CPI Bias and its Implications for Poverty Reduction in Africa

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Abstract
International poverty estimates for countries in Africa commonly rely on national consumer price indexes to adjust trends in nominal consumption over time for changes in the cost of living. However, the consumer price index is subject to various types of measurement bias. This paper uses Engel curve estimations to assess bias in the consumer price index and its implications for estimated poverty trends. The results suggest that in 13 of 16 Sub-Saharan African countries in this study, poverty reduction may be understated because of consumer price index bias. With correction of consumer price index bias, poverty in these countries could fall between 0.4 and 5.2 percentage points per year faster than currently thought. For two countries, however, the paper finds the opposite trend. There is no statistically significant change in poverty patterns after adjusting for consumer price index bias for only one country.

Keywords Africa · CPI bias · Engel curve · Inflation · Poverty

JEL Classification E30 · E31 · I32 · O12 · C82

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1 Introduction

Consumer price indexes (CPIs) play an important role for our understanding of poverty trends in Africa. This is because international poverty estimates rely on national CPIs to express nominal consumption estimates from household surveys in real terms and the base year of the international poverty line.\(^1\) However, there are concerns that CPIs may not always adequately reflect changes in the cost of living. Recent studies suggest that consumption growth and poverty reduction in Sub-Saharan Africa in the recent past may have been stronger than widely believed (see Kenny 2011; Young 2012; Pinkovskiy and Sala-i-Martin 2014), though others have challenged this notion (see Harttgen et al. 2013a). Underlying these differing views about levels and trends in poverty and living standards in the region are often concerns about missing or inaccurate data, including concerns about the accuracy of measured inflation (see Beegle et al. 2016).

There are several reasons why CPIs may not correctly measure changes in the cost of living. The most well-known causes, which have received considerable attention in the United States and other developed countries, are commodity substitution bias, outlet substitution bias, quality change bias and bias from the introduction of new goods (Schultze and Mackie 2002; Hausman 2003). Additional caveats arise for CPIs in Sub-Saharan Africa, due to weaknesses in country statistical systems, and when CPIs are used specifically for the purpose of measuring poverty trends (Beegle et al. 2016). These include concerns about the representativeness of CPI weights for the poor (see Günther and Grimm 2007) and urban bias of the underlying input data (see Gaddis 2016).

The Engel curve method introduced by Costa (2001) and Hamilton (2001) attempts to address some of the above biases, mostly commodity and outlet substitution bias. Engel’s law arises from the observation that the food budget share in household consumption declines with the increase in real household income. This suggests that movements in the food budget share over time can reveal changes in real incomes, conditional on changes in relative prices and household characteristics. As a corollary, among demographically similar households at the same level of real income, differences in food budget shares at different points in time might signal mismeasurement of the true change in cost of living.

This Engel curve method has been applied to different countries in the world, such as Australia (Barrett and Brzozowski 2010), Brazil and Mexico (De Carvalho Filho and Chamon 2012), Canada (Beatty and Larsen 2005), China (Chamon and De Carvalho Filho 2014; Nakamura et al. 2016), India (Almas et al. 2019), Indonesia (Olivia and Gibson 2013), the Republic of Korea (Chung et al. 2010), New Zealand (Gibson and Scobie 2010), Norway (Larsen 2007), the Russian Federation (Gibson et al. 2008), and the United States (Costa 2001; Hamilton 2001; Logan 2009; Gorry and Scrimgeour 2018). However, to the best of our knowledge, no such analysis exists for countries in Africa.

This paper aims to study the direction and magnitude of CPI bias for Sub-Saharan African countries using the Engel curve method and estimate the implications of this bias on the measured change in the incidence of poverty. The paper also addresses one critique of the Engel method to estimate CPI bias – that it fails to distinguish the bias that is due to “true” CPI inflation and that which arises from inflation inequality across the consumption distribution. This paper hence not only contributes to the

\(^1\) The current international poverty line stands at $1.90 per person per day in 2011 international dollars. See PovcalNet for the latest international poverty estimates: http://iresearch.worldbank.org/PovcalNet/.
literature on biases in CPIs referenced above, but also to the broader literature reassessing poverty trends in Africa in light of challenges in the underlying statistical data (Young 2012; Pinkovskiy and Sala-i-Martin 2014; Harttgen et al. 2013a).

Using comparable consumption data from 16 Sub-Saharan African countries, namely, Burkina Faso, Cameroon, Côte d'Ivoire, Democratic Republic of Congo, Ethiopia, Ghana, Madagascar, Mauritius, Mozambique, Nigeria, Rwanda, Senegal, South Africa, Tanzania, Togo, and Uganda, combined with monthly food, non-food, and overall CPI data from the respective national statistical offices (NSOs) our results suggest that the official CPIs mostly overestimate increases in the cost of living. In the 13 countries where our results indicate that CPIs overestimate inflation, the average annual CPI upward bias ranges from 0.6% in Cameroon to 45.6% in Nigeria. Three countries, Burkina Faso, Ghana, and Uganda, experience a negative bias between −12.8% a year in Uganda and −6.1% in Ghana. These estimates of CPI bias are statistically significant, except for Cameroon.

Armed with these estimates of bias in national CPIs, we study the implications for measured trends in international poverty in urban areas. Correcting for CPI bias, urban poverty falls significantly faster than suggested by current international poverty numbers in 11 countries. Based on our estimates, the difference in poverty reduction resulting from CPI-bias adjustment could be as large as −5.17 percentage points per year in Tanzania between 2008 and 2012. Only two countries, Uganda and Ghana, experience significantly slower poverty reduction rates with the correction of CPI bias. The change in urban poverty trend due to CPI bias correction is statistically insignificant in Mauritius and Madagascar (2005–2010). While we advise to interpret individual country estimates and the magnitude of point estimates with a degree of caution, this is suggestive evidence that African countries may have been more successful in reducing poverty than currently thought.

The paper is organized as follows. Section II explains why CPIs in Sub-Saharan Africa may be biased and outlines the Engel curve method. Section III describes our empirical methodology and the data sources. Section IV shows the estimates of the CPI bias and conducts several robustness checks. Section V assesses the implications of CPI bias for measured poverty trends, and section VI triangulates these results with the broader empirical literature assessing trends in living standards and poverty in the region. Section VII concludes.

2 Literature Review

2.1 CPI Bias in Sub-Saharan Africa

The CPI measures the rate at which the prices of a specific basket of goods and services change from month to month. To compute the CPI, NSOs require price and quantity data for a variety of goods and services. Virtually all NSOs in Sub-Saharan Africa run regular monthly consumer price data collection programs, which form the basis for computing the CPI. In addition, estimating a weighted average of price changes relative to a base period requires data on consumed quantities as budget shares, also denoted as (basket) weights. These quantity data

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2 See Almas et al. (2019) for a similar exercise for India.
typically come from nationally representative household budget surveys (HBS), which most NSOs field in irregular intervals (see Beegle et al. 2016).3

Most NSOs use a fixed-base Laspeyres-type index and staged aggregation approach to compute the CPI (see United Nations 2009). In a first step, individual price quotations are combined to elementary aggregates that represent broad categories of goods purchased by consumers in a specific locality and type of outlet. In the second step, elementary aggregates are combined to commodity-group indexes (for example, food and beverages, apparel, transport) and ultimately the all-item CPI using budget shares estimated from the HBS for a base period.

It is well-known that Laspeyres indexes tend to overstate changes in the cost of living. This is because they hold quantities fixed in the base period and disregard consumer substitution behavior towards goods that have become relatively cheaper over time (Deaton 1998). Since many countries in Sub-Saharan Africa lack regular HBS programs, the budget shares underlying the CPI can be seriously outdated. According to metadata of the International Labour Organization (ILO 2013), which depict national practices in computing CPIs as of July 2012, 13% of the population in the region was living in countries in which the weights were based on data from the 1990s, and an additional 23% was living in countries where weights were dated between 2000 and 2004 (see Beegle et al. 2016). While such outdated budget shares are clearly a source of concern, it is important to note that substitution bias does not necessarily decline with more frequent weights updates (Shapiro and Wilcox 1996; Greenlees 1997; Deaton 1998).

A related issue is that CPIs often do not reflect differences in the prices of the same product purchased at various outlets if distribution channels change over time. This is referred to as the outlet substitution bias. In many African countries, for example, the popularity of supermarkets that offer discounted prices has been growing, at least in urban areas. Because the CPI does not account for the shift among consumers towards these possibly less expensive retail outlets (for items previously purchased in traditional stores), it overstates actual inflation.

CPIs also do not account for changes in the quality of existing goods and services in the basket, which leads to a quality change bias. Over the years, as technology has evolved, many products have exhibited dramatic improvements (for example, greater functionality or safety, greater nutritional value, and so on). However, it is typically very difficult to separate out how much of the price change recorded for a specific product is associated with a change in quality and how much is associated with actual inflation.4 Similarly, it often takes many years until newly available goods and services are introduced into the CPI computation, the new product bias. Because the CPI fails to capture the benefits to consumers from greater availability of products and brands, changes in the cost of living are typically overstated.

The CPIs in many countries in Sub-Saharan Africa suffer from additional sources of bias and measurement error. An important example is urban bias. Because a number of NSOs in the region collect price data solely in urban areas, their CPIs reflect changes in prices experienced by the urban population, in some cases, the population living in the capital city

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3 The term HBS is used to denote national household surveys collecting consumption data, this includes a range of surveys that go by different labels, e.g. Living Standards Survey, Income, Expenditure and Consumption Survey, etc.

4 NSOs in developed countries often use splicing procedures, which attribute a certain fraction of the overall price change to quality, or rely on hedonic estimation techniques, which explicitly model quality. Nonetheless, there is evidence that some degree of quality improvement is typically not captured and that quality change bias often leads to an overestimation of inflation (Boskin et al. 1996, 1998; Hausman 2003).
only. For example, as of July 2012 (the reporting date of the information collected in ILO 2013), Tanzania’s national CPI reflected the prices surveyed in urban areas in 21 regions across the country. Meanwhile, national CPIs of Angola, Burkina Faso, Comoros, Côte d’Ivoire, Djibouti, Liberia, Mali, Senegal and Togo only reflected the prices of goods and services in the main city, sometimes including the surrounding areas. When price data in rural areas are not available, CPIs are based on urban price data, with the (arguably strong) assumption that urban and rural prices move in parallel. What is more, even when HBS data are nationally representative, some countries compute budget shares for urban households only. In Tanzania, for instance, CPI weights until 2009 were based on consumption patterns among urban households in the 2001 HBS. In 2010, as part of the process of rebasing the index to the HBS 2007, the reference population for the weights was broadened to include rural households (Tanzania NBS 2010).

Finally, for poverty analysis, a concern is that the weights are not representative of poor households’ consumption patterns. CPI weights are computed as the consumption shares of an aggregate reference population, which attaches a weight to each household in proportion to its total expenditures. Because of this CPI weights reflect consumption patterns of households at the upper end of the distribution (Nicholson 1975; Deaton 1998). In times of changing relative prices, such as during food price shocks, inflation measured by the CPI can then differ from the inflation experienced by poorer population groups (Günther and Grimm 2007). While this feature is often described as the CPI’s *plutocratic bias* (Prais 1959), it is important to note that plutocratic weights are preferred for some purposes of the CPI, such as the deflation of economic aggregates (Pollak 1998) and are hence (at least partly) an explicit component in the design of the index.  

2.2 The Engel Curve Method

The Engel curve method attempts to address some of the above biases, mostly the commodity and outlet substitution biases. The method takes as a starting point Engel’s Law and the idea that movements in food budget shares that cannot be explained by changes in relative prices and household characteristics reveal changes in real incomes. As a result, any systematic difference over time in the food budget shares of demographically similar households at the same level of real income (CPI deflated) and facing the same relative prices is assumed to reflect mismeasurement in the CPI. This Engel curve method was first introduced by Costa (2001) and Hamilton (2001). Using nationwide consumption surveys between 1888 and 1994 in the United States, Costa (2001) finds that the CPI underestimated increases in the true cost of living until 1919, but consistently overestimated them thereafter. Hamilton (2001), using a different set of data, the Panel Study of Income Dynamics between 1974 and 1991 in the United States, finds a similar trend. In particular, he estimates the annual CPI upward bias at approximately three percentage points between 1974 and 1981 and slightly less than one percentage points between 1981 and 1991. The results of Costa (2001) and Hamilton (2001) are also broadly consistent with the findings of Boskin et al. (1996, 1998), who calculate the

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5 In addition, however, democratic weighting is also practically infeasible at the level of elementary aggregates, which explains the near universality of plutocratic weights for CPIs (Schultze and Mackie 2002; Gaddis 2016).

6 According to Hausman (2003), the method only accounts for commodity and outlet substitution bias. Beatty and Larsen (2005), however, argue that it also captures some quality change bias arising from increased durability.
contribution of each source of CPI bias separately, and conclude that between 1979 and 1995 the United States CPI exhibited an upward bias of 1.1 percentage points per year.

Since then the Engel curve method has been applied to various other countries. In two papers referring to Canada, Beatty and Larsen (2005) and Brzozowski (2006) find that the Canadian CPI overstated changes in the cost of living among specific demographic groups. Similarly, Barrett and Brzozowski (2010), in a study on the Australian CPI, show there was cumulative upward bias of 34% between 1975 and 2003, although the magnitude of the bias varies by household type and time period considered. In New Zealand, Gibson and Scobie (2010) argue that the country’s CPI overestimated inflation by an amount similar to the bias in the United States. In contrast, Larsen (2007), following the same method but using data on Norway in the 1990s, concludes that the CPI understated the increase in the cost of living.

More recently, the application of the Engel curve method has been extended to developing and transitional economies in Asia and Latin America. De Carvalho Filho and Chamon (2012) argue that post-reform growth in real household incomes in Brazil and Mexico was underestimated because the CPI overstated the increase in the cost of living. Gibson et al. (2008) obtain similar results using data from Russia during the transition period between 1992 and 2001. In Indonesia, Olivia and Gibson (2013) find that the CPI bias was negative during the 1997–98 financial crisis, but consistently positive since 2000. In China, Nakamura et al. (2016) find that official inflation rates show less variability over time than actual inflation rates.

While Engel curve estimates have become a widely used methodology to cross-triangulate official inflation trends, the method is not without limitations. Its major weakness is that any (residual) drift in the Engel curve that cannot be explained by the covariates in the regression model is attributed to CPI bias. This assumption may not hold if there are additional, unobserved forces that shift the Engel curve - such as changes in preferences, or variations in the way consumption data are collected. Analysis in Gibson et al. (2017), for example, suggests that the method does not perform well in a spatial context. A similar concern is that even though the method controls for changes in household characteristics, biases can arise from assumptions about the nature of relationship between these covariates and the food share. For example, Logan (2009) argues that the effect of household size on demand varies over time and that this is not captured by the standard Engel curve estimation because of the way demographic effects are modeled. Using household survey data on the United States from 1888 and 1935, Logan (2009) finds that when changing household size effects are taken into account, estimates of CPI bias are reduced by 25%.8

A related critique is that Engel curve estimates conflate various types of CPI bias and are hence difficult to interpret. As noted earlier, Engel curve estimations are used primarily to tackle biases arising from commodity and outlet substitution. However, as argued by Almas et al. (2018), the method may conflate the above form of CPI bias with inflation inequality across the distribution (plutocratic bias). As noted earlier, CPIs, due to their plutocratic weights, measure changes in cost-of-living of households at the upper end of the distribution. Conversely, the Engel curve method estimates changes in cost-of-living for a household at a specific point in the expenditure distribution, one which, however, is not well defined by the

7 Examples of using the Engel curve method to estimate spatial price indexes are Almas (2012) and Coondoo et al. (2011). The former focuses on price-level differences across countries and the latter on within-country regional price differences.
8 However, it is unclear whether the household size correction decomposes or modifies CPI bias estimates.
Hamilton-Costa method. Differences between the two measures of inflation could hence either reflect bias in the CPI, or inflation inequality across the distribution, though it is not entirely clear how important such inflation inequality is in practice. A study for Burkina Faso shows that distributional differences in inflation can be significant in times of rapidly changing prices, e.g. after a drought or other supply side shock (Gunther and Grimm 2007). Studies for the US, on the other hand, often find little systematic inequality in inflation across the income distribution (Kokoski 2000; Kaplan and Schulhofer-Wohl 2017).

Only few Engel curve-based studies account for inflation inequality across the distribution. De Carvalho Filho and Chamon (2012) and Chamon and De Carvalho Filho (2014) estimate CPI bias for different percentiles of the distribution under the assumption that CPI bias is a linear function of (CPI-deflated) log expenditure. Nakamura et al. (2016), in a study that focuses on the lack of variability in China’s official inflation estimates, use a method proposed in Feenstra and Reinsdorf (2000) to compute exact price indexes for different income groups. Gibson et al. (2017) compare (spatial) deflators obtained from the Engel curve method with two alternative deflators – a variable weights deflator, which accounts for substitution bias but at the cost of assuming homothetic preferences, and a fixed weights deflator, which is affected by substitution bias but does not rely on the assumption of homothetic preferences. Since the latter two approaches require more disaggregated price data than what is available for the countries in this study, we follow the approach outlined in De Carvalho Filho and Chamon (2012) and Chamon and De Carvalho Filho (2014) and estimate CPI bias for different deciles of the distribution.

3 Empirical Methodology and Data

3.1 Estimation Framework

The Engel curve method introduced by Costa (2001) and Hamilton (2001) formalizes the idea that since households tend to spend less of their budget on food as real income increases, changes in the food budget share over time can signal changes in real incomes. Following Hamilton (2001) and Olivia and Gibson (2013), the following model of the food budget share \( w_{i,j,t} \) for household \( i \) in region \( j \) in year \( t \) can be estimated in countries with sub-national CPI data (see Appendix 2 for a formal exposition):

\[
\begin{align*}
\ln(w_{i,j,t}) = \hat{\gamma} + \gamma & \left[ \ln(1 + \Pi_{F,j,t}) - \ln(1 + \Pi_{N,j,t}) \right] + \beta \left[ \ln Y_{i,j,t} - \ln(1 + \Pi_{j,t}) \right] + \theta X^t \\
& + \sum_{t=1}^{T} \delta_t D_t + \sum_{j=1}^{J} \delta_j D_j + \mu_{i,j,t}
\end{align*}
\]

(1)

where \( \Pi_{F,j,t} \), \( \Pi_{N,j,t} \), and \( \Pi_{j,t} \) are the cumulative percent increases in the overall, food and non-food CPI from year \( 0 \) to year \( t \). \( D_t \) is a dummy variable equal to 1 in year \( t \) and \( D_j \) is a dummy equal to 1 for region \( j \). \( Y_{i,j,t} \) is the household’s total expenditure (in nominal terms), \( X \) is a vector of household characteristics – including household size, share of kids in household, age, gender, education, and marital status of household head – and \( \mu_{i,j,t} \) is the residual. Since Engel’s Law postulates a negative relationship between a household’s food budget share and real income for any homogeneous population group facing the same relative prices, it is important to control for relative price changes and the household’s demographic characteristics.
From this model the following parameters can be estimated: $\gamma$, i.e. the household’s budgetary response to relative food to non-food price changes; $\beta$, that is the response in the food budget to changes in total expenditure; $\theta$, the effect of household characteristics on the food budget share; and finally, $\delta$, i.e. shifts in the food budget share over time and space, conditional on the other variables. The estimated coefficients of the time dummy variables ($\delta_t$) are then used to calculate CPI bias (see Appendix 2).

If sub-national CPI data are not available, which is often the case in Sub-Saharan African countries, eq. (1) cannot be estimated because the coefficient $\gamma$ for the relative prices of food and non-food items in each region $j$ cannot be identified. Using temporal movements in the national price index for food items relative to non-food items is equally not possible because this period-to-period variation is perfectly correlated with the time dummy variables, $D_t$. However, it is possible to estimate the following model of the food budget share:

$$w_{i,t} = 0 + \beta \left[ \ln Y_{i,t} - \ln (1 + \Pi_i) \right] + \theta X^\prime + \sum_{t=1}^{T} \delta_t D_t + \mu_{i,t}$$ (2)

In this case, the estimated coefficients of the time dummy variables ($\delta_t$) measure both CPI bias and the effect on the budget share of the intertemporal variation in the observed prices for food relative to non-food items. Isolating CPI bias then requires an estimate of the flexibility of money from external sources, as described in Appendix 2.

The method discussed above assumes that CPI bias is homogenous across the income distribution. In other words, eq. (1) or (2) only provides an estimate of the bias for the average household. Since we are interested in poverty implications of the bias, it is important to examine the differential effects between the rich and the poor. Following Chamon and De Carvalho Filho (2014), we address this issue by extending eq. (1) or (2) as follows, assuming that the bias is linear to household’s real expenditure:

$$w_{i,j,t} = 0 + \gamma \left[ \ln (1 + \Pi_{F,j,t}) - \ln (1 + \Pi_{N,j,t}) \right] + \left[ \beta + \sum_{t=1}^{T} \lambda_t D_t \right]$$

$$[\ln Y_{i,j,t} - \ln (1 + \Pi_{j,t})] + X^\prime \theta + \sum_{t=1}^{T} \delta_t D_t + \sum_{j=1}^{J} \delta_j D_j + \mu_{i,j,t}$$ (3)

Then, CPI bias at different points in the income distribution can be estimated as:

$$Bias_t = 1 - \exp \left( \frac{-\delta_t}{\beta} \ln Y_{i,j,t} - \ln (1 + \Pi_{j,t}) \right)$$ (4)

Once we have estimated CPI bias, we follow Barrett and Brzozowski (2010) to calculate a ‘correction factor’ that multiplies the measured CPI in year $t$ to give the true cost of living index in year $t$:

$$Correction_t = 1 - Bias_t$$ (5)

To estimate the implication of CPI bias for poverty in year $t$ in a given country $c$, we revise the international poverty line, currently $1.90$ per person per day in 2011 dollars, by adjusting for CPI bias. First, we convert the international poverty line into local currency units in time $0$, that is the year of the sample period closest to 2011 (the year that anchors the poverty line and Purchasing Power Parity exchange) for a given country $c$. Next, we update the poverty line in...
time \( t \), that is the comparison year of the sample period, using the correction factor described in eq. (5).\(^9\) The adjusted poverty line in time \( t \) for country \( c \) is then\(^10\)

\[
AdjustedPovline_{c,t} = \frac{1.90PPP_{c,2011}}{(1 + \Pi_{c,2011})(1 + \Pi_{c,t}Correction_{c,t})}
\]  

where \( PPP_{c,2011} \) is the Purchasing Power Parity conversion factor in year 2011 for country \( c \); \( \Pi_{c,2011} \) is the cumulative percent increase in the CPI from year 0 to year 2011; \( \Pi_{c,t} \) is the cumulative percent increase in the CPI from year 0 to year \( t \); and \( Correction_{c,t} \) is the correction factor for country \( c \) in year \( t \), estimated from eq. (5).

### 3.2 Data

The Engel curve method requires detailed monthly CPI data on food and non-food items at sub-national levels and comparable consumption surveys in multiple years. However, data in Sub-Saharan Africa are challenging in terms of availability and quality. Of the 48 countries in the region, only half have two or more HBSs since the early 2000s (Beegle et al. 2016). Among these, only a limited number collect consumption data using the same (or at least similar) survey design and methodology, thereby rendering the consumption aggregates comparable over time. Obtaining detailed CPI series adds another layer of difficulty. In some of the countries with comparable HBSs, detailed CPI data are either unavailable during the periods of interest or the continuity of the series has been disrupted due to political unrest or other factors, as, for example, in the case for Sierra Leone.

For the purpose of this study we obtain household consumption and CPI data for 16 countries in Sub-Saharan Africa that account for 70% of the region’s population.\(^11\) These countries are Burkina Faso, Cameroon, Côte d’Ivoire, Democratic Republic of Congo, Ethiopia, Ghana, Madagascar, Mauritius, Mozambique, Nigeria, Rwanda, Senegal, South Africa, Tanzania, Togo, and Uganda. For Nigeria and Tanzania we use panel data from the Living Standards Measurement Study—Integrated Surveys on Agriculture (LSMS-ISA) program, partly to address quality concerns with other consumption surveys (World Bank 2014, 2015).\(^12\) Only household survey series considered as comparable over time (in terms of the broad data collection method for consumption data and seasonality) are included in the analysis (see Beegle et al. 2016). Table 1 provides a list of the microdata used in this study.

We obtain monthly national CPI data disaggregated into food and non-food components from the respective NSOs. In terms of geographical coverage, all countries, except Nigeria and Rwanda, only collect prices in urban areas. In other words, the national CPIs in these countries

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\(^9\) Time 0 could be the beginning year or the end year of the sample period. For example, for Rwanda 2005–2010, time 0 is 2010. In the case of Nigeria 2011–2013, time 0 is 2011.

\(^10\) Equation (6) applies to most countries in our sample where time 0 is earlier than 2011. In some special cases where time \( \leq 2011 < time\ 0 \) (Congo, D.R. 2004–2012, Ghana 2005–2012, Mauritius 2006–2012, Tanzania 2008–2012, Tanzania 2010–2012, and Uganda 2009–2012), the adjusted poverty line is calculated as:

\[
AdjustedPovline_{c,t} = \frac{1.90PPP_{c,2011}(1+\Pi_{c,2011})}{(1+\Pi_{c,t}Correction_{c,t})}
\]

In a special case where \( 2011 < time\ 0 < time\ t \) (Nigeria 2011–2013), the adjusted poverty line is calculated as:

\[
AdjustedPovline_{c,t} = 1.90PPP_{c,2011}(1+\Pi_{c,2011})(1+\Pi_{c,t}Correction_{c,t})
\]

\(^11\) We use consumption rather than income because it is generally thought to be a better measure of permanent income and is also easier to measure in economies with large agricultural or other informal sectors (see Deaton 1997).

\(^12\) See LSMS-ISA (database), World Bank, Washington, DC, http://go.worldbank.org/BCLXW38HY0.
reflect the prices paid by urban residents. Conversely, the national CPIs in Nigeria and Rwanda reflect both rural and urban prices. Sub-national CPI data are available for only four countries – Ethiopia, Ghana, Mozambique, and Uganda. These data allow us to estimate the CPI-bias based on eq. (1). The remaining countries only have national CPIs, and we are therefore required to apply eq. (2) for the CPI-bias estimation. Table 2 lists the CPI data used in this study.

Detailed expenditure data are aggregated into two broad groups: food expenditure and total expenditure. Food expenditure is defined as expenditure for the consumption of food, nonalcoholic beverages, alcoholic beverages, and tobacco from own-production, market purchase, and gifts. Total household expenditure includes spending on food and non-food expenditure, such as clothing, housing, household furnishings and equipment, health and personal care, education, transport, communications, recreation, and miscellaneous goods and services. We then merge the consumption data for each household with the monthly CPI during the period when the household was interviewed. This allows for temporal variations in inflation patterns. We use several criteria to select our sample for analysis. First, to minimize the effect of extreme outliers, which may indicate data quality problems, households with a food budget share of less than 2% or greater than 95% are excluded. Second, to render household demographics more homogeneous, we exclude households in which the household head is younger than 21 years of age or older than 75 years of age. These restrictions are similar to those used by Costa (2001), Gibson et al. (2008) and Hamilton (2001) and do not change our results in a significant way. Finally, rural households in all the countries in this study, except Mauritius, Nigeria, and Rwanda, are dropped because the CPIs in these countries reflect prices faced by urban populations only.13 Because of this, our estimates of CPI bias should be interpreted as the wedge between CPI inflation and the change in the cost of living experienced by the average urban household. As noted by Almas et al. (2018), the estimated bias reflects

### Table 1: Household surveys, by Country, Sub-Saharan Africa, 1998–2013

| Country      | Household survey                                                                 | Year        |
|--------------|---------------------------------------------------------------------------------|-------------|
| Burkina Faso | Enquête Burkinaë sur les Conditions de Vie des Ménages                           | 1998–2003   |
| Cameroon     | Enquête Camerounaise Auprès des Ménages                                         | 2001–2007   |
| Congo, D.R.  | Questionnaire de l’enquête                                                      | 2004–2012   |
| Côte d’Ivoire| Enquête Niveau de Vie des Ménages                                               | 2002–2008   |
| Ethiopia     | Welfare Monitoring and Household Income Expenditure Survey                      | 2004–2010   |
| Ghana        | Ghana Living Standards Survey                                                   | 2005–2012   |
| Madagascar   | Enquêtes Périodiques auprès des Ménages                                         | 2001–2005–2010 |
| Mauritius    | Household Budget Survey                                                        | 2006–2012   |
| Mozambique   | Inquérito aos Agregados Familiares Sobre Orçamento Familiar                     | 2002–2008   |
| Nigeria      | General Household Survey                                                       | 2011–2013   |
| Rwanda       | Enquête Intégrale sur les Conditions de Vie des Ménages                         | 2005–2010   |
| Senegal      | Enquête de Suivi de la Pauvreté au Sénégal                                      | 2005–2011   |
| South Africa | Income and Expenditure Survey                                                  | 2005–2010   |
| Tanzania     | Household Budget Survey                                                        | 2000–2007   |
| Tanzania     | Living Standards Measurement Study                                             | 2008–2010–2012 |
| Togo         | Questionnaire des Indicateurs de Base du Bien-être                               | 2006–2011   |
| Uganda       | National Household Survey                                                      | 2009–2012   |

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13 While the national CPIs for Mauritius reflects urban prices only, the Household Budget Survey for Mauritius does not identify households’ location – either urban or rural areas. Therefore, all households must be included for the estimates of CPI bias in the case of Mauritius.
the “true” bias of the CPI and some degree of inflation inequality across the distribution. However, as we show later, in most of the countries in our study, the results show that the bias varies insignificantly across the income distribution.

### 4 Estimated CPI Bias

Table 3 provides summary statistics of the data used in our analysis. As stated in Engel’s Law, the average household food share falls as income rises. Thus, we can see that the average budget share devoted to food could be as low as 30% in upper-middle-income countries such as Mauritius and as high as 74% in low income countries such as Madagascar.

To show how the food budget share changes over time, the averages of the variables in different survey periods are reported for each country. All countries except Ghana experienced a decline in the share of food in total consumption between the first and the last survey periods. According to Engel’s Law, this drop in the budget share of food may indicate improved living standards.

Figure 1 plots Engel curves estimated by locally weighted nonparametric regression between food budget shares and real log total expenditure for 16 Sub-Saharan African countries. The graphs are based on households with a food budget share between 2% and 95% of total consumption and with household heads aged between 21 and 75 years. The solid (reference) lines are the Engel curves of the oldest survey in each country. The dotted lines are the Engel curves for subsequent survey years.\(^{14}\)

All countries in our study show movements of the Engel curves over time. In 13 of the 16 countries, namely, Burkina Faso, Cameroon, Côte d’Ivoire, Democratic Republic of Congo, Ethiopia, Madagascar, Mauritius, Nigeria, Rwanda, Senegal, South Africa, Tanzania, and

\(^{14}\) These are bivariate graphs without any controls.
Togo, the dotted curve lies below the solid reference curve. This indicates that Engel curves have drifted to the left, a signal that the national CPIs in these countries may overstate the increase in cost of living. In Ghana, Mozambique, and Uganda the direction of the CPI bias does not seem consistent across the income distribution. In Ghana, for example, the CPIs appear downward-biased among those people at the lower end of the income distribution, while they appear biased in the opposite direction among people at the upper end of the distribution. The pattern is reversed in Mozambique and Uganda.

While the illustrations in Fig. 1 show a clear drift in the Engel curves for the countries in our study, movements in food budget shares could also be attributed to changes in relative prices, household characteristics, etc. Thus, we use regression analysis to condition on these potentially confounding influences and assess the actual drift in the food Engel curve.

### Table 3  Summary statistics, by Country, Sub-Saharan Africa, 1998–2013

| Country        | Survey year | Food share (mean) | Standard deviation | Log of household consumption (mean) | Standard deviation |
|----------------|-------------|-------------------|--------------------|-------------------------------------|-------------------|
| Burkina Faso   | 1998        | 0.591             | 0.172              | 13.184                              | 0.824             |
|                | 2003        | 0.554             | 0.198              | 13.291                              | 0.770             |
| Cameroon       | 2001        | 0.467             | 0.178              | 13.532                              | 0.745             |
|                | 2007        | 0.461             | 0.167              | 13.345                              | 0.730             |
| Congo, DR      | 2004        | 0.658             | 0.140              | 12.651                              | 0.772             |
|                | 2012        | 0.640             | 0.154              | 12.613                              | 0.742             |
| Cote d’Ivoire | 2002        | 0.520             | 0.192              | 14.063                              | 0.817             |
|                | 2008        | 0.470             | 0.197              | 13.791                              | 0.800             |
| Ethiopia       | 2004        | 0.586             | 0.137              | 9.237                               | 0.528             |
|                | 2010        | 0.514             | 0.131              | 9.207                               | 0.558             |
| Ghana          | 2005        | 0.596             | 0.171              | 8.239                               | 0.726             |
|                | 2012        | 0.731             | 0.246              | 7.501                               | 0.741             |
| Madagascar     | 2001        | 0.775             | 0.177              | 13.350                              | 0.789             |
|                | 2005        | 0.722             | 0.146              | 13.359                              | 0.633             |
|                | 2010        | 0.735             | 0.155              | 13.184                              | 0.653             |
| Mozambique     | 2002        | 0.608             | 0.202              | 9.792                               | 0.840             |
|                | 2008        | 0.586             | 0.188              | 9.946                               | 0.831             |
| Mauritius      | 2006        | 0.309             | 0.112              | 12.133                              | 0.579             |
|                | 2012        | 0.291             | 0.101              | 12.150                              | 0.588             |
| Nigeria        | 2011        | 0.691             | 0.162              | 12.853                              | 0.644             |
|                | 2013        | 0.652             | 0.173              | 12.783                              | 0.684             |
| Rwanda         | 2005        | 0.678             | 0.197              | 13.427                              | 0.929             |
|                | 2010        | 0.610             | 0.170              | 13.566                              | 0.843             |
| Senegal        | 2005        | 0.583             | 0.132              | 14.645                              | 0.742             |
|                | 2011        | 0.536             | 0.153              | 14.636                              | 0.678             |
| South Africa   | 2005        | 0.421             | 0.154              | 11.478                              | 1.137             |
|                | 2010        | 0.269             | 0.180              | 10.973                              | 1.029             |
| Tanzania       | 2000        | 0.713             | 0.122              | 12.457                              | 0.672             |
|                | 2007        | 0.629             | 0.121              | 12.760                              | 0.670             |
| Tanzania       | 2008        | 0.634             | 0.123              | 13.256                              | 0.738             |
|                | 2010        | 0.605             | 0.122              | 13.266                              | 0.730             |
|                | 2012        | 0.581             | 0.121              | 13.281                              | 0.756             |
| Togo           | 2006        | 0.573             | 0.173              | 13.586                              | 0.713             |
|                | 2011        | 0.457             | 0.162              | 13.678                              | 0.801             |
| Uganda         | 2009        | 0.474             | 0.137              | 14.774                              | 0.752             |
|                | 2012        | 0.437             | 0.122              | 14.871                              | 0.726             |

Source: Household surveys
Table 4 reports the results of ordinary least square (OLS) regressions of the Engel functions. All regressions are weighted by population-level sampling weights (as discussed later in this section, unweighted regressions are run as a robustness check). As explained in section III, we apply eq. (1) to Ethiopia, Ghana, Mozambique, and Uganda (linked to the availability of cross-sectional price data) and eq. (9) in Annex 2 to the rest of the countries. We also limit our sample to urban populations for all countries except Mauritius, Nigeria, and Rwanda.

Across all countries, the estimated regression coefficients for CPI-deflated total expenditure are negative and statistically significant. These results are consistent with Engel’s Law that food budget shares decline as households become richer. The coefficients of the various household characteristics show that, in general, food shares are higher among households of

Fig. 1  Engel Curves, Sub-Saharan Africa, 1998–2013

(1) Burkina Faso, 1998–2003
(2) Cameroon 2001-07
(3) Congo, Democratic Republic, 2004-2012
(4) Côte d’Ivoire, 2002–08
(5) Ethiopia, 2004–10
(6) Ghana, 2005–12
larger size, with younger children, and with heads who are married or older. Food shares decline among households in which the heads have higher educational attainment. There is no clear pattern across countries between the gender of the household head and the food budget share.

The signs of the time dummy variables in Table 4 are consistent with the shifts in the food Engel curves illustrated in Fig. 1. They suggest a drift to the left in the food Engel curves in Cameroon, Côte d’Ivoire, the Democratic Republic of Congo, Ethiopia, Madagascar, Mauritius, Mozambique, Nigeria, Rwanda, Senegal, South Africa, Tanzania, and Togo. This drift suggests that growth in real consumption is underestimated. Meanwhile, the food Engel curves in Burkina Faso, Ghana, and Uganda seem to shift to the right, suggesting an overestimation of
Table A1 in appendix 1 shows the results of two robustness checks. The first is to add to the existing model the quadratic log of CPI-deflated total consumption to account for Engel curvature – that is non-linearity in the relationship between a household’s real income and its food share. This concept is first introduced by Costa (2001) as an extension of Hamilton’s work. The second robustness check is to run unweighted regressions, because there has been some debate about the use of sampling weights in regression analysis (see Deaton 1997). Both specifications show similar results for the time dummy variables in our main specification in

Note: Expenditure measured in real terms (i.e. CPI deflated).

Fig. 1 continued.

real consumption growth. The coefficients of the time dummies for Burkina Faso and Cameroon are not statistically significant at the 5% level.

Table A1 in appendix 1 shows the results of two robustness checks. The first is to add to the existing model the quadratic log of CPI-deflated total consumption to account for Engel curvature – that is non-linearity in the relationship between a household’s real income and its food share. This concept is first introduced by Costa (2001) as an extension of Hamilton’s work. The second robustness check is to run unweighted regressions, because there has been some debate about the use of sampling weights in regression analysis (see Deaton 1997). Both specifications show similar results for the time dummy variables in our main specification in
### Table 4  Regression results, by Country, Sub-Saharan Africa, 1998–2013

| Country          | ln(relative food inflation) | ln(real total consumption) | Time dummy | Sample size | Adjusted R2 | Availability of regional CPI | Sample coverage | Year of survey rounds |
|------------------|----------------------------|---------------------------|------------|-------------|-------------|-----------------------------|----------------|----------------------|
| Burkina Faso     | -0.147***                  | -0.056***                 | 0.004      | 4992        | 0.297       | No                          | Urban          | 1998, 2003           |
| Cameroon         | -0.032                     | -0.078***                 | -0.004*    | 12,830      | 0.027       | No                          | National       | 2001, 2007           |
| Congo, D. R.     | -0.071***                  | -0.077***                 | -0.032***  | 14,566      | 0.040       | No                          | Urban          | 2004, 2012           |
| Cote d'Ivoire    | -0.095***                  | -0.093***                 | -0.043***  | 11,151      | 0.050       | No                          | Urban          | 2002, 2008           |
| Ethiopia         | -0.079***                  | -0.117***                 | -0.063***  | 44,600      | 0.022       | Yes                         | National       | 2004, 2010           |
| Ghana            | -0.091***                  | -0.091***                 | -0.042***  | 8852        | 0.048       | No                          | National       | 2006, 2012           |
| Madagascar       | -0.117***                  | -0.071***                 | -0.101***  | 8834        | 0.050       | No                          | National       | 2005, 2010           |
| Madagascar       | -0.079***                  | -0.079***                 | -0.101***  | 11,480      | 0.050       | No                          | National       | 2006, 2012           |
| Mauritius        | -0.079***                  | -0.079***                 | -0.101***  | 12,736      | 0.050       | No                          | National       | 2002, 2008           |
| Mozambique       | -0.244***                  | -0.066***                 | -0.030***  | 8852        | 0.048       | Yes                         | National       | 2002, 2008           |

Regressions are controlled for household size, share of household younger than 5 year old, share of household between 5 and 10 year old, share of household between 10 and 17 year old, head’s age, head’s gender, head’s education, head’s marital status, and regional dummies

Significance level: * = 10%, ** = 5%, *** = 1%
Table 4 (for ease of comparison, repeated in Table A1 under the column OLS). The only exception is Mozambique, where the sign of the time dummy coefficient changes when sampling weights are disregarded, which suggests significant heterogeneity in region-specific bias in this country. Further investigation reveals that the observed results are mostly driven by the bias in urban cities in Namputa province, the most populous province in the country which accounts for approximately 20% of the weighted population. In fact, if we drop Namputa from our sample, the regression results are similar regardless of whether sampling weights are used. Finally, to obtain estimates of CPI bias for the 12 countries that lack cross-sectional CPI data, it was necessary to estimate \( \gamma \) in order to remove any effect of differential inflation rates on food and non-food items in the budget share of food. Appendix 2 explains these calculations in detail.

Table 5 presents estimates of \( \gamma \) for all countries that do not have cross-sectional CPI data. Overall, \( \gamma \) is estimated to range from 0.17 to 0.24, compared with the values of \( \gamma = 0.044 \) used by Olivia and Gibson (2013) for Indonesia, 0.109 by Gibson and Scobie (2010) for New Zealand, 0.19 by Gibson et al. (2008) for Russia, and 0.037 used by Hamilton (2001) for the United States. Because we do not have sufficient data to measure \( \gamma \) for the Democratic Republic of Congo, we assign the country the regional average of 0.22.

To examine whether the bias varies across the income distribution, we use the specification on eq. (3) and (4) and implement one-way ANOVA tests as well as Tukey Honestly Significant Difference (HSD) post-hoc tests to identify the bias in which decile is statistically different from others. Figure 2 presents the bias with 95% confidence intervals by income deciles, and ANOVA test results.15 A general pattern across all countries appears that households in the top deciles faced different bias from the rest of the population. However, such differences are statistically significant in only 6 out of 16 countries, namely Cameroon, Ethiopia, Madagascar (between 2005 and 2010), Mauritius, South Africa, and Togo. Overall, there does not appear to be meaningful inflation inequality across the income distribution for most of the countries.

Finally, Table 6 reports the bias estimates from two different methods described above. Panel A shows our estimates under the assumption of constant bias across all households. Panel B

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Table 5  Estimates of \( \gamma \) for Countries without Cross-sectional CPI Data

| country    | Survey period | \( \gamma \) | Cumulative CPI-bias |
|------------|---------------|--------------|---------------------|
| Burkina Faso | 1998-2003     | 0.231        | -0.447              |
| Cameroon   | 2001-2007     | 0.226        | 0.040               |
| Cote d’Ivoire | 2002-2008   | 0.223        | 0.517               |
| Madagascar | 2001-2010     | 0.202        | 0.718               |
| Madagascar | 2005-2010     | 0.208        | 0.281               |
| Mauritius  | 2006-2012     | 0.167        | 0.330               |
| Nigeria    | 2011-2013     | 0.216        | 0.878               |
| Rwanda     | 2005-2010     | 0.234        | 0.623               |
| Senegal    | 2005-2011     | 0.231        | 0.627               |
| South Africa | 2005-2010   | 0.205        | 0.955               |
| Tanzania   | 2000-2007     | 0.220        | 0.942               |
| Tanzania   | 2008-2012     | 0.234        | 0.877               |
| Togo       | 2006-2011     | 0.239        | 0.899               |

*There is insufficient data to estimate \( \gamma \) for Congo, D.R. Thus, we use the average of all \( \gamma \) estimates (0.22) for this country

15 Due to the length of the results (i.e. testing each pair of deciles separately), details of Tukey HSD post-hoc test results are available upon request.
presents the results specifically for households at the mean of the consumption distribution, assuming the bias varies linearly with log of consumption. In other words, in Panel B, we calculate the specific bias faced by households whose real consumption is the average consumption of the population. There are two reasons why we choose households with the average real consumption as opposed to households at another point of the consumption distribution. First, it is shown above that in most of the countries covered in this study, the bias is not statistically different across the consumption distribution. Second, we want to empirically examine if the bias faced by the “average” household in Panel A is similar to the one faced by households at the exact mean of the consumption distribution. Columns (1) and (4) show the cumulative CPI bias for the 16 countries in our study. Its standard error in bracket is computed...
using the delta method. We assume that in each country this bias is constant over the sample period to calculate the average annual bias presented in column (2) and (5). The correction factor, that is the CPI multiplier to estimate true inflation, is shown in column (3) and (6).

Overall, the bias is similar between Panel A and Panel B. The CPI bias is positive and statistically significant for the sample periods in 12 of the 16 countries in our study, namely, Côte d’Ivoire, the Democratic Republic of Congo, Ethiopia, Madagascar, Mauritius, Mozambique, Nigeria, Rwanda, Senegal, South Africa, Tanzania, and Togo. In these countries, households allocated their budget share on food as if their true cost of living was increasing more slowly than the rate indicated by the CPI. Assuming the bias is constant across all households (results in Panel A), the upward bias ranges from 2.8% a year in Ethiopia between 2004 and 2010 to 43.9% a year in Nigeria between 2011 and 2013. For households whose real consumption is the average consumption of the population (results in Panel B), the upward annual bias ranges from 2.1% in Ethiopia to 45.6% in Nigeria. Meanwhile, three countries experienced the opposite trend in the CPI bias, ranging from −13.2% a year in Uganda between 2009 and 2012 to −5.8% a year in Ghana between 2005 and 2012 if using the...
method in eq. (2) (Panel A results). The range is $-12.9\%$ in Uganda and $-6.1\%$ in Ghana if eq. (3) is applied (Panel B results). The bias is not statistically significant in Cameroon for both methods.

5 Implications for Poverty Trends in Africa

Consumer price indexes (CPIs) play a pivotal role for the measurement of poverty trends in Sub-Saharan Africa. The World Bank’s international poverty estimates currently use an international poverty line of $1.90$ per person per day at 2011 international prices. This poverty line is affected by CPI bias, because CPIs are used to deflate the poverty line between the year of the household survey and 2011 (the benchmark year of the purchasing power parity exchange rates). In addition, some countries in Sub-Saharan Africa use the CPI to update their national poverty lines. National poverty lines are usually based on the Cost of Basic Needs (CBN) approach.
which aims to compute the cost of maintaining some basic living standard. A typical CBN poverty line is calculated from the cost of a food basket that meets certain food energy requirements – for example 2100 cal per person per day – and observed spending on non-food essentials such as clothing and household items (Ravallion 1998). Anyone living below this poverty line is considered poor. Some countries in Africa – for example Uganda and Mauritania – also use the CPI to update their national poverty lines over time. The majority of countries, however, either use specialized price indexes to inflate or deflate the national poverty line over time (often based on unit values computed from the consumption module of the household...

16 Other countries have used the CPI in the past, for example Ethiopia (before the 2010 update) and Zambia (before the 2009 revision of 1996–2006 poverty estimates).
survey) or redraw the poverty line from scratch in each year (Gaddis 2016). As a result, national poverty estimates are much less affected by CPI bias than international poverty estimates, and we focus on the latter in this paper. 17

In this section, we re-assess poverty estimates for the 16 countries in our study to account for the cumulative CPI bias estimated in the previous section. In countries where the CPI overstates the increase in cost of living, the poverty lines adjusted for CPI bias will show a more moderate increase over time (in nominal terms) than the ones typically reported, therefore increasing measured poverty reduction. The opposite effect occurs in countries where the CPI understates inflation. In the 14 countries where prices are only collected in urban areas, we examine the poverty implications of CPI bias in urban settings only. The calculation of the

17 Another reason is that the international poverty line is generally better suited for cross-country comparative analysis, given that national poverty lines are often not comparable across countries.
adjusted poverty lines is described in eq. (6). Table 7 presents official inflation rates and estimates of inflation adjusted for CPI bias using two methods: Panel A shows our estimates using eq. (2) and Panel B presents the results using eq. (3). Table 8, Panel A and Panel B, illustrates the implications of this CPI bias for poverty reduction in all countries in our study.
Table 7 Estimated ‘True’ Inflation, by Country, Sub-Saharan Africa, 1998–2013

| Country          | Survey period | Reported inflation | Panel A – Bias constant across households | Panel B – Bias linear function of real consumption |
|------------------|---------------|--------------------|------------------------------------------|--------------------------------------------------|
|                  |               | (cumulative) (annual) | Correction factor (cumulative) (annual) | True inflation (cumulative) (annual) |
|                  |               | (1) (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Burkin Faso      | 1998–2003     | 0.064 0.013 | 1.419 | 0.090 | 0.018 | 1.406 | 0.090 | 0.018 |
| Cameroon         | 2001–2007     | 0.127 0.021 | 0.958 | 0.121 | 0.020 | 0.965 | 0.122 | 0.020 |
| Congo, D.R.      | 2004–2012     | 2.813 0.352 | 0.486 | 1.367 | 0.171 | 0.500 | 1.407 | 0.176 |
| Cote d’Ivoire    | 2002–2008     | 0.224 0.037 | 0.484 | 0.109 | 0.018 | 0.463 | 0.104 | 0.017 |
| Ethiopia         | 2004–2010     | 1.630 0.272 | 0.831 | 1.355 | 0.226 | 0.875 | 1.427 | 0.238 |
| Ghana            | 2005–2012     | 1.254 0.197 | 1.407 | 1.765 | 0.252 | 1.429 | 1.792 | 0.256 |
| Madagascar       | 2001–2010     | 1.435 0.159 | 0.268 | 0.385 | 0.043 | 0.284 | 0.407 | 0.045 |
| Madagascar       | 2005–2010     | 0.545 0.109 | 0.740 | 0.404 | 0.081 | 0.704 | 0.384 | 0.077 |
| Mauritius        | 2006–2012     | 0.330 0.055 | 0.670 | 0.221 | 0.037 | 0.681 | 0.225 | 0.037 |
| Mozambique       | 2002–2008     | 0.842 0.140 | 0.622 | 0.524 | 0.087 | 0.593 | 0.499 | 0.083 |
| Nigeria          | 2011–2013     | 0.233 0.116 | 0.122 | 0.028 | 0.014 | 0.088 | 0.021 | 0.010 |
| Rwanda           | 2005–2010     | 0.636 0.127 | 0.377 | 0.240 | 0.048 | 0.372 | 0.237 | 0.047 |
| Senegal          | 2005–2011     | 0.178 0.030 | 0.376 | 0.067 | 0.011 | 0.388 | 0.069 | 0.012 |
| South Africa     | 2005–2010     | 0.068 0.014 | 0.045 | 0.003 | 0.001 | 0.021 | 0.001 | 0.000 |
| Tanzania         | 2000–2007     | 0.456 0.065 | 0.076 | 0.035 | 0.005 | 0.072 | 0.033 | 0.005 |
| Tanzania         | 2008–2012     | 0.507 0.127 | 0.126 | 0.193 | 0.048 | 0.137 | 0.070 | 0.017 |
| Tanzania         | 2010–2012     | 0.283 0.142 | 0.381 | 0.036 | 0.018 | 0.410 | 0.116 | 0.058 |
| Togo             | 2006–2011     | 0.210 0.042 | 0.107 | 0.022 | 0.004 | 0.218 | 0.046 | 0.009 |
| Uganda           | 2009–2012     | 0.403 0.134 | 1.396 | 0.563 | 0.188 | 1.386 | 0.559 | 0.186 |
| Country         | Survey period | Official poverty reduction | Panel A – Bias constant across households | Panel B – Bias linear function of real consumption |
|----------------|---------------|---------------------------|------------------------------------------|-----------------------------------------------|
|                |               |                           | Poverty reduction from correction of CPI bias | Poverty reduction from correction of CPI bias |
|                |               |                           | Cumulative (% pt.) (1) | Annual (% pt) (2) | Cumulative (% pt) (3) | Annual (% pt) (4) | Cumulative (% pt) (5) | Annual (% pt) (6) |
| Burkina Faso   | 1998–2003     | -15.74*** (1.432)         | -15.20*** (1.431) | -3.15*** (0.286) | -3.04*** (0.286) | -15.25*** (1.431) | -3.05*** (0.286) |
| Cameroon       | 2001–2007     | -1.71*** (0.441)          | -1.73*** (0.441) | -0.29*** (0.073) | -0.29*** (0.074) | -1.71*** (0.441) | -0.29*** (0.073) |
| Congo, D.R.    | 2004–2012     | 2.25*** (0.851)           | -20.83*** (0.809) | 0.28*** (0.106) | -2.60*** (0.101) | -20.05*** (0.811) | -2.51*** (0.073) |
| Cote d'Ivoire  | 2002–2008     | 0.92 (0.677)              | -5.48*** (0.723) | 0.15 (0.113)    | -0.913*** (0.120) | -5.76*** (0.724) | -0.96*** (0.101) |
| Ethiopia       | 2004–2010     | -16.03*** (0.472)         | -23.30*** (0.486) | -2.67*** (0.079) | -3.88*** (0.081) | -22.15*** (0.484) | -3.69*** (0.081) |
| Ghana          | 2005–2012     | -13.40*** (0.498)         | 2.03*** (0.236)   | -1.91*** (0.071) | 0.29*** (0.034)  | 2.03*** (0.236)   | 0.29*** (0.034)  |
| Madagascar     | 2001–2010     | 16.38*** (1.019)          | -10.29*** (0.987) | 1.82*** (0.113) | -1.14*** (0.110) | -9.74*** (0.989) | -1.08*** (0.110) |
| Madagascar     | 2005–2010     | 7.31*** (0.898)           | -0.01 (0.891)    | 1.46*** (0.180) | 0.00 (0.178)     | -1.02 (0.889)     | 0.20 (0.178)     |
| Mauritius (+)  | 2006–2012     | 0.11 (0.119)              | -0.12 (0.132)    | 0.02 (0.020)    | -0.02 (0.022)    | -0.07 (0.130)     | 0.01 (0.022)     |
| Mozambique     | 2002–2008     | -10.61*** (1.026)         | -16.87*** (1.006) | -1.77*** (0.171) | -2.81*** (0.168) | -18.23*** (1.001) | -3.04*** (0.167) |
| Nigeria (+)    | 2011–2013     | 4.86*** (1.006)           | -5.40*** (0.978) | 2.43*** (0.503) | -2.70*** (0.489) | -5.84*** (0.977) | -2.92*** (0.488) |
| Rwanda (+)     | 2005–2010     | -8.35*** (0.656)          | -14.75*** (0.637) | -1.67*** (0.131) | -2.95*** (0.127) | -14.85*** (0.637) | -2.97*** (0.127) |
| Senegal        | 2005–2011     | 1.10* (0.601)             | -2.26*** (0.633) | 0.18* (0.100)   | -0.38*** (0.106) | -2.12*** (0.632) | -0.35*** (0.105) |
| South Africa   | 2005–2010     | -1.90*** (0.357)          | -15.04*** (0.430) | -0.38*** (0.071) | -3.01*** (0.086) | -15.17*** (0.431) | -3.03*** (0.086) |
Table 8 (continued)

| Country     | Survey period | Official poverty reduction | Panel A – Bias constant across households | Panel B – Bias linear function of real consumption |
|-------------|---------------|----------------------------|-----------------------------------------|------------------------------------------|
|             |               |                            | Poverty reduction from correction of CPI bias | Poverty reduction from correction of CPI bias |
|             |               | Cummulative (% pt.) (1)    | Annual (% pt) (2)                       | Cummulative (% pt.) (3) | Annual (% pt) (4) | Cummulative (% pt.) (5) | Annual (% pt) (6) |
| Tanzania    | 2000–2007     | −17.61***                   | −2.52***                               | −33.00***                               | −4.71***                               | −33.00***                   | −4.71***                   |
|             |               | (0.673)                     | (0.096)                                | (0.629)                                 | (0.090)                                 | (0.629)                     | (0.090)                                 |
| Tanzania    | 2008–2012     | 4.28***                     | 1.07***                                | −14.86***                               | −3.72***                               | −20.70***                   | −5.17***                   |
|             |               | (1.607)                     | (0.402)                                | (1.544)                                 | (0.386)                                 | (1.502)                     | (0.375)                                 |
| Tanzania    | 2010–2012     | 2.10                        | 1.05                                  | −13.36***                               | −6.68***                               | −8.55***                    | −4.27***                   |
|             |               | (1.434)                     | (0.717)                                | (1.376)                                 | (0.688)                                 | (1.403)                     | (0.701)                                 |
| Togo        | 2006–2011     | −0.52                       | −0.10                                 | −6.76***                                | −1.35***                               | −6.38***                    | −1.28***                   |
|             |               | (1.188)                     | (0.238)                                | (1.231)                                 | (0.246)                                 | (1.228)                     | (0.246)                                 |
| Uganda      | 2009–2012     | 0.85                        | 0.28                                  | 2.48*                                   | 0.83*                                  | 2.44*                       | 0.81*                       |
|             |               | (1.325)                     | (0.442)                                | (1.302)                                 | (0.434)                                 | (1.303)                     | (0.434)                                 |

(+) national poverty
Standard errors are in brackets
Significance level: * = 10%, ** = 5%, *** = 1%
The correction factors in Table 7 range widely, from 0.045 in South Africa to 1.42 in Burkina Faso in Panel A, column (3). Similar range is observed in Panel B, column (6). Relative to the base year, the official CPI for the other year of the sample period multiplied by the correction factor indicates the true cost of living for that year. For example, in Côte d’Ivoire, the correction factor for households at the mean of the consumption distribution is estimated at 0.46 in 2002, which means, relative to the 2008 base period, the official CPI for 2002 multiplied by 0.46 shows the actual price level in 2002. In other words, the CPI level in 2002 was overestimated by 54%. Similarly, in Uganda, with the correction factor of 1.39, the price level is understated by 39% in 2009.

How relevant is this CPI bias for estimated poverty trends? Since the CPI bias is measured in percentage terms, a large bias is more consequential if the underlying cumulative inflation is higher. For example, in the case of Burkina Faso, the CPI is estimated to significantly underestimate the true cost of living by 40.6% between 1998 and 2003 (i.e. the correction factor is 1.406 in Table 7, Panel B, column (6)). However, the reported cumulative inflation during the same period is only 6.4%, so that the adjusted inflation increases only moderately to 9.0%. Therefore, the difference in poverty reduction based on the official inflation rate vs. the CPI-bias adjusted inflation rate is marginal. On the other hand, a comparable, though opposite, 50.0% CPI bias in the Democratic Republic of Congo leads to a cumulative bias-adjusted inflation rate of 140.7%, compared with the official inflation rate of 281.3%. As a result, the bias-adjusted poverty reduction in annual terms is 1.7 percentage points faster than the one based on the official inflation rate.

Overall, we observe similar poverty implications between the two methods (Table 8, Panel A and B). For countries experiencing an upward bias, our estimates of CPI bias suggest that the international poverty rate (bias-adjusted) in urban areas fell faster than currently thought by somewhere between 0.29 percentage point per year in Cameroon and 6.7 percentage points per year in Tanzania (2010–2012) (Table 8, Panel A, column (4)). Interestingly, once the bias is adjusted, six countries in our study experience the opposite poverty changes compared to the official trend. Among which, five countries, Democratic Republic of Congo, Madagascar (2001–2010), Nigeria, Senegal, and Tanzania (2008–2012) would see poverty decline with the correction of the CPI bias while the official data shows an increase in poverty rate. The remaining country, Ghana see a reverse pattern: urban poverty would increase slightly after the CPI bias adjustment while the country is officially reported as having a poverty reduction between 2005 and 2012. Three countries with no poverty changes based on official figures turn out to have significant poverty reduction after taking into account the CPI bias. These countries are Cote d’Ivoire, Tanzania (2010–2012), and Togo. Meanwhile, correcting for the bias would lead Uganda from experiencing insignificant changes in urban poverty to an actual slight increase in poverty (Table 8, Panel A, columns (2) and (4)). Figure 3 presents poverty implications when adjusting for the bias faced by households with the average real consumption. The pattern is the same as what has been described above.

6 Reconciling the Results in this Paper with Other Studies

The results in this paper suggest that CPIs in most Sub-Saharan African countries overestimate inflation, which leads to an underestimation of progress in poverty reduction. These results are robust to accounting for non-linearity in the relationship between a household’s real income and its food share and hold up if we run unweighted regressions. But how do these
results compare with those of other studies analyzing the evolution of living standards and poverty in Africa? 18

Our results are qualitatively consistent with Young (2012), who uses Demographic and Health Survey (DHS) data to approximate the level and growth of real consumption based on comparably measured indicators of consumer durable ownership, housing conditions, children’s nutrition and health, and household time and family economics. The study concludes that between (approximately) 1990 and 2005, living standards in Africa grew on average at a rate that is 3.5 to 4 times higher than the growth in real consumption, a divergence that the author attributes to weaknesses in the underlying data sources of household consumption expenditure and prices.

In a similar vein, Beegle et al. (2016) use survey-to-survey imputations to approximate changes in real living standards and poverty in Sub-Saharan Africa. This method requires a consumption survey for a reference year, and then imputes consumption into household surveys for subsequent years, based on the evolution of the non-consumption household characteristics (including assets and other household characteristics) as well as the relationship between those characteristics and consumption, as estimated from the consumption survey. Since any change in consumption and poverty imputed by this method is based on changes in real quantities and independent of price changes, the method is unaffected by CPI bias. This analysis suggests that poverty levels in Africa have declined stronger than suggested by the World Bank’s international poverty database, a result that is in line with the findings in this paper. 19

18 The focus here lies on studies that use micro data.
19 Other studies have shown that Africa has seen rapid improvements in infant mortality (Demombynes and Trommlerová 2016; Lange and Klasen 2017), but not in child nutrition (Harttgen et al. 2013b). However, trends in any one non-monetary indicator may be sensitive to sector-specific interventions – e.g. large-scale immunization campaigns or efforts to distribute insecticide-treated bed nets in the case of child mortality or improvements in water and sanitation services in the case of nutrition – and may not be very indicative of changes in real income.
Both Young (2012) and Beegle et al. (2016) infer trends in living standards and poverty from trends in the household’s ownership of assets, as well other household characteristics. Harttgen et al. (2013a) criticize the reliance on assets in this context and show that changes in asset possession are only weakly related to changes in real consumption, due to preference shifts towards consumer durables, changes in the public provision of services, changing relative prices and inconsistencies between stock (assets) and flow (consumption) measures. They argue further that households accumulate assets even in the absence of real income growth (in Africa and elsewhere), and that there is no solid evidence to believe that official statistics underestimate poverty reduction in Sub-Saharan Africa. At face value, our results are at odds with these findings. However, the analysis in Harttgen et al. (2013a) requires a measure of inflation, to compare asset holdings at a constant level of real consumption over time. While we do not have specific information on the price index they use, bias in the measure of inflation used to fix real consumption could potentially explain some of the discrepancies in results.

A study that comes to radically different conclusions than this paper is Sandefur (2013). The author uses the implicit inflation rates of national poverty lines to generate an alternative series of ‘survey-based deflators’ and compare these deflators to the country’s CPI series. The preliminary results of this analysis (we could not locate a final version online) suggest that CPI series in Africa underestimate price changes and hence overestimate progress in poverty reduction. However, a detailed review of the national poverty lines underlying these ‘survey-based deflators’ in Gaddis (2016, Table A4) suggests that in most countries the national poverty lines are either not comparable over time (for example, because a rural poverty line is compared to a national poverty line, or because the basket of basic needs items changed) or are themselves updated on the basis of the CPI (in which case, any discrepancy between the nominal increase of the national versus international poverty line comes down to discrepancies in the underlying CPI series). This suggests exercising caution in cross-triangulating CPI series based on national poverty lines.

7 Conclusion

In this paper, we estimated Engel curves for demographically similar households in 16 Sub-Saharan African countries. If Engel’s law holds, the coefficients of these curves should not change over time, controlling for relative prices. However, we observe that the Engel curves drift to the left in the majority of countries in this study. Burkina Faso, Ghana, and Uganda are the three countries experiencing the opposite trend. We estimate the bias using two methods: one assuming a constant bias across the income distribution, and another assuming a linear relationship between the bias and households’ real income. We find that CPI bias varies statistically significantly across the income deciles in 5 out of 16 countries covered in the study. Among which, three countries, Madagascar (between 2005 and 2010), Mauritius, and Togo show the bias faced by only the top income decile is statistically significantly different from the rest of the population. A significant variation of bias across multiple income deciles is observed in only two countries, Ethiopia and South Africa.

We find that the average annual CPI upward bias ranges between 0.6% in Cameroon and 45.6% in Nigeria. Conversely, the official CPI understates inflation in Burkina Faso, Ghana, and Uganda by somewhere between 6.1 and 12.9% annually. This CPI bias, however, is not statistically significant in Cameroon.
After adjusting for the effect of this bias, measured urban poverty falls faster than currently thought in countries where the CPI overstates changes in the true cost of living – by up to 5.17 percentage points per year as in the case of Tanzania between 2008 and 2012. Conversely, for countries experiencing downward bias, the progress in poverty reduction is estimated to be slower by as much as 0.8 percentage points per year as in the case of Uganda.

The weakness of this indirect method of estimating the CPI bias is that it is based on the assumption that the Engel curves hold over time. In other words, the observed shift in the Engel curves is attributed entirely to the CPI bias. Thus, the estimation does not take into account other issues that may contribute to the unexplained movement of the budget share of food such as changes in tastes, omitted variables, and so on. In addition, we also assume that the CPI bias has a uniform effect across the income distribution, and across all geographical locations in a given country. Hence, while we regard the estimates in this paper as cautious evidence that international poverty rates in Africa might have fallen faster than indicated by current numbers, additional work would be needed to corroborate the Engel curve estimation results (for example, using the methods outlined in Hausman 2003).

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