Polarization amidst poverty reduction: A case study of Nigeria and Ghana*

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Abstract

Despite sustained real growth over recent decades, reduction in official poverty rates in Nigeria and Ghana has not been up to general expectations. The lack of a faster reduction in poverty despite a significant growth in GDP may be due to an increase in inequality. The latter is, however, just one aspect of the problem. A complementary hypothesis is that both Nigeria and Ghana are also experiencing increasing polarization.

This paper uses newly available data and the relative distribution methodology (Handcock and Morris, 1998, 1999) to present new results on polarization in Nigeria and Ghana. The findings confirm the hypothesis that both the countries are going through a process of economic polarization. Compared to 2003, the distribution of consumption in Nigeria has become more concentrated in upper and lower deciles in 2013, while the middle deciles have thinned. A between-group analysis shows the emergence of a macro-regional gap: while the South-South and South-West regions contribute mainly to polarization in the upper tail, households in the North East and North West zones—the conflict-stricken areas—are more likely to fall in the lower national deciles. Likewise, the distributional changes occurred over the last 20 years hollowed out the middle of the Ghanaian household consumption distribution and increased the concentration of households around the highest and lowest deciles. When looking at the drivers of polarization, household characteristics, educational attainment and access to basic infrastructures all tended to increase over time the size of the upper and lower tails of the consumption distribution, and as a consequence the degree of polarization.

JEL classification: C14; D31; D63

Keywords: Nigeria; Ghana; consumption expenditure; poverty and inequality; polarization; relative distribution; decomposition analysis

1 Introduction

Nigeria and Ghana have been before 2015 among the fastest growing economies in Sub-Saharan Africa (SSA), with per capita growth rates averaging 5–6%. In the last decade they also managed to reduce poverty substantially. In Nigeria, the poverty rate in per capita terms declined by 10 percentage points, from 46% in 2004 to 36.1% in 2013. In Ghana, poverty declined from 28% in 2005 to 21% in 2013.

In both countries, however, in the last decade poverty reduction was not commensurate with the fast GDP growth. Compared with the rest of SSA and other low-middle-income (LMI) countries, poverty reduction in Nigeria and Ghana has been less responsive to economic growth. Growth to poverty elasticity (GEP) estimates indicate that for every 1% growth in GDP per capita, poverty declined by only 0.6% in Nigeria and 0.7% in Ghana. Both countries' growth elasticity to poverty is half of that of the SSA average and only one fourth of that of LMI countries. The GEP was also lower than that of a number of African countries, such as Rwanda and Ethiopia, which enjoyed high growth rates in the last decade.

Three factors determined this low responsiveness in the last decade. First, high growth rates have been accompanied by comparatively high rates of population growth. Population, in particular in Nigeria, has been growing at an average rate of 2.7% per year and fertility rates remain particularly high. Second, like other resource-rich economies in the developing world, Nigeria and Ghana shows a low labour absorptive capacity. Third, inequality has been growing and has adversely affected poverty reduction; in Nigeria only half of the consumption per capita growth translated into poverty reduction, and in Ghana only 70%.

Despite the different sizes, the similarities between the two countries do not end here. Both, during the period of fast growth and poverty reduction, experienced a rapid increase in welfare *polarization* driven—in particular in Nigeria—by the increasing divide between Northern and Southern parts of the countries (Aigbokhan, 2000; Araar, 2008; Awoyemi and Araar, 2009; Awoyemi et al., 2010; Ogunyemi and Oni, 2011; Ogunyemi et al., 2011; Ogunyemi, 2013; Clementi et al., 2014, 2015; Molini and Paci, 2015; Clementi et al., 2016; World Bank, 2016). Polarization is the combination of the divergence from the global mean income and the convergence toward local mean incomes; it differs from inequality because the latter is the overall dispersion of the distribution, that is, the distance of every individual from the median or mean income. In income-polarized societies, people are clustered around the group means and tend to be remote from the mean or median of the overall distribution. Within each group, there is income homogeneity and often narrowing income inequality. Thus, we may talk of increasing "identification". Between the two groups, we talk, rather, about increasing "alienation" (Duclos et al., 2004). The overall impact of the forces of identification and of alienation between two groups of significant size leads to effective opposition, a situation that may give rise to social tensions and conflict (Esteban and Ray, 1999, 2008, 2011). Also, the group at the top of the distribution possesses voice, while the other group, which is made up of those at the bottom, are voiceless in matters that affect their welfare and society at large.

The present study adds to the existing literature on inequality, polarization and poverty in Nigeria and Ghana on a number of fronts. First, it uses a very intuitive yet little explored method, the "relative distribution" introduced by (Handcock and Morris, 1998, 1999), to analyze the recent distributional changes occurred in the Nigeria and Ghana. The strength of this method consists in providing a non-parametric framework for taking into account all the distributional differences that could arise in the comparison of distributions over time and space. In this way, it enables to summarize multiple features of the expenditure distribution that would not be detected easily from a comparison of standard measures of inequality and polarization. Second, another goal of this paper is to document not just national, but also sub-national patterns of polarization. Nigeria and Ghana are highly heterogeneous, so that drivers of polarization can indeed differ across macro regions. Finally, the paper develops within the relative distribution framework a novel methodology to identify the drivers of distributional changes and quantify their impact on the welfare distribution—the main value added being it enables a very granular analysis of the distributional changes that an analysis based on standard inequality decompositions would not allow.

The paper is organized as follows. Section 2 reviews the approaches to measuring economic polarization. Section 3 outlines the distinctive features of the relative distribution methodology and presents the new decomposition method used to identify the drivers of polarization. Section 4 discusses the data. Section 5 details the main findings of the study. Section 6 concludes.

2 Some background on the income polarization literature

Over the last two decades, the issue of polarization has come to be assigned increasing importance in the analysis of income distribution. Notwithstanding the pains the polarization literature has suffered to distinguish itself from pure inequality measurement—see e.g. Foster and Wolfson (1992), Levy and Murnane (1992), Esteban and Ray (1994) and Wolfson (1994, 1997)—it now seems to be fairly widely accepted that polarization is a distinct concept from inequality.

Broadly speaking, the notion of polarization is concerned with the disappearance of the middle class, which occurs when there is a tendency to concentrate in the tails—rather than the middle—of the income distribution. One of the main reasons for looking at income polarization this way, which is usually referred to as "bi-polarization", is that a well-off middle class is important to every society because it contributes significantly to economic growth, as well as to social and political stability (e.g. Easterly, 2001, Pressman, 2007, and Birdsall, 2010). In contrast, a society with high degree of income polarization may give rise to social conflicts and tensions. Therefore, in order for such risks to be minimized, it is necessary to monitor the economic evolution of the society using indices that look at the dispersion of the income distribution from the middle toward either or both of the two tails. Measures of income polarization that correspond to this case have been proposed in the literature by Foster and Wolfson (1992), Wolfson (1994, 1997), Wang and Tsui (2000), Chakravarty and Majumder (2001), Rodríguez and Salas (2003), Chakravarty et al. (2007), Silber et al. (2007), Chakravarty (2009), Chakravarty and D'Ambrosio (2010), Lasso de la Vega et al. (2010), and others.

A more general notion of income polarization, which was originally proposed by Esteban and Ray (1994), regards the latter as "clustering" of a population around two or more poles of the distribution, irrespective of where they are located along the income scale. The notion of income polarization in a multi-group context is an attempt at capturing the degree of potential conflict inherent in a given distribution (see Esteban and Ray, 1999, 2008, 2011). The idea is to consider society as an amalgamation of groups, where the individuals in a group share similar attributes with the other members (i.e. have a mutual sense of "identification") but in terms of the same attributes they are different from the members of the other groups (i.e. have a feeling of "alienation"). Political or social conflict is therefore more likely the more homogeneous and separate the groups are, that is when the within-group income distribution is more clustered around its local mean and the between-group income distance is longer. In addition to Esteban and Ray (1994), indices regarding the concept of income polarization as conflict among groups have been investigated, among others, by Gradín (2000), Milanovic (2000), D'Ambrosio (2001), Zhang and Kanbur (2001), Reynal-Querol (2002), Duclos et al. (2004), Lasso de la Vega and Urrutia (2006), Esteban et al. (2007), Gigliarano and Mosler (2009) and Poggi and Silber (2010).

Much of the literature so far considered has analyzed summary measures of income polarization. Another strand uses kernel density estimation and mixture models in order to describe changes in polarization patterns over time, not just of personal incomes (as in Jenkins, 1995, 1996, Pittau and Zelli, 2001, 2004, 2006, and Conti et al., 2006) but also of the cross-country distribution of per capita income (see Quah, 1996a,b, 1997, Bianchi, 1997, Jones, 1997, Paap and van Dijk, 1998, Johnson, 2000, Holzmann et al., 2007, Henderson et al., 2008, Pittau et al., 2010, Anderson et al., 2012, and others). The analysis of the shape of the income distribution provides indeed a picture from which at least three important distributional features can be observed simultaneously (Cowell et al., 1996): income levels and changes in the location of the distribution as a whole; income inequality and changes in the spread of the distribution; clumping and polarization as well as changes in patterns of clustering at different modes. Finally, a rather recent (yet non-parametric) approach that combines the strengths of summary polarization indices with the details of distributional change offered by the kernel density estimates—the so-called "relative distribution"—has been employed by Alderson et al. (2005), Massari (2009), Massari et al. (2009a,b), Alderson and Doran (2011, 2013), Borraz et al. (2013), Clementi and Schettino (2013, 2015), Clementi et al. (2014, 2015, 2016), Molini and Paci (2015), Petrarca and Ricciuti (2015) and Nissanov and Pittau (2016) to assess the evolution of the middle class and the degree of household income polarization in a number of middle- and high-income countries in the world.

3 Relative distribution methods

3.1 The relative distribution: basic concepts

In the current application, the relative distribution approach has some important advantages over the other mentioned methods of investigating income polarization. First, it readily lends itself to simple and informative graphical displays of relative data that reveal precisely where and by how much an income distribution changed over time. Second, by providing the potential for decomposition into location and shape components, it allows one to examine several hypotheses regarding the origins of distributional change—such as whether the change consists of an equal absolute subtraction or addition to all incomes that moves the overall distribution either to the left or to the right (while leaving the shape unaltered) or of shape modifications which, by definition, are independent of location shifts.[1] Lastly, it allows us to quantify the degree of polarization due to changes in distributional shape only (i.e. net of location shifts), thus enabling one to isolate aspects of inter-distributional inequality that are often hidden when also changes in location are examined.

Basically, the relative distribution method can be applied whenever the distribution of some quantity across two populations is to be compared, either cross-sectionally or over time.[2] To proceed, it is necessary to single out one of the two populations, refer to it as the "comparison" population, and refer to the other as the "reference" population. More formally, let Y_0 be the income variable for the reference population and Y the income variable for the comparison population. The relative distribution of Y to Y_0 is defined as the distribution of the random variable:

$$R = F_0\left(Y\right), \tag{1}$$

which is obtained from Y by transforming it by the cumulative distribution function of Y_0, F_0. As a random variable, R is continuous on the outcome space $[0, 1]$, and its realizations, r, are referred to as "relative data". Intuitively, the relative data can be interpreted as the set of positions that the income observations of the comparison population would have if they were located in the income distribution of the reference population. The probability density function of R, which is called the "relative density", can be obtained as the ratio of the density of the comparison population to the density of the reference population evaluated at the relative data r:

$$g\left(r\right) = \frac{f\left(F_0^{-1}\left(r\right)\right)}{f_0\left(F_0^{-1}\left(r\right)\right)} = \frac{f\left(y_r\right)}{f_0\left(y_r\right)}, \quad 0 \leq r \leq 1, \quad y_r \geq 0, \tag{2}$$

where $f\left(\cdot\right)$ and $f_0\left(\cdot\right)$ denote the density functions of Y and Y_0, respectively, and $y_r = F_0^{-1}\left(r\right)$ is the quantile function of Y_0. The relative density has a simple interpretation, as it describes where households at various quantiles in the comparison distribution are concentrated in terms of the quantiles of the reference distribution. As for any density function, it integrates to 1 over the unit interval, and the area under the curve between two values r_1 and r_2 is the proportion of the comparison population whose income values lie between the ${r_1}^{\text{th}}$ and ${r_2}^{\text{th}}$ quantiles of the reference population.

When the relative density function shows values near to 1, it means that the two populations have a similar density at the r^{th} quantile of the reference population, and thus R has a uniform distribution in the interval $[0, 1]$. A relative density greater than 1 means that the comparison population has more density than the reference population at the r^{th} quantile of the latter. Finally, a relative density function less than 1 indicates the opposite. In this way one can distinguish between growth, stability or decline at specific points of the income distribution.

[1] Of course, both the location and shape effects—named respectively as "growth" and "inequality" (or "distributional") effect (Kakwani, 1993; Bourguignon, 2003, 2004)—may also concur together in producing the distributional change.

[2] Here we limit ourselves to illustrating the basic concepts behind the use of the relative distribution method. Interested readers are referred to Handcock and Morris (1998, 1999; but see also Hao and Naiman, 2010, ch. 5) for a more detailed explication and a discussion of the relationship to alternative econometric methods for measuring distributional differences. A method very similar in spirit to the relative distribution has recently been developed by Silber et al. (2014).

3.2 The location/shape decomposition of the relative distribution

As we have said before, one of the major advantages of this method is the possibility to decompose the relative distribution into changes in location, usually associated with changes in the median (or mean) of the income distribution, and changes in shape (including differences in variance, asymmetry and/or other distributional characteristics) that could be linked with several factors like, for instance, polarization. Formally, the decomposition can be written as:

$$g\left(r\right)=\underbrace{\frac{f\left(y_r\right)}{f_0\left(y_r\right)}}_{\substack{\text{Overall relative}\\ \text{density}}}=\underbrace{\frac{f_{0L}\left(y_r\right)}{f_0\left(y_r\right)}}_{\substack{\text{Density ratio for}\\ \text{the location effect}}}\times\underbrace{\frac{f\left(y_r\right)}{f_{0L}\left(y_r\right)}}_{\substack{\text{Density ratio for}\\ \text{the shape effect}}}, \tag{3}$$

where $f_{0L}\left(y_r\right)=f_0\left(y_r+\rho\right)$ is a density function adjusted by an additive shift with the same shape as the reference distribution but with the median of the comparison one.[3] The value ρ is the difference between the medians of the comparison and reference distributions. If the latter two distributions have the same median, the density ratio for location differences is uniform in $[0,1]$. Conversely, if the two distributions have different median, the "location effect" is increasing (decreasing) in r if the comparison median is higher (lower) than the reference one. The second term, which is the "shape effect", represents the relative density net of the location effect and is useful to isolate movements (re-distribution) occurring between the reference and comparison populations. For instance, we could observe a shape effect function with some sort of (inverse) U-shaped pattern if the comparison distribution is relatively (less) more spread around the median than the location-adjusted one. Thus, it is possible to determine whether there is polarization of the income distribution (increases in both tails), "downgrading" (increases in the lower tail), "upgrading" (increases in the upper tail) or convergence of incomes towards the median (decreases in both tails).

3.3 Relative polarization indices

The relative distribution approach also includes a *median relative polarization* index (MRP), which is based on changes in the shape of the income distribution to account for polarization. This index is normalized so that it varies between -1 and 1, with 0 representing no change in the income distribution relative to the reference year. Positive values represent more polarization—i.e. increases in the tails of the distribution—and negative values represent less polarization—i.e. convergence towards the center of the distribution. The MRP index for the comparison population can be estimated as (Morris et al., 1994, p. 217):

$$\mathrm{MRP}=\frac{4}{n}\left(\sum_{i=1}^{n}\left|r_i-\frac{1}{2}\right|\right)-1, \tag{4}$$

[3] Median adjustment is preferred here to mean adjustment because of the well-known drawbacks of the mean when distributions are skewed. A *multiplicative* median shift can also be applied. However, the multiplicative shift has the drawback of affecting the shape of the distribution. Indeed, the equi-proportionate income changes increase the variance and the rightward shift of the distribution is accompanied by a flattening (or shrinking) of its shape (see e.g. Jenkins and Van Kerm, 2005).

where r_i is the proportion of the median-adjusted reference incomes that are less than the i^{th} income from the comparison sample, for $i = 1, \ldots, n$, and n is the sample size of the comparison population.

The MRP index can be additively decomposed into the contributions to overall polarization made by the lower and upper halves of the median-adjusted relative distribution, enabling one to distinguish downgrading from upgrading. In terms of data, the *lower relative polarization* index (LRP) and the *upper relative polarization* index (URP) can be calculated as follows:

$$\text{LRP} = \frac{8}{n}\left[\sum_{i=1}^{n/2}\left(\frac{1}{2} - r_i\right)\right] - 1, \tag{5}$$

$$\text{URP} = \frac{8}{n}\left[\sum_{i=n/2+1}^{n}\left(r_i - \frac{1}{2}\right)\right] - 1, \tag{6}$$

with $\text{MRP} = \frac{1}{2}(\text{LRP} + \text{URP})$. As the MRP, LRP and URP range from -1 to 1, and equal 0 when there is no change.

3.4 Adjustment for covariates

Similarly to what is observed for location and shape decomposition, it is possible to adjust the relative distribution for changes in the distribution of covariates measured on the households, which often vary systematically by population. The covariate adjustment technique can be used to separate the impacts of changes in population composition from changes in the covariate-response relationship.[4] This decomposition according to covariates draws on the definition of a counter-factual distribution for the response variable in the reference population that is *composition-adjusted* to have the same distribution of the covariates as the comparison population.

Assume for simplicity that the covariate Z is categorical.[5] Let $\{\pi_k^0\}_{k=1}^K$ and $\{\pi_k\}_{k=1}^K$, where K is the number of categories of the covariate, denote the probability mass functions of Z for the reference and comparison populations, *i.e.* their composition according to the covariate. For conditional comparisons of the response variable Y across the two populations one can consider the density of Y_0 given that $Z_0 = k$:

$$f_{Y_0|Z_0}(y|k), \quad k = 1, \ldots, K, \tag{7}$$

and the density of Y given that $Z = k$:

$$f_{Y|Z}(y|k), \quad k = 1, \ldots, K. \tag{8}$$

[4]Recently, there have been several papers that have studied decomposition methods to explain changes in the unconditional distribution of an outcome variable due to either changes in the distribution of the covariates, or changes in the conditional distribution of the outcome given covariates, or both—see for instance the extensive survey by Fortin et al. (2011) on the wage decomposition literature. Benefits and drawbacks of some of these methods, and how they are often largely subsumed by the relative distribution framework, are reviewed in Handcock and Morris (1999, ch. 2).

[5]The extensions to continuous and multivariate covariates are considered in Handcock and Morris (1999, ch. 7).

These densities represent the covariate-response relationship. The marginal densities of Y_0 and Y can be written, respectively, as:

$$f_0(y) = \sum_{k=1}^{K} \pi_k^0 f_{Y_0|Z_0}(y|k) \qquad \text{and} \qquad f(y) = \sum_{k=1}^{K} \pi_k f_{Y|Z}(y|k). \tag{9}$$

Then, the counter-factual distribution with the covariate composition of the comparison population and the covariate-response relationship of the reference population is:

$$f_{0C}(y) = \sum_{k=1}^{K} \pi_k f_{Y_0|Z_0}(y|k), \tag{10}$$

and can be used to decompose the overall relative distribution into a component that represents the effect of changes in the marginal distribution of the covariate (the "composition effect") and a component that represents the changes in the covariate-response relationship (the "residual effect"). The decomposition can be represented in the following terms:

$$g(r) = \underbrace{\frac{f(y_r)}{f_0(y_r)}}_{\substack{\text{Overall relative}\\ \text{density}}} = \underbrace{\frac{f_{0C}(y_r)}{f_0(y_r)}}_{\substack{\text{Density ratio for}\\ \text{the composition effect}}} \times \underbrace{\frac{f(y_r)}{f_{0C}(y_r)}}_{\substack{\text{Density ratio for}\\ \text{the residual effect}}}. \tag{11}$$

Comparison of $f(y_r)$ to $f_{0C}(y_r)$—*i.e.* the residual effect—holds the population composition constant, and therefore isolate changes of income distribution due to the fact that returns to the selected covariate changed over time. By contrast, $f_{0C}(y_r)$ and $f_0(y_r)$ have the same covariate-response relationship, and the comparison between them—*i.e.* the composition effect—isolate the changes due to the different composition of the population under the assumption that the conditional distribution of income remain unchanged.

3.5 Blinder-Oaxaca type decomposition of location and shape differences

In this section we present a novel method for analyzing the effects of covariates on the observed distributional changes due to both the location and shape shifts. Novel because in the original relative distribution framework, the method proposed to measure the impact of polarization drivers does not provide intuitive results and it is of limited use for policy making purposes. By contrast, our method that combines the relative distribution approach and the regression based decompositions, can produce an easily interpretable set of results.

In the relative distribution setting, the exploration of the distributional impacts of changes in covariates requires that the overall relative density is adjusted for these changes using the technique described in the previous section. This technique partials out the impact of changes in the distribution of the covariates—the "composition effect"—and the modifications in the conditional distributions of household consumption expenditure given the covariate levels—the "residual effect". Conceptually, this parallels the traditional regression-based decomposition that separates changes in covariates (the X's) from changes in the "returns" to the covariates (the regression coefficients, or β's). However, the covariate adjustment technique proposed by Handcock and Morris does not provide a simple and intuitively accessible way of dividing up the changes exclusively due to a location shift or shape differences into the contribution of changes in the distribution of each single covariate and that of the changing "returns" to the covariates; also, differently from what happens in the classical regression decomposition approach, its drawback is making it difficult to summarize the contributions above into a single value as, for example, the estimated coefficients obtained by the regression procedure would make it possible to quantify.

The framework we propose integrates the spirit of the relative distribution approach and recent developments from the regression-based decomposition literature. This can be regarded as an extension of the covariate adjustment technique developed by Handcock and Morris and can be used to quantify the impact of an arbitrary number of covariates on distributional differences due to both location and shape shifts, so as to identify the key drivers of these changes.

In detail, we decompose the component relative distributions that represent differences in location and shape by applying a procedure recently proposed by Firpo et al. (2009) for the decomposition of wage differentials. The method is based on running unconditional quantile regressions to estimate the impact of changing the distribution of explanatory variables along the entire distribution of the dependent variable and using the traditional Blinder (1973) and Oaxaca (1973) decomposition framework to decompose differentials at selected quantiles of the consumption distribution.

To estimate the unconditional quantile regression, we have first to derive the *re-centered influence function* (RIF) for the τ^{th} quantile of the dependent variable distribution—consumption, in our case—which can be shown as (Firpo et al., 2009; Essama-Nssah and Lambert, 2012; Fortin et al., 2011):

$$\text{RIF}\left(c; q_\tau, F_C\right) = \begin{cases} q_\tau + \frac{\tau}{f_C(q_\tau)}, & c > q_\tau, \\ q_\tau - \frac{1-\tau}{f_C(q_\tau)}, & c < q_\tau, \end{cases} \tag{12}$$

where q_τ is the sample quantile and $f_C\left(q_\tau\right)$ is the density of consumption C at the τ^{th} quantile. In practice, the RIF is estimated by replacing all unknown quantities by their observable counterparts. In the case of (12) unknown quantities are q_τ and $f_C\left(q_\tau\right)$, which are estimated by the sample τ^{th} quantile of C and a standard non-parametric kernel density estimator, respectively. Firpo et al. (2009) show that the unconditional quantile regression can be implemented by running a standard OLS regression of the estimated RIF on the covariates X:[6]

$$\mathbb{E}\left[\text{RIF}\left(C; q_\tau, F_C\right) \middle| X = x\right] = X\beta_\tau, \tag{13}$$

where the coefficient β_τ represents the approximate marginal effect of the explanatory variable X on the τ^{th} unconditional quantile of the household consumption distribution. Applying the law of iterated expectations to the above equation, we also have:

$$q_\tau = \mathbb{E}_X\left[\mathbb{E}\left[\text{RIF}\left(C; q_\tau, F_C\right) \middle| X = x\right]\right] = \mathbb{E}\left[X\right]\beta_\tau. \tag{14}$$

This yields an *unconditional quantile interpretation*, where β_τ can be interpreted as the effect of increasing the mean value of X on the unconditional quantile q_τ.[7]

[6] This can be performed using the Stata's command `rifreg`, which is available for download at `http://faculty.arts.ubc.ca/nfortin/datahead.html`.

[7] As discussed in more detail by Fortin et al. (2011), one important reason for the popularity of OLS regressions in

Using unconditional quantile (RIF) regression, an aggregate decomposition for location and shape differences can then be implemented in a spirit similar to the Blinder-Oaxaca decomposition of mean differentials as follows:

$$\hat{\Delta}_{\tau}^{t} = \hat{c}_{\tau}^{t} - \hat{c}_{\tau}^{0} = \hat{\Delta}_{X}^{t} + \hat{\Delta}_{\beta}^{t} + \hat{\Delta}_{I}^{t}, \tag{15}$$

where the total difference in consumption at the same quantile τ of the year t's comparison and year 0's reference distributions, $\hat{\Delta}_{\tau}^{t}$, is decomposed into one part that is due to differences in observable characteristics (endowments) of the households, $\hat{\Delta}_{X}^{t}$, one part that is due to differences in returns (coefficients) to these characteristics, $\hat{\Delta}_{\beta}^{t}$, and a third part—for which no clear interpretation exists—that is due to interaction between endowments and coefficients, $\hat{\Delta}_{I}^{t}$. In particular, once the RIF regressions for the τ^{th} quantile of the comparison and reference consumption distributions have been run, the estimated coefficients can be used as in the standard Blinder-Oaxaca decomposition to perform a detailed decomposition into contributions attributable to each covariate. The aggregate decomposition can be generalized to the case of the detailed decomposition in the following way:[8]

$$\begin{aligned}\hat{\Delta}_{\tau}^{t} = & \underbrace{\sum_{k=1}^{K} \left(\bar{X}_{k}^{t} - \bar{X}_{k}^{0}\right) \hat{\beta}_{\tau,k}^{0}}_{\hat{\Delta}_{X}^{t}} + \underbrace{\left(\hat{\alpha}^{t} - \hat{\alpha}^{0}\right) + \sum_{k=1}^{K} \left(\hat{\beta}_{\tau,k}^{t} - \hat{\beta}_{\tau,k}^{0}\right) \bar{X}_{k}^{0}}_{\hat{\Delta}_{\beta}^{t}} \\ & + \underbrace{\sum_{k=1}^{K} \left(\bar{X}_{k}^{t} - \bar{X}_{k}^{0}\right) \left(\hat{\beta}_{\tau,k}^{t} - \hat{\beta}_{\tau,k}^{0}\right)}_{\hat{\Delta}_{I}^{t}},\end{aligned} \tag{16}$$

where k represents the k^{th} covariate and $\hat{\alpha}$ and $\hat{\beta}_{\tau,k}$ are the estimated intercept and slope coefficients, respectively, of the RIF regression models for the comparison and reference samples.

Specifically, since we use an additive median shift to identify and separate out changes due

economics is that they provide consistent estimates of the impact of an explanatory variable, X, on the population *unconditional* mean of an outcome variable, Y. This important property stems from the fact that the conditional mean, $\mathbb{E}[Y|X=x]$, averages up to the unconditional mean, $\mathbb{E}[Y]$, due to the law of iterated expectations. As a result, a linear model for conditional means, $\mathbb{E}[Y|X=x] = X\beta$, implies that $\mathbb{E}[Y] = \mathbb{E}[X]\beta$, and OLS estimates of β also indicate what is the impact of X on the population average of Y. When the underlying question of economic and policy interest concerns other aspects of the distribution of Y, however, estimation methods that "go beyond the mean" have to be used. A convenient way of characterizing the distribution of Y is to compute its quantiles. A quantile regression model for the τ^{th} conditional quantile $q_{\tau}(X)$ postulates that $q_{\tau}(X) = X\beta_{\tau}$. By analogy with the case of the mean, β_{τ} can be interpreted as the effect of X on the τ^{th} conditional quantile of Y given X. Unlike conditional means, however, conditional quantiles do not average up to their unconditional population counterparts, i.e. $q_{\tau}(Y) \neq \mathbb{E}_{X}[q_{\tau}(X)] = \mathbb{E}[X]\beta_{\tau}$, where $q_{\tau}(Y)$ is the unconditional quantile. As a result, the estimated β_{τ} cannot be interpreted as the effect of increasing the mean value of X on q_{τ}. RIF regression offers instead a simple way of establishing a direct link between unconditional quantiles of the distribution of Y and household characteristics X because of (14), which says that the conditional expectation of (13)—the expected value of the RIF—is equal to the unconditional quantile of interest.

[8]Following Jones and Kelley (1984), we focus here on the so-called "threefold" decomposition, which uses the same reference distribution for both $\hat{\Delta}_{X}^{t}$ and $\hat{\Delta}_{\beta}^{t}$ but introduces the interaction term $\hat{\Delta}_{I}^{t}$. Equations (15) and (16) can also be written by reversing the reference and comparison distribution designation for both $\hat{\Delta}_{X}^{t}$ and $\hat{\Delta}_{\beta}^{t}$, as well as by allocating the interaction term to either $\hat{\Delta}_{X}^{t}$ or $\hat{\Delta}_{\beta}^{t}$ so as to implement a "twofold" decomposition. However, while these various versions are used in the literature, using one or the other does not involve any specific estimation issue (Fortin et al., 2011). Hence, for the sake of exposition, we shall utilize the decomposition introduced in the text for the rest of our analysis.

to location differences in the consumption distribution, the decompositions above are carried out using the medians ($\tau = 0.5$) of the location-adjusted and unadjusted reference populations, so that the total difference to be decomposed according to (15) and (16) is:

$$\hat{\Delta}^{0L}_{0.5} = \hat{c}^{0L}_{0.5} - \hat{c}^{0}_{0.5} = \rho, \tag{17}$$

where ρ denotes the difference between the medians of the year t's comparison and year 0's reference distributions (see Section 3.2). As location-adjustment is performed by adding to every household consumption expenditure of the original reference population to match its median with that of the comparison population, without altering the shape, the decomposition of the differential (17) can be operated once and its results assumed to hold simultaneously across the entire relative distribution representing changes exclusively due to a location shift. For what concerns the shape shift, the differentials to be decomposed are instead as follows:

$$\hat{\Delta}^{t}_{\tau} = \hat{c}^{t}_{\tau} - \hat{c}^{0L}_{\tau}, \quad \tau = 0.1, \ldots, 0.9, \tag{18}$$

where the quantiles c_τ are estimated as deciles of the comparison and location-adjusted distributions—the latter having the median of the comparison sample but the shape of the reference one.

Notice that the differentials (18) represent *horizontal* distances, or decile gaps, between the distributions involved in the decomposition exercise, whereas the idea underlying the relative distribution framework typically focuses on *vertical* ratios, or relative proportions. Hence, the "declining middle class" scenario would suggest that negative differentials $\hat{\Delta}^{t}_{\tau}$ are to be expected for deciles below the median, whereas for those above the median the total differences given by (18) should be positive. Intuitively, this is because in this case the population shifts from the center of the consumption distribution to the upper and lower deciles, so that the cut-off points identifying the deciles below the median in the comparison distribution comes before those of the reference distribution along the consumption scale, while cut points for deciles above the median comes after.

4 Data

We posit that a comparison of surveys separated relatively further in time is likely to capture more accurately the effect of structural changes in welfare distribution such as inequality, polarization or poverty. This is because in general, absent major shocks, these measures—especially polarization—tend to evolve relatively slowly. In principle, Nigerian and Ghanaian surveys present some desirable features that are ideal for conducting long term structural changes. First, they collect consumption, which has proven preferable to income because it is less volatile (see e.g. Deaton and Zaidi, 2002, and Haughton and Khandker, 2009). For example, in agricultural economies income is more volatile and affected by growing and harvest seasons, so that relying on income as an indicator of welfare might under- or over-estimate living standards significantly. Second, consumption is a better measure of permanent welfare, because households can borrow, draw down savings, or get public and private transfers to smooth short-run fluctuations. Third, consumption measures what individuals have purchased, while income measures the potential claims of a person. Finally, the surveys also provide detailed information on several other modules that can be used to assess the evolution of non-income measures of well-being.

4.1 The Nigerian household consumption data

The National Bureau of Statistics (NBS) has conducted two Nigeria Living Standard Surveys (henceforth NLSS) in 2003/04 and 2009/10, which it uses to monitor progress in poverty reduction.[9] These surveys are representative at state level, use a month-long diary to collect consumption, and collect data for a year (12-month survey). But NBS also conducts other household surveys, most notably the General Household Survey (GHS) cross-section and panel.

The GHS panel is a randomly selected sub-sample of the GHS cross-section, which was collected for the first time in 2010/11. It consists of 5,000 households, and to date two waves have been completed: 2010/11 (Wave 1) and 2012/13 (Wave 2). It is representative at national, rural/urban and zonal (geo-political) levels. In addition to the questions asked in a normal GHS cross section survey, it contains detailed data on agricultural production and other household income earning activities. Consumption data are substantially more detailed, and resemble the consumption data of HNLSS but collected using a 7-day recall period. In every panel wave, households are interviewed two times: once in the "post-planting" period, ranging from August to November, and once in the "post-harvesting" period, ranging from February to April.

At first glance, these diverse surveys spanning several years would seem to be the data of choice for studying polarization in Nigeria. Unfortunately, these surveys present several challenging problems for studying welfare changes. In particular, the most obvious pair of surveys to compare, the NLSS 2003/04 and 2009/10, could not be used because of major data quality problems (World Bank, 2013). This means that in order to enable the data comparison over a longer time span (a decade) we need to create two comparable data sets. To do so, we employ survey-to-survey imputation techniques derived from poverty mapping literature (Elbers et al., 2003). The surveys that fit the purpose are NLSS 2003/04 and GHS panels (see Appendix A for a detailed explanation of the methodology applied).

4.2 The Ghanaian household survey data

The data used in this paper come from the Ghana Living Standard Survey (GLSS), a nation-wide survey conducted by the government-run Ghana Statistical Service that provides information for assessing the living conditions of Ghanaian households.

The GLSS has emerged as one of the most important tools for the welfare monitoring system in Ghana. It provides detailed information on approximately 200 variables, including several socio-economic and demographic characteristics, and information on household consumption of purchased and home-produced goods as well as asset ownership. Each of the waves is organized into 4 modules, which are stored in the; individual, the labor force, the household and the household expenditure files, for which survey questionnaires are readily available.

[9] The 2003/04 was officially labeled Nigeria Living Standard Survey, while the 2009/10 was dubbed Harmonized Nigeria Living Standard Survey. Because these are essentially the same type of surveys, and conducted as a series with the same purpose in mind, we shall refer to them as NLSSs.

The Ghana Statistical Service has conducted six rounds of the GLSS since 1987, thereby providing over 20 years of comparable data. The second, third, fourth and fifth rounds were carried out, respectively, in 1988, 1991/92, 1998/99 and 2005/06. Recently, data for the sixth round of GLSS have also become available, so that the proposed case study paper will be one of the first studies using this data set. However, only the last four rounds, from 1991/92 (GLSS-3) to 2012/12 (GLSS-6), have been based on the same questionnaire and are therefore fully comparable.

The availability of comparable and extensive information represents a success on its own. Ghana is one of the few countries in Africa that has produced comparable, high-quality household data covering over two decades. This is an important achievement because the availability of such rich and comparable information beginning in 1991, as well as the quality improvements of the surveys over the years and the fact that they collect data on both the monetary and the non-monetary dimensions of welfare, permit the establishment of an accurate picture of inequality and polarization over time, including the drivers behind these phenomena. As a measure of well-being we will use household consumption for 1991/92 (GLSS-3), 1998/99 (GLSS-4), 2005/06 (GLSS-5) and 2012/13 (GLSS-6). The GLSS collects sufficiently detailed information to facilitate estimates of the total consumption of each household. It relies on consumption per adult equivalent[10] to capture differences in need by age and economies of scale in consumption. Scales of consumption by age and sex are computed by the Ghana Statistical Service.

The GLSS is based on a two-stage (non-stratified) sample design. Therefore, when the data are analyzed, sampling weights are used to account for the survey design. Besides, to enhance comparability of consumption data over the four waves, all expenditures have been deflated across both space[11] and time and expressed in 2005 constant prices—as well as converted, when necessary, from Ghanaian second cedi (GHC) to Ghanaian third cedi (GHS), i.e. for GLSS-3 to GLSS-5.

A summary of distributional statistics obtained from the GLSS data sets is given in Table 1. Besides the growth of the real mean and median consumption expenditures, the most notable feature is the picture that emerges across different indicators of inequality. The consumption shares of the poorest percentiles of the population decreased between approximately 0.9 and 1.4% a year in the period examined, in contrast to what is observed for the richest percentiles, whose shares experienced average yearly increases of around 0.2%. Inequality in household consumption was initially constant, but widened considerably between 1998/99 and 2005/06—a jump of about 7% in the Gini's coefficient and 20% in the Theil's index.[12] Inequality has remained constant at the higher level after 2005/06, but the trends in the shares of consumption of the bottom and top quintiles have continued in the same direction.

However, the narrative about inequality is more nuanced than the summary measures suggest. The summary measures of inequality analyzed above only partially capture the changes at various

[10] We use adult equivalent scales because also the official consumption, poverty and inequality figures are expressed in adult equivalent terms.

[11] The price deflator differs across the ten regions in which Ghana is divided and within each region by urban and rural areas.

[12] Running a simple t-test of the difference between Gini and Theil indices from the 1998/99 and 2005/06 samples yields a p-value of around zero, which confirms the finding that points to increasing inequality over the 1998–2005 period at any of the usual significance levels.

Table 1: Summary measures of Ghanaian household total consumption expenditure, 1991/92 to 2012/13

	1991/92	1998/99	2005/06	2012/13
Observations	4,523	5,998	8,687	16,772
Mean	459.91	568.45	736.80	883.48
Median	352.66	438.04	559.44	655.60
Consumption shares				
Bottom 5	1.11	1.00	0.79	0.82
Bottom 10	2.71	2.42	2.08	2.13
Bottom 20	6.82	6.21	5.65	5.63
Top 20	44.78	44.47	46.59	46.94
Top 10	29.16	28.17	30.75	30.43
Top 5	18.52	17.41	19.95	19.17
Inequality measures				
Gini	0.38	0.38	0.41*	0.41
Theil	0.25	0.25	0.30*	0.29

* Denotes statistically significant change from the previous period at the 5 % level (p-value < 0.05).

Source: authors' own calculation using GLSS data sets.

Table 2: Inter-quantile consumption ratios by GLSS Wave, 1991/92 to 2012/13

Wave	p10/p50	p25/p50	p75/p25	p75/p50	p90/p10	p90/p50
1991/92	0.46	0.66	2.37	1.56	5.23	2.42
1998/99	0.41	0.63	2.60	1.64	6.00	2.48
2005/06	0.39	0.61	2.63	1.62	6.36	2.46
2012/13	0.39	0.62	2.68	1.66	6.73	2.65

Source: authors' own calculation using GLSS data sets.

points of the consumption distribution. The results of a simple inter-quantile analysis can provide more detailed information on the changes occurring at all points of the distribution (see Table 2). They show that the ratio of average consumption among the top 10 of the distribution to the average consumption among the bottom 10 had risen considerably even before 1998/99, suggesting that the more well-off had benefited more than the poorest decile from the economic growth in 1991-98. Over the years, the consumption levels of the top and the bottom of the distribution continued to diverge at a steady rate so that the gap expanded by 30% over the full period.[13] The divergence was widening because the bottom 10 was being left behind, rather than because the top 10 was gaining disproportionally compared with the rest of the population. The average consumption of the 90th percentile rose little relative to the median, while the average consumption of the bottom 10 had deteriorated by nearly 20% by 2005/06. The bottom 10 appears to be losing ground also compared with other households in the bottom 25, who are also losing ground to the median but only half as quickly.

These preliminary findings denote a clear tendency towards rising polarization in household

[13]The gap between 90th and 10th deciles is probably a lower bound of the real one. In general, household surveys do not contain good estimates of upper percentiles of welfare (Alvaredo and Piketty, 2010). When using consumption to rank welfare, as it is normally done in low/er middle income countries, the situation is further aggravated. Consumption is very accurate in capturing the well-being of poorer people, yet it is rather imprecise in capturing that of people living in upper percentiles.

consumption over the period. The notion of "polarization" commonly refers to the case where there is a significant number of individuals who are very poor but there exists also a non-negligible share of the population that is quite rich. Such a gap between the poor and the rich implies evidently that there is no sizable middle class.[14] As we will see later when applying relative distribution methods, the distributional changes occurred between 1991/92 and 2012/13 hollowed out the middle of the Ghanaian household consumption distribution and increased the concentration of households around the highest and lowest deciles, hence leading to an increase of polarization.

5 Empirical results

5.1 Nigeria

5.1.1 Changes in the Nigerian household consumption distribution

Summary measures for household total consumption expenditure per capita in 2003/04 and 2012/13 are presented in Table 3.[15] Besides the growth of the real mean and median consumption expenditures, the most notable feature is that consumption shares of the poorest percentiles of the population decreased between approximately 1.3% and 1.6% a year in the period examined, in contrast to what is observed for the richest percentiles, whose shares experienced average yearly increases of around 1.7%.

The Gini index grew at an annual average rate of 1.5% between 2003/04 and 2012/13, while the increment in inequality detected by the Theil index is more pronounced, with an average growth rate of 4.2% per annum. As for polarization, a sizable increase is detected by both the Foster-Wolfson (1992) and Duclos-Esteban-Ray (2004) measures, which amounts to around 1.7% per year in the first case and almost 1.5% in the second.

Further insight on the key changes occurring in the distribution of total per capita consumption expenditure of Nigerian households is provided by Figure 1, which shows the density overlay for the two survey waves.[16] Two major observations are apparent from this figure: first, the whole distribution shifted rightward following the increment in the median, and second, there was also an alteration of the shape—the consumption distribution is in fact more dispersed in 2012/13 than in 2003/04, as it appears to be characterized by a smaller peak and a fatter upper tail that are quite visible in the density overlay. The declines in the mass at the lower and middle ranges of the distribution, and the concomitant spreading out of expenditures in its top half, are also noticeable from Table 3, where the reported values of the standard deviation, skewness, and kurtosis all show a remarkable growth from one survey wave to the next.

[14] In this paper we will analyze the median-based approach to the measurement of polarization. Since it subdivides the population into two subgroups—those above the median and those below the median, respectively—we refer to this as the case of "bi-polarization". For an explanation of the main differences between the concept of bi-polarization and that of "multi-polar" polarization, see Section 2 and the surveys contained in, e.g., Chakravarty (2009, ch. 4), Deutsch et al. (2013) and Chakravarty (2015).

[15] In order to enhance comparability of consumption data over the years, all expenditures have been deflated across both space and time and are expressed in 2010 Naira.

[16] To handle data sparseness, the two densities have been estimated by using an adaptive kernel estimator with a Silverman's plug-in estimate for the pilot bandwidth (see e.g. Van Kerm, 2003). The advantage of this estimator is that it does not over-smooth the distribution in zones of high expenditure concentration, while keeping the variability of the estimates low where data are scarce—as, for example, in the highest expenditure ranges.

Table 3: Summary measures of Nigerian household total consumption expenditure per capita

	2003/04	2012/13
Mean	84,874	99,084
Median	71,168	76,193
Standard deviation	58,707	122,250
Skewness	2.48	39.32
Kurtosis	15.55	2,818.97
Consumption shares		
Bottom 5%	1.05	0.93
Bottom 10%	2.64	2.29
Bottom 20%	6.90	5.97
Top 20%	41.14	45.45
Top 10%	25.43	29.52
Top 5%	15.35	18.97
Inequality measures		
Gini	0.34	0.39
Theil	0.20	0.29
Polarization measures[a]		
Foster-Wolfson	0.30	0.35
Duclos-Esteban-Ray	0.21	0.24

Note: (a) the Duclos-Esteban-Ray index has been computed with the polarization sensitivity parameter α set at 0.5.

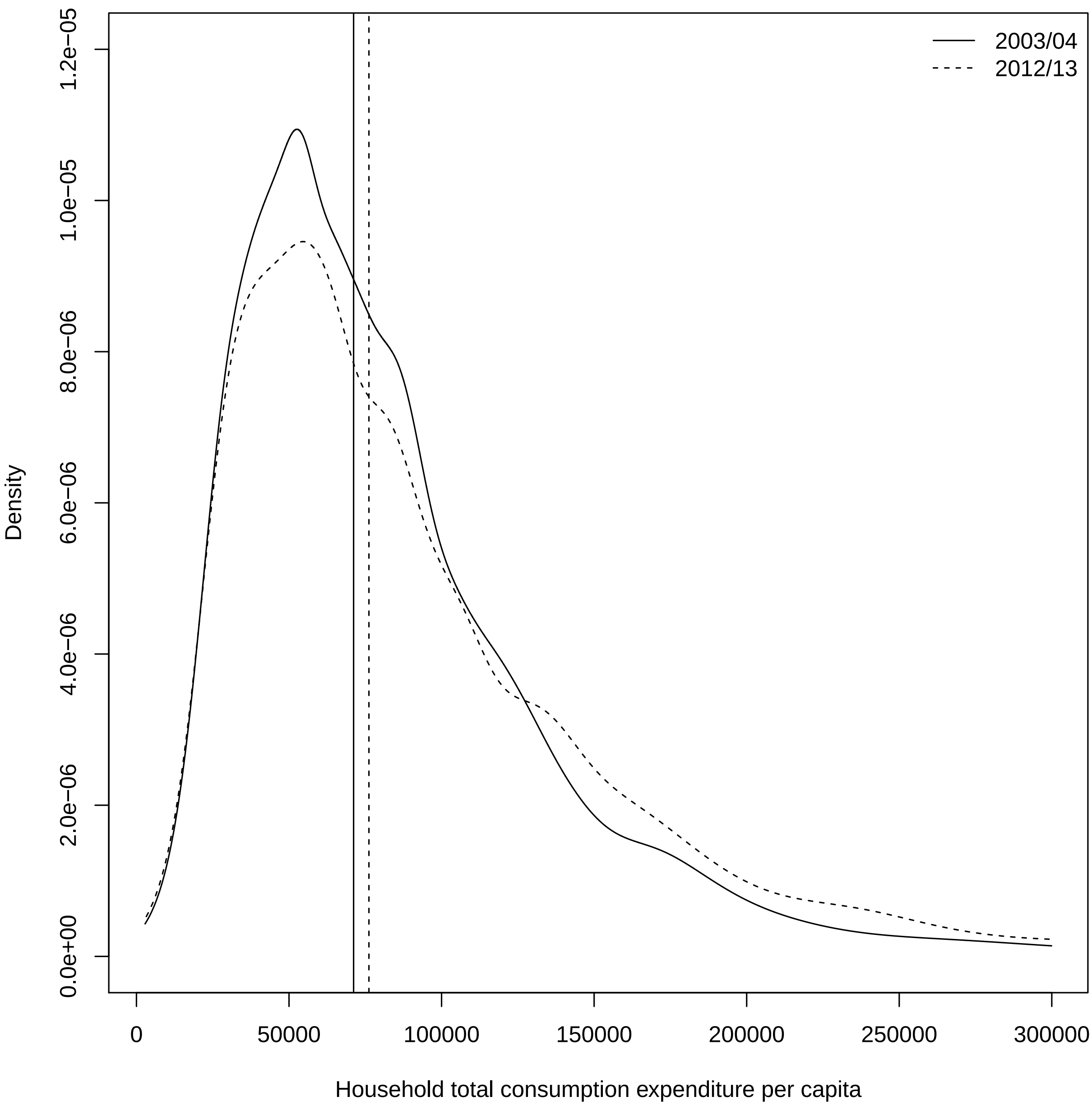
However, the graphical display above does not provide much information on the relative impact that location and shape changes had on the differences in the two distributions at every point of the expenditure scale. It also does not convey whether the upper and lower tails of the consumption distribution were growing at the same rate and for what reasons (i.e. location and/or shape driven). As already pointed out in Section 3, this is exactly what the relative distribution method is particularly good at pulling out of the data.

We have chosen 2003/04 as the reference distribution throughout the analysis. It is important to note that reversing the reference and comparison population designation will change the view provided by the relative distribution graph and the displays of the estimated effects of location and shape shifts, because these are defined in terms of the reference population scale. The relative polarization indices, however, are *symmetric*, meaning that they are effectively invariant to whether the 2003/04 or 2012/13 consumption distribution is chosen as the reference: in fact, swapping the comparison and reference populations yields indices of the same magnitude and opposite sign (e.g. Handcock and Morris, 1999, pp. 71–72, and Hao and Naiman, 2010, pp. 88–89). Thus, reversing the reference and comparison distributions designation will not alter our findings in a substantive way—if not for the fact that polarization would now be analyzed in the reverse direction of time.

The relative density of total per capita consumption expenditure of Nigerian households between 2003/04 and 2012/13 is examined in Figure 2(a).[17] This plot shows the fraction of households in 2012/13 that fall into each percentile of the 2003/04 distribution. Households in the low and middle classes moved toward high and, to a less extent, lowest deciles. Indeed, if we

[17]The relative density function has been obtained by fitting a local polynomial to the estimated relative data. Throughout, we rely on the R statistical package `reldist` (Handcock, 2015) to implement the relative distribution method.

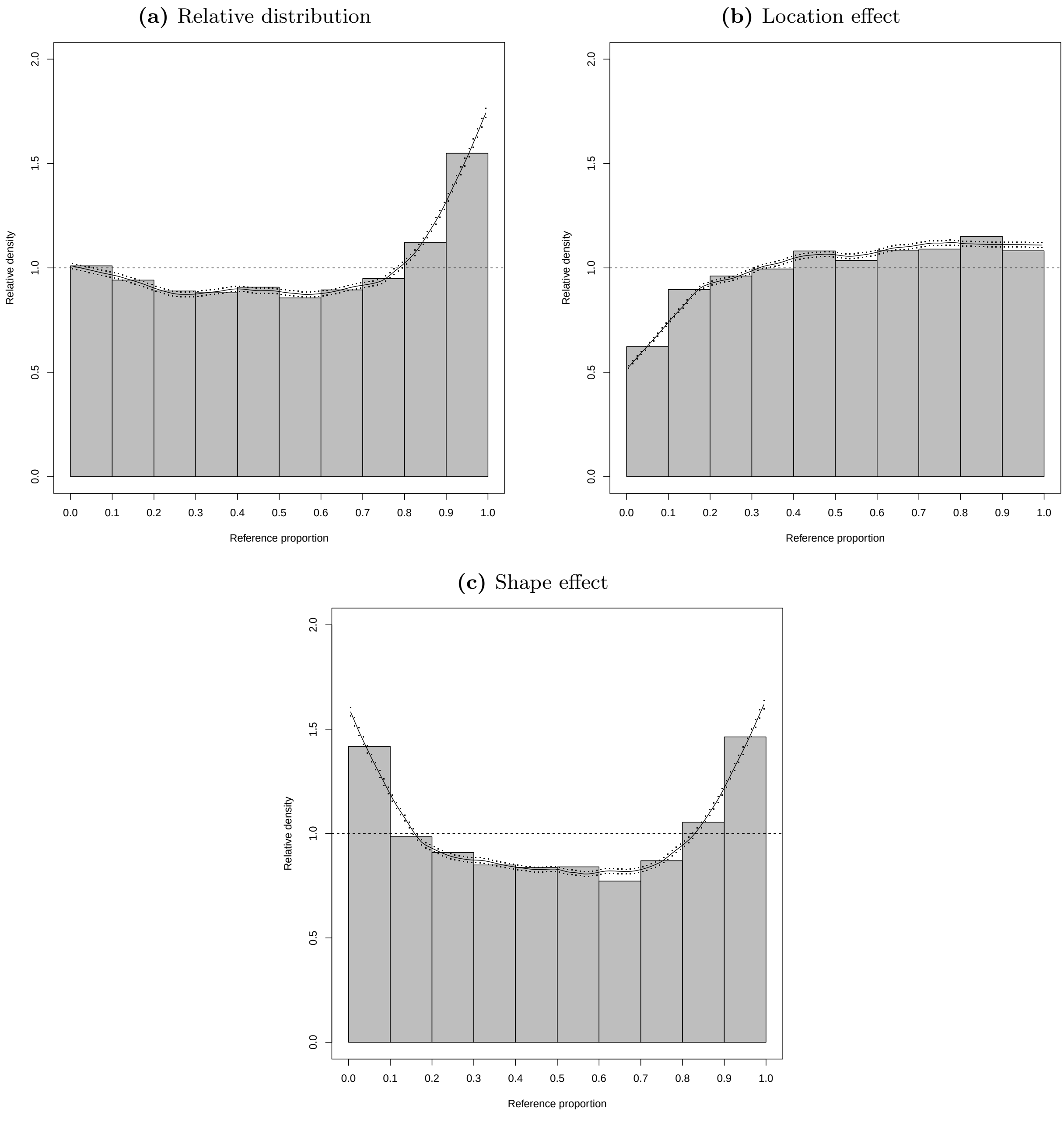
Figure 1: The distribution of total household consumption expenditure in Nigeria, 2003/04 and 2012/13. Expenditures in the upper tiers of the densities have been truncated for better presentation of the graph, where the vertical lines denote the medians of the two survey waves



choose any percentile approximately between the 2nd and the 80th in the 2003/04 distribution, the fraction of households in 2012/13 whose consumption rank corresponds to the chosen percentile is less than the analogous fraction of households in 2003/04.

To get a more detailed picture, we decompose the relative density into location and shape effects according to Equation (3). Figure 2(b) presents the effect only due to the median shift, that is the pattern that the relative density would have displayed if there had been no change in distributional shape but only a location shift of the density. The effect of the median shift was quite large. This alone would have moved out of the four lowest deciles of the reference distribution a substantial fraction of GHS panel 2012/13 households and placed them in any of the remaining deciles. Note, however, that neither tail of the observed relative distribution is

Figure 2: Changes in the Nigerian household consumption distribution between 2003/04 and 2012/13. The bars represent the decile breakdown of the relative distribution, showing the fraction of 2012/13 households that fall into each 2003/04 decile, while dotted lines indicate the 95% pointwise confidence limits based on the asymptotic normal approximation (Handcock and Morris, 1999, p. 144)



well reproduced by the median shift. For example, the top decile of Figure 2(b) is about 1.1, below the value of 1.5 observed in the actual data, and the bottom deciles of the same figure are also substantially lower than observed. These differences are explained by the shape effect presented in Figure 2(c), which shows the relative density net of the median influence. Without the higher median, the greater dispersion of consumption expenditures in GHS panel 2012/13 would have led to relatively more low-consuming households in 2012/13, and this effect was mainly concentrated in the bottom decile. By contrast, at the top of the distribution the higher spread worked in the same direction of the location shift: operating by itself, it would have

Table 4: Relative polarization indices

Index[a]	Value	LB[b]	UB[c]	*p*-value[d]
MRP	0.12	0.11	0.13	0.00
LRP	0.11	0.08	0.14	0.00
URP	0.13	0.10	0.16	0.00

Notes: (a) MRP = median relative polarization index, LRP = lower relative polarization index, URP = upper relative polarization index; (b) lower bound of the 95 percent confidence interval; (c) upper bound of the 95 percent confidence interval; (d) refers to the null hypothesis of no change with respect to the reference distribution, *i.e.* that the index equals 0.

increased the share of households in the top decile of the 2012/13 consumption distribution by nearly 50%. In sum, once changes in real median expenditure are netted out, a U-shaped relative density is observed, indicating that income (proxied by consumption) polarization was hollowing out the middle of the Nigerian household consumption distribution—with a cumulative loss that more than halved the number of households in deciles 2 through 8 of the 2012/13 distribution.

A link between what we have observed in the graphical analysis and the quantification of the degree of polarization is captured by the relative polarization indices. These indices keep track of changes in the shape of the distribution and measure their direction and magnitude. Table 4 reports the median, lower and upper polarization indices computed from the data using Equations (4)–(6), along with their 95% confidence intervals and the p-values for testing the null hypothesis of no change with respect to the reference distribution.

Using weighted estimates of relative polarization measures, the 95% confidence interval for the MRP has been calculated as: CI = weighted estimate $\pm\, 1.96 \times$ SE, where SE $= 4\sqrt{\frac{c_1}{m} + \frac{c_2}{n}}$ is the standard error of MRP based on the sample variances c_1 and c_2 of, respectively, $\left\{\left|Q_i - \frac{1}{2}\right|\right\}_{i=1}^{m}$ and $\left\{\left|Q_i - \frac{1}{2}\right|\right\}_{i=1}^{n}$—i.e. the absolute deviations around the median of the location-matched quasirelative data $\{Q_i\}_{i=1}^{m,n}$ (m and n denote the comparison and reference sample sizes). As for the p-value, since our data sets are large survey samples for which the sample sizes tend to be large, we use the normal approximation to the exact distribution of the MRP estimate as the basis for a test for a given significance level α, that is: $P\left(|\text{MRP}| \leq z_{\alpha/2} \times \text{SE}\right) \approx 1 - \alpha$, where $z_{\alpha/2}$ is the $100 \times (1 - \alpha)$ percentile of the standard normal distribution. Estimation of confidence intervals and p-values for the lower relative polarization (LRP) and upper relative polarization (URP) indices is similar. For more details, we refer the reader to Handcock and Morris (1999, ch. 10).

The median index is significantly positive, implying a dispersion of the consumption distribution from the middle toward either or both of the two tails. The lower and upper polarization estimates indicate that both tails of the distribution are significantly positively polarized. The upper index, however, is slightly larger, indicating greater polarization in the upper tail of the distribution than in the lower tail.

5.1.2 Covariate decompositions

So far we have focused on comparing the distribution of Nigerian household consumption expenditure between two points in time. However, there are often covariates measured on the households which vary over time, and the impact of these changes on the observed outcomes could be of interest to economic policy and suggest possibilities worthy of consideration by its designers. In the relative distribution setting, exploring the distributional impacts of changes in a covariate requires that the relative distribution is adjusted for these changes using the methods from Section 3.4. This makes it possible to separate the impacts of changes in the distribution of the covariate (the "composition effect") from changes in the conditional distributions of household consumption expenditure given the covariate levels (the "residual effect"). Our Nigerian consumption microdata provide an opportunity to use this covariate adjustment technique as they contain a large set of covariates describing various socio-demographic characteristics of the respondents, household assets and characteristics of the dwelling. Here, the analysis is restricted to the following covariates: sex of household head; literacy status of household head; zone; main material used for floor; main source of drinking water; main cooking fuel; main toilet facility. This selection was inspired both from previous poverty research—which advocates the inclusion of covariates that change over time, but excluding those of them that are likely to change markedly in the face of evolving economic conditions (e.g. Stifel and Christiaensen, 2007)—and the fact that many of the covariates excluded from the analysis did not affect the statistical significance of the predicting model used to impute the 2003/04 data.

Summary statistics for the population subgroups defined by the levels of the covariates analyzed and the corresponding average percentage changes between 2003/04 and 2012/13 are given in Tables 5 and 6. Both the mean and median consumption expenditures rose during the period analyzed for many population subgroups—exceptions are represented by households headed by illiterate individuals, households with inadequate housing infrastructures (such as unsafe water, low quality flooring material, no toilet facility and firewood as the main cooking device) and households living in the North East and North West zones of the country. At the same time, apart from households in the North Central region, all groups experienced increasing inequality according to both the Gini coefficient and the Theil index. Population and consumption shares changed instead more heterogeneously, following patterns of increases and decreases with different magnitudes over time. In particular, there appears to have been almost no change in the proportion of male-headed households, while female-headed households declined somewhat. By contrast, the fractions of households with a literate head and good quality housing infrastructures (such as safe water, medium-high quality flooring material and non-firewood cooking devices) grew considerably relative to their counterparts—households with no toilet facility, however, are more common in 2012/13 than in 2003/04. Finally, the proportions of households that consist of individuals living in the northern zones of the country increased between 2003/04 and 2012/13, whereas households in the southern regions declined slightly.

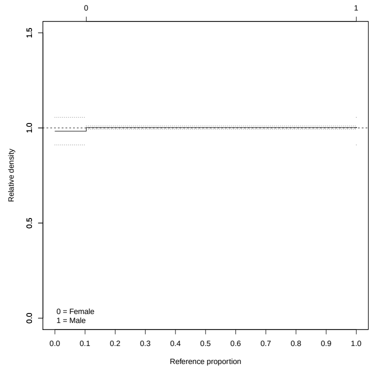
The above population trends are also visible from Figure 3, which plots the relative distributions of the covariates for 2012/13 to 2003/04. Conceptually, these relative densities are similar to the one constructed for consumption expenditure in the previous section, though the graphs are not nearly as smooth because of natural discreteness of the covariates. By reading across the bottom axis one can see the frequencies of reference households cumulated by levels of the covariates, while reading off the y-axis for a given level of the categorical variables allows one to find the relative frequency of comparison households in each group defined by that level. The labels at the top show the categories of the covariates, and can be used for both the reference and comparison populations.

Table 5: Summary measures for nigerian household consumption expenditure by population subgroups, 2003/04 and 2012/13

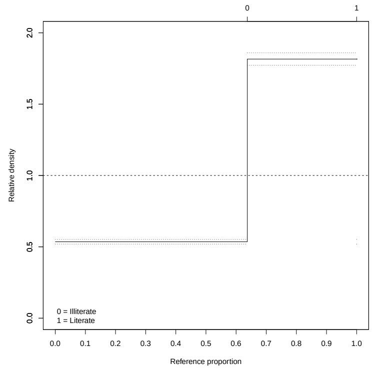
	2003/04						2012/13					
	Mean	Median	Pop. share	Cons. share	Gini	Theil	Mean	Median	Pop. share	Cons. share	Gini	Theil
Sex of the household head												
Male	83,692	69,897	0.90	0.88	0.34	0.20	97,125	74,340	0.90	0.88	0.39	0.29
Female	95,049	81,550	0.10	0.12	0.32	0.18	116,276	90,664	0.10	0.12	0.39	0.29
Literacy status of household head												
Illiterate	76,980	65,113	0.64	0.58	0.33	0.19	76,391	60,686	0.34	0.26	0.38	0.33
Literate	98,741	83,335	0.36	0.42	0.34	0.19	110,838	86,203	0.66	0.74	0.38	0.26
Zone												
North Central	79,120	67,318	0.14	0.13	0.34	0.19	86,507	74,273	0.14	0.12	0.33	0.18
North East	86,745	74,290	0.12	0.13	0.33	0.18	78,168	65,903	0.14	0.11	0.35	0.22
North West	72,003	59,182	0.25	0.21	0.35	0.21	70,037	53,134	0.25	0.18	0.38	0.40
South East	93,147	74,442	0.12	0.13	0.37	0.23	111,485	80,006	0.12	0.13	0.43	0.33
South South	85,468	70,298	0.17	0.17	0.34	0.19	114,467	87,784	0.15	0.18	0.38	0.25
South West	98,279	86,632	0.20	0.23	0.30	0.15	140,493	118,426	0.20	0.28	0.32	0.19
Main material used for floor												
Medium quality/High quality	94,154	79,889	0.61	0.67	0.33	0.19	103,085	80,192	0.91	0.95	0.39	0.29
Low quality	70,616	59,955	0.39	0.33	0.33	0.18	58,794	45,057	0.09	0.05	0.36	0.24
Main source of drinking water												
Piped/Unprotected	84,337	71,298	0.62	0.62	0.34	0.19	94,766	70,509	0.46	0.44	0.39	0.32
Protected	85,761	71,025	0.38	0.38	0.35	0.20	102,709	81,482	0.54	0.56	0.39	0.27
Main cooking fuel												
Charcoal/Kerosene/Oil/ Electricity/Gas/Other	112,935	94,852	0.25	0.34	0.32	0.17	157,614	129,633	0.26	0.41	0.34	0.21
Firewood	75,369	64,282	0.75	0.66	0.33	0.18	78,857	64,111	0.74	0.59	0.36	0.26
Main toilet facility												
Flush toilet/Improved pit Latrine/Uncovered pit Latrine/Other	86,957	72,732	0.83	0.85	0.34	0.20	105,467	81,057	0.78	0.83	0.40	0.30
No facility	74,782	64,066	0.17	0.15	0.32	0.17	75,919	63,770	0.22	0.17	0.34	0.20

Figure 3: The relative distributions of the covariates for 2012/13 to 2003/04. The upper axes are labelled by the levels of categorical variables. The dotted lines are 95% pointwise confidence bounds

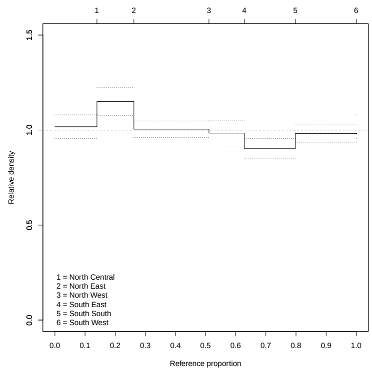
(a) Sex of household head



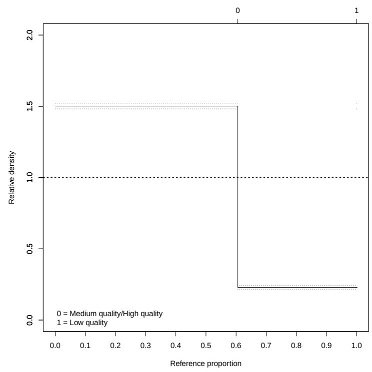
(b) Literacy status of household head



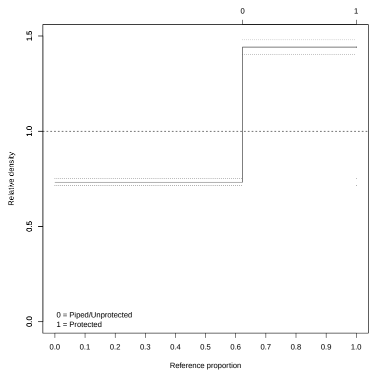
(c) Zone



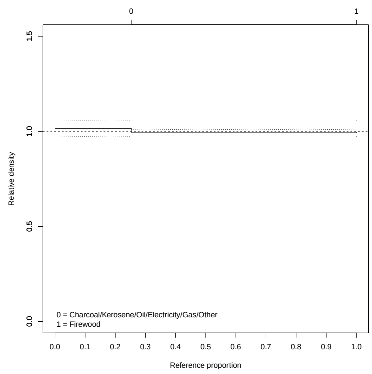
(d) Main material used for floor



(e) Main source of drinking water



(f) Main cooking fuel



(g) Main toilet facility

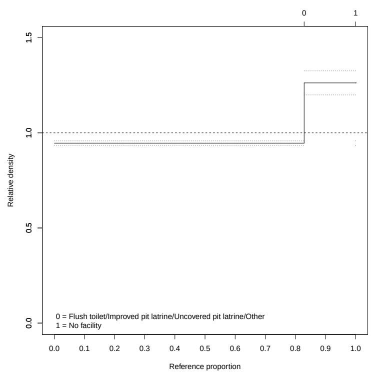


Table 6: Summary measures for Nigerian household consumption expenditure by population subgroups, average annual compound percentage changes from 2003/04 to 2012/13

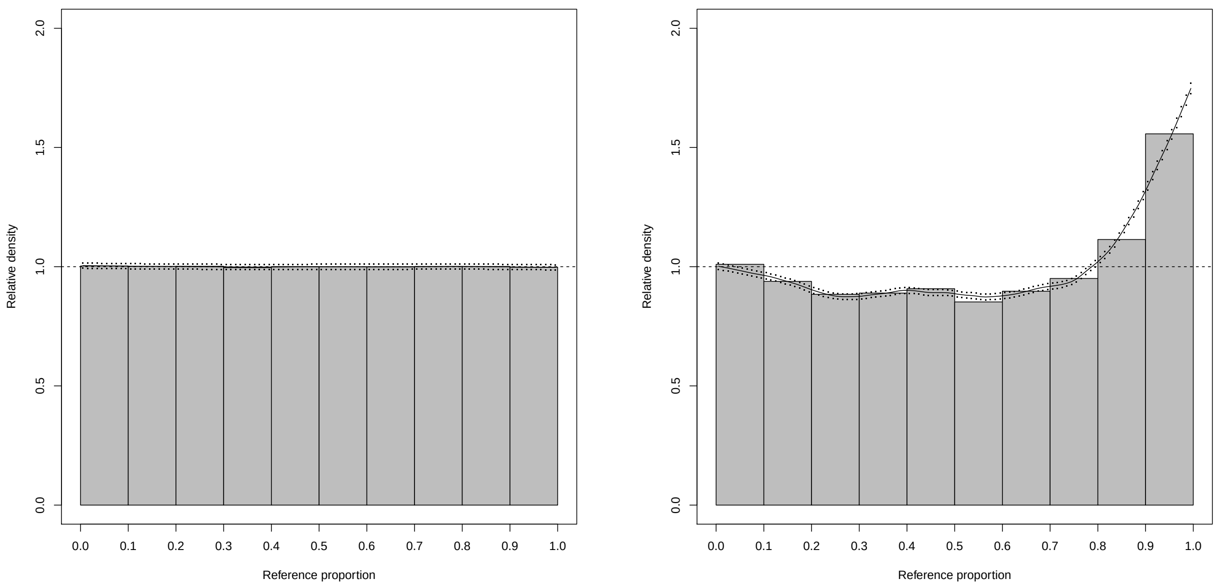
	Mean	Median	Pop. share	Cons. share	Gini	Theil
Sex of the household head						
Male	1.67	0.69	0.02	-0.04	1.51	4.44
Female	2.26	1.18	-0.19	0.33	2.03	5.42
Literacy status of household head						
Illiterate	-0.09	-0.78	-6.70	-8.37	1.31	6.52
Literate	1.29	0.38	6.85	6.39	1.48	3.52
Zone						
North Central	1.00	1.10	0.19	-0.54	-0.33	-0.63
North East	-1.15	-1.32	1.56	-1.32	0.68	2.21
North West	-0.31	-1.19	0.05	-1.96	0.98	7.16
South East	2.02	0.80	-0.18	0.10	1.61	3.81
South South	3.30	2.50	-1.12	0.40	1.45	3.11
South West	4.05	3.53	-0.20	2.07	0.96	3.08
Main material used for floor						
Medium quality/High quality	1.01	0.04	4.62	3.88	1.63	4.75
Low quality	-2.02	-3.12	-15.10	-18.23	1.04	3.16
Main source of drinking water						
Piped/Unprotected	1.30	-0.12	-3.40	-3.81	1.72	5.92
Protected	2.02	1.54	4.15	4.44	1.30	3.20
Main cooking fuel						
Charcoal/Kerosene/Oil/ Electricity/Gas/Other	3.77	3.53	0.17	2.17	0.74	2.23
Firewood	0.50	-0.03	-0.06	-1.27	0.90	3.94
Main toilet facility						
Flush toilet/Improved pit Latrine/Uncovered pit Latrine/Other	2.17	1.21	-0.62	-0.19	1.65	4.76
No facility	0.17	-0.05	2.62	1.04	0.58	1.70

However, as already mentioned earlier in this section, in order to assess the impact of changes in population characteristics on the Nigerian consumption distribution the relative density must be decomposed by the distributions of the covariates. This is shown in Figure 4 for the region of residence (zone) covariate, which presents both the covariate composition effect as well as the effect of residual changes—i.e. the expected relative density of Nigerian consumption expenditures had the covariate composition of the 2003/04 and 2012/13 populations been identical. The results in panel (a) are pretty close to a uniform distribution, suggesting that the observed differences in population composition according to the selected covariate had little effect on the overall changes occurred over the decade. This perception is confirmed by the adjusted distribution graphed in panel (b) which, in the absence of a major compositional effect, is not much different than the original one depicted in Figure 2(a). Results for other covariates—not shown for brevity, but available upon request—are very similar: there were slight decreases in the bottom half and tiny growth at the top of the distribution associated with some of the compositional shifts in these covariates, but the observed changes were only partly driven by modifications in the characteristics of the population.

A similar conclusion can be drawn when looking at Table 7, which presents the set of relative polarization indices for each group defined by the covariates obtained by comparing their

Figure 4: Adjusting the relative density of Nigerian consumption expenditure for changes in the region of residence (zone) covariate distribution between 2003/04 and 2012/13

(a) Zone compositional effect **(b)** Zone-adjusted relative distribution



consumption distributions over time. Note that, by comparing the subgroup distributions over time, we are effectively controlling for the compositional differences, even though no explicit composition *effect* is identified. If each of the group-specific polarization indices were close to 0, this would imply that after holding changes in the distributions of the covariates constant there is no residual polarization in consumption expenditures. The polarization we observe in the overall consumption distribution would then be due entirely to changing characteristics of the population over time. Instead, we see a different scenario. Apart from the North Central households and those with an illiterate head and no toilet facility, the estimates indicates a statistically significant increase of polarization in the subgroup distributions, except for households who reside in the North East and North West regions of the country and those with inadequate flooring in dwelling units, for whom some convergence toward the median is detected. The growth of polarization stems from a shift away from the median of both tails, and this seems to happen asymmetrically, as the LRP indices are in many cases more positive than the URPs—thus indicating more polarization in the lower than in the upper tail. Households headed by men, women or illiterates and households with good flooring material in dwellings, unsafe water and cooking with firewood, instead, are more polarized in the upper than in the lower tail of their consumption distribution—or at least they are so the same way. Overall, these patterns confirm that compositional shifts contributed little to the observed consumption polarization or, in other words, holding the changes in population characteristics constant does almost nothing to reduce overall polarization.[18]

The above conclusion suggests that the main drivers of polarization are to be searched elsewhere, namely in the changes occurring over the decade in the consumption distributions of the

[18]This finding can also serve as a check of whether the observed changes in Nigerian consumption distribution are robust to sample size variations. That is, had the modifications in population characteristics due to artefacts of the sample size, rather than to real population trends, our results would not be affected by them.

Table 7: Relative polarization indices for different population subgroups

	MRP				LRP				URP			
	Index[a]	LB[b]	UB[c]	*p*-value[d]	Index[a]	LB[b]	UB[c]	*p*-value[d]	Index[a]	LB[b]	UB[c]	*p*-value[d]
Sex of the household head												
Male	0.11	0.10	0.13	0.00	0.10	0.07	0.13	0.00	0.13	0.09	0.16	0.00
Female	0.15	0.11	0.19	0.00	0.15	0.07	0.22	0.00	0.15	0.08	0.23	0.00
Literacy status of household head												
Illiterate	-0.01	-0.03	0.01	0.23	-0.03	-0.07	0.02	0.11	0.01	-0.03	0.05	0.33
Literate	0.10	0.08	0.12	0.00	0.08	0.04	0.13	0.00	0.12	0.08	0.16	0.00
Zone												
North Central	0.02	-0.01	0.06	0.10	0.03	-0.04	0.10	0.19	0.01	-0.06	0.08	0.35
North East	-0.07	-0.11	-0.04	0.00	-0.07	-0.14	0.00	0.02	-0.08	-0.15	-0.01	0.02
North West	-0.10	-0.14	-0.07	0.00	-0.15	-0.21	-0.09	0.00	-0.05	-0.12	0.01	0.06
South East	0.14	0.10	0.18	0.00	0.14	0.07	0.21	0.00	0.14	0.07	0.21	0.00
South South	0.21	0.17	0.25	0.00	0.23	0.15	0.31	0.00	0.19	0.11	0.26	0.00
South West	0.21	0.17	0.25	0.00	0.23	0.16	0.31	0.00	0.18	0.11	0.26	0.00
Main material used for floor												
Medium quality/High quality	0.08	0.06	0.09	0.00	0.05	0.02	0.09	0.00	0.10	0.06	0.13	0.00
Low quality	-0.14	-0.17	-0.10	0.00	-0.26	-0.32	-0.20	0.00	-0.01	-0.10	0.07	0.36
Main source of drinking water												
Piped/Unprotected	0.04	0.02	0.06	0.00	-0.03	-0.07	0.01	0.10	0.11	0.07	0.16	0.00
Protected	0.16	0.14	0.19	0.00	0.21	0.17	0.25	0.00	0.12	0.07	0.16	0.00
Main cooking fuel												
Charcoal/Kerosene/Oil/ Electricity/Gas/Other	0.21	0.18	0.24	0.00	0.28	0.22	0.34	0.00	0.15	0.09	0.21	0.00
Firewood	0.03	0.01	0.04	0.00	0.01	-0.02	0.04	0.26	0.04	0.01	0.07	0.01
Main toilet facility												
Flush toilet/Improved pit latrine/Uncovered pit latrine/Other	0.16	0.14	0.18	0.00	0.17	0.14	0.21	0.00	0.15	0.11	0.18	0.00
No facility	0.02	-0.01	0.05	0.16	0.02	-0.04	0.08	0.30	0.01	-0.04	0.07	0.31

Notes: (a) MRP = median relative polarization index, LRP = lower relative polarization index, URP = upper relative polarization index; (b) lower bound of the 95 percent confidence interval; (c) upper bound of the 95 percent confidence interval; (d) refers to the null hypothesis of no change with respect to the reference distribution, *i.e.* that the index equals 0.

groups defined by the covariates. While the covariate adjustment technique identifies the impact of changing population characteristics on the distribution of consumption expenditures, comparing the groups defined by the covariates directly makes it possible to analyze the changes within and between these groups' consumption distributions. As already observed, most population subgroups were both location-shifted (Tables 5 and 6) and more polarized (Table 7). To see what impact these location and shape shifts in the subgroups' distributions had on their relative positions within the overall consumption distribution, we compare the changes in deciles of the between-group relative distributions for 2003/04 and 2012/13 to the changes that would have occurred if only the medians or shapes of the groups had changed. More specifically, for each decile we decompose the absolute change:

$$g\left(C : R\right) - g\left(C_0 : R_0\right), \tag{19}$$

where $g\left(C : R\right)$ and $g\left(C_0 : R_0\right)$ denote respectively the relative density for comparison (C) to reference (R) groups of the categorical variables in 2012/13 and 2003/04, into the marginal effect of the median shift from the 2003/04 relative density:

$$g\left(C_{0L} : R_{0L}\right) - g\left(C_0 : R_0\right), \tag{20}$$

and those of the shape changes in the subgroups' consumption distributions:

$$g\left(C_{0L} : R\right) - g\left(C_{0L} : R_{0L}\right), \tag{21}$$

$$g\left(C : R\right) - g\left(C_{0L} : R\right), \tag{22}$$

where R_{0L} and C_{0L} denote the distributions of the reference and comparison groups adjusted to have the same median as 2012/13 but with the same shape as 2003/04.[19] Summing up to the total difference given by Equation (19), these effects form a complete decomposition and allow us to determine what proportion of households were moved into or out of a decile of the overall distribution by changes in relative median and group-specific shape.

The spatial distribution of household consumption expenditure definitely provided the most attractive results. Figure 5 presents the decomposition for each of the six Nigerian macro-regions as compared to the rest of the country. The solid bars show the total change by decile from Equation (19), and each of the lines represents one of the three components in the decomposition defined by Equations (20)–(22). We can see two ongoing distinctive patterns, both accentuating polarization. In the South South and the South West, relative to the rest of the country, residents tend to move out of the lower deciles of the distribution due to changes in relative median. More precisely, had the location effect been the only one operating, we would have seen in both cases a clear transition of Southeners from lower to upper deciles of the national distribution. However, the shape effect of both regions moved in the opposite direction, partially offsetting the positive impact of growth. Particularly in the lower deciles, the shape change is positive, indicating a clear trend of lower polarization in these areas that goes in the opposite direction *vis-à-vis* the

[19] The decomposition follows the spirit of that presented in Bernhardt et al. (1995) and Handcock and Morris (1998, 1999), to whom we refer the reader for more details.

national (residual) trend. This pattern is mirrored by what is going on in the upper deciles: a location effect higher than in the rest of the country (especially in the South West) and an accentuated tendency to upper polarization in both regions. For what concerns the North East and the North West, the conflict-stricken areas, had the location effect been the only operating force we would have seen a disproportionate increase of people in these regions occupying the lower national deciles compared to the rest of the country—they basically lagged behind. The increase of polarization in the rest of the country helped to offset this effect, filling the lower deciles of households from other regions too, whereas for the rest of the distribution we observe in practice a generalized decline of the relative position of these regions in the national distribution. Finally, while the North Central improves relative to the rest of the country in lower deciles, the South East comes to show a more articulated pattern of distributional change.

Results for the other covariates (not shown here but available upon request) looked as expected: compared to 2003/04, households with an illiterate head or not having good cooking material, toilet, floor and safe water were all increasingly occupying the lower deciles of the distribution, and the gap in terms of consumption with the rest was increasing. Instead, the relative fraction of households headed by females in the upper deciles of the distribution was rising during the period, whereas male-headed households were moving into the deciles below the median. In spite of the fact that Nigerian society is mainly patriarchal, where men have better access to productive resources than women, the poor seems more among men than women.

5.2 Ghana

5.2.1 Changes in the Ghanaian consumption distribution

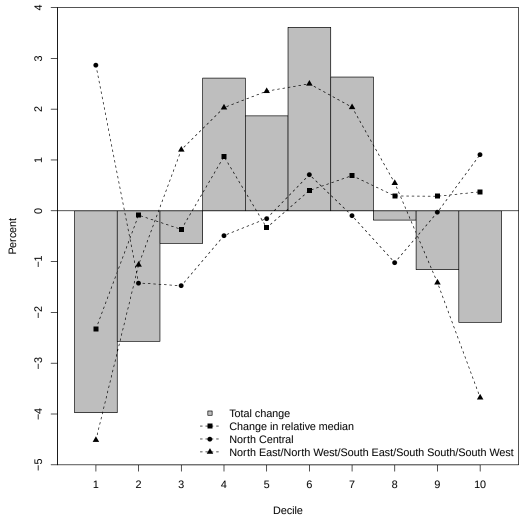
To introduce the results for Ghana, in Figure 6(a) we present two probability density functions of the Ghanaian distribution of total consumption expenditure. The solid line is the distribution of household consumption in 1991/92, taken as the baseline throughout the analysis. The density drawn with the dotted line, which we will treat as the comparison, is the distribution in 2012/13. Examining these two distributions, we see that the reference or 1991/92 distribution has a slight right skewness, while the comparison distribution has a larger median and variance.

The relative density of total consumption expenditure of Ghanaian households between 1991/92 and 2012/13 is examined in Figure 6(b), showing the fraction of households in 2012/13 that fall into each decile of the 1991/92 distribution. The graph offers the immediate impression that the proportion of households in the upper deciles increased dramatically throughout the two decades, while the proportion in the bottom and around the middle declined. Indeed, if we choose any decile between the first and the seventh in the 1991/92 distribution, the fraction of households in 2012/13 whose consumption rank corresponds to the chosen decile is less than the analogous fraction of households in 1991/92.

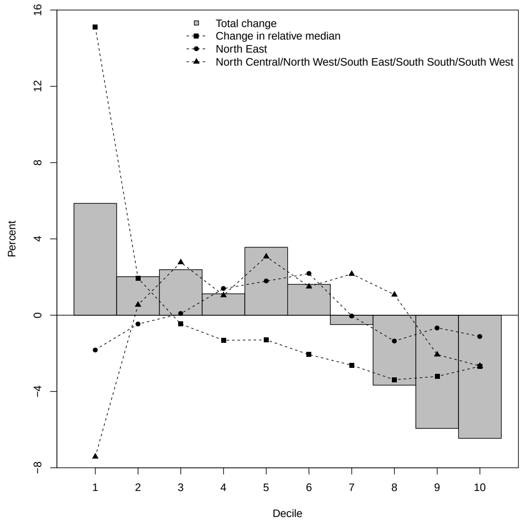
While the display of the relative distribution points to the dominant trend for the entire period, the dominant trend may be masking some of the more subtle changes. To see these, we decompose the relative density into location and shape effects. Figure 6(c) presents the effect only due to the median shift that is the pattern that the relative density would have displayed if there had been no change in distributional shape but only a location shift of the density. The effect of the median shift was quite large. This alone would have virtually eliminated

Figure 5: Sources of distributional change in the 2012/13 to 2003/04 relative distribution of consumption expenditures by zone

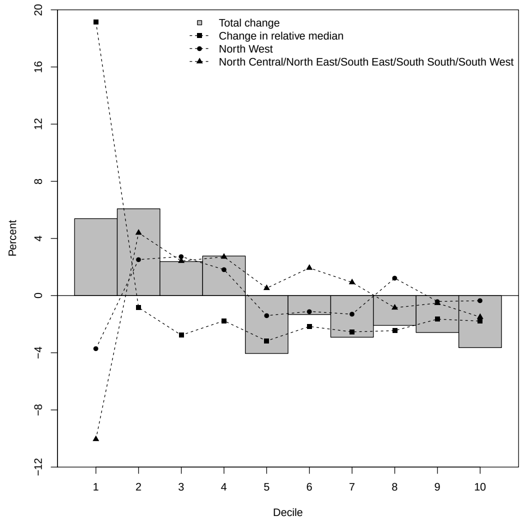
(a) North Central



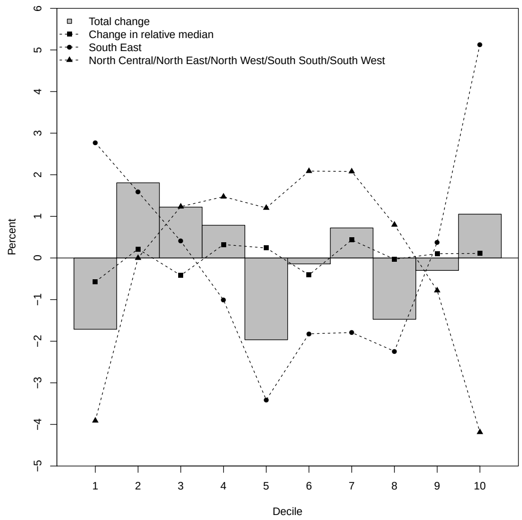
(b) North East



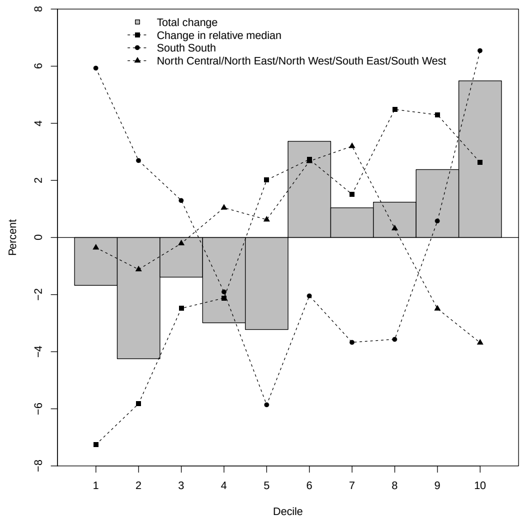
(c) North West



(d) South East



(e) South South



(f) South West

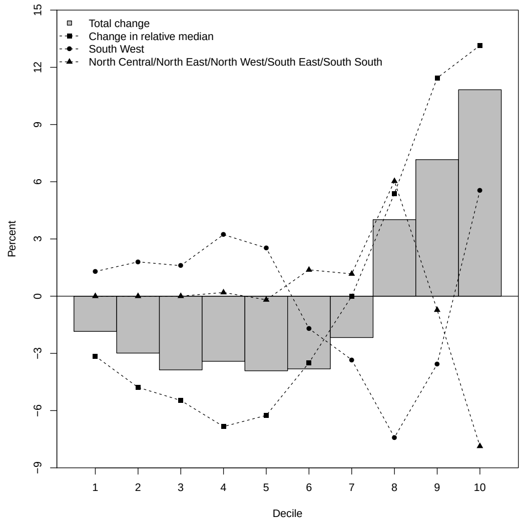
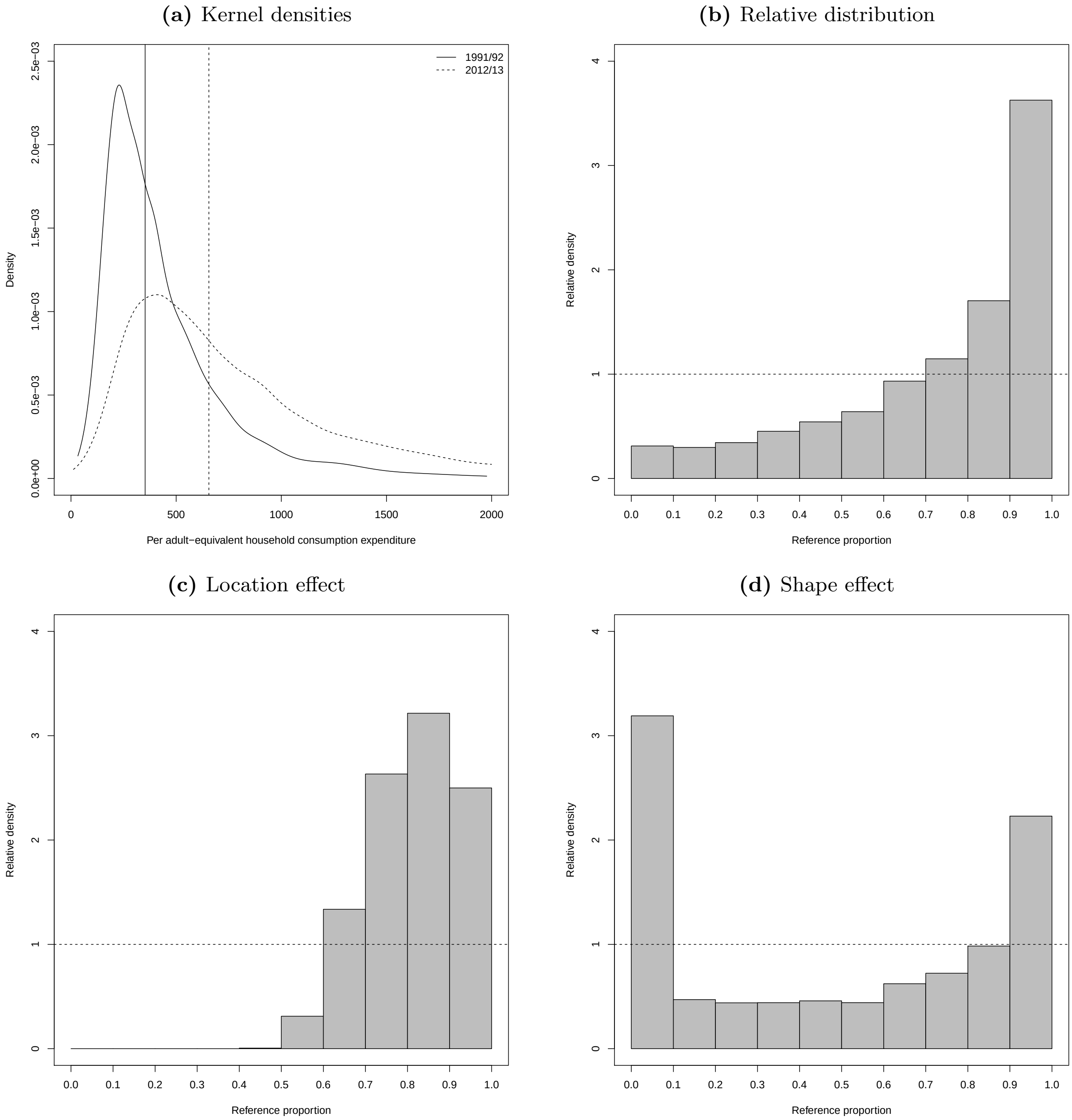


Figure 6: Changes in the Ghanaian household consumption distribution between 1991/92 and 2012/13. Expenditures in the upper tiers of the kernel densities have been truncated for better presentation of the graph, where the vertical lines denote the medians of the two survey waves



the households in the first four deciles of the 1991/92 consumption distribution and placed a considerable fraction of them in the top end of the 2012/13 distribution. Note, however, that neither tail of the observed relative distribution is well reproduced by the median shift. For example, the top decile of Figure 6(c) is about 2.5, below the value of 3.6 observed in the actual data, and the bottom deciles of the same figure are also substantially lower than observed.

These (and other) differences are explained by the shape effect presented in Figure 6(d), which shows the relative density net of the median influence. Without the higher median, the greater dispersion of consumption expenditures would have led to relatively more low-consuming households in 2012/13, and this effect was mainly concentrated in the bottom decile. By contrast, at the top of the distribution the higher spread worked in the same direction of the location shift: operating by itself, it would have increased the share of households in the top decile of the 2012/13 consumption distribution by nearly 120%. In sum, once changes in real median expenditure are netted out, a U-shaped relative density is observed, indicating that polarization was hollowing out the middle of Ghanaian household consumption.

Relative distribution methods permit us to also analyze how re-distribution across households took place over the entire time period. For each wave of the GLSS between 1991/92 and 2012/13, Figure 7 shows the shape effect of the household consumption relative density using 1991/92 as the reference sample.[20] Following the plot through each successive wave, one is offered with the immediate impression that the fraction of households at both the top and bottom tails of the Ghanaian consumption distribution increased consistently over the course of the last two decades, while the fraction in the middle declined. Polarization, or the "hollowing out of the middle", has been therefore the consistent trend in distributional inequality for all the GLSS waves since 1991/92. Because this period was also characterized by a sizable shift in location, viewed together these results indicate that, in the course of the upswing in consumption expenditures, some households fell behind, while others shifted toward the top, joining the ranks of those whose consumption put them in the top decile in 1991/92.

To summarize these changes, we present in Figure 8 the set of relative polarization indices computed from the GLSS data.[21] These indices track changes in the shape of the distribution only, and they code the direction as well as the magnitude of the change. The overall index (MRP) rises continuously and the rise is statistically significant from the outset, thus confirming the visual impression from Figure 6(d). Decomposing the MRP into the contributions from the lower and upper tails of the distribution, it also appears that "downgrading" dominated "upgrading" in the polarization upswing—the value of the LRP is indeed always greater than that of the URP.

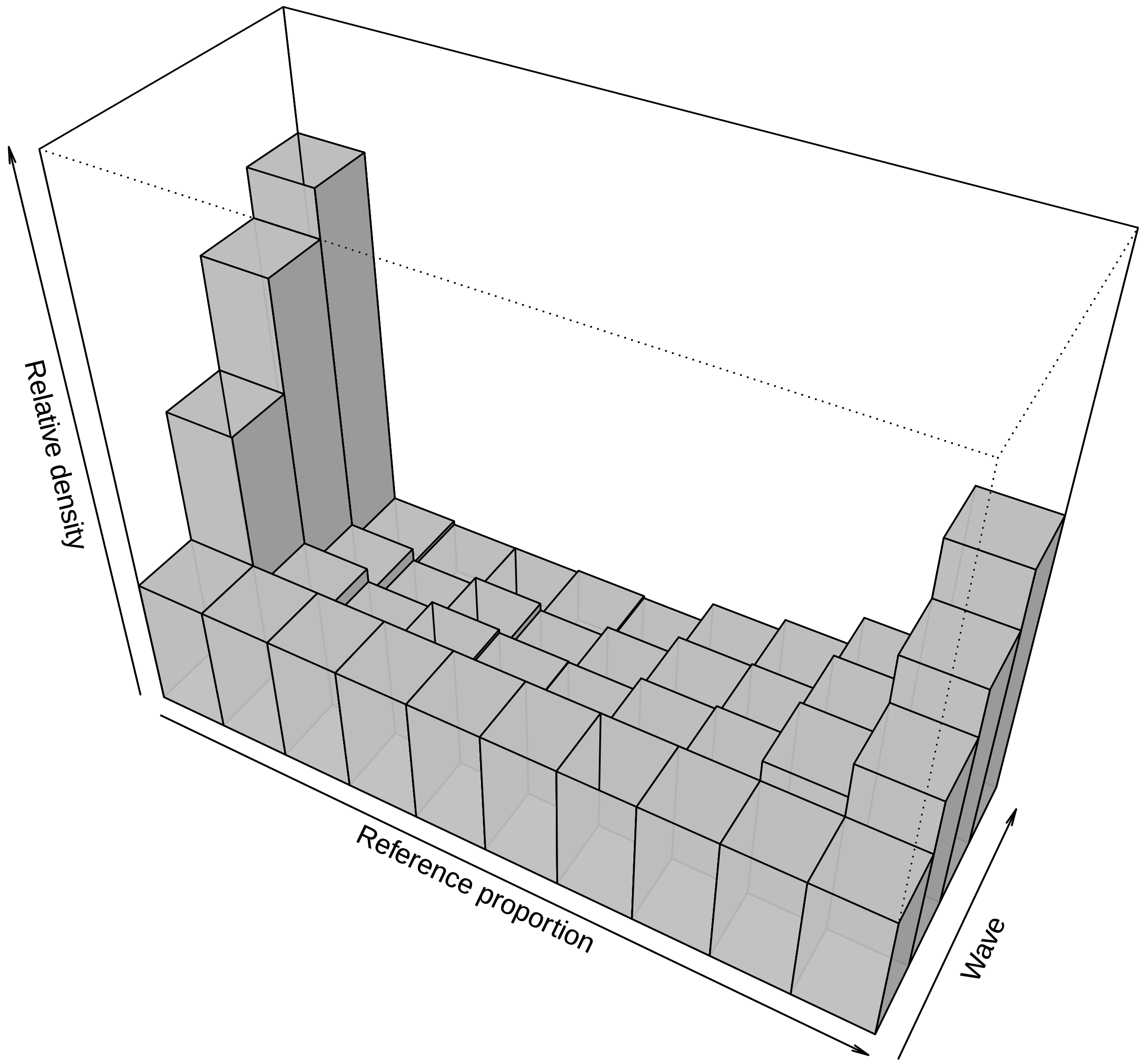
5.2.2 Temporal decomposition

To get a more compact picture of the timing and nature of the polarization trend described above, we can break the 21-year period into 3 sub-periods—1991–98, 1998–2005, and 2005–12—and highlight the changes that took place within each of them. The top three panels of Figure 9 show the relative distribution for each sub-period. In contrast to the 21-year decile series, which takes 1991/92 as the reference distribution for all waves, each panel here takes the beginning year of the sub-period for the reference distribution and the end year for the comparison. The displays clearly point to the median up-shift in household consumption expenditure as the dominant trend for each sub-period. These are the images of a "rising tide that lifts all boats", i.e. the effect of a location shift that was the most influential contributor to the overall pattern during all sub-periods. The differences due to the median shift—representing what the relative density would have looked like if there had been no change in distributional shape—are plotted in the middle row panels of Figure 9. As expected, the strongest effects were in the bottom deciles, confirming

[20] The relative distribution, and therefore its shape effect, is by definition flat in the reference year (Morris et al., 1994, p. 211).

[21] Since the value of the three indices always equals 0 in the baseline year (Morris et al., 1994, p. 209), polarization summaries for 1991/92 were not included in the graphical display.

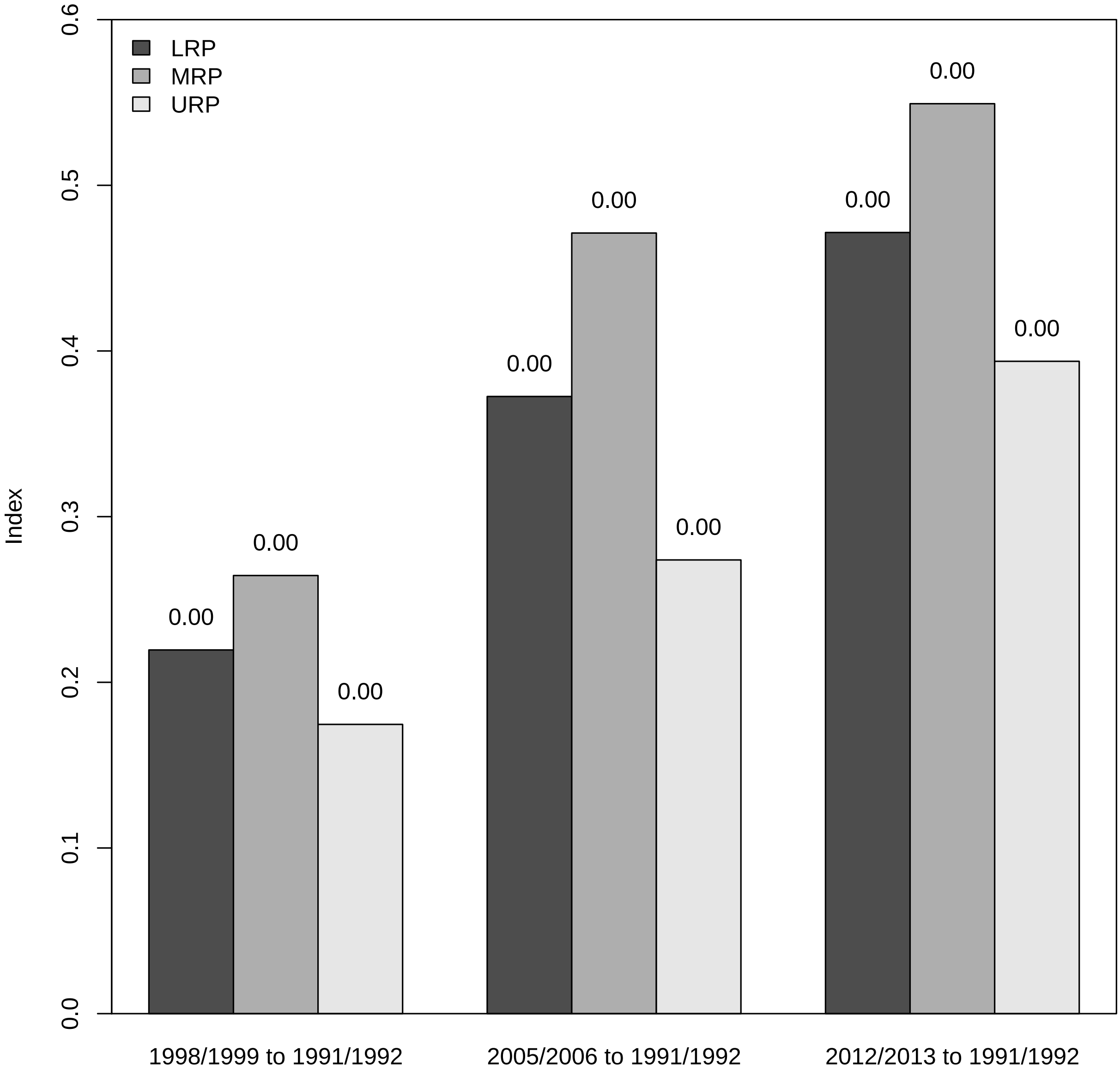
Figure 7: Median-adjusted relative consumption distribution series for Ghana, 1991/92 to 2012/13



that more low-consuming households joined the ranks of those whose consumption levels put them in the top half of the reference distributions. However, once changes in location are netted out, there is also an indication of growing polarization that is not evident in the overall relative distributions. The differences explained by the shape changes are presented in the bottom row panels of Figure 9, where the median-adjusted relative distributions take an approximate U-shape. Strong growth occurred in the fraction of households at the top and bottom tails of the period-specific consumption distributions, while sizable declines occurred in the middle. This polarizing trend seems nearly symmetric for the years 2005 to 2012, while throughout the 1990s and up to the mid-2000s the growth in the lower tail of the distribution was noticeably stronger than in the upper tail.

The relative polarization indices, shown in Table 8, capture these changes well. The MRP index is always positive and statistically significant (p-value $= 0.00$). Decomposing the MRP into the contributions to distributional change made by the segments of the distribution above and

Figure 8: Relative polarization indices by wave. The number above each bar indicates the p-value for the null hypothesis that the index equals 0.



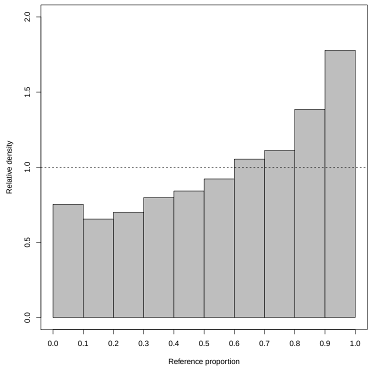
below the median, it appears that "downgrading" dominated "upgrading" in the polarization upswing over the course of the first two sub-periods: the value of the lower relative polarization index (LRP) is indeed greater than that of the upper relative polarization index (URP)—0.26 vs. 0.17 and 0.27 vs. 0.11, respectively—which is consistent with the visual impression from the shape shifts above. The values of the indices in the 2005–12 period denote instead a nearly perfectly symmetric polarization in each tail.

5.2.3 The drivers of growing polarization in Ghanaian household consumption

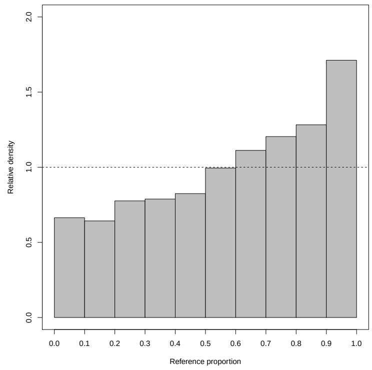
The presentation of polarization results over the three sub-periods requires a considerable amount of space. For the sake of brevity, we chose to present only part of the results and made an effort to present the main findings in an abridged format. For example, we decided not to comment on the econometric results of the unconditional quantile regression, and to place the location effect

Figure 9: Location and shape decomposition of the relative consumption distribution for Ghana by sub-periods. The top row shows the overall change by sub-period, the middle shows the effect of the median shift (the shape-adjusted relative distribution), and the bottom shows the effect of the shape changes (the median-adjusted relative distribution)

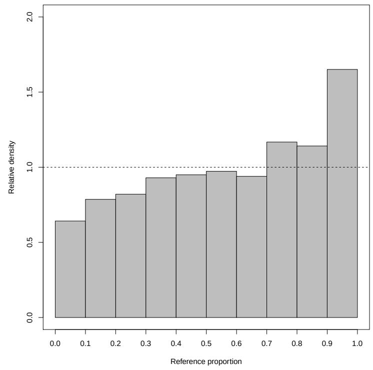
(a) 1998/99 to 1991/92



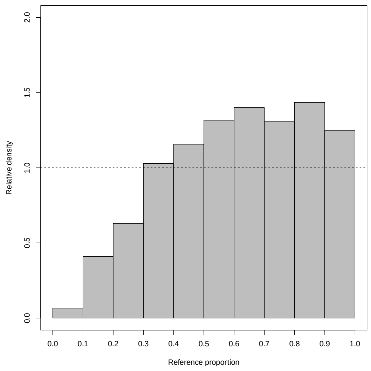
(b) 2005/06 to 1991/92



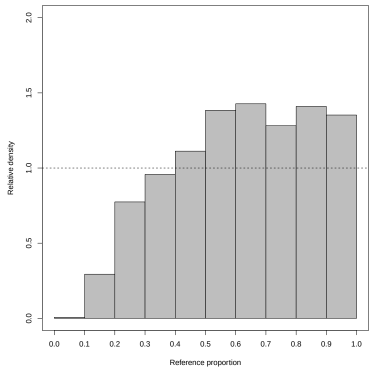
(c) 2012/13 to 2005/06



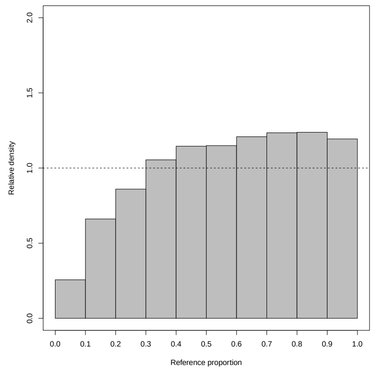
(d) 1998/99 to 1991/92



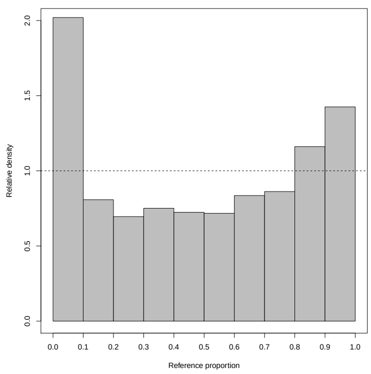
(e) 2005/06 to 1991/92



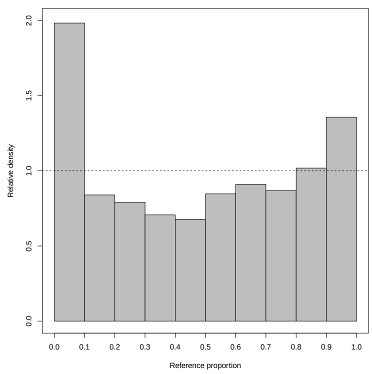
(f) 2012/13 to 2005/06



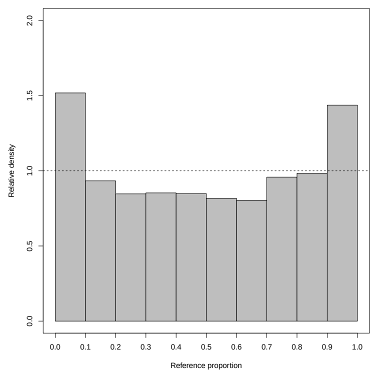
(g) 1998/99 to 1991/92



(h) 2005/06 to 1991/92



(i) 2012/13 to 2005/06



decomposition graphs in Appendix B, and, regarding the polarization decomposition results, to focus our attention only on the top percentiles results (top two and bottom two).

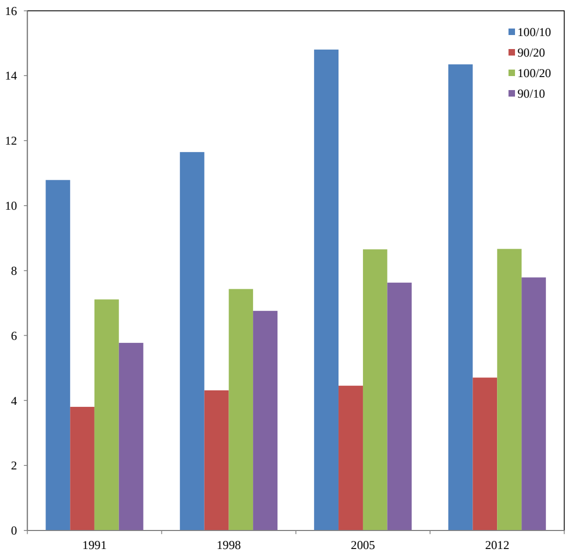
Overall this is not a big limitation since, as shown in panels (a) and (b) of Figure 10, the inter-quantile analysis has detected a significant variation in the percentiles cut-offs (between deciles inequality, measured by interquartile ratios) primarily among these deciles and a very limited one among the rest of the distribution. Furthermore, the other component of polarization, the so-called "identification" (measured by deciles' coefficient of variation, CV) tended to be more accentuated in these deciles rather in the central ones. Looking at sub-periods, it clearly emerges

Table 8: Relative polarization indices by sub-periods, 1991/92 to 2012/13

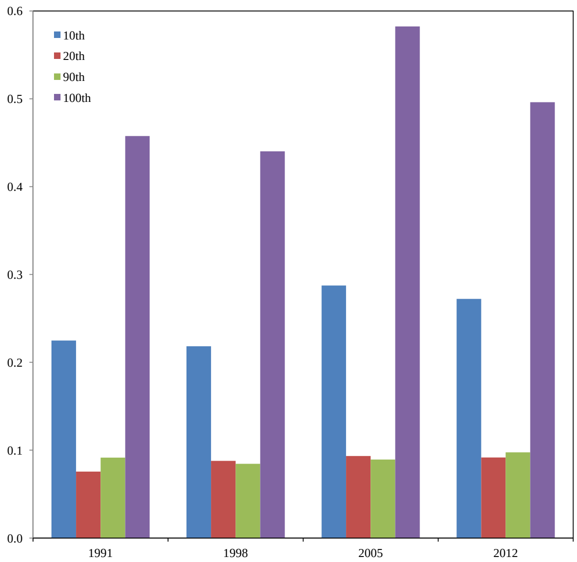
	Index	*p*-value
1998/99 to 1991/92		
MRP	0.22	0.00
LRP	0.26	0.00
URP	0.17	0.00
2005/06 to 1998/99		
MRP	0.19	0.00
LRP	0.27	0.00
URP	0.11	0.00
2012/13 to 2005/06		
MRP	0.14	0.00
LRP	0.14	0.00
URP	0.14	0.00

Figure 10: Inter-decile ratio by year, using counter-factual distributions, and coefficient of variation, by year and decile

(a) Inter-decile ratio



(b) Coefficient of variation



that, in 1991–98 and 2005–12, the between component was compensated by a high identification component, thus neutralizing the modification of inequality; differently, in the sub-period 2005–08 it appears both a sustained growth of between component and an important reduction of identification component (growth of CV) specially for what concern the 10^{th} and 90^{th} percentiles.

Table 9 compares the counter-factual cut-off points (labelled with "c")—the cut-offs of the reference distribution augmented with the location effect between the two sub-periods—with the cut-offs of the comparison distribution. In all three sub-periods, the cut-offs of the bottom percentiles of the comparison distribution are significantly lower than those of the reference, indicating, as we discussed in previous section, lower relative polarization, whereas for the top percentiles the opposite holds: the comparison distribution cut-offs are higher than the reference ones, indicating upper relative polarization.

The Oaxaca-Blinder (OB) methodology (Oaxaca, 1973; Blinder, 1973) decomposes the dif-

Table 9: Counterfactual reference cut-offs vs. comparison cut-offs: by deciles and sub-periods

Decile	1991c	1998	1998c	2005	2005c	2012
1st	248.74	181.03	302.43	216.83	312.99	258.36
2nd	296.69	246.72	368.12	304.00	400.17	357.47
8th	704.60	803.14	924.54	1,011.40	1,107.56	1,242.97
9th	940.64	1,084.86	1,206.26	1,377.14	1,473.31	1,738.20

Source: authors' own calculation using GLSS data sets.

ference between cut-offs into that part that is due to group differences in the magnitudes of the determinants (endowments effect) of consumption, on the one hand, and group differences in the effects of these determinants (coefficients effect), on the other. Coefficient and endowment variations are aggregated by groups of variables: primary, secondary and tertiary education are grouped into the education attainment group, private, public and self- employment of household head are grouped into employment category, the infrastructure index captures the access to basic services,[22] urbanization and residence in regions other than Upper East (urban and regional dummies having as baseline Upper East) and household structure (household size and all other household characteristics). The interaction term and the constant are also included so that the sum of all decomposition elements adds up to the total differences between cut-offs. Below any decomposition graph, we present a table summarizing the main variable trends for upper and lower polarization.

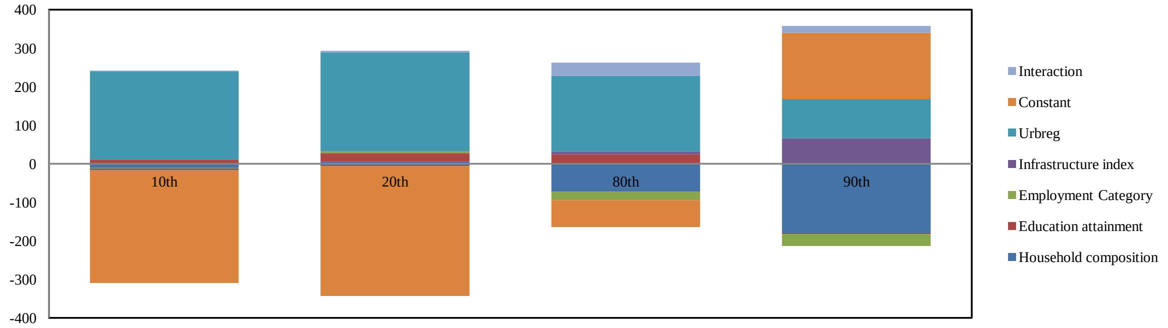
Recalling previous section results regarding 1991–98 sub-period, the polarization increased as testified by the shifts leftward and rightward of the lower and upper cut-offs, respectively. The polarization decomposition shows how the combined effect of household composition, infrastructure index and the constant increased the lower polarization while location effects and education tended to reduce the effect. On the upper deciles nearly the same variables played a pro-polarization role (Figure 11). Between 1991 and 1998 growth concentrated in urban areas and in few regions on the Coast or in the immediate inland (Ashanti region) among households with relatively higher levels of education and with access to a number of basic infrastructures. This group of households occupying the top two deciles of the distribution distances itself from the rest of other groups determining an increase in the upper polarization.

The 1998–2005 sub-period sees polarization growing. In this decade, Ghana experienced a boom in cocoa production and exports. The cocoa boom generated, in the western and coastal areas, a high demand for the workforce, but also for capital and infrastructure, and the skills of the workforce and the rise in revenues even at lower levels translated into a higher demand for capital, infrastructure and skills (Molini and Paci, 2015). These resources were relatively scarce, and the price effect and variation in returns was, thus, substantial. In these areas, the cocoa boom had a positive impact on poverty, but did not benefit everybody equally.

The drivers of polarization, both upper and lower, were very similar (Figure 12). Household characteristics, educational attainment and basic infrastructures all tended to have pro-inequality outcome and increased the tails size of the 2005 distribution, indeed more polarization. It is worth

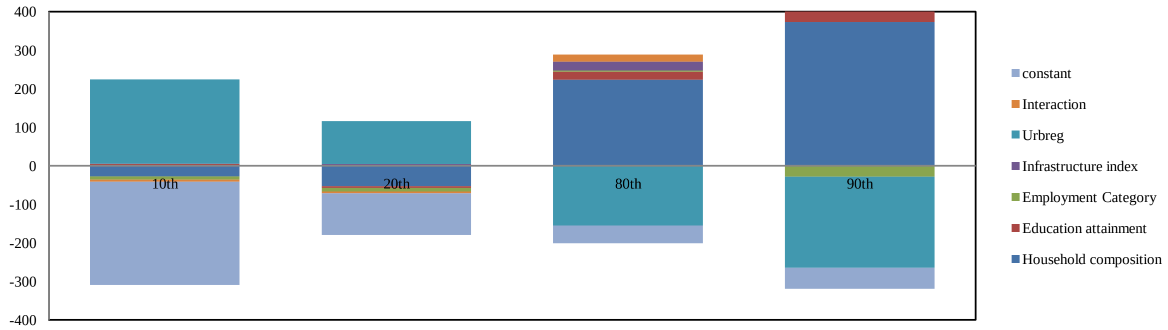
[22] The infrastructure index is obtained by combining four variables through principal component analysis: access to protected water, access to electricity, access to protected sanitation, and access to safe sources of cooking.

Figure 11: Blinder-Oaxaca type decompositions, 1991–98



Total	Lower polarization	Upper polarization
Urbreg	---	+++
Infrastructure	+	+
Education	--	++
Employment	-	-
Household	+	----
Constant	++++	++

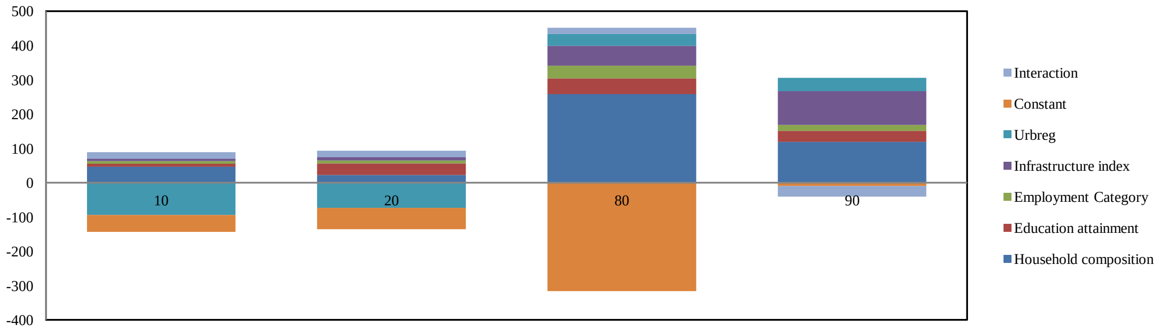
Figure 12: Blinder-Oaxaca type decompositions, 1998–2005



Total	Lower polarization	Upper polarization
Urbreg	---	---
Infrastructure	+	+
Education	++	++
Employment	+	-
Household	++	++++
Constant	+	+

noting the particular importance of changes in the household structure in explaining the upper polarization. Top deciles were particularly benefitting from the demographic dividend stemming from smaller families and lower dependency ratios. The only set of variables that countered this increase were the location/urban ones. The cocoa boom and the relatively good performance of many rural areas in the Central and Coastal part of the country such as Ashanti, Volta, Eastern, Western and Central region (Molini and Paci, 2015) explains this positive distributional impact.

Figure 13: Blinder-Oaxaca type decompositions, 2005–12



Total	**Lower polarization**	**Upper polarization**
Urbreg	++++	++
Infrastructure	-	+++
Education	-	++
Employment	-	++
Household	--	++++
Constant	++	---

Finally, between 2005 and 2012, the upper polarization substantially stagnates. Compared to the previous sub-period, the distributional changes of this sub-period are driven by a positive variation in endowments and stagnation in the returns on covariates (see Appendix B). This seems to suggest that the high returns obtained in the previous period encouraged households to invest in assets and human capital. This clearly reduced their scarcity, but, at the same time, returns massively declined. The greater availability of people in the non-farm sector who had low levels of educational attainment (typically primary school) determined a clear decline in their relative returns (Molini and Paci, 2015).

Differently from the previous period, urban and regional variables drive polarization (Figure 13). Households residing in Greater Accra and the urban areas of Ashanti region performed well and increased their relative economic advantage over the rest of the country. Interestingly, the drivers of upper polarization are very similar to those playing a role in the 1991–98 sub-period. In addition to the urban and regional variables, the infrastructure index, the employment variables and education had a strong impact on polarization. As for 1998–2005, the variations in household composition benefits the top percentiles and contributes significantly to the increase of polarization.

6 Summary and conclusions

The topic of the increasing gap between the richest and the poorest is gaining momentum thanks, in particular, to the large attention that has been obtained in recent research on world inequalities (see e.g. Stiglitz, 2012, 2015, Piketty, 2014, and Atkinson, 2015, inter alia). The overall idea that emerges is that in the last 20/30 years both developing and developed countries went through dramatic distributional changes that increased disparities.

Specifically with regard to Sub-Saharan Africa, there have been two different narratives in the last two decades. The first paints a picture of an emerging continent where middle classes are expanding and prosperity is reaching large swaths of the population (African Development Bank, 2011; Fine et al., 2012). The other narrative acknowledges the relatively robust growth in the past two decades, but points to slow reduction in poverty. According to this second narrative, the lack of faster reduction in poverty may be due, in part, to increasing disparities.

Nigeria, the most populous country in the African continent, has been enjoying a stable and sustained growth for over a decade since 2003. Yet despite this, the outcomes in terms of poverty reduction have not been satisfactory: while poverty seems to have declined in the coastal South and around the Federal Capital, Abuja, a large belt of North-Eastern states have experienced a clear stagnation in poverty reduction.

Over the last decade, Nigeria has also been going through significant changes in the distribution of economic resources that generated mainly, but not exclusively, an increase in polarization. In income-polarized societies people cluster around group means and tend to be far from the mean/median of the overall distribution, which results in the inability of the middle class to consolidate its position. This has several economic consequences for a country, but may also be the underlying cause of growing political instability seen in recent years in many middle income countries.

Studies of polarization in Nigeria are few and have tackled the topic with a narrow lense. This paper contributes to our understanding of polarization in Nigeria by using an approach that improves upon previous studies in several ways. First, it considers a longer time horizon—close to a decade—which allows for major changes in welfare distributions to emerge. Second, it tackles a major deficiency—lack of comparability of the available data in Nigeria—by making use of survey-to-survey estimation techniques (Elbers et al., 2003) to achieve comparability of the distributions of interest. Finally, and most importantly, it employs the "relative distribution" approach Handcock and Morris (1998, 1999) to analyze changes in the Nigerian household consumption distribution in the considered period. The novelty of this method consists in providing a non-parametric framework for taking into account all of the distributional differences that could arise in the comparison of distributions over time and space. In this way, we are able to summarize multiple features of the expenditure distribution that would not be detected easily from a comparison of standard measures of inequality and polarization.

The analysis reveals significant changes in the consumption distribution. We find a clear rise in polarization, meaning that the distributional movements observed between 2003/04 and 2012/13 hollowed out the middle of the Nigerian household consumption distribution and increased concentration of the mass toward higher and lower deciles.

This pattern of distributional change, however, is not entirely homogeneous within the country, but varies from zone to zone. Through covariates analysis, controlling for spatial characteristics of household head, we show that in the South (South-West and South-South) lower deciles tend to be emptied relative to the rest of the country, confirming the tendency for households from these zones to contribute to upper polarization. In the North-West and in the conflict-stricken North-East, we see the opposite. The overall impact was a generalized hollowing out of the center and a further accentuation of the North-South divide already characterizing the country.

Understanding the political and economic consequences of these sharp distributional changes is beyond the scope of this paper. However, polarization is increasingly becoming a concern in many developing countries. Recent episodes in Brazil, Egypt and Turkey suggest the existence of a link between polarization and conflict, yet so far no relevant empirical evidence has been produced to underpin the existing theoretical models (Esteban and Schneider, 2008). Nigeria is clearly an ideal candidate for such analysis, and our future research will be directed in understanding how existing conflicts in Nigerian society can be interpreted and linked to the patterns of polarization.

The case of Ghana also presents interesting specificities. Since 1991, poverty had declined very fast, inequality has not increased dramatically and yet the country has seen a rapid surge in polarization. The relative distribution analysis suggest that the distributional changes hollowed out the middle of the Ghanaian household consumption distribution and increased the concentration of households around the highest and lowest deciles.

Using a novel methodology to identify the drivers of distributional changes and quantify their impact on the welfare distribution, our results indicate that, although there is some heterogeneity across the various sub-periods in particular in terms of magnitude, household characteristics, educational attainment and access to basic infrastructures all tended to increase over time the size of the upper and lower tails of the consumption distribution and as a consequence the degree of polarization. Urban/rural and regional variables started to have a strong impact on polarization only in the last decade; households residing in Greater Accra and the urban areas of Ashanti region performed well and increased their relative economic advantage over the rest of the country.

From a policy perspective, the pro-polarization impact of variables that tend to change slowly over time is of particular concern. It is very unlikely that policy makers can find a quick fix to the problem and any intervention will produce results only in the long run. This implies that the country needs to start now to develop a strategy that, if not able to immediately reverse polarization, at least can mitigate its impact. The creation of a modern social protection system, the expansion in the access to basic services, the continued effort to expand primary and secondary education are all interventions that can pay off and help the country to maintain its social cohesion.

References

African Development Bank. *Annual Report*. Statistics Department of the African Development Bank Group, 2011. Available at http://www.afdb.org/knowledge/publications/annual-report/annual-report-2011/.

F. C. Ahmed, C. Dorji, S. Takamatsu, and N. Yoshida. *Hybrid Survey to Improve the Reliability of Poverty Statistics in a Cost-Effective Manner*. Policy Research Working Paper 6909, World Bank Group, Washington, DC, 2014. Available at http://documents.worldbank.org/curated/en/2014/06/19641283/hybrid-survey-improve-reliability-poverty-statistics-cost-effective-manner.

B. E. Aigbokhan. *Poverty, Growth and Inequality in Nigeria: A Case Study*. AERC Research Paper 102, African Economic Research Consortium, Nairobi, 2000. Available at http://www.aercafrica.org/index.php/publications/view_document/112-poverty-growth-and-inequality-in-nigeria-a-case-study.

A. S. Alderson and K. Doran. Global Inequality, Within-Nation Inequality, and the Changing Distribution of Income in Seven Transitional and Middle-Income Societies. In C. Suter, editor, *Inequality Beyond Globalization: Economic Changes, Social Transformations, and the Dynamics of Inequality*, pages 183–200. Transaction Publishers, New Brunswick, NJ, 2011.

A. S. Alderson and K. Doran. How Has Income Inequality Grown? The Reshaping of the Income Distribution in LIS Countries. In J. C. Gornick and M. Jäntti, editors, *Income Inequality: Economic Disparities and the Middle Class in Affluent Countries*, pages 51–74. Stanford University Press, Stanford, CA, 2013.

A. S. Alderson, J. Beckfield, and F. Nielsen. Exactly How Has Income Inequality Changed? Patterns of Distributional Change in Core Societies. *International Journal of Comparative Sociology*, 46:405–423, 2005.

F. Alvaredo and T. Piketty. The Dynamics of Income Concentration in Developed and Developing Countries: A View from the Top. In L. F. López-Calva and N. Lustig, editors, *Declining Inequality in Latin America: A Decade of Progress?*, pages 72–99. Brookings Institution Press, Baltimore, MD, 2010.

G. Anderson, O. Linton, and T. W. Leo. A Polarization-Cohesion Perspective on Cross-Country Convergence. *Journal of Economic Growth*, 17:49–69, 2012.

A. Araar. *On the Decomposition of Polarization Indices: Illustrations with Chinese and Nigerian Household Surveys*. Working Paper 08-06, Centre Interuniversitaire sur le Risque, les Politiques Économiques et l'Emploi (CIRPÉE), Montréal, 2008. Available at http://www.cirpee.org/fileadmin/documents/Cahiers_2008/CIRPEE08-06.pdf.

A. B. Atkinson. *Inequality: What Can Be Done?* Harvard University Press, Cambridge, MA, 2015.

T. T. Awoyemi and A. Araar. *Explaining Polarization and its Dimensions in Nigeria: A DER Decomposition Approach*. Paper prepared for the 14$^{\text{nd}}$ Annual Conference on Econometric Modelling for Africa, Abuja, Nigeria, July 8–10, 2009. Available at http://www.africametrics.org/documents/conference09/papers/Awoyemi_Araar.pdf.

T. T. Awoyemi, I. B. Oluwatayo, and A. Oluwakemi. *Inequality, Polarization and Poverty in Nigeria*. Working Paper 2010-04, Partnership for Economic Policy (PEP), Nairobi, 2010. Available at http://www.pep-net.org/communications/working-papers/.

P. Backiny-Yetna, D. Steele, and I. Y. Djima. *The Impact of Household Food Consumption Data Collection Methods on Poverty and Inequality Measures in Niger*. Policy Research Working Paper 7090, World Bank Gorup, Washington, DC, 2014. Available at http://documents.worldbank.org/curated/en/2014/11/20353374/impact-household-food-consumption-data-collection-methods-poverty-inequality-measures-niger.

K. Beegle, J. De Weerdt, J. Friedman, and J. Gibson. *Methods of Household Consumption Measurement through Surveys: Experimental Results from Tanzania*. Policy Research Working Paper 5501, World Bank Group, Washington, DC, 2010. Available at http://documents.worldbank.org/curated/en/2010/12/13233228/methods-household-consumption-measurement-through-surveys-experimental-results-tanzania.

A. Bernhardt, M. Morris, and M. S. Handcock. Women's Gains or Mens Losses? A Closer Look at the Shrinking Gender Gap in Earnings. *American Journal of Sociology*, 101:302–328, 1995.

M. Bianchi. Testing for Convergence: Evidence from Nonparametric Multimodality Tests. *Journal of Applied Econometrics*, 12:393–409, 1997.

N. Birdsall. *The (Indispensable) Middle Class in Developing Countries; or, the Rich and the Rest, Not the Poor and the Rest*. Working Paper 207, Center for Global Development, Washington, DC, 2010. Available at http://www.cgdev.org/files/1423994_file_Birdsall_Indispensable_Middle_FINAL.pdf.

A. Blinder. Wage Discrimination: Reduced Forms and Structural Estimates. *The Journal of Human Resources*, 8:436–455, 1973.

F. Borraz, N. González, and M. Rossi. Polarization and the Middle Class in Uruguay. *Latin American Journal of Economics*, 50:289–326, 2013.

F. Bourguignon. The Growth Elasticity of Poverty Reduction: Explaining Heterogeneity across Countries and Time Periods. In T. S. Eicher and S. J. Turnovsky, editors, *Inequality and Growth: Theory and Policy Implications*, pages 3–26. The MIT Press, Cambridge, MA, 2003.

F. Bourguignon. *The Poverty-Growth-Inequality Triangle*. Working Paper 125, Indian Council for Research on International Economic Relations, New Delhi, 2004. Available at http://www.icrier.org/pdf/wp125.pdf.

S. R. Chakravarty. *Inequality, Polarization and Poverty: Advances in Distributional Analysis*. Springer-Verlag Inc., New York, NY, 2009.

S. R. Chakravarty. *Inequality, Polarization and Conflict: An Analytical Study*. Springer-Verlag Inc., New York, NY, 2015.

S. R. Chakravarty and C. D'Ambrosio. Polarization Orderings of Income Distributions. *Review of Income and Wealth*, 56:47–64, 2010.

S. R. Chakravarty and A. Majumder. Inequality, Polarization and Welfare: Theory and Applications. *Australian Economic Papers*, 40:1–13, 2001.

S. R. Chakravarty, A. Majumder, and S. Roy. A Treatment of Absolute Indices of Polarization. *Japanese Economic Review*, 58:273–293, 2007.

F. Clementi and F. Schettino. Income Polarization in Brazil, 2001–2011: A Distributional Analysis Using PNAD Data. *Economics Bulletin*, 33:1796–1815, 2013.

F. Clementi and F. Schettino. Declining Inequality in Brazil in the 2000s: What is Hidden Behind? *Journal of International Development*, 27:929–952, 2015.

F. Clementi, A. L. Dabalen, V. Molini, and F. Schettino. *The Centre Cannot Hold: Patterns of Polarization in Nigeria*. WIDER Working Paper 149, World Institute for Development Economic Research, United Nations University, Helsinki, 2014. Available at http://www.wider.unu.edu/publications/working-papers/2014/en_GB/wp2014-149/.

F. Clementi, A. L. Dabalen, V. Molini, and F. Schettino. When the Centre Cannot Hold: Patterns of Polarization in Nigeria. *Review of Income and Wealth*, doi:10.1111/roiw.12212, 2015.

F. Clementi, V. Molini, and F. Schettino. *All That Glitters is Not Gold: Polarization Amid Poverty Reduction in Ghana*. Policy Research Working Paper 7758, World Bank Group, Washington DC, 2016. Available at http://documents.worldbank.org/curated/en/2016/07/26585411/all-glitters-not-gold-polarization-amid-poverty-reduction-ghana.

P. L. Conti, M. G. Pittau, and R. Zelli. Metodi non parametrici nell'analisi della distribuzione del reddito: problemi empirici ed aspetti metodologici. *Rivista di Politica Economica*, 96: 195–242, 2006.

F. A. Cowell, S. P. Jenkins, and J. A. Litchfield. The Changing Shape of the UK Income Distribution: Kernel Density Estimates. In J. Hills, editor, *New Equalities: The Changing Distribution of Income and Wealth in the United Kingdom*, pages 49–75. Cambridge University Press, Cambridge, UK, 1996.

C. D'Ambrosio. Household Characteristics and the Distribution of Income in Italy: An Application of Social Distance Measures. *Review of Income and Wealth*, 47:43–64, 2001.

A. Deaton and J. Dréze. Poverty and Inequality in India: A Re-examination. *Economic and Political Weekly*, 37:3729–3748, 2002.

A. Deaton and M. Grosh. Consumption. In M. Grosh and P. Glewwe, editors, *Designing Household Survey Questionnaires for Developing Countries: Lessons from 15 Years of the Living*

Standards Measurement Study, volume 1, pages 91–133. Oxford University Press, Oxford, UK, 2000.

A. Deaton and V. Kozel. Data and Dogma: The Great Indian Poverty Debate. *World Bank Research Observer*, 20:177–199, 2005.

A. Deaton and S. Zaidi. *Guidelines for Constructing Consumption Aggregates for Welfare Analysis*. LSMS Working Paper 135, Worl Bank, Washington, DC, 2002. Available at https://openknowledge.worldbank.org/handle/10986/14101.

J. Deutsch, A. Fusco, and J. Silber. The BIP Trilogy (Bipolarization, Inequality and Polarization): One Saga but Three Different Stories. *Economics: The Open-Access, Open-Assessment E-Journal*, 7:1–33, 2013.

M. Douidich, A. Ezzrari, R. Van der Weide, and P. Verme. Estimating Quarterly Poverty Rates Using Labor Force Surveys: A Primer. *World Bank Economic Review*, doi:10.1093/wber/lhv062, 2015.

J.-Y. Duclos, J.-M. Esteban, and D. Ray. Polarization: Concepts, Measurement, Estimation. *Econometrica*, 72:1737–1772, 2004.

W. Easterly. The Middle Class Consensus and Economic Development. *Journal of Economic Growth*, 6:317–335, 2001.

C. Elbers, J. O. Lanjouw, and P. Lanjouw. Micro-Level Estimation of Poverty and Inequality. *Econometrica*, 71:355–364, 2003.

B. Essama-Nssah and P. J. Lambert. Influence Functions for Policy Impact Analysis. In J. A. Bishop and R. Salas, editors, *Inequality, Mobility and Segregation: Essays in Honor of Jacques Silber*, volume 20 of *Research on Economic Inequality*, pages 135–159. Emerald Group Publishing Limited, Bingley, UK, 2012.

J.-M. Esteban and D. Ray. On the Measurement of Polarization. *Econometrica*, 62:819–851, 1994.

J.-M. Esteban and D. Ray. Conflict and Distribution. *Journal of Economic Theory*, 87:379–415, 1999.

J.-M. Esteban and D. Ray. Polarization, Fractionalization and Conflict. *Journal of Peace Research*, 45:163–182, 2008.

J.-M. Esteban and D. Ray. Linking Conflict to Inequality and Polarization. *The American Economic Review*, 101:1345–1374, 2011.

J.-M. Esteban and G. Schneider. Polarization and Conflict: Theoretical and Empirical Issues: Introduction. *Journal of Peace Research*, 45:131–141, 2008.

J.-M. Esteban, C. Gradín, and D. Ray. An Extension of a Measure of Polarization, with an Application to the Income Distribution of Five OECD Countries. *Journal of Economic Inequality*, 5:1–19, 2007.

F. H. G. Ferreira, J. Gignoux, and M. Aran. Measuring Inequality of Opportunity with Imperfect Data: The Case of Turkey. *Journal of Economic Inequality*, 9:651–680, 2011.

D. Fine, A. van Wamelen, S. Lund, A. Cabral, M. Taoufiki, N. Dörr, A. Leke, C. Roxburgh, J. Schubert, and P. Cook. *Africa at Work: Job Creation and Inclusive Growth*. Report, McKinsey Global Institute, Washington, DC, 2012. Available at http://www.mckinsey.com/insights/africa/africa_at_work.

S. Firpo, M. Fortin, and T. Lemieux. Unconditional Quantile Regressions. *Econometrica*, 77: 953–973, 2009.

N. Fortin, T. Lemieux, and S. Firpo. Decomposition Methods in Economics. In O. Ashenfelter and D. Card, editors, *Handbook of Labor Economics*, volume 4A, chapter 1, pages 1–102. North Holland, Amsterdam, 2011.

J. E. Foster and M. C. Wolfson. *Polarization and the Decline of the Middle Class: Canada and the US*. OPHI Working Paper 31, University of Oxford, Oxford, 1992. Available at http://www.ophi.org.uk/working-paper-number-31/, now in *Journal of Economic Inequality*, 8:247–273, 2010.

C. Gigliarano and K. Mosler. Constructing Indices of Multivariate Polarization. *Journal of Economic Inequality*, 7:435–460, 2009.

C. Gradín. Polarization by Sub-Populations in Spain, 1973–91. *Review of Income and Wealth*, 46:457–474, 2000.

M. S. Handcock. *Relative Distribution Methods*. Los Angeles, CA, 2015. Version 1.6-4. Project home page at http://www.stat.ucla.edu/~handcock/RelDist.

M. S. Handcock and M. Morris. Relative Distribution Methods. *Sociological Methodology*, 28: 53–97, 1998.

M. S. Handcock and M. Morris. *Relative Distribution Methods in the Social Sciences*. Springer-Verlag Inc., New York, NY, 1999.

L. Hao and D. Q. Naiman. *Assessing Inequality*. SAGE Publications, Inc., Thousand Oaks, CA, 2010.

J. Haughton and S. R. Khandker. *Handbook on Poverty and Inequality*. World Bank, Washington, DC, 2009.

D. J. Henderson, C. Parmeter, and R. R. Russell. Modes, Weighted Modes, and Calibrated Modes: Evidence of Clustering Using Modality Tests. *Journal of Applied Econometrics*, 23: 607–638, 2008.

H. Holzmann, S. Vollmer, and J. Weisbrod. *Twin Peaks or Three Components? Analyzing the World's Cross-Country Distribution of Income*. IAI Discussion Paper 162, University of Göttingen, Göttingen, 2007. Available at http://www2.vwl.wiso.uni-goettingen.de/ibero/papers/DB162.pdf.

S. P. Jenkins. Did the Middle Class Shrink During the 1980s? UK Evidence From Kernel Density Estimates. *Economic Letters*, 49:407–413, 1995.

S. P. Jenkins. Recent Trends in the UK Income Distribution: What Happened and Why? *Oxford Review of Economic Policy*, 12:29–46, 1996.

S. P. Jenkins and P. Van Kerm. Accounting for Income Distribution Trends: A Density Function Decomposition Approach. *Journal of Economic Inequality*, 3:43–61, 2005.

P. A. Johnson. A Nonparametric Analysis of Income Convergence Across the US States. *Economics Letters*, 69:219–223, 2000.

C. I. Jones. On the Evolution of the World Income Distribution. *Journal of Economic Perspectives*, 11:19–36, 1997.

F. L. Jones and J. Kelley. Decomposing Differences Between Groups. A Cautionary Note on Measuring Discrimination. *Sociological Methods and Research*, 12:323–343, 1984.

N. Kakwani. Poverty and Economic Growth with Application to Côte d'Ivoire. *Review of Income and Wealth*, 39:121–139, 1993.

Y. Kijima and P. Lanjouw. *Poverty in India During the 1990s – A Regional Perspective.* Policy Research Working Paper 3141, World Bank Group, Washington, DC, 2003. Available at http://documents.worldbank.org/curated/en/2003/10/2579638/poverty-india-during-1990s-regional-perspective.

M. C. Lasso de la Vega and A. M. Urrutia. An Alternative Formulation of Esteban-Gradín-Ray Extended Measure of Polarization. *Journal of Income Distribution*, 15:42–54, 2006.

M. C. Lasso de la Vega, A. Urrutia, and H. Díez. Unit Consistency and Bipolarization of Income Distributions. *Review of Income and Wealth*, 56:65–83, 2010.

F. Levy and R. J. Murnane. U.S. Earnings Levels and Earnings Inequality: A Review of Recent Trends and Proposed Explanations. *Journal of Economic Literature*, 30:1333–1381, 1992.

R. Massari. *Is Income Becoming More Polarized in Italy? A Closer Look With a Distributional Approach.* DSE Working Paper 1, Sapienza University of Rome, Rome, 2009. Available at http://phdschool-economics.dse.uniroma1.it/website/WorkingPapers/MassariWP1.pdf.

R. Massari, M. G. Pittau, and R. Zelli. A Dwindling Middle Class? Italian Evidence in the 2000s. *Journal of Economic Inequality*, 7:333–350, 2009a.

R. Massari, M. G. Pittau, and R. Zelli. Caos calmo: l'evoluzione dei redditi familiari in Italia. In L. Cappellari, P. Naticchioni, and S. Staffolani, editors, *L'Italia delle disuguaglianze*, pages 19–28. Carocci editore, Rome, 2009b.

B. Milanovic. *A New Polarization Measure and Some Applications.* Mimeo, 2000. Available at http://siteresources.worldbank.org/INTDECINEQ/Resources/polariz.pdf.

V. Molini and P. Paci. *Poverty Reduction in Ghana: Progress and Challenges.* Technical report, Worl Bank, Washington, DC, 2015. Available at https://openknowledge.worldbank.org/handle/10986/22732.

M. Morris, A. D. Bernhardt, and M. S. Handcock. Economic Inequality: New Methods for New Trends. *American Sociological Review*, 59:205–219, 1994.

Z. Nissanov and M. G. Pittau. Measuring Changes in the Russian Middle Class Between 1992 and 2008: A Nonparametric Distributional Analysis. *Empirical Economics*, 50:503–530, 2016.

R. Oaxaca. Male-Female Wage Differentials in Urban Labour Markets. *International Economic Review*, 14:693–709, 1973.

O. I. Ogunyemi. *Gender, Market Participation and Income Polarisation Among Farming and Non-Farming Households in Nigeria.* Paper presented at the World Bank Workshop on Agriculture Myths and Facts, Washington DC, US, November 20–22, 2013.

O. I. Ogunyemi and O. A. Oni. Income Bipolarization and Poverty: Evidence from Rural Nigeria. *Journal of American Science*, 7:722–731, 2011.

O. I. Ogunyemi, O. A. Oni, T. T. Awoyemi, and S. A. Yusuf. Income Polarization and Bipolarization Across Rural Households' Socio-Economic Features in Nigeria. *World Rural Observations*, 3:62–72, 2011.

R. Paap and H. K. van Dijk. Distribution and Mobility of Wealth of Nations. *European Economic Review*, 42:1269–1293, 1998.

I. Petrarca and R. Ricciuti. *Relative Income Distribution in Six European Countries: Market and Disposable Income.* Working Paper 2, Department of Economics, University of Verona, Verona, 2015. Available at http://dse.univr.it/home/workingpapers/wp2015n2.pdf.

T. Piketty. *Capital in the Twenty-First Century.* The Belknap Press of Harvard University Press, Cambridge, MA, 2014.

M. G. Pittau and R. Zelli. Income Distribution in Italy: A Nonparametric Analysis. *Statistical Methods and Applications*, 10:175–189, 2001.

M. G. Pittau and R. Zelli. Testing for Changing Shapes of Income Distribution: Italian Evidence in the 1990s From Kernel Density Estimates. *Empirical Economics*, 29:415–430, 2004.

M. G. Pittau and R. Zelli. Trends in Income Distribution in Italy: A Non-Parametric and a Semi-Parametric Analysis. *Journal of Income Distribution*, 15:90–118, 2006.

M. G. Pittau, R. Zelli, and P. A. Johnson. Mixture Models, Convergence Clubs and Polarization. *Review of Income and Wealth*, 56:102–122, 2010.

A. Poggi and J. Silber. On Polarization and Mobility: A Look at Polarization in the Wage-Career Profile in Italy. *Review of Income and Wealth*, 56:123–140, 2010.

S. Pressman. The Decline of the Middle Class: An International Perspective. *Journal of Economic Issues*, 41:181–200, 2007.

D. T. Quah. Convergence Empirics Across Economies with (Some) Capital Mobility. *Journal of Economic Growth*, 1:95–124, 1996a.

D. T. Quah. Twin Peaks: Growth and Convergence in Models of Distribution Dynamics. *The Economic Journal*, 106:1045–1055, 1996b.

D. T. Quah. Empirics for Growth and Distribution: Stratification, Polarization, and Convergence Clubs. *Journal of Economic Growth*, 2:27–59, 1997.

M. Reynal-Querol. Ethnicity, Political Systems and Civil War. *Journal of Conflict Resolution*, 46:29–54, 2002.

J. G. Rodríguez and R. Salas. Extended Bi-Polarization and Inequality Measures. *Research on Economic Inequality*, 9:69–83, 2003.

J. Silber, M. Hanoka, and J. Deutsch. On the Link Between the Concepts of Kurtosis and Bipolarization. *Economics Bulletin*, 4:1–6, 2007.

J. Silber, J. Deutsch, and G. Yalonetzky. On Bi-Polarization and the Middle Class in Latin America: A Look at the First Decade of the Twenty-First Century. *Review of Income and Wealth*, 60:S332–S352, 2014.

D. Stifel and L. Christiaensen. Tracking Poverty Over Time in the Absence of Comparable Consumption Data. *World Bank Economic Review*, 21:317–341, 2007.

J. E. Stiglitz. *The Price of Inequality: How Today's Divided Society Endangers Our Future*. W. W. Norton & Company, New York, NY, 2012.

J. E. Stiglitz. *The Great Divide: Unequal Societies and What We Can Do About Them*. W. W. Norton & Company, New York, NY, 2015.

A. Tarozzi. Calculating Comparable Statistics From Incomparable Surveys, With an Application to Poverty in India. *Journal of Business & Economic Statistics*, 25:314–336, 2007.

P. Van Kerm. Adaptive Kernel Density Estimation. *The Stata Journal*, 3:148–156, 2003.

Y.-Q. Wang and K.-Y. Tsui. Polarization Orderings and New Classes of Polarization Indices. *Journal of Public Economic Theory*, 2:349–363, 2000.

M. C. Wolfson. When Inequalities Diverge. *The American Economic Review*, 84:353–358, 1994.

M. C. Wolfson. Divergent Inequalities: Theory and Empirical Results. *Review of Income and Wealth*, 43:401–421, 1997.

World Bank. *Where Has All the Growth Gone? A Poverty Update for Nigeria: A Policy Note*. Technical report, World Bank Group, Washington, DC, 2013. Available at http://documents.worldbank.org/curated/en/2013/08/19873872/all-growth-gone-poverty-update-nigeria-policy-note.

World Bank. *Nigeria Economic Report*. Technical report, World Bank Group, Washington, DC, 2014. Available at http://documents.worldbank.org/curated/en/2014/07/19883231/nigeria-economic-report-no-2.

World Bank. *Nigeria Poverty Assessment: A Tale of Two Countries*. Technical report, World Bank Group, Washington, DC, 2016.

X. Zhang and R. Kanbur. What Difference Do Polarisation Measures Make? An Application to China. *Journal of Development Studies*, 37:85–98, 2001.

A Imputation method

Poverty figures computed on the two surveys NLSS 2003/04 and 2009/10 present a dubious regional pattern: in 2003, Lagos state, source of about 30% of Nigerian GDP, ranks among the poorest States in the country. In 2009–10, poverty drops by about 30 percentage points in Lagos, but dramatically increases in other States such as Ebony and Enugu that, according to most other indicators of well-being, fare relatively well. Second, the 2009/10 survey showed massive under-reporting of consumption, where we observe steady decline of consumption over the course of the field-work that cannot be explained by any seasonal patterns of consumption in Nigeria. Third, both in 2003/04 and 2009/10 the national poverty rates, around 60% in per capita terms, seem disproportionally higher than most poverty rates of other African countries with similar GDP per capita of around 1,000 dollar in 2005 prices, even before the almost doubling of Nigerian GDP after its recent re-basing. A recent report on poverty in Nigeria based on GHS panel data shows that poverty rate is around 35% in per capita terms (World Bank, 2014). Fourth, as described in the main text, NLSS and the GHS surveys are not comparable, because the former uses a diary method for collecting consumption while the latter uses the recall method. Preliminary results measuring poverty and inequality computed from the GHS panel and the HNLSS appear substantially different between the two surveys (World Bank, 2014). Therefore, the direct comparison between the two GHS rounds and the NLSS surveys is incorrect given the different methods used to collect data.

There is increasing empirical evidence that shows how revisions to questionnaires can affect respondents' answers in ways that make comparisons with previous data difficult or impossible (Deaton and Grosh, 2000, Deaton and Kozel, 2005, and Tarozzi, 2007, for the great India poverty debate on this issue). For example, the choice of recall period (seven, 30 or any other number of days before the interview) or the disaggregation of the expenditure items can deeply influence reports on expenditure. Other changes such as the switch from a diary-based collection to a recall-based collection can dramatically change aggregate food consumption expenditures, a relevant component of total expenditures in many developing countries. In a carefully designed experiment, Beegle et al. (2010) found that in Tanzania recall modules measure lower consumption than a carefully supervised personal diary, with larger gaps among poorer households and for households with more adult members. In the Bangladesh context, Ahmed et al. (2014) also find that a switch from diary to recall reduces consumption aggregates simply because households remember their expenses better when entering them regularly in a diary. Therefore, switching the data collection methods from diary to recall likely makes poverty estimates and all other consumption-based measures or statisticsincluding polarizationnon-comparable with those of previous rounds in which consumption data were collected by diary. Backiny-Yetna et al. (2014), comparing data collected with recall and diary method in Niger, find that the diary data mean is 28% lower than the recall data mean. The gap is not only at the mean of the distribution, but at any level with clear consequences for inequality measures.

This means that in order to enable the data comparison over a longer time span (a decade) we need to create two comparable data sets. To do so, we apply survey-to-survey imputation techniques (Elbers et al., 2003) on the original NLSS 2003/04 and GHS panel surveys. First, for both panel Waves 1 and 2, we constructed a very comprehensive consumption aggregate following the best-practice guidelines provided in Deaton and Zaidi (2002). Consumption aggregates for every wave were obtained by averaging the consumption aggregates of each visit ("post-planting" and "post-harvesting"). Given the importance of obtaining accurate estimates that are comparable over time, it is crucial to calibrate models in a year when both household consumption data and non-consumption data are available, and then use the model to impute household consumption data for years when only the non-consumption data are available. In our case, we can use either GHS panel Wave 1 or 2 to calibrate the consumption model. We chose Wave 1. As we will discuss in greater detail below, we will use the panel Wave 2 to test and validate our model, that is to check the accuracy of our prediction and in a second stage use the same model to impute the 2003/04 data. Next, we use the model of consumption using the GHS panel Wave 1 to impute and obtain comparable consumption for HNLSS 2003/04, which serves as the baseline data.

The imputation process follows the methodology developed in Elbers et al. (2003). Stifel and Christiaensen (2007) provide theoretical guidance regarding variables to be included in imputation models. They recommend including covariates that do change over time, but call for excluding variables whose rates of return are likely to change markedly in the face of evolving economic conditions. In our specific case, the seven years between the two surveys represent a standard time gap for survey-to-survey estimation. For example, Deaton and Dréze (2002) and Kijima and Lanjouw (2003) estimate a model of household consumption based on 1993/94 data to impute consumption for the 1999/2000 survey round. Douidich et al. (2015) use data from 2000/01 survey to impute consumption data into a 2006/07 survey. Following Stifel and Christiaensen (2007), we included several household durables but excluded mobile phones, as their relationship with total household expenditure has been changing rapidly in the last ten years. In fact, ten years ago ownership of mobile phones was a good predictor of high income. Today, such phones are prevalent among the lower- and middle-income classes and even among the poor (Ahmed et al., 2014). Other variables include household characteristics, location, and interaction of zones with household covariates. Most of the variables are significant and show the expected sign, and, more importantly, the model yields an R^2 of 0.46 (see Table A.1).

The procedure follows two stages. First, we use OLS to estimate a model of log per capita real expenditures using the sample from panel Wave 1. The model is specified as:

$$\ln (Y_{ik}) = \alpha + \beta X_{ik} + \gamma Z_k + (\eta_k + \epsilon_{ik}) , \tag{A.1}$$

where α is an intercept, X_{ik} is the vector of explanatory variables for household i and location k, β is the vector of regression coefficients, Z_k is the vector of location specific variables, γ is the vector of coefficients and the residual is decomposed into two independent components: the location-specific effect, η_k, and a household-specific effect, ϵ_{ik}. This structure allows for both a location effect—common to all households in the same area—and heteroskedasticity in the household-specific errors.

Second, to control for this location effect and heteroskedasticity, we draw the errors from the distribution of residuals for households in the same zone. Therefore, we divide the sample into six groups based on six macro zones.[23] To obtain the imputed distribution, we also divide the

[23] As robustness check, the sample was divided into ten groups based on deciles of a wealth index (Ferreira et al.,

Table A.1: Regression results of POV_MAP imputation model

Dependent variable: log of consumption per capita in 2010 Naira spatially deflated		
Explanatory variable[a]	Coefficient[b]	*t*-statistic
Number of people in household	-0.06***	-7.23
Population age less than 15 years and population aged over 64 years	-0.03***	-4.07
Children between 0 and 4 years old	-0.07***	-3.56
Adult females	-0.02	-1.52
Number of females 65 years and above	-0.03	-1.36
Age of household head	0.00	-0.22
Age of household head squared	0.00	-1.37
Marital status of household head	0.07***	7.10
Marital status of household head is polygamous marriage	0.03	0.67
Sex of household head	0.04	0.96
Number of years of education for household head	0.01***	6.96
Literacy status of household head	0.09**	2.37
Self-employed in nonagricultural sector	0.05***	3.08
Sector of activity by broad group of household head	-0.04	-0.93
Ownership of dwelling unit	0.12***	3.72
Area of residence (in square meters)	0.08***	4.82
Ownership of radio	0.06***	4.98
Ownership of television	0.08***	4.34
Ownership of refrigerator	0.07***	3.62
Ownership of motorcycle	0.02	0.66
Ownership of sewing machine	-0.01	-0.33
Ownership of stove	0.00	-0.01
Ownership of bicycle	0.14**	2.02
Ownership of car	0.25***	6.39
Ownership of generator	0.12***	3.36
Ownership of iron	0.02	0.64
Ownership of fan	-0.03	-0.88
Ownership of bed or mattress	0.01	0.21
Main material used for floor - Low quality	-0.06***	-3.12
Main material used for floor - Medium quality	-0.08***	-4.91
Main source of drinking water - Protected	0.07	1.62
Main source of drinking water - Unprotected	0.12**	2.56
Main cooking fuel - Firewood	-0.22***	-4.11
Main cooking fuel - Kerosene/Oil	-0.10*	-1.88
Main cooking fuel - Other	-0.18***	-2.86
Main toilet facility - No facility	-0.01	-0.24
Main toilet facility - Flush toilet	0.07*	1.95
Garbage and trash disposal	-0.01*	-1.92
_cons	11.58***	92.23
R^2	0.46	

Notes: (a) state level dummies (Lagos state omitted) and zone interacted variables (South West zone omitted) not reported; (b) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

sample of the target distribution—NLSS 2003/04—into six sub-samples corresponding to the macro groups of Equation (A.1) identified for drawing the error terms. Following the bootstrap principle, residuals distribution is drawn for a number $R = 50$ of replications so as to obtain a number R of distributions.

For the purpose of visual representation, among these distributions we selected a "representative" one, i.e. the one having the median standard deviation among all the simulated distributions. However, we ran our diagnostics and calculate relative distribution indexes over

2011) and six macro zones obtaining 60 clusters. Final results are practically the same.

Table A.2: Mean and standard deviation of relative polarization indices over $R = 50$ simulation runs for three alternative imputation techniques

	MRP[a]	LRP[b]	URP[c]
POV_MAP[d]			
Mean	0.13	0.12	0.13
Standard deviation	0.00	0.01	0.01
MI_REG[e]			
Mean	0.11	0.14	0.09
Standard deviation	0.01	0.02	0.01
MI_PMM[f]			
Mean	0.11	0.11	0.11
Standard deviation	0.01	0.02	0.01

Notes: (a) MRP = median relative polarization index; (b) LRP = lower relative polarization index; (c) URP = upper relative polarization index; (d) POV_MAP = multiple imputation method using Equation (A.1); (e) MI_REG = Gaussian normal regression imputation method; (f) MI_PMM = predictive mean matching imputation method.

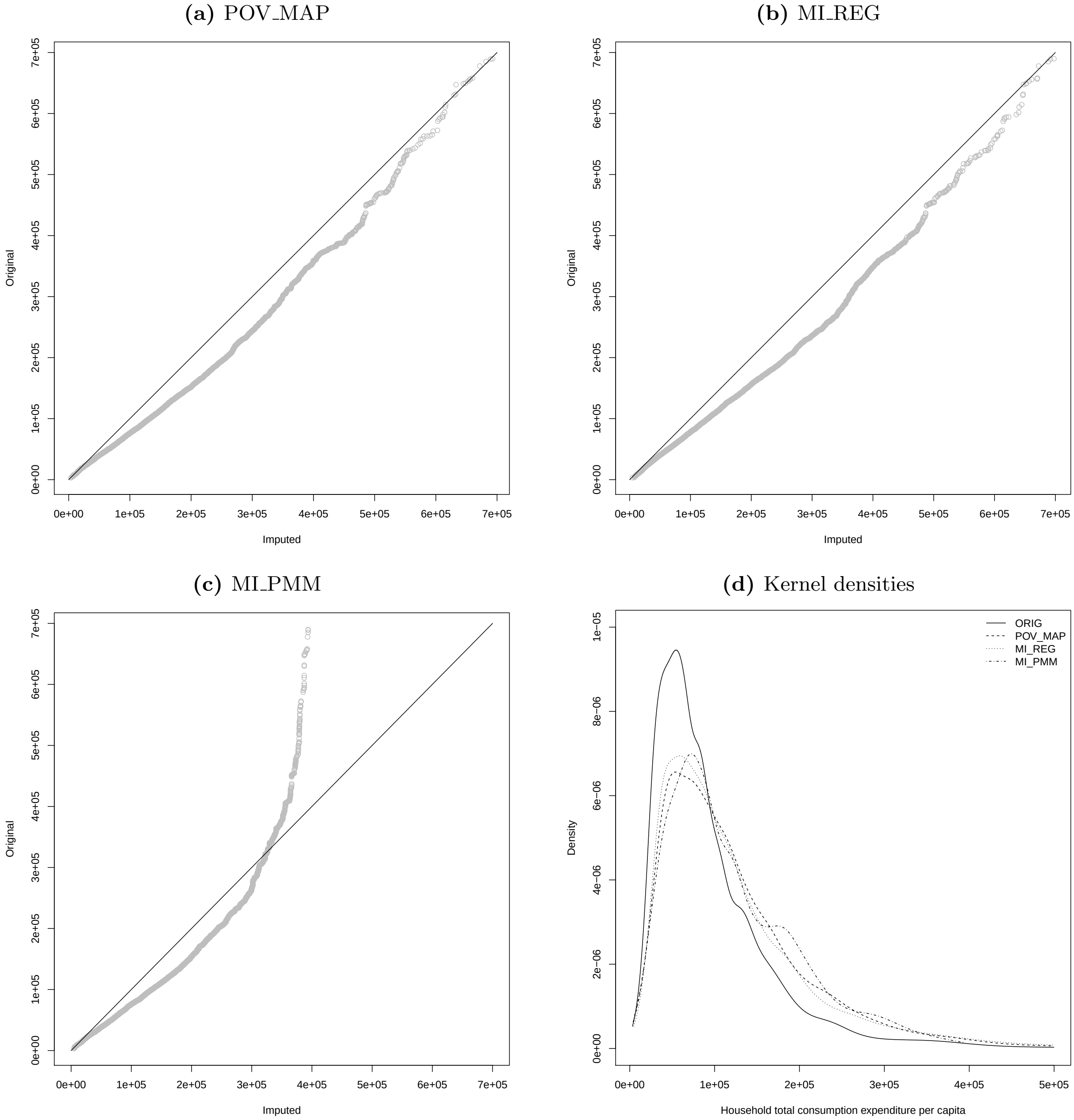
all the simulated distributions. The findings show that differences are marginal.[24] A synthesis of results is presented in Table A.2.

We apply different procedures to test the validity of the model. First, by means of in-sample criteria, i.e. by evaluating the R^2 size of the predicting model (A.1). We also use out-of-sample data and test the predictive capacity of the model on a known consumption distribution (GHS panel 2012/13) by quantile-to-quantile analysis and other visually oriented techniques, such as kernel density comparison. Results are also consistent when using different imputation methods. The model in Equation (A.1) is compared to two alternative imputation techniques both in its ability to simulate the GHS panel 2012/13 consumption distribution and in yielding similar polarization results: these are the Gaussian normal regression imputation method (MI_REG)[25] and the predictive mean matching imputation method (MI_PMM).[26] In Figure A.1, panels (a) to (c), the three methods are compared via the quantile-to-quantile plot. Our method (labelled as POV_MAP) is equivalent to MI_REG in minimizing the distance between real 2012/13 distribution and the simulated one. Both are more accurate than MI_PMM in predicting values located in the upper tail of the distribution. As an additional robustness test, in panel (d) of the same figure we compare the kernel density of the 2012/13 consumption distribution (ORIG), POV_MAP simulation and the two multiple imputation outcomes. The three methods produce similar distributions, but again MI_PMM truncates the upper tail of the distribution.

Our method (labelled POV_MAP) better minimizes the distance between real 2012/2013 distribution and the simulated one, in particular for values located in the upper tail of the distribution. As an Although very similar in their out-of-sample performance, we eventually preferred to use POV_MAP because of the correction for heteroskedasticity and location effect. In Table A.2 we also present some results from the other methods, but just to corroborate findings derived from POV_MAP imputation.

[24]Results can be provided upon request.
[25]http://www.stata.com/manuals13/mimiimputeregress.pdf.
[26]http://www.stata.com/manuals13/mimiimputepmm.pdf.

Figure A.1: Post-imputation diagnostic plots



B Supplementary tables

Table B.1: Location effect RIF-regression results

		1991		1998		2005		2012	
	Number of obs	4,523		5,998		8,687		16,772	
	F(25, 4497)	61.57		144.54		166.58		273.29	
	Prob > F	0.00		0.00		0.00		0.00	
	R-squared	0.27		0.29		0.32		0.32	
	Adj R-squared	0.26		0.29		0.32		0.31	
	Root MSE	241.33		322.80		413.75		500.16	
		Coef.	*P>z*	*Coef.*	*P>z*	*Coef.*	*P>z*	*Coef.*	*P>z*
Demographic Features	**Household size**	**-15.08**	0.00	**-21.83**	0.00	**-29.53**	0.00	**-33.16**	0.00
	Share of Children	**-32.44**	0.27	**-79.78**	0.02	**-20.62**	0.60	**-32.67**	0.41
	Share of Care-Dependent Persons	**9.47**	0.76	**-0.58**	0.99	**83.26**	0.03	**-16.22**	0.70
	Household Head Age	**-0.40**	0.36	**-0.57**	0.24	**-0.95**	0.07	**-1.18**	0.03
	Sex of Household Head	**-16.34**	0.16	**7.83**	0.54	**56.80**	0.00	**60.86**	0.00
	Share of Adult Males	**139.49**	0.00	**122.12**	0.00	**110.30**	0.00	**213.38**	0.00
	Share of Adult Females	**207.10**	0.00	**265.36**	0.00	**327.24**	0.00	**418.16**	0.00
Education Features	**Up to Primary School**	**9.42**	0.55	**21.63**	0.18	**41.40**	0.03	**41.15**	0.02
	Up to Secondary School	**32.80**	0.01	**55.43**	0.00	**84.64**	0.00	**111.18**	0.00
	Higher than Secondary School	**100.94**	0.00	**129.84**	0.00	**232.60**	0.00	**302.11**	0.00
Socioeconomic Features	**Private Workers**	**41.62**	0.04	**48.09**	0.02	**93.72**	0.00	**57.21**	0.01
	Public Workers	**56.47**	0.00	**53.63**	0.01	**100.33**	0.00	**58.92**	0.04
	Non Agricoltural Self Employeed	**57.42**	0.00	**44.95**	0.00	**117.33**	0.00	**132.62**	0.00
	Agricoltural Self Employeed	**36.81**	0.04	**-7.08**	0.65	**6.11**	0.75	**10.02**	0.61
Other	**Assets**	**40.53**	0.00	**78.13**	0.00	**78.43**	0.00	**117.91**	0.00
	Western	**-34.48**	0.21	**339.59**	0.00	**267.86**	0.00	**211.91**	0.00
	Central	**65.31**	0.02	**152.87**	0.00	**261.49**	0.00	**146.10**	0.00
	Greater Accra	**-3.50**	0.90	**349.13**	0.00	**131.97**	0.00	**323.70**	0.00
	Volta	**17.54**	0.54	**206.22**	0.00	**165.38**	0.00	**160.94**	0.00
	Eastern	**9.02**	0.76	**229.43**	0.00	**299.66**	0.00	**169.09**	0.00
	Ashanti	**42.01**	0.12	**253.64**	0.00	**223.86**	0.00	**186.47**	0.00
	Brong Ahafo	**-29.55**	0.28	**248.58**	0.00	**173.82**	0.00	**187.04**	0.00
	Northern	**7.51**	0.79	**146.83**	0.00	**162.93**	0.00	**59.73**	0.00
	Upper East	**-106.72**	0.00	**28.75**	0.18	**-5.44**	0.82	**89.90**	0.00
	Urban Area Residence	**102.49**	0.00	**27.64**	0.05	**143.21**	0.00	**92.73**	0.00
	Constant	**338.30**	0.00	**219.03**	0.00	**266.81**	0.00	**295.86**	0.00

Table B.2: Location effect OB results

		1998-91		2005-1998		2012-05	
	Median predicted (1)		438.18		559.53		655.62
	Median predicted (2)		352.69		438.18		559.53
		Coef.	*P>z*	*Coef.*	*P>z*	*Coef.*	*P>z*
	Difference	**85.49**	0.00	**121.36**	0.00	**96.09**	0.00
		Endowments					
Demographic Features	**Household size**	**7.26**	0.00	**-1.53**	0.17	**3.92**	0.00
	Share of Children	**-0.17**	0.43	**0.85**	0.05	**0.14**	0.63
	Share of Care-Dependent Persons	**0.10**	0.77	**0.00**	0.99	**0.16**	0.39
	Household Head Age	**-0.30**	0.41	**0.12**	0.56	**-0.30**	0.25
	Sex of Household Head	**0.51**	0.21	**1.25**	0.54	**-0.97**	0.03
	Share of Adult Males	**2.10**	0.00	**2.36**	0.00	**0.25**	0.46
	Share of Adult Females	**4.43**	0.00	**1.69**	0.04	**3.10**	0.00
Education Features	**Up to Primary School**	**0.64**	0.55	**-0.67**	0.20	**2.32**	0.04
	Up to Secondary School	**0.39**	0.29	**1.18**	0.04	**0.92**	0.13
	Higher than Secondary School	**2.30**	0.00	**0.78**	0.13	**3.05**	0.00
Socioeconomic Features	**Private Workers**	**0.57**	0.11	**2.18**	0.03	**2.89**	0.00
	Public Workers	**-2.22**	0.00	**-0.83**	0.05	**-0.71**	0.08
	Non Agricoltural Self Employeed	**1.83**	0.00	**-1.52**	0.01	**6.74**	0.00
	Agricoltural Self Employeed	**2.36**	0.04	**0.31**	0.65	**-0.07**	0.77
Other	**Assets (see note)**	**11.05**	0.00	**12.20**	0.00	**23.96**	0.00
	Western	**-0.37**	0.36	**-3.06**	0.08	**-2.33**	0.03
	Central	**0.79**	0.16	**-4.27**	0.00	**0.26**	0.80
	Greater Accra	**-0.11**	0.91	**-3.38**	0.10	**3.21**	0.00
	Volta	**1.06**	0.54	**-14.02**	0.00	**1.99**	0.00
	Eastern	**-0.34**	0.76	**6.69**	0.00	**-8.74**	0.00
	Ashanti	**0.85**	0.20	**-2.60**	0.11	**6.22**	0.00
	Brong Ahafo	**1.29**	0.29	**4.72**	0.00	**1.09**	0.12
	Northern	**-0.23**	0.80	**8.28**	0.00	**-3.27**	0.00
	Upper East	**3.53**	0.00	**0.76**	0.19	**0.04**	0.84
	Urban Area Residence	**2.69**	0.01	**0.65**	0.12	**17.60**	0.00
	Total	**40.02**	0.00	**12.16**	0.01	**61.45**	0.00

Table B.2: Continued

		Coefficients					
Demographic Features	**Household size**	**-42.27**	0.07	**-44.53**	0.05	**-21.26**	0.39
	Share of Children	**-9.85**	0.28	**12.62**	0.25	**-2.44**	0.83
	Share of Care-Dependent Persons	**-0.40**	0.82	**4.20**	0.10	**-4.66**	0.08
	Household Head Age	**-7.63**	0.80	**-17.61**	0.60	**-10.72**	0.76
	Sex of Household Head	**15.43**	0.16	**29.74**	0.03	**3.12**	0.88
	Share of Adult Males	**-3.67**	0.67	**-2.67**	0.80	**25.30**	0.04
	Share of Adult Females	**14.82**	0.20	**17.06**	0.23	**25.64**	0.10
Education Features	**Up to Primary School**	**1.39**	0.59	**3.60**	0.44	**-0.04**	0.99
	Up to Secondary School	**9.06**	0.24	**12.04**	0.20	**11.50**	0.28
	Higher than Secondary School	**0.80**	0.47	**5.18**	0.01	**3.92**	0.09
Socioeconomic Features	**Private Workers**	**0.40**	0.83	**3.45**	0.15	**-4.41**	0.25
	Public Workers	**-0.37**	0.91	**4.30**	0.17	**-3.17**	0.29
	Non Agricoltural Self Employeed	**-2.33**	0.53	**15.84**	0.00	**2.83**	0.56
	Agricoltural Self Employeed	**-4.36**	0.06	**2.16**	0.59	**0.47**	0.89
Other	**Assets (see note)**	**-15.35**	0.00	**-0.04**	0.98	**0.81**	0.12
	Western	**37.21**	0.00	**-7.90**	0.04	**-5.65**	0.12
	Central	**9.07**	0.02	**12.56**	0.00	**-10.12**	0.00
	Greater Accra	**41.40**	0.00	**-32.32**	0.00	**26.68**	0.00
	Volta	**15.50**	0.00	**-5.83**	0.24	**-0.33**	0.90
	Eastern	**31.40**	0.00	**7.38**	0.04	**-17.52**	0.00
	Ashanti	**33.44**	0.00	**-5.31**	0.34	**-6.28**	0.25
	Brong Ahafo	**32.38**	0.00	**-5.43**	0.03	**1.21**	0.70
	Northern	**13.18**	0.00	**1.03**	0.62	**-12.43**	0.00
	Upper East	**7.34**	0.00	**-0.72**	0.30	**4.54**	0.00
	Urban Area Residence	**-24.47**	0.00	**40.81**	0.00	**-19.02**	0.03
	Constant	**-119.27**	0.02	**47.78**	0.38	**29.04**	0.62
	Total	**32.83**	0.00	**97.41**	0.00	**17.01**	0.04
		Interaction					
	Total	**12.64**	0.01	**11.79**	0.02	**17.63**	0.00

Table B.3: Shape effect RIF-regression results

		1991							
		10th		20th		80th		90th	
	Number of obs	4523		4523		4523		4523	
	R-squared	0.127		0.1734		0.2317		0.1763	
	Adj R-squared	0.1221		0.1688		0.2274		0.1717	
	Root MSE	166.26		171.9		537.4		1044.6	
		Coef.	P>z	Coef.	P>z	Coef.	P>z	Coef.	P>z
Demographic Features	Household size	-5.455	0.006	-6.928	0.000	-32.832	0.000	-51.281	0.000
	Share of Children	-21.170	0.320	-43.926	0.048	-111.941	0.064	-104.837	0.351
	Share of Care-Dependent Persons	-8.818	0.678	-3.716	0.866	46.025	0.526	47.323	0.743
	Household Head Age	0.267	0.433	0.040	0.905	-1.449	0.088	-2.502	0.090
	Sex of Household Head	-9.927	0.223	-20.890	0.014	-12.108	0.600	8.489	0.843
	Share of Adult Males	38.180	0.045	60.945	0.002	295.954	0.000	614.298	0.000
	Share of Adult Females	51.753	0.010	59.880	0.007	527.357	0.000	1061.252	0.000
Education Features	Up to Primary School	-1.718	0.888	6.207	0.603	-4.850	0.863	46.613	0.352
	Up to Secondary School	20.687	0.015	10.693	0.231	70.770	0.003	126.750	0.002
	Higher than Secondary School	31.035	0.031	46.767	0.002	79.310	0.323	226.447	0.165
Socioeconomic Features	Private Workers	16.356	0.195	29.349	0.017	-6.958	0.876	-3.960	0.961
	Public Workers	23.548	0.029	33.154	0.003	109.050	0.002	105.537	0.119
	Non Agricoltural Self Employeed	29.897	0.001	25.997	0.006	125.672	0.000	117.759	0.030
	Agricoltural Self Employeed	10.539	0.385	13.894	0.250	56.689	0.091	43.785	0.459
other	Assets (see note)	0.153	0.969	7.849	0.058	109.418	0.000	220.129	0.000
	Western	36.647	0.135	21.765	0.343	-150.440	0.006	-151.534	0.072
	Central	53.456	0.024	57.058	0.011	7.668	0.896	72.621	0.422
	Greater Accra	39.498	0.091	26.341	0.230	-31.771	0.612	19.447	0.851
	Volta	61.673	0.008	43.929	0.047	-65.669	0.255	-58.228	0.513
	Eastern	49.943	0.040	34.317	0.139	-25.750	0.669	-1.156	0.990
	Ashanti	55.452	0.017	49.261	0.022	9.256	0.866	126.459	0.137
	Brong Ahafo	43.935	0.070	27.833	0.226	-40.178	0.475	51.060	0.558
	Northern	-39.280	0.145	-24.473	0.315	7.602	0.895	103.440	0.240
	Upper East	-80.541	0.030	-105.691	0.001	-94.546	0.114	5.736	0.952
	Urban Area Residence	39.315	0.000	63.669	0.000	183.278	0.000	237.926	0.000
	Constant	196.253	0.000	273.832	0.000	755.886	0.000	875.930	0.000

		1998							
		10th		20th		80th		90th	
	Number of obs	5998		5998		5998		5998	
	R-squared	0.1861		0.247		0.2613		0.1856	
	Adj R-squared	0.1827		0.2439		0.2582		0.1821	
	Root MSE	210.52		222.58		679.77		1115.3	
		Coef.	P>z	Coef.	P>z	Coef.	P>z	Coef.	P>z
Demographic Features	Household size	-8.061	0.000	-10.717	0.000	-48.615	0.000	-64.869	0.000
	Share of Children	3.000	0.887	-23.086	0.318	-128.827	0.046	-103.057	0.292
	Share of Care-Dependent Persons	-6.929	0.746	-3.083	0.891	90.496	0.212	232.394	0.064
	Household Head Age	0.064	0.849	0.004	0.991	-2.302	0.009	-5.539	0.000
	Sex of Household Head	3.588	0.677	6.933	0.456	40.865	0.097	73.518	0.050
	Share of Adult Males	4.293	0.838	21.861	0.325	265.513	0.000	514.394	0.000
	Share of Adult Females	64.299	0.005	105.117	0.000	563.185	0.000	913.254	0.000
Education Features	Up to Primary School	22.156	0.055	39.210	0.001	-0.712	0.978	-14.756	0.692
	Up to Secondary School	36.533	0.000	49.809	0.000	110.820	0.000	95.150	0.013
	Higher than Secondary School	49.212	0.000	55.819	0.000	283.759	0.000	461.548	0.000
Socioeconomic Features	Private Workers	16.356	0.086	32.899	0.008	15.531	0.748	-23.545	0.753
	Public Workers	40.818	0.000	66.810	0.000	-3.288	0.941	-51.651	0.447
	Non Agricoltural Self Employeed	21.088	0.029	37.049	0.000	87.867	0.002	89.237	0.038
	Agricoltural Self Employeed	-16.849	0.157	-4.316	0.714	6.674	0.829	-11.287	0.787
other	Assets (see note)	12.241	0.015	28.248	0.000	166.629	0.000	205.553	0.000
	Western	320.415	0.000	370.078	0.000	291.636	0.000	265.460	0.000
	Central	286.159	0.000	277.257	0.000	31.524	0.311	-21.939	0.600
	Greater Accra	295.482	0.000	334.505	0.000	481.309	0.000	626.103	0.000
	Volta	246.610	0.000	267.853	0.000	148.898	0.000	192.025	0.000
	Eastern	301.459	0.000	336.623	0.000	111.418	0.000	41.520	0.315
	Ashanti	290.869	0.000	316.334	0.000	227.152	0.000	206.419	0.000
	Brong Ahafo	298.072	0.000	327.446	0.000	217.315	0.000	180.736	0.000
	Northern	168.506	0.000	186.967	0.000	183.467	0.000	199.252	0.000
	Upper East	46.488	0.309	75.230	0.017	73.709	0.034	103.582	0.031
	Urban Area Residence	23.203	0.008	17.726	0.078	56.254	0.039	26.511	0.523
	Constant	-95.854	0.004	-63.309	0.025	686.530	0.000	1047.534	0.000

		2005							
		10th		20th		80th		90th	
	Number of obs	8687		8687		8687		8687	
	R-squared	0.2751		0.2835		0.2675		0.1993	
	Adj R-squared	0.273		0.2814		0.2654		0.197	
	Root MSE	264.97		283.64		839.63		1665.2	
		Coef.	P>z	Coef.	P>z	Coef.	P>z	Coef.	P>z
Demographic Features	Household size	-11.481	0.001	-16.324	0.000	-37.092	0.000	-42.325	0.000
	Share of Children	-21.264	0.448	16.977	0.552	4.329	0.954	-43.474	0.770
	Share of Care-Dependent Persons	1.704	0.942	70.784	0.005	140.652	0.081	296.548	0.073
	Household Head Age	0.292	0.454	-0.634	0.137	-3.989	0.000	-9.267	0.000
	Sex of Household Head	-4.637	0.663	5.414	0.670	26.778	0.427	-36.410	0.551
	Share of Adult Males	-1.022	0.969	18.970	0.454	607.424	0.000	1266.318	0.000
	Share of Adult Females	35.172	0.177	93.504	0.001	1005.516	0.000	1902.945	0.000
Education Features	Up to Primary School	11.959	0.444	12.918	0.416	25.062	0.404	-52.649	0.262
	Up to Secondary School	49.626	0.000	45.676	0.000	83.413	0.003	97.339	0.041
	Higher than Secondary School	60.760	0.000	84.781	0.000	749.659	0.000	1593.065	0.000
Socioeconomic Features	Private Workers	0.785	0.941	16.916	0.253	46.997	0.275	-0.101	0.999
	Public Workers	15.506	0.143	43.499	0.002	-0.238	0.997	-194.885	0.119
	Non Agricoltural Self Employeed	6.937	0.521	32.707	0.007	127.038	0.000	135.402	0.034
	Agricoltural Self Employeed	-28.917	0.023	-30.328	0.036	-29.284	0.413	-159.341	0.015
other	Assets (see note)	21.879	0.000	27.756	0.000	188.612	0.000	326.087	0.000
	Western	551.981	0.000	466.272	0.000	27.460	0.570	-15.321	0.857
	Central	559.237	0.000	442.462	0.000	51.717	0.260	30.788	0.701
	Greater Accra	516.243	0.000	391.291	0.000	-130.627	0.009	-193.990	0.041
	Volta	536.039	0.000	422.699	0.000	-37.205	0.424	-139.346	0.044
	Eastern	549.423	0.000	476.980	0.000	9.435	0.826	-147.021	0.035
	Ashanti	530.775	0.000	421.197	0.000	37.754	0.325	-31.740	0.639
	Brong Ahafo	533.946	0.000	413.071	0.000	-23.683	0.566	-195.735	0.004
	Northern	381.093	0.000	289.666	0.000	46.548	0.171	11.381	0.836
	Upper East	199.095	0.000	100.351	0.001	-150.825	0.000	-271.516	0.000
	Urban Area Residence	1.532	0.887	48.864	0.000	237.192	0.000	226.167	0.000
	Constant	-242.144	0.000	-50.372	0.171	761.965	0.000	1114.916	0.000

		2012							
		10th		20th		80th		90th	
	Number of obs	16772		16772		16772		16772	
	R-squared	0.183		0.2469		0.2508		0.1817	
	Adj R-squared	0.1818		0.2458		0.2497		0.1805	
	Root MSE	318.58		332.91		1247		1952.8	
		Coef.	P>z	Coef.	P>z	Coef.	P>z	Coef.	P>z
Demographic Features	Household size	-12.197	0.000	-19.064	0.000	-51.072	0.000	-58.851	0.000
	Share of Children	-23.808	0.285	3.240	0.898	196.073	0.041	101.440	0.486
	Share of Care-Dependent Persons	-19.570	0.339	7.047	0.779	-194.972	0.075	-223.423	0.187
	Household Head Age	0.495	0.118	-0.443	0.246	-4.086	0.001	-6.454	0.000
	Sex of Household Head	40.090	0.000	31.608	0.006	83.433	0.054	-2.726	0.966
	Share of Adult Males	-26.099	0.208	14.638	0.522	1079.797	0.000	1472.291	0.000
	Share of Adult Females	79.726	0.000	139.779	0.000	1526.836	0.000	1827.092	0.000
Education Features	Up to Primary School	48.043	0.000	65.186	0.000	-23.149	0.474	-130.811	0.001
	Up to Secondary School	51.855	0.000	96.777	0.000	158.345	0.000	152.420	0.001
	Higher than Secondary School	57.790	0.000	115.883	0.000	910.024	0.000	1609.224	0.000
Socioeconomic Features	Private Workers	-3.799	0.795	3.564	0.819	103.041	0.047	45.853	0.563
	Public Workers	11.994	0.343	28.896	0.048	95.782	0.260	14.767	0.913
	Non Agricoltural Self Employeed	33.467	0.001	54.073	0.000	211.442	0.000	72.857	0.249
	Agricoltural Self Employeed	-3.837	0.763	11.873	0.364	-45.604	0.331	-191.766	0.002
other	Assets (see note)	59.076	0.000	63.786	0.000	215.654	0.000	248.610	0.000
	Western	392.030	0.000	319.200	0.000	53.351	0.320	-111.482	0.133
	Central	390.644	0.000	341.750	0.000	-44.980	0.389	-173.548	0.011
	Greater Accra	372.125	0.000	319.881	0.000	568.413	0.000	649.232	0.000
	Volta	378.333	0.000	283.748	0.000	-15.238	0.739	-69.710	0.297
	Eastern	403.282	0.000	328.038	0.000	-98.929	0.041	-200.132	0.003
	Ashanti	412.474	0.000	336.057	0.000	25.368	0.583	-90.714	0.169
	Brong Ahafo	413.233	0.000	315.229	0.000	29.976	0.504	-92.848	0.136
	Northern	265.261	0.000	185.813	0.000	-32.858	0.411	-41.996	0.477
	Upper East	284.615	0.000	229.203	0.000	-89.991	0.025	-174.426	0.003
	Urban Area Residence	56.025	0.000	72.423	0.000	59.626	0.073	36.098	0.425
	Constant	-194.757	0.000	-16.084	0.594	541.794	0.000	1201.148	0.000

Table B.4: Shape effect OB results

		1998-1991							
		10th percentile		20th percentile		80th percentile		90th percentile	
	cut-off quantile predicted (1)	181.033		246.724		803.142		1084.860	
	cut-off quantile predicted (2)	248.745		296.689		704.604		940.641	
		Coef.	*P>z*	*Coef.*	*P>z*	*Coef.*	*P>z*	*Coef.*	*P>z*
	difference	**-67.712**	0.010	**-49.965**	0.00	**98.539**	0.00	**144.219**	0.00
		endowments							
Demographic Features	Household size	2.625	0.010	3.334	0.001	15.800	0.000	24.678	0.000
	Share of Children	-0.111	0.469	-0.231	0.268	-0.589	0.282	-0.552	0.490
	Share of Care-Dependent Persons	-0.092	0.689	-0.039	0.870	0.481	0.543	0.494	0.751
	Household Head Age	0.202	0.476	0.030	0.911	-1.094	0.166	-1.889	0.168
	Sex of Household Head	0.310	0.272	0.652	0.057	0.378	0.620	-0.265	0.850
	Share of Adult Males	0.576	0.082	0.920	0.016	4.466	0.002	9.269	0.002
	Share of Adult Females	1.106	0.017	1.280	0.013	11.272	0.000	22.684	0.000
Education Features	Up to Primary School	-0.118	0.888	0.425	0.605	-0.332	0.863	3.189	0.357
	Up to Secondary School	0.247	0.300	0.128	0.457	0.847	0.275	1.516	0.270
	Higher than Secondary School	0.708	0.045	1.066	0.006	1.808	0.335	5.163	0.181
Socioeconomic Features	Private Workers	0.225	0.265	0.403	0.080	-0.096	0.884	-0.054	0.964
	Public Workers	-0.927	0.041	-1.305	0.008	-4.291	0.007	-4.153	0.135
	Non Agricoltural Self Employeed	0.955	0.010	0.830	0.026	4.015	0.004	3.762	0.062
	Agricoltural Self Employeed	0.675	0.389	0.890	0.255	3.632	0.098	2.805	0.463
other	Assets (see note)	0.042	0.969	2.139	0.061	29.825	0.000	60.002	0.000
	Western	0.389	0.295	0.231	0.455	-1.596	0.156	-1.607	0.241
	Central	0.644	0.160	0.688	0.137	0.092	0.907	0.875	0.501
	Greater Accra	1.241	0.118	0.828	0.255	-0.998	0.622	0.611	0.855
	Volta	3.730	0.010	2.657	0.053	-3.972	0.260	-3.522	0.516
	Eastern	-1.869	0.056	-1.284	0.158	0.964	0.675	0.043	0.990
	Ashanti	1.116	0.082	0.992	0.091	0.186	0.875	2.546	0.213
	Brong Ahafo	-1.924	0.081	-1.219	0.236	1.759	0.481	-2.236	0.562
	Northern	1.202	0.164	0.749	0.329	-0.233	0.897	-3.167	0.257
	Upper East	2.666	0.036	3.498	0.002	3.129	0.122	-0.190	0.953
	Urban Area Residence	1.032	0.019	1.672	0.009	4.812	0.010	6.247	0.018
	Total	14.651	0.000	19.333	0.000	70.265	0.000	126.251	0.000
		coefficients							
Demographic Features	Household size	-16.326	0.375	-23.738	0.197	-98.883	0.021	-85.126	0.186
	Share of Children	5.030	0.421	4.337	0.516	-3.514	0.849	0.370	0.990
	Share of Care-Dependent Persons	0.075	0.950	0.025	0.984	1.763	0.665	7.337	0.334
	Household Head Age	-9.345	0.670	-1.672	0.941	-39.195	0.486	-139.551	0.132
	Sex of Household Head	8.628	0.254	17.763	0.028	33.820	0.117	41.516	0.253
	Share of Adult Males	-7.152	0.232	-8.249	0.184	-6.425	0.720	-21.085	0.512
	Share of Adult Females	3.190	0.678	11.503	0.161	9.110	0.724	-37.633	0.425
Education Features	Up to Primary School	2.721	0.156	3.761	0.052	0.472	0.914	-6.994	0.327
	Up to Secondary School	6.343	0.223	15.657	0.005	16.031	0.264	-12.649	0.570
	Higher than Secondary School	0.503	0.322	0.250	0.669	5.652	0.052	6.500	0.245
Socioeconomic Features	Private Workers	0.000	1.000	0.219	0.838	1.390	0.733	-1.211	0.860
	Public Workers	2.270	0.246	4.425	0.044	-14.770	0.050	-20.666	0.102
	Non Agricoltural Self Employeed	-1.646	0.499	2.065	0.435	-7.063	0.354	-5.329	0.681
	Agricoltural Self Employeed	-2.723	0.108	-1.810	0.281	-4.973	0.274	-5.475	0.447
other	Assets (see note)	-4.935	0.061	-8.328	0.003	-23.356	0.013	5.950	0.738
	Western	28.226	0.000	34.646	0.000	43.972	0.000	41.477	0.000
	Central	24.096	0.000	22.801	0.000	2.470	0.720	-9.792	0.344
	Greater Accra	30.056	0.000	36.183	0.000	60.243	0.000	71.230	0.000
	Volta	15.192	0.000	18.395	0.000	17.627	0.002	20.558	0.016
	Eastern	35.830	0.000	43.065	0.000	19.540	0.044	6.079	0.662
	Ashanti	37.196	0.000	42.198	0.000	34.428	0.001	12.634	0.401
	Brong Ahafo	29.584	0.000	34.878	0.000	29.975	0.000	15.096	0.197
	Northern	19.660	0.000	20.006	0.000	16.640	0.009	9.066	0.332
	Upper East	6.883	0.033	9.803	0.000	9.117	0.016	5.302	0.363
	Urban Area Residence	-5.267	0.190	-15.019	0.001	-41.525	0.001	-69.112	0.001
	Constant	-292.108	0.000	-337.141	0.000	-69.356	0.481	171.605	0.271
	Total	-84.016	0.000	-73.975	0.000	-6.809	0.617	0.098	0.996
		interaction							
	Total	1.654	0.620	4.677	0.168	35.082	0.000	17.870	0.227

		2005-1998							
		10th percentile		20th percentile		80th percentile		90th percentile	
	cut-off quantile predicted (1)	216.832		304.003		1011.395		1377.144	
	cut-off quantile predicted (2)	302.431		368.122		924.540		1206.258	
		Coef.	*P>z*	*Coef.*	*P>z*	*Coef.*	*P>z*	*Coef.*	*P>z*
	difference	**-85.598**	0.000	**-64.118**	0.00	**86.855**	0.00	**170.886**	0.00
		endowments							
Demographic Features	Household size	-0.563	0.203	-0.749	0.185	-3.397	0.168	-4.533	0.169
	Share of Children	-0.032	0.892	0.247	0.355	1.381	0.092	1.104	0.330
	Share of Care-Dependent Persons	0.022	0.797	0.010	0.912	-0.291	0.417	-0.747	0.313
	Household Head Age	-0.013	0.900	-0.001	0.994	0.480	0.426	1.155	0.396
	Sex of Household Head	0.575	0.677	1.110	0.457	6.544	0.098	11.773	0.051
	Share of Adult Males	0.083	0.841	0.423	0.340	5.139	0.001	9.956	0.000
	Share of Adult Females	0.409	0.100	0.668	0.058	3.580	0.041	5.805	0.042
Education Features	Up to Primary School	-0.690	0.078	-1.220	0.007	0.022	0.979	0.459	0.699
	Up to Secondary School	0.779	0.039	1.062	0.026	2.363	0.032	2.029	0.084
	Higher than Secondary School	0.295	0.142	0.334	0.153	1.700	0.143	2.765	0.150
Socioeconomic Features	Private Workers	0.740	0.093	1.489	0.011	0.703	0.749	-1.065	0.754
	Public Workers	-0.635	0.012	-1.039	0.005	0.051	0.944	0.803	0.477
	Non Agricoltural Self Employeed	-0.711	0.050	-1.249	0.005	-2.962	0.009	-3.008	0.060
	Agricoltural Self Employeed	0.738	0.168	0.189	0.716	-0.292	0.831	0.494	0.789
other	Assets (see note)	1.911	0.020	4.411	0.000	26.018	0.000	32.096	0.000
	Western	-2.889	0.086	-3.337	0.083	-2.630	0.092	-2.394	0.108
	Central	-7.986	0.000	-7.737	0.000	-0.880	0.327	0.612	0.608
	Greater Accra	-2.864	0.106	-3.242	0.103	-4.665	0.107	-6.068	0.111
	Volta	-16.760	0.000	-18.204	0.000	-10.119	0.000	-13.051	0.000
	Eastern	8.787	0.000	9.812	0.000	3.248	0.003	1.210	0.331
	Ashanti	-2.980	0.113	-3.241	0.110	-2.327	0.119	-2.115	0.134
	Brong Ahafo	5.665	0.000	6.223	0.000	4.130	0.001	3.435	0.007
	Northern	9.508	0.000	10.550	0.000	10.352	0.000	11.243	0.000
	Upper East	1.234	0.314	1.997	0.022	1.957	0.040	2.750	0.037
	Urban Area Residence	0.547	0.057	0.418	0.148	1.327	0.104	0.625	0.554
	Total	-4.830	0.119	-1.075	0.749	41.431	0.000	55.335	0.000
		coefficients							
Demographic Features	Household size	-19.781	0.403	-32.433	0.116	66.645	0.100	130.384	0.034
	Share of Children	-5.178	0.490	8.549	0.276	28.413	0.180	12.714	0.738
	Share of Care-Dependent Persons	0.432	0.785	3.700	0.029	2.512	0.644	3.214	0.757
	Household Head Age	10.682	0.656	-29.798	0.249	-78.810	0.190	-174.171	0.093
	Sex of Household Head	-4.995	0.548	-0.922	0.923	-8.554	0.736	-66.752	0.125
	Share of Adult Males	-1.202	0.874	-0.654	0.932	77.320	0.000	170.041	0.000
	Share of Adult Females	-8.029	0.399	-3.201	0.749	121.931	0.000	272.815	0.000
Education Features	Up to Primary School	-1.860	0.600	-4.795	0.188	4.701	0.518	-6.911	0.528
	Up to Secondary School	5.397	0.364	-1.704	0.803	-11.298	0.481	0.902	0.971
	Higher than Secondary School	0.583	0.469	1.461	0.166	23.503	0.000	57.080	0.000
Socioeconomic Features	Private Workers	-1.176	0.276	-1.207	0.407	2.377	0.627	1.771	0.826
	Public Workers	-2.332	0.087	-2.148	0.210	0.281	0.968	-13.195	0.315
	Non Agricoltural Self Employeed	-3.096	0.329	-0.950	0.788	8.570	0.386	10.099	0.549
	Agricoltural Self Employeed	-1.973	0.488	-4.253	0.164	-5.879	0.447	-24.206	0.057
other	Assets (see note)	-1.307	0.166	0.067	0.949	-2.982	0.360	-16.352	0.006
	Western	25.489	0.000	10.588	0.005	-29.079	0.000	-30.906	0.006
	Central	31.567	0.000	19.097	0.000	2.334	0.716	6.095	0.561
	Greater Accra	32.856	0.000	8.452	0.097	-91.076	0.000	-122.056	0.000
	Volta	41.283	0.000	22.087	0.000	-26.545	0.002	-47.266	0.000
	Eastern	26.045	0.000	14.742	0.000	-10.712	0.055	-19.803	0.021
	Ashanti	42.736	0.000	18.680	0.001	-33.738	0.000	-42.424	0.003
	Brong Ahafo	17.130	0.000	6.219	0.016	-17.502	0.000	-27.341	0.000
	Northern	13.607	0.000	6.573	0.008	-8.764	0.004	-12.025	0.008
	Upper East	3.218	0.014	0.530	0.562	-4.735	0.000	-7.910	0.000
	Urban Area Residence	-7.653	0.119	10.997	0.041	63.900	0.000	70.510	0.005
	Constant	-267.688	0.000	-108.460	0.019	-45.963	0.658	-54.017	0.763
	Total	-75.244	0.000	-58.785	0.000	26.849	0.084	70.291	0.006
		interaction							
	Total	-5.525	0.117	-4.259	0.251	18.575	0.058	45.260	0.008

		2012-2005							
		10th percentile		20th percentile		80th percentile		90th percentile	
	cut-off quantile predicted (1)	258.359		357.472		1242.974		1738.198	
	cut-off quantile predicted (2)	312.995		400.165		1107.558		1473.306	
		Coef.	*P>z*	*Coef.*	*P>z*	*Coef.*	*P>z*	*Coef.*	*P>z*
	difference	**-54.636**	0.000	**-42.693**	0.00	**135.417**	0.00	**264.892**	0.00
		endowments							
Demographic Features	Household size	1.525	0.026	2.169	0.006	4.929	0.003	5.624	0.007
	Share of Children	0.141	0.490	-0.113	0.584	-0.029	0.957	0.288	0.784
	Share of Care-Dependent Persons	0.003	0.958	0.135	0.359	0.269	0.426	0.568	0.421
	Household Head Age	0.094	0.544	-0.204	0.302	-1.282	0.118	-2.978	0.106
	Sex of Household Head	0.079	0.682	-0.093	0.689	-0.458	0.464	0.623	0.578
	Share of Adult Males	-0.002	0.981	0.043	0.688	1.373	0.433	2.861	0.432
	Share of Adult Females	0.333	0.215	0.886	0.012	9.527	0.000	18.030	0.000
Education Features	Up to Primary School	0.671	0.447	0.725	0.419	1.406	0.407	-2.954	0.266
	Up to Secondary School	0.539	0.126	0.496	0.146	0.905	0.166	1.056	0.229
	Higher than Secondary School	0.796	0.001	1.110	0.001	9.817	0.000	20.862	0.000
Socioeconomic Features	Private Workers	0.024	0.942	0.523	0.264	1.452	0.286	-0.003	0.999
	Public Workers	-0.110	0.269	-0.308	0.098	0.002	0.997	1.380	0.248
	Non Agricoltural Self Employeed	0.398	0.523	1.878	0.010	7.294	0.001	7.774	0.038
	Agricoltural Self Employeed	0.337	0.090	0.354	0.109	0.342	0.459	1.859	0.078
other	Assets (see note)	6.683	0.000	8.478	0.000	57.610	0.000	99.602	0.000
	Western	-4.793	0.029	-4.048	0.029	-0.238	0.614	0.133	0.870
	Central	0.547	0.794	0.433	0.795	0.051	0.847	0.030	0.928
	Greater Accra	12.544	0.000	9.508	0.000	-3.174	0.022	-4.714	0.061
	Volta	6.449	0.001	5.086	0.001	-0.448	0.454	-1.677	0.094
	Eastern	-16.027	0.000	-13.914	0.000	-0.275	0.828	4.289	0.047
	Ashanti	14.755	0.000	11.709	0.000	1.050	0.340	-0.882	0.646
	Brong Ahafo	3.357	0.105	2.597	0.106	-0.149	0.640	-1.231	0.173
	Northern	-7.654	0.000	-5.818	0.000	-0.935	0.197	-0.229	0.840
	Upper East	-1.334	0.031	-0.672	0.053	1.011	0.039	1.819	0.034
	Urban Area Residence	0.188	0.887	6.004	0.000	29.145	0.000	27.790	0.000
	Total	19.544	0.000	26.963	0.000	119.193	0.000	179.922	0.000
		coefficients							
Demographic Features	Household size	-4.196	0.861	-16.036	0.468	-81.830	0.099	-96.735	0.199
	Share of Children	-0.515	0.943	-2.784	0.719	38.860	0.117	29.369	0.486
	Share of Care-Dependent Persons	-0.997	0.493	-2.988	0.074	-15.733	0.014	-24.374	0.028
	Household Head Age	9.409	0.687	8.903	0.738	-4.525	0.950	130.825	0.267
	Sex of Household Head	34.322	0.002	20.101	0.127	43.476	0.302	25.848	0.702
	Share of Adult Males	-6.156	0.451	-1.064	0.899	115.965	0.000	50.566	0.274
	Share of Adult Females	12.565	0.195	13.050	0.216	147.019	0.000	-21.391	0.739
Education Features	Up to Primary School	5.458	0.064	7.906	0.013	-7.292	0.275	-11.822	0.200
	Up to Secondary School	0.967	0.886	22.155	0.005	32.488	0.096	23.881	0.408
	Higher than Secondary School	-0.168	0.865	1.755	0.165	9.051	0.196	0.912	0.948
Socioeconomic Features	Private Workers	-0.554	0.800	-1.613	0.535	6.769	0.406	5.550	0.676
	Public Workers	-0.269	0.831	-1.118	0.468	7.353	0.362	16.054	0.256
	Non Agricoltural Self Employeed	4.910	0.070	3.954	0.198	15.620	0.140	-11.575	0.487
	Agricoltural Self Employeed	3.002	0.163	5.051	0.031	-1.953	0.782	-3.881	0.719
other	Assets (see note)	0.762	0.107	0.738	0.106	0.554	0.404	-1.587	0.226
	Western	-16.164	0.000	-14.863	0.000	2.616	0.720	-9.718	0.395
	Central	-14.784	0.000	-8.832	0.004	-8.480	0.165	-17.919	0.053
	Greater Accra	-20.053	0.000	-9.936	0.030	97.265	0.000	117.326	0.000
	Volta	-11.777	0.000	-10.376	0.000	1.640	0.737	5.200	0.469
	Eastern	-19.609	0.000	-19.985	0.000	-14.540	0.094	-7.127	0.582
	Ashanti	-19.861	0.002	-14.294	0.008	-2.079	0.837	-9.901	0.533
	Brong Ahafo	-11.061	0.002	-8.965	0.004	4.917	0.379	9.428	0.262
	Northern	-13.950	0.009	-12.507	0.003	-9.563	0.131	-6.428	0.509
	Upper East	4.074	0.069	6.138	0.000	2.898	0.258	4.625	0.244
	Urban Area Residence	20.530	0.000	8.876	0.144	-66.896	0.000	-71.607	0.009
	Constant	-48.775	0.350	-61.874	0.194	-316.333	0.012	-9.930	0.961
	Total	-92.892	0.000	-88.608	0.000	-2.735	0.873	115.590	0.000
		interaction							
	Total	18.712	0.000	18.952	0.000	18.958	0.024	-30.621	0.021