(0.0142)		
crops	0.0343***	(0.0130)		
econ_index	0.0869***	(0.0144)	0.0398	(0.0242)
health_index	0.0348***	(0.0108)	0.0301	(0.0296)
zones included	Yes		No	
Chi2 (parameter homogeneity)		7039.68		
P-value of Chi2		0.00		
Chi2 (significance of agro-ecological zones)	259.13		-	
P-value of Chi2	0.00		-	
seasons included	Yes		Yes	
Chi2 (significance of seasonal effects)	7.93		8.76	
P-value of Chi2	0.05		0.03	
Chi2 (regression)	4433.64		1573.43	
P-value of Chi2	0.00		0.00	
Chi2 (random effects)	880.18		254.47	
P-value of Chi2	0.00		0.00	
intracluster correlation coefficient (ICC)	0.17		0.21	
Observations	10038		2233	

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

Table 3: Elasticities of poverty intensity, headcount, and gap, rural

Variable	Headcount		Gap		Intensity		Percentage Share	
	Elasticity	SE	Elasticity	SE	Elasticity	SE	Headcount	Gap
sexh	-0.2554***	(0.0020)	-0.0358***	(0.0051)	-0.2912***	(0.0055)	87.71	12.29
ageh	-0.0984***	(0.0006)	-0.0136***	(0.0016)	-0.1120***	(0.0017)	87.86	12.14
num_9	0.4772***	(0.0040)	0.0775***	(0.0058)	0.5547***	(0.0075)	86.03	13.97
num10_17	0.1879***	(0.0024)	0.0283***	(0.0011)	0.2162***	(0.0030)	86.91	13.09
numf18_59	0.0045***	(0.0000)	0.0007***	(0.0001)	0.0052***	(0.0001)	86.54	13.46
numm18_59	0.4055***	(0.0029)	0.0580***	(0.0068)	0.4634***	(0.0076)	87.51	12.52
num_60	0.0902***	(0.0021)	0.0132***	(0.0017)	0.1035***	(0.0029)	87.15	12.75
plsc	-0.0419***	(0.0012)	-0.0057***	(0.0012)	-0.0476***	(0.0019)	88.03	11.97
jce	-0.0505***	(0.0017)	-0.0003	(0.0054)	-0.0508***	(0.0056)	99.41	0.59
msce	-0.0523***	(0.0023)	-0.0116***	(0.0043)	-0.0639***	(0.0051)	81.85	18.15
tertiary	-0.0362***	(0.0034)	0.0002	(0.0009)	-0.0360***	(0.0035)	100.56	-0.56
jcefem	-0.0211***	(0.0011)	-0.0010	(0.0028)	-0.0221***	(0.0030)	95.48	4.52
jcemal	0.0027***	(0.0001)	-0.0000	(0.0003)	0.0026***	(0.0003)	103.85	0.00
mscefem	-0.0047***	(0.0004)	-0.0014	(0.0011)	-0.0061***	(0.0012)	77.05	22.95
mscemal	-0.0044***	(0.0002)	-0.0010**	(0.0004)	-0.0054***	(0.0005)	81.48	18.52
prim_ind	-0.0034***	(0.0002)	-0.0002**	(0.0001)	-0.0036***	(0.0006)	94.44	5.56
second_ind	-0.0032***	(0.0002)	-0.0008***	(0.0003)	-0.0040***	(0.0004)	80.00	20.00
tert_ind	-0.0477***	(0.0018)	-0.0049**	(0.0024)	-0.0526***	(0.0031)	90.68	9.32
landpc	-0.0269***	(0.0024)	0.0033	(0.0036)	-0.0236***	(0.0042)	113.98	-13.98
crops	-0.0146***	(0.0005)	0.0018	(0.0021)	-0.0128***	(0.0021)	114.06	-14.06
econ_index	-0.0024	(0.0021)	0.0003	(0.0033)	-0.0021	(0.0040)	114.29	-14.29
health_index	-0.0527***	(0.0010)	-0.0081***	(0.0009)	-0.0608***	(0.0014)	86.68	13.32
Observations				10038				

Notes: In parentheses are bootstrapped standard errors (SE) after 1000 replications. *** indicates significant at 1%; ** at 5%; and, * at 10%.

Table 4: Elasticities of poverty intensity, headcount, and gap, urban

Variable	Headcount		Gap		Intensity		Percentage Share	
	Elasticity	SE	Elasticity	SE	Elasticity	SE	Headcount	Gap
sexh	0.0294***	(0.0004)	0.0041***	(0.0011)	0.0335***	(0.0012)	87.76	12.24
ageh	-0.1515***	(0.0017)	-0.0185***	(0.0039)	-0.1700***	(0.0044)	89.12	10.88
num_9	0.6007***	(0.0111)	0.0713***	(0.0081)	0.6721***	(0.0146)	89.38	10.61
num10_17	0.1731***	(0.0047)	0.0128***	(0.0048)	0.1859***	(0.0069)	93.11	6.89
numf18_59	0.1203***	(0.0022)	0.0162***	(0.0043)	0.1364***	(0.0051)	88.20	11.88
numm18_59	0.4844***	(0.0072)	0.0637***	(0.0153)	0.5482***	(0.0176)	88.36	11.62
num_60	0.0400***	(0.0029)	0.0049***	(0.0012)	0.0449***	(0.0034)	89.09	10.91
plsc	-0.0266***	(0.0016)	-0.0039***	(0.0003)	-0.0304***	(0.0018)	87.50	12.83
jce	-0.0871***	(0.0041)	-0.0141***	(0.0009)	-0.1012***	(0.0048)	86.07	13.93
msce	-0.3809***	(0.0142)	-0.0705*	(0.0377)	-0.4515***	(0.0415)	84.36	15.61
tertiary	-0.5985***	(0.0336)	-0.0024	(0.0200)	-0.6010***	(0.0399)	99.58	0.40
jcefem	-0.0316***	(0.0016)	-0.0048*	(0.0029)	-0.0364***	(0.0036)	86.81	13.19
jcemal	-0.0039***	(0.0002)	-0.0005***	(0.0001)	-0.0044***	(0.0002)	88.64	11.36
mscefem	-0.0729***	(0.0042)	-0.0131	(0.0099)	-0.0860***	(0.0111)	84.77	15.23
mscemal	-0.0109***	(0.0005)	-0.0020*	(0.0011)	-0.0129***	(0.0012)	84.50	15.50
prim_ind	0.0000***	(0.0000)	0.0000***	(0.0000)	0.0000***	(0.0000)	-	-
second_ind	-0.0074***	(0.0005)	-0.0007***	(0.0002)	-0.0080***	(0.0006)	92.50	8.75
tert_ind	-0.1077***	(0.0033)	-0.0078***	(0.0027)	-0.1155***	(0.0044)	93.25	6.75
econ_index	-0.0825***	(0.0036)	-0.0030	(0.0026)	-0.0854***	(0.0045)	96.60	3.51
health_index	-0.0398***	(0.0020)	-0.0086**	(0.0041)	-0.0484***	(0.0047)	82.23	17.77
Observations				2233				

Notes: In parentheses are bootstrapped standard errors (SE) after 1000 replications. *** indicates significant at 1%; ** at 5%; and, * at 10%.
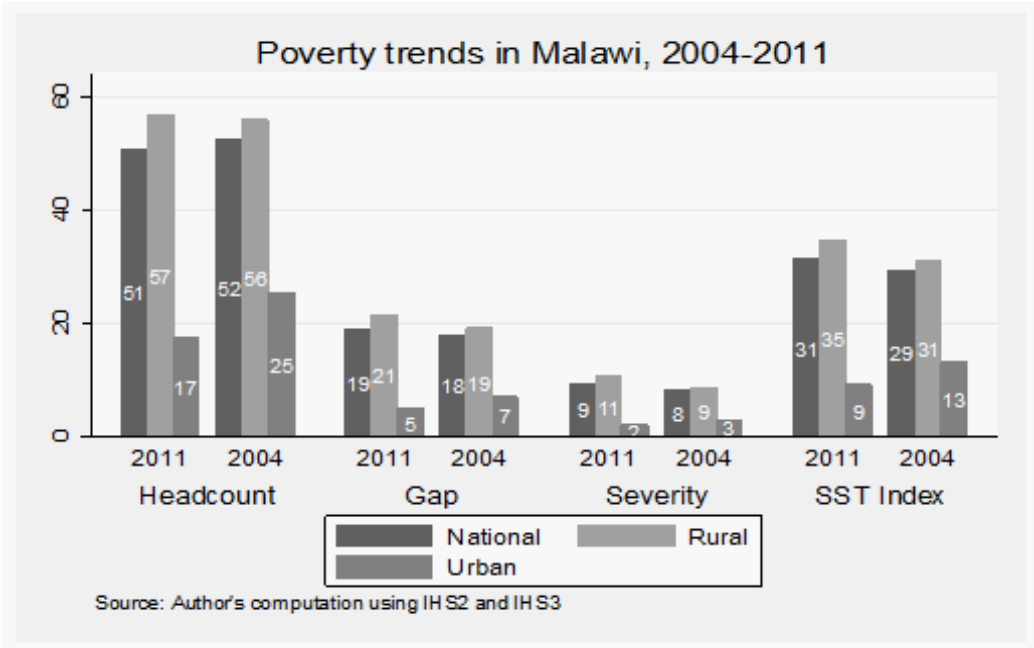
Figure 1: Trends and levels of poverty, 2004-2011

Figure 2: Testing for normality of residuals