To Err is Human: Inconsistencies in Food Conversion Factors and Inequality in Malawi

Mussa, Richard

Department of Economics, Chancellor College, University of Malawi

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Richard Mussa*

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Abstract

One of the key deficiencies of household survey data for measuring poverty and inequality is that survey nonresponse depends on the income of the respondent, whereby rich people are less likely to cooperate with household surveys than poor people. This nonrandom nonresponse may hide the true level of poverty and inequality. Another potential problem with household survey data which has received scant attention in the literature is the quality of food conversion factors. Nonrandom errors and inconsistencies in food conversion factors can potentially have a nontrivial impact on measured poverty and inequality.The paper looks at the impact of errors and inconsistencies in food conversion factors on measured consumption inequality. Malawi has been used as case study with data from the Second and the Third Integrated Household Surveys (IHS2 and IHS3). Two consumption aggregates are used; an official aggregate which is contaminated by errors and inconsistencies in food conversion factors and a new aggregate which cleans out these problems. The paper finds that the inconsistencies and errors in the conversion factors were not random in that they affected the richest households more than the poorest households. Consequently, the official aggregate understates the level of inequality as measured by the Gini coefficient. Inequality is underestimated by 4.4 and 2.3 Gini points for 2004/5 and 2010/11 respectively. The disparities are not only sizable but they are also statistically significant. I also find that the official aggregate progressively underestimates the share accruing to higher percentiles. Nonparametric tests for Lorenz dominance confirm that these differences in measured inequality are robust. Using the new aggregate, the paper also finds that inequality is not worsening overtime as the official aggregate suggests. All this implies that the quality of food conversion factors is critical for the accurate measurement of levels of and trends in inequality.

Keywords: Conversion factors; inequality; Malawi

1 Introduction

There is considerable debate regarding the relative merits and demerits of using national accounts data as opposed to survey data to measure poverty and inequality. Using national accounts data a number of studies (e.g. Sala-i-Martin (2002, 2006), and Pinkovskiy

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

and Sala-i-Martin (2009, 2014, 2016) find more substantial declines in world poverty. However, studies based on survey data paint a different picture of slow progress in reducing poverty (e.g. Chen and Ravallion (2001, 2004, 2010). This difference arises from the fact that the growth rate of consumption or income from household surveys is slower than that of consumption or income measured in national accounts (Deaton, 2005; Pinkovskiy and Sala-i-Martin, 2016). This in turn means that survey-based estimates overstate the extent of poverty and inequality. Pinkovskiy and Sala-i-Martin (2016) show that surveys relative to national accounts perform worse in developing countries that are richer and that are growing faster.

One of the key deficiencies of household survey data for measuring poverty and inequality is that survey nonresponse depends on the income of the respondent, whereby rich people are less likely to cooperate with household surveys than poor people (Deaton, 2005; Pinkovskiy and Sala-i-Martin, 2016). This nonrandom nonresponse may hide the true level of poverty and inequality. Another potential problem with household survey data which has received scant attention in the literature is the quality of food conversion factors. Nonrandom errors and inconsistencies in food conversion factors can potentially have a nontrivial impact on measured poverty and inequality. In developing countries, current household consumption which is generated from a household living standards survey is preferred to current household income as an indicator of living standards (Haughton and Khandker, 2009). Consumption comprises food and non-food items, and by Engel's law the food component is larger than the non-food component. To construct the consumption aggregate for each household one needs food conversion factors to transform non-standard units of measurement such as heaps, pails, plates, cups and basins into standard units such as grams or kilograms.

To the best of my knowledge, there is no study which has assessed the impact of nonrandom quality problems of food conversion factors on measured consumption inequality. In this paper, I close this knowledge gap by using Malawi as a case study to quantify the impact of these errors and inconsistencies in food conversion factors on consumption inequality. Official inequality figures are based on consumption data which is contaminated by these errors and inconsistencies, consequently, the study provides answers to two questions: Are the levels of inequality in Malawi worse than officially estimated? Is inequality worsening overtime? Malawi is an interesting case because although it has experienced a strong economic growth performance in the recent past, official poverty statistics indicate that the impact of this growth on poverty has been marginal. Specifically, 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 (NSO, 2015). But official poverty figures show that the percentage of poor people in Malawi was 52.4% in 2004, and just marginally declined to 50.7% in 2011 (NSO, 2005, 2012).

This discrepancy between economic performance from the national accounts and survey based poverty figures cannot entirely be explained by the fact that survey data is slow moving as compared to national accounts data. As a matter of fact, a re-examination of these poverty figures which addresses errors and inconsistencies in food conversion factors by Pauw et al. (2016) finds lower levels of poverty and a much larger decline in poverty of 8.4 percentage points from 47.0% in 2004 to 38.6% in 2011. In terms of consumption inequality, official figures which are based on the consumption aggregate that is fraught with errors and inconsistencies in food conversion factors suggest that inequality has been worsening overtime; the Gini coefficient significantly increased from 0.390 in 2004/5 to 0.452 in 2010/11. Just like the levels and trend of poverty, these levels and trajectory of inequality in Malawi merit further re-examination.

This paper generates three key findings regarding consumption inequality in Malawi. First, the difference between the official and the new aggregate gets progressively larger as one moves from the poorest to the richest households; implying that. the inconsistencies and errors in the conversion factors were not random as they affected the richest households more than the poorest households. Second, the official aggregate understates levels of consumption inequality. Third, consumption inequality is not worsening overtime as official figures suggest. These results are significant as they suggest that the quality of food conversion factors is critical for the measurement of inequality. Perhaps more importantly, given that many developing countries use consumption as an indicator of welfare, they also have implications on the possibility that inequality is also underestimated in other countries.

The remainder of this paper is structured as follows. A description of the data used in the study is given in Section 2. Section 3 presents the methodology. This is followed by a discussion of empirical results in Section 4. Finally, Section 5 concludes.

2 Data

The data used in the paper come from the Second and the Third Integrated Household Surveys (IHS2 and IHS3) conducted by the National Statistical Office (NSO). The two surveys are comparable overtime, and they are statistically designed to be representative at both national, district, urban and rural levels. Both surveys used a stratified two-stage sample design where all districts constitute the strata. Within each district, and for IHS2 and IHS3 respectively, the primary sampling units (PSUs) selected at the first stage are the census enumeration areas (EA) defined for the 1998 and 2008 Malawi Population and Housing Censi. Sample EAs were selected within each district systematically with probability proportional to size. In the second stage, a random systematic sampling was used to select households from the household listing for each sample EA. The IHS2 was done from March 2004 to March 2005, while the IHS3 was conducted from March 2010 to March 2011. The total number of households in the IHS2 is 11280; 1440 (representing

12.8%) are urban households, and 9840 (representing 87.2%) are rural households. The IHS3 collected information from a sample of 12271 households; 2233 (representing 18.2%) are urban households, and 10038 (representing 81.8%) are rural households.

Both surveys collected information on food consumption at the household level using the last seven days as the recall period. They collected data on 115 and 124 food items for IHS2 and IHS3 respectively. The food items are organized into eleven categories: cereals, grains and cereals products; roots, tubers and plantains; nuts and pulses; vegetables; meat, fish and animal products; fruits; cooked food from vendors; milk and milk products; sugar, fats and oil; beverages; and spices and miscellaneous. The quantity of food consumed by a household comes from three possible sources; purchased, own production, and gifts or donations. Each one of the three components requires the specification of quantity unit codes, ranging from standard units (metric) such as kilograms and litres to non-standard units such as heaps, pails, plates, cups and basins. The non-standard units are first converted into grams by using conversion factors. The conversion factors are compiled by the Malawi National Statistical Office (NSO) after surveying retail markets across Malawi to measure actual weights of common food items typically traded in non-metric units.

All other metric units (e.g. kilograms and litres) are also converted to grams. Only purchased food items have monetary expenditure amounts, and these expenditures are then used to compute unit values (Malawi Kwacha per gram) by dividing expenditure on a food item by its corresponding quantity in grams. Expenditure on a food item is then generated by simply multiplying its unit value by the total quantity consumed[1]. Total food expenditure for each household is just a total of these item-specific expenditures. In the two surveys, a significant majority of the quantity unit codes are non-standard. Precisely, only 22.6% and 33.5% of the unit codes in IHS3 and IHS2 respectively are standard. The dominance of non-standard units means that the quality of conversion factors is critical as it can affect the calculation of unit values for food items consumed by a household, which in turn can affect the computation of total household consumption expenditure i.e. the welfare indicator. Analysis by Verduzco-Gallo et al. (2014) which was complemented by Beck et al. (2015) and Pauw et. al. (2016) uncovered inconsistencies and errors in the official conversion factors which come with the IHS2 and IHS3 datasets, and they consequently developed a new and cleaner set of conversion factors to address these problems[2].

Similar to Pauw et al. (2016) and Beck et al. (2015), this paper uses the revised

[1] To compute the unit values, the procedure used in generating the official aggregate is adopted. Specifically, if a household consumed a food item not purchased in the past seven days, the median unit value from its cluster is used to value that consumption. If no other household consumed the same item in that cluster or if there were not enough observations to obtain a reliable unit value, the median unit value from the immediate upper level (e.g. district) is used to value that consumption.

[2] An example of these inconsistencies in the official conversion factors is the case of sachets of cooking oil in the IHS2 which weigh approximately 50g. The official conversion conversion factor is 456g. Thus, there is an almost ten-fold overestimation of the quantity by official conversion factor (Beck et al. 2015).

set of conversion factors to generate a new annualized consumption aggregate for each household. Both the official and the new consumption aggregates have the same non-food component, but only differ in their food component. Figure 1 presents non-parametric estimates of the density of the two consumption aggregates (in logs) for 2004/5 (the left panel) and 2010/11 (the right panel). The official aggregate is represented by continuous lines and those for the new aggregate by dashed lines. For both years, the distribution of the new consumption aggregate is to the right of the official aggregate. This means that in both years the official aggregate understates household welfare. This in turn explains why Pauw et al. (2016) and Beck et al. (2015) found lower levels of poverty in both years by using the new aggregate as compared to the official aggregate.

The plots also show the elongation of the right tail of the distribution of the new consumption aggregate; implying that the richest individuals are richer than is the case when the official aggregate is used. Table 2 quantifies this right-tail elongation. For both years, the 99th percentile of the new aggregate is about 18% larger than that of the official aggregate. Furthermore, the left tail of the distributions of the new aggregate are also elongated, and this especially more evident when one looks at the 2004/5 aggregate. This means that with the new aggregates, the poorest individuals are poorer than suggested by the official aggregates. The results for this left-tail elongation show that the 1st percentile of the new aggregate for 2004/5 is 3% smaller than that of the official aggregate, however, the right-tail elongation is clearly more pronounced than the left-tail one.

Essentially, the results suggest that the difference between the official and the new aggregate gets progressively larger as one moves from the poorest to the richest households. All this means that the inconsistencies and errors in the conversion factors were not random as they affected the richest households more than the poorest households. This twin-tail elongation has implications for measuring inequality as it suggests that the gap between the haves and the have nots is wider than officially estimated. This paper quantifies these inequality differences.

3 Methods

Given its popularity, official inequality measurement in Malawi uses the Gini coefficient (see for example NSO (2005, 2012)). In order to be consistent with official statistics, and to ensure comparability, I investigate differences in measured inequality between the official consumption aggregate and the new aggregate by using the Gini coefficient. Ignoring sampling weights for ease of exposition, the Gini coefficient, G, is defined as follows (see for example (Duclos and Araar, 2006))

$$G = \frac{2}{\mu} cov(Q(p), p) \tag{1}$$

where, $Q(p)$ is a quantile function, and it gives per capita consumption expenditure of that individual whose rank or percentile in the distribution is $p \in [0,1]$, $\mu = \frac{1}{N}\sum_{i=1}^{N} Q\left(p_i\right)$ is the mean of per capita consumption expenditure, and $cov(.)$ is a covariance. The value of the Gini coefficient ranges between 0 and 1; with 0 implying perfect equality, and 1 denoting perfect inequality.

I test for the statistical significance of two differences in the Gini coefficients. First, for each year, I look at the difference in the Gini coefficients between the official and the new consumption aggregate, $\Delta G = G^{\text{official}} - G^{\text{new}}$. If $\Delta G < 0\,(\Delta G > 0)$ then the official aggregate understates (overstates) inequality in a given year. Second, for each aggregate, I test for the difference in the Gini coefficient between the two periods, 2004/5 and 2010/11, $\Delta G' = G^{\text{official}}_{2004/5} - G^{\text{official}}_{2010/11}$. If $\Delta G' < 0\,(\Delta G' > 0)$ then inequality using the official aggregate has fallen (risen) overtime. For the new aggregate, this difference is computed in a similar manner. Bootstrapped standard errors which account for complex survey design features are used for the statistical tests. I also talk about the economic significance of the differences by simply looking at their magnitude.

The Gini coefficient despite its popularity has a number of weaknesses (Jann, 2016). First, a Gini coefficient does not allow one to obtain a more detailed picture about the changes in the distribution which lead to changes in the Gini coefficient. Second, the Gini coefficient does not capture significant changes in the shape of a distribution even if the Gini coefficient itself remains unchanged. Finally, except for the highest value (1) and the lowest value (0), the interpretation of specific intermediate values is rather difficult. In addition to the Gini coefficient, I use percentile shares which overcome these weaknesses.

Percentile shares are becoming popular for analysing inequalities (Piketty, 2014; Piketty and Saez, 2014). They measure the proportions of total outcome (total consumption in the context of this study) that accrue to different groups defined in terms of their relative ranks in the distribution. Formally, a percentile share (with no sampling weights to avoid notational clutter) is defined as (Jann, 2016)

$$S(p_\ell, p_{\ell-1}) = L(p_\ell) - L(p_{\ell-1}) \tag{2}$$

where $L(p_\ell) = \frac{\sum_{i=1}^{N} y_i I_{y_i \le Q_{p_\ell}}}{\sum_{i=1}^{N} y_i}$ and $L(p_{\ell-1}) = \frac{\sum_{i=1}^{N} y_i I_{y_i \le Q_{p_{\ell-1}}}}{\sum_{i=1}^{N} y_i}$ are ordinates of a Lorenz curve in finite population form, $I_{y_i \le Q_{p_{\ell-1}}}$ is an indicator function equal to 1 if $y_i \le Q_{p_{\ell-1}}$ is true and 0 otherwise. As is the case with the Gini coefficient, I also consider two differences or contrasts. First, I examine differences in measured percentile shares between the official and the new consumption aggregate. Second, for each aggregate, the paper explores the difference in percentile shares between the two periods, 2004/5 and 2010/11.

These distributional contrasts are computed as arithmetic differences. Given percentile share estimates from the official and new consumption aggregate, the estimated vector of arithmetic contrasts is expressed as (Jann, 2016)

$$\hat{\mathbf{s}}^{\text{official}}(\mathbf{p}) - \hat{\mathbf{s}}^{\text{new}}(\mathbf{p}) \tag{3}$$

where for each aggregate $\hat{\mathbf{s}}(\mathbf{p}) = \begin{bmatrix} S_1 & S_2 & \cdots & S_k \end{bmatrix}$ is a $1 \times k$ vector of a disjunctive and exhaustive set of percentile shares across the domain of p using cutoffs $\mathbf{p} = \begin{bmatrix} p_1 & p_2 & \cdots & p_k \end{bmatrix}$ with $p_\ell < p_{\ell-1}$ for all $\ell = 0, ..., k$ and $p_1 = 0$ and $p_k = 1$. Jann (2016) derives the variance matrix for this difference as

$$\sum\nolimits_{\hat{\mathbf{s}}} = \begin{bmatrix} \mathbf{I}_k & -\mathbf{I}_k \end{bmatrix} \widehat{V} \left\{ \begin{bmatrix} \hat{\mathbf{s}}^{\text{official}}(\mathbf{p}) & \hat{\mathbf{s}}^{\text{new}}(\mathbf{p}) \end{bmatrix} \right\} \begin{bmatrix} \mathbf{I}_k & -\mathbf{I}_k \end{bmatrix}' \tag{4}$$

where $\mathbf{I}_k$ is an identity matrix of dimension k.and $\widehat{V}\{\cdots\}$ is the joint variance matrix of the percentile shares across the aggregates. Between-year differences in percentiles shares are computed analogously. I then use the standard errors from $\sum_{\hat{\mathbf{s}}}$ to test for the statistical significance of the differences. These standard errors are adjusted for survey settings. Similar to the Gini coefficients, the sizes of the differences are used to assess their economic significance.

The two scalar inequality measures, the Gini coefficient and percentile shares, are dependent on the imposition of stronger normative criteria. It is quite plausible that the observed inequality differences even when they are statistically significant are primarily driven by these strict assumptions. To make sure that the differences are robust to the normative criteria embodied in these scalar indices of inequality, I use a nonparametric Lorenz dominance test developed by Barrett et al. (2014). Let $L_{\text{official}}(p)$ and $L_{\text{new}}(p)$ denote Lorenz curves of the official and new consumption aggregates respectively. Within each year, the paper tests the following competiting hypotheses

$$\begin{aligned} H_0^1 &: \; L_{\text{official}}(p) \leq L_{\text{new}}(p) \text{ for all } \; p \in [0,1] \\ H_1^1 &: \; L_{\text{official}}(p) > L_{\text{new}}(p) \text{ for some } p \in [0,1] \end{aligned} \tag{5}$$

The null hypothesis is that the Lorenz curve for the new aggregate lies everywhere above that for the official aggregate, and this measures weak Lorenz dominance of L_{new} over L_{official}. Under the null, inequality as measured by using the new aggregate is lower than inequality based on the official aggregate.

Strict Lorenz dominance can also be tested by swapping the roles of L_{new} and L_{official}such that the following hypotheses are tested

$$\begin{aligned} H_0^2 &: \; L_{\text{new}} \leq L_{\text{official}}(p) \text{ for all } \; p \in [0,1] \\ H_1^2 &: \; L_{\text{new}} > L_{\text{official}}(p) \text{for some } p \in [0,1] \end{aligned} \tag{6}$$

This in turn means that H_0^1 and H_1^2 together indicate strict dominance of L_{new} over L_{official}. The Lorenz curves for the two aggregates can coincide and this is represented by H_0^1 and H_0^2. I therefore also test the hypothesis of equality, $H_0^{eq} : L_{\text{official}}(p) = L_{\text{new}}(p)$ for all $p \in [0,1]$. Two test statistics for the null in equations (5) and (6) can be used. One is a Kolmogorov-Smirnov type test statistic based on the largest positive difference between the two Lorenz curves, and the second is a Cramer von Mises test statistic based on the integral of the positive difference between the two Lorenz curves (Barrett et al. 2014).

The two test statistics give similar results (Barrett et al. 2014), and for this reason I use a Kolmogorov-Smirnov type test statistic in this paper. The limiting distributions of the test statistics are both nonstandard and depend on the underlying Lorenz curves. Consequently, the Lorenz dominance test is based on the application of bootstrapping to approximate the asymptotic distribution of the test statistics (Barrett et al. 2014). Asymptotic p-values from the bootstrap are then used to test the different hypotheses. The test statistic for the null of Lorenz curve equality is based on the standard two-sample Kolmogorov-Smirnov test. Between-year Lorenz dominance tests are conducted in a similar manner.

4 Results

4.1 Within-Year Inequality

Tables 3 and 4 report within-year percentile shares and Gini coefficients for 2004/5 and 2010/11 respectively. The inequality measures are estimated for the new and official consumption aggregates. Statistical significance test results for the difference in measured inequality between the two aggregates are also included. In order to capture spatial differences, the results are also disaggregated into rural and urban areas.

Regardless of consumption aggregate used, the results indicate high levels of inequality with the share of the poorest 20% in total consumption markedly lower than of the top 20%. Precisely, and looking at the national level, the contribution of the bottom 20% ranges from about 5% to about 8%, while the contribution of the richest 20% ranges from about 42% to about 58%. Additionally, both aggregates show that the share of the poorest 20% in total consumption is larger in rural areas than in urban areas. For example, in 2010/11, and employing the new aggregate, the bottom 20% contribute 6.0% in rural areas and 4.4% in urban areas. I now turn to the main focus of this paper, and compare and contrast the inequality results for the two consumption aggregates.

Within each year and across rural and urban areas, the Gini coefficient for the official aggregate is lower than that for the new aggregate. This means that the official aggregate understates inequality as measured by the Gini coefficient. At the national level, inequality is underestimated by 4.4 and 2.3 Gini points for 2004/5 and 2010/11 respectively. The disparities are not only sizable but they are also statistically significant. The magnitude of the mismeasurement is larger in 2004/5 than in 2010/11. Furthermore, the extent of the underestimation varies with location with the underestimation in both years larger in rural areas than in urban areas. For instance, in 2004/5, inequality is understated by 6.1 Gini points in rural areas while it is mismeasured by a magnitude of 1.1 Gini points in urban areas.

The results for the Gini coefficient do not show a more detailed picture about differences across the entire distribution of the two aggregates. Percentile shares provide this detailed picture. In both 2004/5 and 2010/11, the official aggregate shows that the contribution of the bottom 20% is larger than that for the new aggregate. For example, at the national level, according to the official aggregate, the bottom 20% contributes 7.0% and 5.6% in 2004/5 and 2010/11 respectively, in contrast, the corresponding contributions for the new aggregate are 6.3% and 5.1% in 2004/5 and 2010/11 respectively. These differences are also observed in both rural and urban areas. The results further reveal that the difference in the 20th percentile between the two aggregates is more pronounced in rural areas than in urban areas. For instance, using the 2004/5 results, the difference in the shares for the poorest 20% between the two aggregates are -0.93 and -0.12 for rural and urban areas respectively. These differences are not only quantitatively large but they are also statistically significant.

The pattern is however reversed as one moves up the percentiles; in this instance, the official aggregate progressively underestimates the share accruing to higher percentiles. This is more evident when one looks at the contributions of the richest 20%. Focusing on the national level, in 2004/5 the contributions of the top 20% are 46.6% and 50.3% for the official and new aggregates respectively. Similarly, for 2010/11, the richest 20% contribute 45.2% when the official aggregate is adopted while it is 47.4% when the new aggregate is employed instead. The observed differences for top the 20% are statistically significant, and moreover they are larger in magnitude (in absolute terms) as compared to the results for the bottom 20%.

Are these observed differences in measured inequality between the two aggregates robust? As noted earlier, the two inequality measures are premised on stronger normative criteria. It may well be that these observed inequality differences are primarily driven by these strict assumptions. As a sensitivity check, I use p-values from the nonparametric Lorenz dominance test results in Table 5. The computation of the p-values for each test pair used 100 bootstrap replications to simulate the distributions of the Kolmogorov-Smirnov type test statistics. Just like before, the results are presented at the national, rural, and urban levels for the years 2004/5 and 2010/11. For each one of the three areas, the first row in the table reports p-values for the test of the null hypothesis that the new aggregate weakly Lorenz dominates the official aggregate against the alternative that the null is false. In the second row, the hypothesis is reversed in that the null hypothesis that the official aggregate weakly Lorenz dominates the new aggregate is tested. The last row tests the null of Lorenz curve equality.

The test results show that at all the three levels for the two years, the null of weak Lorenz dominance of the new aggregate cannot be rejected at the 1% significance level. Furthermore, I fail to reject the null of weak Lorenz dominance of the official aggregate at the 1% significance level. These two results together suggest that the new aggregate strictly Lorenz dominates the official aggregate, and that inequality as measured by using the new aggregate is significantly higher than inequality measured by using the official aggregate. All this therefore means that the finding that the official consumption inequality figures understate the levels of inequality in Malawi is robust to assumptions which underpin the Gini coefficient and percentile shares.

4.2 Between-Year Inequality

The above discussion has looked at a levels question in the sense that the findings unambiguously show that levels of inequality are underestimated when the official aggregate is adopted. The next question that I address in this paper is about trends: Is consumption inequality worsening overtime as the official figures suggest? Does the new aggregate show different inequality trends in Malawi? Table 6 shows differences in measured percentile shares and Gini coefficients between 2004/5 and 2010/11. The results are also spatially disaggregated into rural and urban areas.

As hinted already, the results show that when the errors and inconsistencies in food conversion factors are ignored by using the official aggregate there is a clear pattern of worsening consumption inequality at the national level and for rural areas in Malawi. Nationally, consumption inequality as measured by the Gini coefficient worsened by 6.2 Gini points from 0.39 in 2004/5 to 0.452 in 2010/11, and for rural areas, inequality increased by 3.6 Gini points from 0.339 in 2004/5 to 0.375 in 2010/11. The changes at the national level and for rural areas are both economically large and statistically significant. However, the change in urban inequality of 0.07 Gini points is statistically indistinguishable from zero, and moreover, the change is quantitatively small. Thus, when the official aggregate is used, one comes to the conclusion that urban inequality has remained unchanged between the two periods.

This trend of worsening inequality nationally and for rural areas as measured by the Gini coefficient is however in stark contrast to the trend that one gets after correcting the errors and inconsistencies in food conversion factors by using the new aggregate. The results show that consumption inequality increased by 4.0 Gini points from 0.434 in 2004/5 to 0.474 in 2010/11 at the national level, by 1.3 Gini points from 0.400 in 2004/5 to 0.413 in 2010/11 for rural areas, and by 2.6 Gini points from 0.495 in 2004/5 to 0.521 in 2010/11 for urban areas. Notably, in terms of size, the change in urban inequality of

0.07 Gini points from the official aggregate pales in comparison to the change of 2.6 Gini points from the new aggregate. All these changes despite being fairly large in magnitude, they are all statistically insignificant. This means that when the Gini coefficient is used as an inequality measure, the changes in inequality based on the new aggregate are not different from zero statistically speaking. Critically, using the new aggregate a different and more accurate conclusion about the path of inequality in Malawi is reached: inequality as measured by the Gini coefficient is not worsening overtime.

The results in Table 6 also show the changes across the different percentiles between the two periods, and these provide a much fuller picture of the changes across the entire distribution of each aggregate. The pattern of the changes in terms of whether the contribution of a given percentile is increasing or decreasing depends on the percentile that one is looking at. For both consumption aggregates, the contribution of the bottom 20% to total consumption has declined overtime while the contribution of the richest 20% has increased overtime. For the official aggregate and looking at the national level, the share in total consumption of the bottom 80% has declined between the two years. These changes range from -1.44 percentage points for the first quintile to -0.67 percentage points for the fourth quintile. In contrast, the share of the richest 20% has increased by 4.88 percentage points. These changes are statistically significant. A similar pattern is observed for rural areas, however, for urban areas the changes at all percentiles are statistically insignificant. This is consistent with the earlier finding for the Gini coefficient which showed significant worsening inequality at the national level and for rural areas only.

Although the direction of the changes in the shares of a given percentile are similar to those of the official aggregate at the national level and for rural areas, they are only statistically significant for the bottom 20%. In addition, the magnitudes of the changes for the new aggregate are smaller. At the national level, the decrease in the contribution of the bottom 20% for the official aggregate is 1.44 percentage points while it is 1.19 percentage points for the new aggregate. For urban areas, the changes in the shares across the different percentiles for the two aggregates are similar in that they are both not statistically different from zero.

I also use nonparametric Lorenz dominance test results in Table 7 to investigate sensitivity of the results to the restrictive normative assumptions underlying the Gini coefficient and the percentile shares. The first row in the table reports p-values for the test of the null hypotheses that each aggregate in 2010/11 weakly Lorenz dominates that of 2004/5. The second row tests the null hypotheses where the years for each aggregate have been switched. The last row tests the null that the Lorenz curves between the two years for each aggregate are identical.

The results indicate that at the national level and for rural areas the official aggregate for 2010/11 strictly Lorenz dominates that of 2004/5 at the 1% significance level. Furthermore, I fail to reject the null of Lorenz equality for urban areas at all conventional levels of significance. This suggests that measured inequality based on the official aggregate has worsened between 2010/11 and 2004/5 in rural areas but has remained unchanged in urban areas. Thus, the finding that inequality based on the official aggregate increased between the two years at the national level and for rural areas is robust to assumptions which underpin the Gini coefficient and percentile shares.

A totally different and more correct conclusion is however arrived at when the new aggregate is used. The null hypothesis of equality of the Lorenz curves of the new aggregate between the two years cannot be rejected at all conventional levels of significance. This means that when the quality of food conversion factors is improved by using the new aggregate, one comes the robust conclusion that inequality at the national, rural, and urban levels is not getting worse in Malawi. Thus, although the levels of inequality are understated by the official aggregate, the inequality trend is such that inequality is not getting worse.

5 Concluding Comments

The paper has looked at the impact of errors and inconsistencies in food conversion factors on measured consumption inequality. Malawi has been used as case study with data from the Second and the Third Integrated Household Surveys (IHS2 and IHS3). Two consumption aggregates are used; an official aggregate which is contaminated by errors and inconsistencies in food conversion factors and a new aggregate which cleans out these problems. The paper finds that the inconsistencies and errors in the conversion factors were not random in that they affected the richest households more than the poorest households. Consequently, the official aggregate understates the level of inequality as measured by the Gini coefficient. Inequality is underestimated by 4.4 and 2.3 Gini points for 2004/5 and 2010/11 respectively. The disparities are not only sizable but they are also statistically significant. I also find that the official aggregate progressively underestimates the share accruing to higher percentiles. Nonparametric tests for Lorenz dominance confirm that these differences in measured inequality are robust. Using the new aggregate, the paper also finds that inequality is not worsening overtime as the official aggregate suggests.

The findings can be linked to Malawi's economic growth performance. Official inequality and poverty statistics paint a rather dismal impact of the high growth experienced over the study period: poverty declined only marginally and inequality worsened. With respect to inequality, this paper concludes that although the levels of inequality are higher than official figures suggest, inequality is not worsening. Growth was not ruthless as previously thought. Besides, as shown by Pauw et al. (2016), the high growth also led to larger and not marginal poverty reduction. These findings have implications on the accurate measurement levels of and trends in inequality. The results indicate that the inconsistencies in the quality of the conversion factors are nonrandom as they disfavour the richest households which in turn leads to a misleading picture of the extent of inequality. What all this means is that the Malawi Government's National Statistics Office should be pay serious attention to ensuring that the quality of the conversion factors is improved, which in turn would lead to improved measurement of inequality and poverty in the future. Besides, given that developing countries use consumption as an indicator of welfare, the issue of quality of food conversion factors is critical as it suggests as is the case with Malawi that measured inequality is potentially underestimated in developing countries. This underestimation has nothing to do with fact that survey nonresponse is income-dependent.

References

Barrett, GF, SG. Donald and Bhattacharya D. 2014. Consistent Nonparametric Tests for Lorenz Dominance, *Journal of Business and Economic Statistics,* vol. 32:1-13.

Beck, U., Pauw, K. and Mussa, R. 2015. Methods matter: The sensitivity of Malawian poverty estimates to definitions, data, and assumptions. 2015/126. Helsinki: UNU-WIDER.

Chen, S, and Ravallion, M. 2001. How Did the World's Poorest Fare in the 1990s?, *Review of Income and Wealth,* 47: 283-300.

Chen, S, and Ravallion, M. 2004. How Have the World's Poorest Fared since the Early 1980s?, *World Bank Research Observer,* 19: 141-169.

Chen, S, and Ravallion, M. 2010. The Developing World Is Poorer Than We Thought, but No Less Successful in the Fight against Poverty, *Quarterly Journal of Economics* 125: 1577-1625.

Deaton, A. 2005. Measuring poverty in a growing world (or measuring growth in a poor world), *Review of Economics and Statistics*, 87: 1-19.

Duclos, JY and Araar, A. 2006. Poverty and Equity: Measurement, Policy and Estimation with DAD. Springer, London.

Haughton, JJ and Khandker, SR. 2009. Handbook on Poverty and Inequality, Washington: World Bank Publications.

NSO (National Statistics Office). 2005. Integrated Household Survey 2004-2005. Volume I: Household Socio-economic Characteristics, National Statistics Office, Zomba, Malawi.

NSO (National Statistics Office). 2012. Integrated Household Survey 2004-2005. Household Socio-economic Characteristics Report, National Statistics Office, Zomba, Malawi.

NSO (National Statistics Office). 2015. Statistical Year Book, National Statistics Office, Zomba, Malawi.

Pauw,K, Beck U, and Mussa, R. 2016. Did rapid smallholder-led agricultural growth fail to reduce rural poverty? Making sense of Malawi's poverty puzzle, in: Arndt C, McKay A, and F. Tarp (eds), Growth and Poverty in Sub-Saharan Africa, Oxford University Press: Oxford; p. 89-111.

Piketty, T. 2014. Capital in the Twenty-First Century. Cambridge, MA: The Belknap Press.

Piketty, T., and Saez E. 2014. Inequality in the long run. *Science,* 344: 838-843.

Pinkovskiy, ML, and Sala-i-Martin, X. 2009. Parametric Estimations of the World Distribution of Income.NBER Working Paper No.15433.

Pinkovskiy, ML, and Sala-i-Martin, X. 2014. Africa is on Time. *Journal of Economic Growth* 19:311-338.

Pinkovskiy, ML, and Sala-i-Martin, X. 2016. Lights, Camera,....Income! Illuminating the National Accounts-Household Surveys Debate, *The Quarterly Journal of Economics*, doi: 10.1093/qje/qjw003

Sala-i-Martin, X. 2002. The Disturbing 'Rise'of Global Income Inequality, NBER Working Paper No. 8904.

Sala-i-Martin, X. 2006. The World Distribution of Income: Falling Poverty and ...Convergence, Period. *Quarterly Journal of Economics,* 121: 351-397.

Verduzco-Gallo, I, Ecker, E. Pauw, K. 2014. Changes in Food and Nutrition Security in Malawi: Analysis of Recent Survey Evidence. International Food Policy Research Institute, MASSP Working Paper No. 6.

Jann, B. 2016. Assessing inequality using percentile shares, *The Stata Journal,*16: 264-300.

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

Indicator/Area	2005	2011
GDP growth	6.2[a]	6.1[b]
Poverty headcount		
National	52.41	50.64
Rural	55.86	56.62
Urban	25.4	17.28
Gini Coefficient		
National	0.39	0.45
Rural	0.34	0.38
Urban	0.48	0.49

[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)

Figure 1: Kernel density plots of the two consumption aggregates by survey year

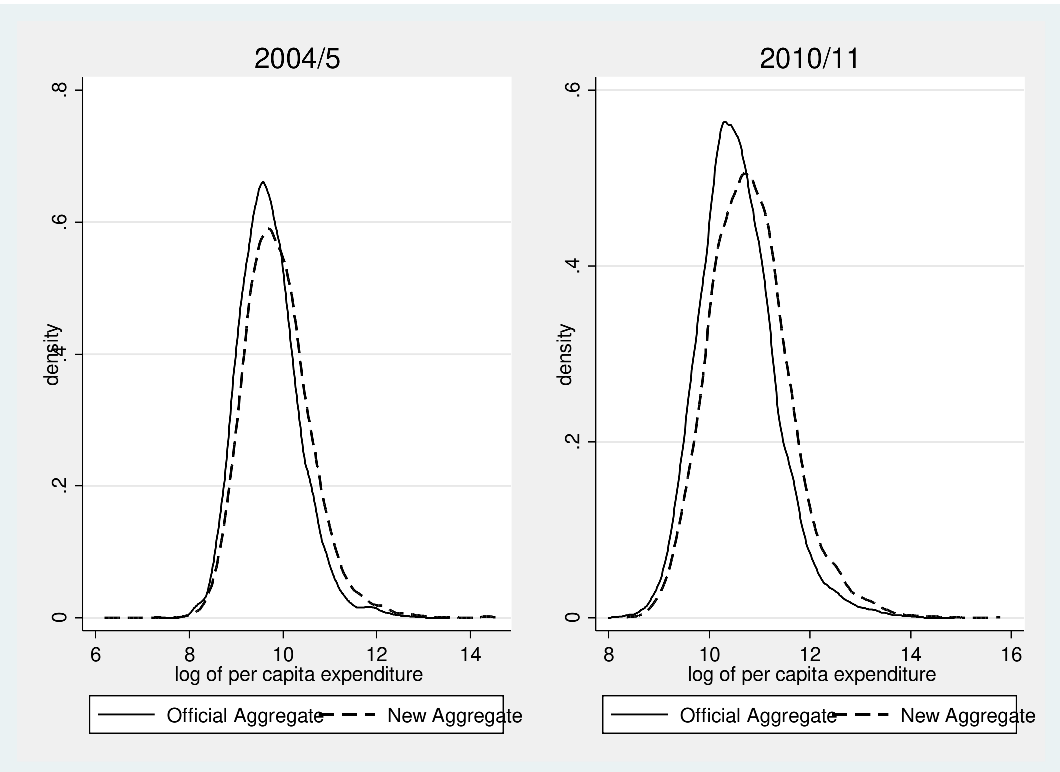

Table 2: Percentile differences between official and new consumption aggregate

Percentiles	1%	5%	50%	95%	99%
2010/11					
Official Aggregate	9002.96	13591.66	41582.57	174874.86	424445.16
New Aggregate	9437.97	14361.14	47055.75	201620.44	500225.28
% Difference	4.83	5.66	13.16	15.29	17.85
2004/5					
Official Aggregate	5109.88	7006.50	17934.94	61517.50	143998.73
New Aggregate	4950.42	6985.89	18487.63	68023.33	171124.50
% Difference	-3.12	-0.29	3.08	10.58	18.84

Table 3: Within-year percentile share and Gini coefficient differences, 2004/5

Percentile	National			Rural			Urban		
	Official	New	Difference	Official	New	Difference	Official	New	Difference
0-20	6.997	6.311	-0.686***	7.795	6.865	-0.930***	5.111	4.993	-0.118**
	(0.084)	(0.132)	(0.114)	(0.075)	(0.164)	(0.154)	(0.206)	(0.204)	(0.044)
20-40	10.849	9.901	-0.948***	11.930	10.647	-1.283***	8.498	8.252	-0.247***
	(0.112)	(0.197)	(0.175)	(0.090)	(0.244)	(0.235)	(0.287)	(0.290)	(0.062)
40-60	14.815	13.735	-1.080***	16.093	14.593	-1.499***	12.240	11.789	-0.451***
	(0.138)	(0.265)	(0.241)	(0.099)	(0.328)	(0.320)	(0.362)	(0.362)	(0.080)
60-80	20.742	19.712	-1.030**	22.141	20.641	-1.500***	18.913	18.651	-0.261*
	(0.174)	(0.368)	(0.343)	(0.117)	(0.454)	(0.449)	(0.465)	(0.482)	(0.118)
80-100	46.597	50.341	3.744***	42.042	47.254	5.212***	55.237	56.314	1.077***
	(0.449)	(0.933)	(0.857)	(0.285)	(1.163)	(1.142)	(1.130)	(1.148)	(0.216)
Gini Coefficient	0.390	0.434	0.044***	0.339	0.400	0.061***	0.484	0.495	0.011***
	(0.014)	(0.022)	(0.018)	(0.005)	(0.024)	(0.024)	(0.028)	(0.029)	(0.003)
Observations	11280	11280	11280	9840	9840	9840	1440	1440	1440

Notes: Official and New denote the official consumption and new consumption aggregates respectively. Standard errors in parentheses. *** indicates significant at 1%; ** at 5%; and, * at 10%.

Table 4: Within-year percentile share and Gini coefficient differences, 2010/11

Percentile	National			Rural			Urban		
	Official	New	Difference	Official	New	Difference	Official	New	Difference
0-20	5.557	5.118	-0.439***	6.700	5.989	-0.711***	4.752	4.425	-0.327
	(0.088)	(0.131)	(0.111)	(0.087)	(0.105)	(0.080)	(0.200)	(0.323)	(0.272)
20-40	9.404	8.877	-0.527**	11.077	10.148	-0.930***	8.273	7.777	-0.495
	(0.127)	(0.215)	(0.190)	(0.112)	(0.155)	(0.130)	(0.289)	(0.542)	(0.466)
40-60	13.488	13.125	-0.363	15.478	14.710	-0.768***	12.424	11.670	-0.754
	(0.169)	(0.308)	(0.276)	(0.134)	(0.210)	(0.184)	(0.368)	(0.769)	(0.701)
60-80	20.073	19.708	-0.365	22.221	21.601	-0.620*	19.465	18.222	-1.243
	(0.225)	(0.446)	(0.409)	(0.168)	(0.285)	(0.259)	(0.492)	(1.160)	(1.081)
80-100	51.478	53.172	1.695	44.524	47.553	3.029***	55.087	57.906	2.819
	(0.546)	(1.066)	(0.973)	(0.398)	(0.690)	(0.623)	(1.122)	(2.699)	(2.510)
Gini Coefficient	0.452	0.474	0.023**	0.375	0.413	0.038***	0.491	0.521	0.030
	(0.014)	(0.017)	(0.013)	(0.007)	(0.016)	(0.015)	(0.028)	(0.036)	(0.028)
Observations	12271	12271	12271	10038	10038	10038	2233	2233	2233

Notes: Official and New denote the official consumption and new consumption aggregates respectively. Standard errors in parentheses. *** indicates significant at 1%; ** at 5%; and, * at 10%.

Table 5: P-values for within-year Lorenz dominance tests

Test Pair	2004/5 National	2004/5 Rural	2004/5 Urban	2010/11 National	2010/11 Rural	2010/11 Urban
$L_{new} \geq L_{official}$	1.000	1.000	1.000	1.000	1.000	1.000
$L_{official} \geq L_{new}$	0.000	0.000	0.000	0.012	0.012	0.012
$L_{official} = L_{new}$	0.000	0.000	0.000	0.000	0.000	0.000

Notes: $L_{new} \geq L_{official}$ ($L_{official} \geq L_{new}$) denotes the null that the new consumption aggregate (the official consumption aggregate) Lorenz dominates the official consumption aggregate (the new consumption aggregate). $L_{official} = L_{new}$ denotes that the Lorenz curves are identical i.e. no Lorenz dominance.

Table 6: Between-year differences in percentile shares and Gini coefficients

Percentile	National Official	National New	Rural Official	Rural New	Urban Official	Urban New
0-20	-1.440***	-1.193***	-1.095***	-0.876***	-0.360	-0.569
	(0.122)	(0.186)	(0.115)	(0.195)	(0.287)	(0.382)
20-40	-1.445***	-1.024	-0.852***	-0.499	-0.226	-0.474
	(0.170)	(0.912)	(0.144)	(0.289)	(0.407)	(0.614)
40-60	-1.327***	-0.610	-0.615***	0.116	0.183	-0.120
	(0.218)	(0.406)	(0.167)	(0.390)	(0.516)	(0.850)
60-80	-0.668*	-0.004	0.080	0.960	0.552	-0.429
	(0.284)	(0.578)	(0.205)	(0.536)	(0.677)	(1.256)
80-100	4.880***	2.831	2.482***	0.299	-0.150	1.592
	(0.707)	(2.417)	(0.490)	(1.352)	(1.592)	(2.933)
Gini Coefficient	0.062***	0.040	0.036***	0.013	0.007	0.026
	(0.020)	(0.028)	(0.008)	(0.029)	(0.040)	(0.046)
Observations	23551	23551	19878	19878	3673	3673

Notes: Official and New denote the official consumption and new consumption aggregates respectively. Differences are between percentile shares and Gini coefficients for 2010/11 and 2004/5 for each consumption aggregate. Standard errors in parentheses. *** indicates significant at 1%; ** at 5%; and, * at 10%.

Table 7: Between-year differences in percentile shares and Gini coefficients

Test Pair	National Official	National New	Rural Official	Rural New	Urban Official	Urban New
$L_{2010/11} \geq L_{2004/5}$	0.900	0.300	0.900	0.300	0.900	0.300
$L_{2004/5} \geq L_{2010/11}$	0.000	0.122	0.000	0.130	0.810	0.122
$L_{2004/5} = L_{2010/11}$	0.000	0.200	0.000	0.200	0.288	0.200

Notes: $L_{2010/11} \geq L_{2004/5}$ ($L_{2004/5} \geq L_{2010/11}$) denotes the null that a consumption aggregate for year 2010/11 (2004/5) Lorenz dominates that for year 2004/5 (2010/11). $L_{2004/5} = L_{2010/11}$ denotes that the Lorenz curves are identical i.e. no Lorenz dominance.