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Abstract

This paper examines spatial price adjustment methodology for welfare and poverty measurement. To measure and compare the levels of household welfare and poverty in a country, costs of living need to be appropriately taken into account. This is particularly important when analyzing sub-national poverty, such as the comparison of poverty between urban and rural areas, large cities and small towns, etc. Despite the importance of spatial price adjustment, the theory and practice have various unclear issues. Taking advantage of the price data availability for Ghana, this case study investigates several spatial price adjustment approaches, thereby suggesting which is promising based on the pros and cons of each method. While this study is in line with recent studies that stress the importance of detailed information about product specification in the price data, the findings shed light on the potential use of consumer price index (CPI) price data for spatial price adjustment for poverty measurement. The results also demonstrate the tendency to underestimate urban poverty.

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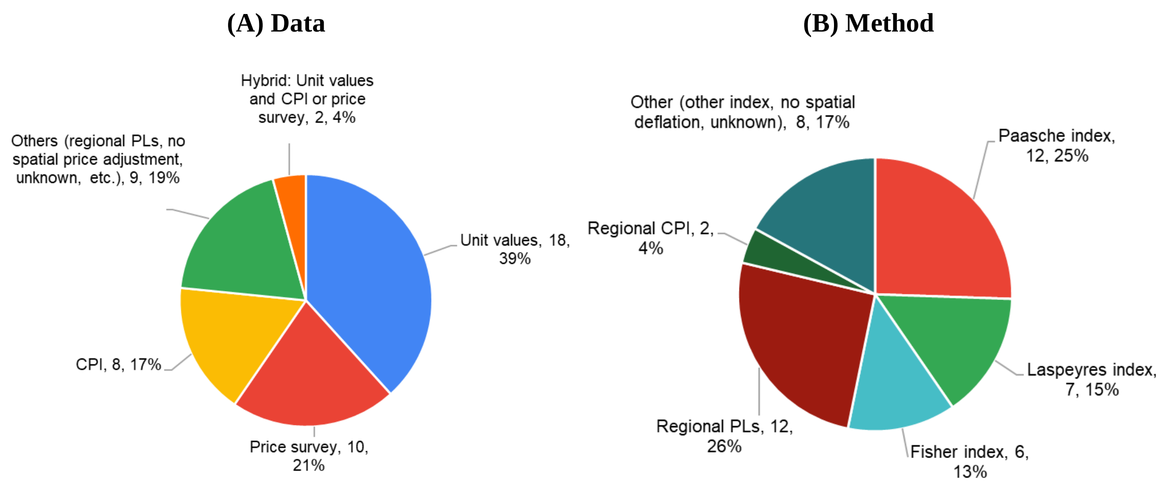
1. Introduction

A key component of welfare measurement is price adjustment. The basis for poverty and inequality analysis is household welfare, which is commonly measured by household consumption (Deaton and Zaidi 2002; Ravallion 2008).[2] To compare the welfare level of households over time and across regions, household consumption aggregates need to be adjusted by accounting for inflation (that is, temporal price adjustment) and cost of living differences across regions (that is, spatial price adjustment).[3] The latter becomes important when policy makers need to know not only who are poor but also where poverty is concentrated. Despite the importance of spatial price adjustment on welfare measurement for poverty and inequality analysis, its underpinning theory is not necessarily clear to guide the practice. Many low- and medium-income countries apply different methods, without a rigorous methodological foundation, often facing the limited availability of price data suitable for spatial price adjustment as the biggest challenge.[4]

The recently collected survey by the World Bank illustrates how the current practice of spatial price adjustment varies among Sub-Saharan African countries (Figure 1).[5] In terms of data sources (Panel A), about 40 percent of African countries rely on survey unit values, which is a proxy measure of prices calculated by dividing households' expenditures by the purchased quantity for each good based on household budget surveys. While unit values might be useful in cases where price data are lacking, the problems related to unit values have been reported in several studies (Gibson and Kim 2019; McKelvey 2011). Another 21 percent countries use market price surveys, which are often collected in parallel to the official household budget surveys. A small number of countries use their consumer price index (CPI data for spatial price adjustment. The methodology of spatial price adjustment is more divided (Panel B), including Paasche index (25 percent), Laspeyres index (15 percent), Fisher index (13 percent), and so on.

Figure 1. Data and methods used for spatial price adjustment in Sub-Saharan African countries



Source: World Bank data

Our study builds on, among others, a recent research on spatial prices by Gibson, Le, and Kim (2017). They compare the performance of different spatial price measurement approaches with the primary

[2] Some countries rely on household income, instead of consumption, for poverty measurement (Ferreira et al. 2016).
[3] 'Region' refers to sub-national regions in this paper unless otherwise noted.
[4] Some approaches to circumventing the data limitation include the Engel curve method and the price data collection from local experts (Gibson and Le 2018)
[5] Africa refers to Sub-Saharan Africa in this paper unless otherwise mentioned.

purpose to assess the reliability of a 'no price data' approach (that is, Engel curve-based method). The strength of the study is the use of Vietnam price survey that contains detailed product specification information, which gives them the golden standard to assess the performance of the Engel curve method. The analysis by Gibson, Le, and Kim (2017) demonstrates that the Engel curve method is unlikely to work for spatial price adjustment. We strongly agree with their argument that price data with detailed product quality information are necessary for spatial price adjustment for poverty measurement. However, we do not necessarily insist on investment in the collection and expansion of market price surveys. Our analysis instead sheds light on the potential use of the CPI raw price data for spatial price adjustment.

Improving spatial price adjustment methodology requires several key methodological issues to be clarified. First, *how can standard price index approaches be improved given the limited data availability?* The majority of low-income countries apply a spatial price index, such as Paasche and Laspeyres price indexes, to deflate consumption aggregates in official poverty measurement. The calculation of these price indexes hinges on many—often inexplicitly made—assumptions and data requirements. It is important to understand how to improve this price index approach. Second, *how should non-food goods and services (particularly housing) be treated in measuring spatial differentials in costs of living?* Price data, including unit values, often lack detailed information about non-food goods and services. Measuring and adjusting their prices is not straightforward. Finally, *what are the promising alternatives to the standard price index approaches?* As the availability and quality of price data is the key bottleneck, investing in the data in the long term is required. In this regard, how can CPI price data be useful for spatial price adjustment?

To examine the methodological issues above, we test different methods with different price data by focusing on Ghana. The methods we test include bilateral and multilateral price index approaches, the country product dummy (CPD) approach, and the spatial Engel curve approach. We apply these methods to the market price survey data collected in parallel to the official household budget survey (Ghana Living Standard Survey Round Seven, or GLSS7) and CPI raw price data.

The preliminary findings are summarized as follows. We find a wider gap between Paasche and Laspeyres indexes in poor regions, suggesting that Fisher index is better. Our results also demonstrate that considering only food prices may create a substantial bias in spatial price measurement as non-food prices (housing) vary widely across regions. This is particularly true in the regions with major urban markets, such as Greater Accra. Proper account of housing costs raises poverty levels in urban Ghana and Greater Accra. We also find that the CPD works well when missing price observations exist across regions and detailed variety product or item-level information is available. Controlling for detailed quality information in the application of the CPD to the CPI data results in the falling price level of Greater Accra. CPI price data appear to be useful in source data to bring in non-food items in measuring spatial price differentials and improving overall spatial price index for poverty measurement.

This paper is structured as follows. Section 2 reviews the theory and practice of spatial price adjustment to set out key issues to be addressed. Section 3 describes our methodology by explaining our empirical approach and data. Section 4 presents the results. Section 5 discusses the results and concludes.

2. Spatial price adjustment: Theory and practice

By reviewing the literature and practices used in spatial price adjustments for poverty measurement, we identify the following key methodological questions. First, how can standard price index approaches be improved given the limited data availability? Second, how should non-food items (particularly housing) be treated in measuring spatial differentials in costs of living? Finally, what are the promising alternatives to the standard price index approaches? We discuss this one by one in this section.

2.1. How can standard price index approaches be improved given the limited data availability?

Choice of price index

Calculating a bilateral price index for spatial price adjustment is a common approach in practice. The most commonly used indexes include Paasche, Laspeyres, Fisher, and (to a lesser extent) Tornqvist indexes. Paasche index (*P*) and Laspeyres index (*L*) are respectively expressed as follows:

$$P = \frac{\sum_{j=1}^{J} q_{ij} p_{ij}}{\sum_{j=1}^{J} q_{ij} p_{kj}}, \tag{1}$$

$$L = \frac{\sum_{j=1}^{J} q_{kj} p_{ij}}{\sum_{j=1}^{J} q_{kj} p_{kj}}, \tag{2}$$

where *k* indicates the base region, *i* indicates every other region, and *j* indicates each item in the consumption basket, and *q* and *p* are quantities and prices, respectively. Paasche price index is sometimes calculated at the household level as $P^h = \frac{p^h \cdot q^h}{p^0 \cdot q^h}$.[6] Deaton and Zaidi (2002) argue that to convert total expenditure into money metric utility, the price index must be tailored to the household's own demand pattern, a demand pattern that varies with the household's income, demographic composition, location, and other characteristics. Paasche index gives a utility consistent measure (first order approximation) as recommended by Deaton and Zaidi (2002).

While the standard fixed-weight price index approach is commonly used, it has many limitations when used for spatial price adjustment in poverty measurement. One of the problems is substitution bias, which is expected to matter more in the measurement of spatial price variation than in the measurement of temporal price changes. A variable-weight superlative price index, such as Fisher and Törnqvist, is closer to the true cost-of-living index (Balk 2008; Diewert 1976) due to less substitution bias if preferences are homothetic. However, in case of non-homothetic preferences (which is likely to be the case in reality), the superlative index has an income bias. Fischer index (F) is a geometric average of Laspeyres and Paasche indexes,

$$F = (L \times P)^{1/2}, \tag{3},$$

and Törnqvist index (*T*) is expressed as

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[6] This household-level Paasche index can be rewritten as $P^h = (\sum w_k^h (\frac{p_k^0}{p_k^h}))^{-1}$, which can be approximated by $\ln P^h \approx \sum w_k^h \ln(p_k^h / p_k^0)$, where p^0 is the reference price vector (typically the median of the prices observed from individual households) and w_k^h is the share of household *h*'s budget devoted to good *k*.

$$T = \exp[\sum_{j=1}^{J} \left(\frac{w_{kj}+w_{ij}}{2}\right) \ln(\frac{p_{ij}}{p_{kj}})], \quad (4),$$

where w_{ij} is the average share that item j has in the consumption basket in region i.

The Laspeyres price index provides an upper limit on the true cost of living index (COLI) based on the standard of living in the initial price situation, while the Paasche price index provides a lower limit on the true COLI based on the standard of living in the given price situation. Laspeyres index is relatively easy to calculate but sensitive to a substitution bias. Fisher index is also utility consistent (second-order approximation), bounded by Paasche and Laspeyres indexes. However, Fisher index is susceptible to income bias in case of non-homothetic preference. Tornqvist is another superlative index but less commonly used in practice for poverty measurement.

For the purpose of poverty and inequality analysis, Fisher price index is expected to work well as the gap between Paasche and Laspeyres price indexes tends to be wide in poor areas. However, the degree of Paasche-Laspeyres spread is an empirical question.

Reference area and transitivity

Real household consumptions—that is, nominal consumptions deflated by a spatial price index—are compared to a poverty line to measure poverty. An important issue in a bilateral price index approach is the choice of reference area. Reference area in spatial price index needs to be same as the location where the basket for poverty line is priced. For instance, if a poverty line is constructed based on the costs of basket items measured by the national prices (PL_A), the consumption expenditure of household i in region r needs to be spatially deflated as

$$EXP_{i,r} \times \pi_r^A = DEXP_{i,r}^A, \quad (5)$$

where π_r^A is a spatial price index that adjusts the consumption from the region r prices to the national prices (A). The price index π_r^A can be considered as the ratio of price levels between region r and the national average A (p_A/p_r). Then, poverty status of household i can be identified by

$$DEXP_{i,r}^A \lesseqgtr PL_A. \quad (6)$$

Similarly, if a poverty line is constructed based on the capital region prices (a), household consumption needs to be deflated by a spatial price index π_r^a, which indicates the price level ratio between region r and region a.

It is important to note that changing reference area *ex post* does not work if the spatial price index does not satisfy transitivity. In other words,

$$EXP_{i,r} \times \pi_r^A \times \pi_A^a \neq DEXP_{i,r}^a. \quad (7)$$

The GEKS procedure (Deaton and Heston 2010) is proposed to transform a bilateral index to a multilateral index.

$$GF^c = (\prod_{j=1}^{M} F^{1j} F^{jc})^{1/M} \quad (8)$$

where F^{1j} is the Fisher index for region j with region 1 as the reference area. This procedure is equivalent to taking a geometric mean of every possible combination of two regions. The International

Comparison Program (ICP) calculates purchasing power parity (PPP) based on a similar method (World Bank 2015a, 2015b). The CPD method can also give a multilateral price index.[7]

Choice of data (market price survey versus CPI)

While the choice of price index calculation methods matters, the quality and types of price data used for the calculation may be even more important. There are three types of data commonly available for spatial price adjustment. The first type of price data is the market price survey data that is typically collected in parallel with an official household budget survey. The second type of price data that can be potentially used for spatial price adjustment is the CPI price data. The third type of price data is unit values that can be calculated based on the consumption module of official household budget surveys. Table 1 summarizes the characteristics of these price data.[8]

Table 1. Characteristics of price data

	Price survey	CPI price data	Unit values
Geographical coverage	Moderate	Only major urban markets	Detailed
Number of outlets	Limited	Large	Household
Number of food items	Moderate	Large	Moderate
Number of non-food items	Limited	Moderate	Limited
Other advantages	Implemented together with the household budget survey	Temporal price adjustment can be linked	• No additional costs of data collection • Household characteristics can be linked
Other disadvantages	• Quality information limited • Not commonly available	Disaggregated information confidential	• Quality information limited • Non-standard unit

Although not many Sub-Saharan African countries have collected market price surveys (see the list of countries in Table A1 in Appendix A), those price data are potentially a good source for spatial price adjustment. The market price surveys are often collected in a sample of communities or market centers close to the enumeration areas (EAs) in parallel with official nationally representative budget surveys. Typically, only one price is recorded for each item in each community. A major disadvantage of market price surveys is the lack of detailed quality information. Without detailed information about item descriptions, it is not possible to compare prices of the same products across regions. Gibson, Le, and Kim (2017) explain that Vietnam's price survey was carefully designed to record detailed information for each product.

[7] The GEKS procedure can also be applied to Törnqvist index (Caves, Christensen, & Diewert 1982; Balk 2008). Another common approach to calculate a multilateral index is the Geary-Khamis method, which is used by the Penn World Table (Feenstra, Inklaar, and Timmer 2015) and the regional price parities in the United States (Aten 2017).

[8] Also see Chapter V of United Nations Statistics Division (2005). Aside from these commonly available price data, there are other types of price data, such as the price data collected for the PPP calculation under the ICP, scanner data collected by private companies, and price inventories of specific goods and services (agricultural products, housing, and so on). For example, recent research that takes advantage of scanner data demonstrates the impacts of quality (or item) variations on the costs of living across cities. Handbury and Weinstein (2015) use detailed barcode data to address heterogeneity bias (stemming from the comparison of different goods in different locations) and variety bias (stemming from not correcting for the fact that some goods are unavailable in some locations), finding that prices are lower (as opposed to higher) in larger cities in the United States. Feenstra, Xu, and Antoniades (2017) analyze China in a similar way and compare it to the United States. Another research with scanner data includes Handbury (2013), which constructs a spatial price index for different income levels (that is, nonhomothetic) across the U.S. metropolitan areas. It finds that price levels for high-income households tend to be overestimated when standard homothetic index is used.

CPI price data are another potential source for spatial price adjustment. Unlike market price surveys, CPI price data exists in almost all countries (Berry et al. 2019). Since CPI is an indicator of inflation, it does not indicate spatial differentials in costs of living.[9] However, it is possible to calculate the spatial price index by using the CPI price data (not CPI values per se). The problem is that many countries collect price information only in urban areas (see Table A2 in Appendix A). Nevertheless, if the geographic coverage of the data is adequate, using the same price data for spatial and temporal price adjustment can be an efficient and consistent approach. In addition, compared to market price surveys, a wide variety of food and non-food price information is collected in the CPI data, and the data collection is frequent (for example, monthly). A well-known issue is that the basket used for the calculation of CPI is often skewed toward higher-income households (Gaddis 2016). For spatial price adjustment for poverty analysis, it may be useful to exclude items that are not relevant to low-income households.[10]

When price data (based on price surveys) are not available, unit values are often used as a proxy for price. As shown in Figure 1, about 40 percent of African countries currently rely on unit values for spatial price adjustment for their official poverty measurement. Since Deaton (1988) established the use of unit values several decades ago, various adjustment methods have been devised to address concerns about the reliability of unit values (see Gibson n.d.). Recent research, however, has emphasized limitations in the use of unit values as a proxy for price data (Gibson and Kim 2019; McKelvey 2011). Among the problems raised is the substitution bias due to unobserved quality differences in unit values.

Thus, it is recommended to avoid resorting to unit values for spatial price adjustment unless price data are available. However, it is not a priori clear whether to use market price survey data or CPI price data as their quality matters.

2.2. How should non-food items (particularly housing) be treated in measuring spatial differentials in costs of living?

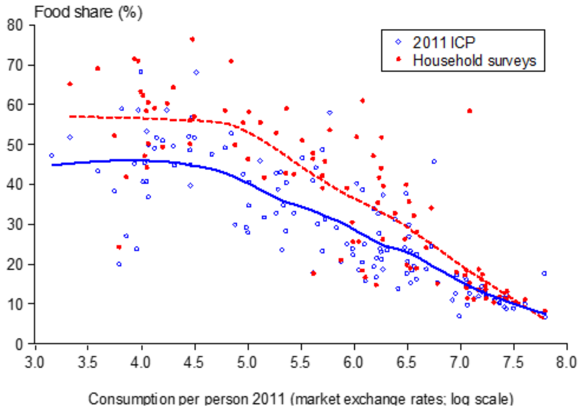
Treatment of non-food prices

As people become richer, they tend to spend a lesser portion of their budget on food expenditures. This empirical association between income and food budget share is known as Engel's law. Similar pattern is observed even at a cross-country comparison, as the average food budget share is higher in low- and medium-income countries (Figure 2). In many African countries, people typically spend more than half of their budget on food expenditures. However, this does not justify the construction of a spatial deflator for poverty measurement solely on food prices. As economies develop, non-tradable non-food items tend to account for a large portion of price dispersion across regions (for example, Balassa-Samuelson effect), highlighting the importance of measuring those prices.

[9] Some countries report regional CPIs. Such regional CPIs still do not indicate price differences across regions as they only indicate inflation in each region.

[10] For example, Rwanda uses CPI price data to calculate a cost of living index for poverty measurement (NISR 2016). In the calculation of the COLI, they use only items that are included in the basket used for poverty line construction. Another interesting study is Dikhanov et al. (2017), which calculates the PPP by focusing on items relevant for low-income households in Africa.

Figure 2. Engel curves of world countries



Source: Ravallion & Chen (2015)

A sound spatial price adjustment requires price information about a variety of non-food goods and services. For example, the ICP collects for the PPP calculation the following non-food price information at the aggregated category level: clothing and footwear; housing, water, electricity, gas, and other fuels; furnishing, household equipment, and routine maintenance of the house; health; transport; communication; recreation and culture; education; restaurants and hotels; and other miscellaneous goods and services (World Bank 2015b). However, it is challenging to properly compare prices of non-food items across regions due to the heterogeneity of the items and lack of information about the quality difference particularly for the market price survey data and the survey unit values. Calculating unit values of non-food items is particularly difficult, with a few exceptions, such as fuel that is sometimes less susceptible to quality bias.

Treatment of housing

The approach to capturing housing prices in subnational price measurement varies. While the regional price parities are calculated based on the CPI price data in the United States (Aten 2017), housing rent information is retrieved from another source: the American Community Survey (ACS). Similarly, Weinand and von Auer's (2019) calculation of regional PPP for Germany based on the CPI price data relies on another database for housing prices, collected by a federal agency from advertisements in newspapers and the Internet. These methodological choices and differences in source data reflect the difficulty of relying on the CPI price data for housing prices. In case of the CPI-based subnational PPP in the United Kingdom (ONS 2018), housing prices are not considered at all. Unlike subnational PPP work in the developed countries, a reliable housing price database (which includes low-quality and/or informal housing and rural housing) rarely exists in developing countries. Thus, Living Standards Measurement Survey (LSMS)-type of household surveys are often used for housing rent information. For instance, Gibson, Le, and Kim (2017) use self-reported dwelling values in Vietnam's household survey.

Conceptually, there are different treatments of housing in spatial price measurement, such as Acquisitions approach, Payments approach, and Uses approach (Melser and Hill 2007). Among these is the Uses approach recommended by Melser and Hill (2007) for welfare measurement, as the cost-of-living index measures the change in the cost of maintaining a given standard of living or level of utility (CPI Manual, 2004). Rental equivalence method is a common tool in the Uses approach.

While we agree with the use of the rental equivalence approach, there are two key methodological decisions to be made in incorporating housing prices to spatial price index calculation. The first question is how to consider those who pay no rent. In practice, either actually paid or imputed housing rents or (self-reported) housing values are used to incorporate housing costs in measuring costs of living across space. While housing rents are often imputed for owner-occupied housing units, rental housing markets need to be reasonably large for such imputation. This makes it difficult to impute housing rents in rural areas, where rental units are scarce. Rent imputation can also be useful for housing units with non-market rate rents, such as public housing. More relevant in the context of the developing world is informal housing. Residents in informal settlements sometimes pay no rents or negligible rents. When constructing consumption aggregate for welfare measurement, it may be better to use imputed rents for those residents. If the actual rent values do not reflect market values of their housing units, the welfare levels of the residents could be underestimated.[11] By contrast, in case of constructing spatial price index, it may not be necessary to impute rents for informal settlements.

The second question is whether to adjust for housing quality differences in spatial price adjustment for welfare and poverty measurement. There are several ways to calculate housing price index across space. A simple way is to take the average (or median) of housing rents at some geographic level. For example, Moretti (2013) averages gross housing rents (that is, housing rents plus utilities) of two- or three-bedroom apartments in each U.S. metropolitan areas. An alternative, and common approach is to estimate a hedonic regression model:

$$y_{ij} = \alpha + \beta X_{ij} + \gamma_j D_j + \varepsilon_{ij}, \tag{9}$$

where y is housing rents (or the natural logarithm of housing rents) of housing unit i in region j, X is a vector of housing characteristics, and D is a location dummy. The coefficients for the location dummy indicate price levels (relative to the reference location) after controlling for observed difference in housing quality. This type of hedonic approach is commonly used to calculate the housing price index (for example, Moulton 1995). However, it may not be appropriate to control for housing quality in measuring spatial price differentials unless the data well represent the market.[12]

2-3. What are the alternatives to the standard price index approaches? How are they better?

CPD approach

A challenge in spatial comparison of prices is that some items are not sold in some regions. The biggest advantage of the CPD approach is that it can handle such missing values in price observations across regions (Rao 2004, 2005; Summers 1973). The CPD can be used to either aggregate the price data from the variety level to the item (or basic heading) level or directly calculate a price index, which satisfies transitivity (Rao 2005). The ICP applies the CPD method for the aggregation to the basic heading level in its PPP calculation (World Bank 2015b).

[11] For housing rent imputation for welfare measurement (not for spatial price adjustment), see Balcazar et al. (2017).

[12] Hedonic regression estimation requires sampling weights so the data represent housing availability in the market. For instance, let us consider two cities: City A has many high-quality housing units and a small number of low-quality housing units, while City B has many low-quality housing units and a few high-quality housing units. If the rent values of high-quality housing are the same in both cities (and low-quality housing costs exactly the same in both cities), the hedonic regression in Equation 9 concludes that housing prices are equivalent in the two cities, which is misleading since people pay a lot more in City A.

The CPD model is formulated as follows. The price of item i in region j (p_{ij}) is the product of the price level of item i relative to other items (π_i), the price level (or the purchasing power parity) of region j with respect to other regions (η_j), and a random disturbance term (u_{ij}):

$$p_{ij} = \pi_i \cdot \eta_j \cdot u_{ij}, \tag{10}$$

which can be rewritten as follows:

$$\ln p_{ij} = \ln \pi_i + \ln \eta_j + \ln u_{ij}. \tag{11}$$

This model can be estimated as an ordinary least squares (OLS) regression model.

$$\ln p_{ij} = \sum_{i=2}^{N} \alpha_i D_i + \sum_{j=2}^{N} \beta_j D_j + \varepsilon_{ij} \tag{12}$$

where $\alpha_i = \ln\pi_i$, $\beta_j = \ln\eta_j$, and D_i and D_j are item and region dummy variables. The price level of region j is calculated as $\eta_j = \exp(\hat{\beta}_j)$. A weighted version of the CPD model (WCPD) is estimated as a weighted least squares regression model. Gibson, Le, and Kim (2017) propose two types of weights w_{ij}. With s_{ij} as the average budget share of item i in region j, variable weights, $(s_{ij} + s_{i0})/2$, allow for substitution, while fixed weights, s_{i0}, do not depend on homothetic preferences. Spatial price index based on variable weights and fixed weights is calculated as follows:

$$\rho_j^{vw} = [\textstyle\sum_{i=1}^{N} (\frac{s_{ij}+s_{i0}}{2}) \ln(\frac{p_{ij}}{p_{i0}})], \tag{13}$$

$$\rho_j^{fw} = [\textstyle\sum_{i=1}^{N} (s_{i0}) \ln(\frac{p_{ij}}{p_{i0}})]. \tag{14}$$

Gibson, Le, and Kim (2017) propose fixed-weights and variable-weights approaches.[13] When the CPD is applied to individual price quotes, additional controls, such as outlet types and urban/rural, can be included (Hill and Syed 2015).

CPI price data for spatial price adjustment

Applying the CPD method to the CPI price database may be an effective and efficient approach for spatial price adjustment for welfare measurement for several reasons. First, the CPI price database is composed of a large and comprehensive set of price data. Second, price data are frequently collected for the CPI. Third, using the same price data for spatial and temporal price adjustment can create a lower bias for welfare measurement. The use of CPI data, however, requires the following: (a) good geographic coverage of price data collection to ensure regional representativeness, (b) recording of detailed product descriptions consistent across regions, and (c) choice of basket items relevant to poor/low-income households. In addition, housing information in the CPI database is often inappropriate for spatial comparison of prices.

A few but growing number of countries have either officially reported or published as experiments subnational PPPs calculated based on the CPI price data. Those examples include the United States (Aten 2017), the United Kingdom (ONS 2018), Germany (Weinand and von Auer 2019), and Italy (Biggeri and Laureti 2014; Laureti and Rao 2018). An example from a developing country is Dikhanov, Palanyandy, and Capilit (2011) for the Philippines. Admittedly, most low- and medium-

[13] The variable-weights approach is equivalent to Tornqvist index as shown in Diewert 2005.

income countries do not have the CPI price data readily suitable for spatial price adjustment. Gibson rightly points out in the handbook published by the United Nations Statistics Division (2005, 184),

> The final choice, of relying on existing price collection efforts, is unlikely to work in many settings. The Consumer Price Index in many countries relies almost solely on urban prices, so these would not be applicable for calculating either poverty lines or spatial deflators and for imputing the value of consumption for rural households. Moreover, as explained above, the commodity weighting in a CPI is much more towards the consumption pattern of richer households, so the index values are unlikely to be relevant to poverty-related analysis.

And recommends as follows:

> Given the need for price data and the concerns about both unit values and relying on existing price collection efforts, it would be worthwhile for statistical agencies to invest more effort in gathering prices from local stores and markets and opinions about prices when their household surveys are fielded.

While this remains true, there are a few countries that have considerably invested in CPI data collection even in Africa, such as Ghana, Rwanda, and South Africa.

In the next section, we explain our methodology to examine the issues described above based on a case study of Ghana.

3. Methodology

3.1. Empirical approach

To empirically examine the methodological questions discussed, we compare the results of price, poverty, and equality measures based on different methods and datasets. The main methods we test are (a) the bilateral/multilateral price index approach, (b) the CPD approach, and (c) the Engel curve approach. The main datasets include (a) the market price survey data collected in parallel to the household budget survey and (b) CPI raw price data.

Price index approach

We first calculate several bilateral price indexes, such as Paasche index (Equation 1), Laspeyres index (Equation 2), and Fisher index (Equation 3), as described in Section 2.1, and compare the spatial price patterns indicated by them. We then compare poverty and inequality measures—both at the national and regional level—based on household consumption aggregates deflated by those spatial price indexes. We also compare these results with those based on a multilateral price index (GEKS-Fisher index in Equation 8) to assess how transitivity (or lack thereof) influences the results.

Non-food prices

As discussed in Section 2.2, the treatment of non-food items, particularly housing, is a vital issue in the calculation of spatial price indexes. The combination of the CPD method and the CPI price data allows to include many non-food items without losing quality information in the price data. In the approach, we compare the spatial patterns of non-food prices with those of food items. In addition, we test the sensitivity of price measures to the omission of quality information (for both food and non-food items) by comparing the results with or without variety-level quality information in price observations.

For housing, we examine different approaches in the following three aspects. First, we explore the influence of controlling for quality differences in housing across regions. We compare the results of spatial price measures based on the median values (that is, no control of quality) or hedonic regression (that is, with control of quality). Second, we also compare the results based on price index that uses actually paid rents (that is, only rental units) and imputed rents (that is, owner-occupied and/or rent-free units included). Finally, we investigate how rural housing should be considered in measuring spatial cost of living differentials. In an analysis, we exclude housing prices in rural areas.

Alternative approaches

We examine the two types of CPD methods. The first approach is to use the weighted CPD (Equation 12) to calculate the multilateral price index by applying to the item-level price data for which budget share information is available as the weight. Both variable weights (Equation 13) and fixed weights (Equation 14) are calculated, following Gibson, Le, and Kim (2017). The result of this approach is compared with a multilateral price index calculated by a GEKS-Fisher index method. Of particular interest in this comparison is how handling missing values by the CPD approach affects the spatial price measures.

The second CPD approach is to use the CPD as a way to aggregate price data from the variety level to the item level. As already mentioned, this CPD approach has the advantage of distinguishing price observations in detail. After the elementary aggregation through the CPD, we apply either the standard price index approach or another weighted CPD at the item level to obtain a price index.

An alternative approach to measuring spatial prices and welfare is the Engel curve method. We report the methodology and results in Annex B.

3.2. Ghana context

The official poverty in Ghana is measured based on the nationally representative household budget survey (GLSS). The seventh round of GLSS covered 14,009 households in 1,000 EAs over a 12-month period between October 2016 and September 2017 (GSS 2018).[14] The sampling was designed so that the survey gives information representative at urban and rural areas respectively, and 10 regions. Consumption aggregates include both food (including auto-consumption) and non-food (including imputed housing rents) consumption.[15] Consumption aggregates are converted to per adult-equivalent annual consumption for the purpose of poverty measurement to reflect differences in household size and composition and differences in calorie requirements of household members.

[14] The previous rounds of GLSS surveys were conducted in 1987/88, 1988/89, 1991/92, 1998/99, 2005/06, and 2012/13.
[15] However, we notice that housing rents (either paid rents or imputed rents) are not included in the consumption aggregates officially used to measure poverty.

Table 2. Official poverty rates and spatial price indexes in Ghana

		Official price index		
	Poverty rate	Total	Food	Non-food
National	23.41	0.96	0.94	1.01
Urban	7.76	0.97	0.96	1.02
Rural	39.52	0.95	0.93	1
Western	21.10	1.02	1	1.04
Central	13.77	0.98	0.94	1.03
Greater Accra	2.47	1.02	1.02	1.04
Volta	37.27	0.99	0.94	1.08
Eastern	12.56	0.95	0.94	0.96
Ashanti	11.60	0.95	0.9	1.03
Brong Ahafo	26.81	0.94	0.91	0.97
Northern	61.08	0.97	0.98	0.96
Upper East	54.83	0.86	0.8	0.93
Upper West	70.86	0.92	0.9	0.96

Note: Price index is calculated by the population weighted average of monthly (from October 2016 to September 2017) index values. Because of this, Greater Accra's value is not equal to 1.
Source: Authors' calculations based on the GLSS7.

Consumption aggregates are deflated both temporally and spatially. The temporal deflation adjusts the differences in the timing of data collection between October 2016 and September 2017. Monthly regional CPI indexes are used for the within-survey-months temporal deflation. The spatial deflation on the other hand adjusts for the differences in the cost of living across the 10 regions based on the official regional CPI values. The reference region of the spatial deflation is Greater Accra (January 2017).

Ghana measures poverty based on the single poverty line approach: that is, there is only one poverty line (GSS 2018). Spatial cost of living differentials is adjusted at the consumption side (as opposed to the multiple poverty line approach where poverty lines account for spatial price differences). The poverty line value is GH₵1,760.8 per adult equivalent per year, which was deflated by using a mixed deflator based on CPI raw price data and survey weights from the original poverty line of January 2013 (GH₵1,314). The official poverty headcount ratio in Ghana in 2016/17 is 23.4 percent, where urban and rural poverty is 7.8 percent and 39.5 percent, respectively (GSS 2018). Gini coefficients are 41.6 at the national level, 36.5 in urban areas, and 40.5 in rural areas.

3.3. Price data

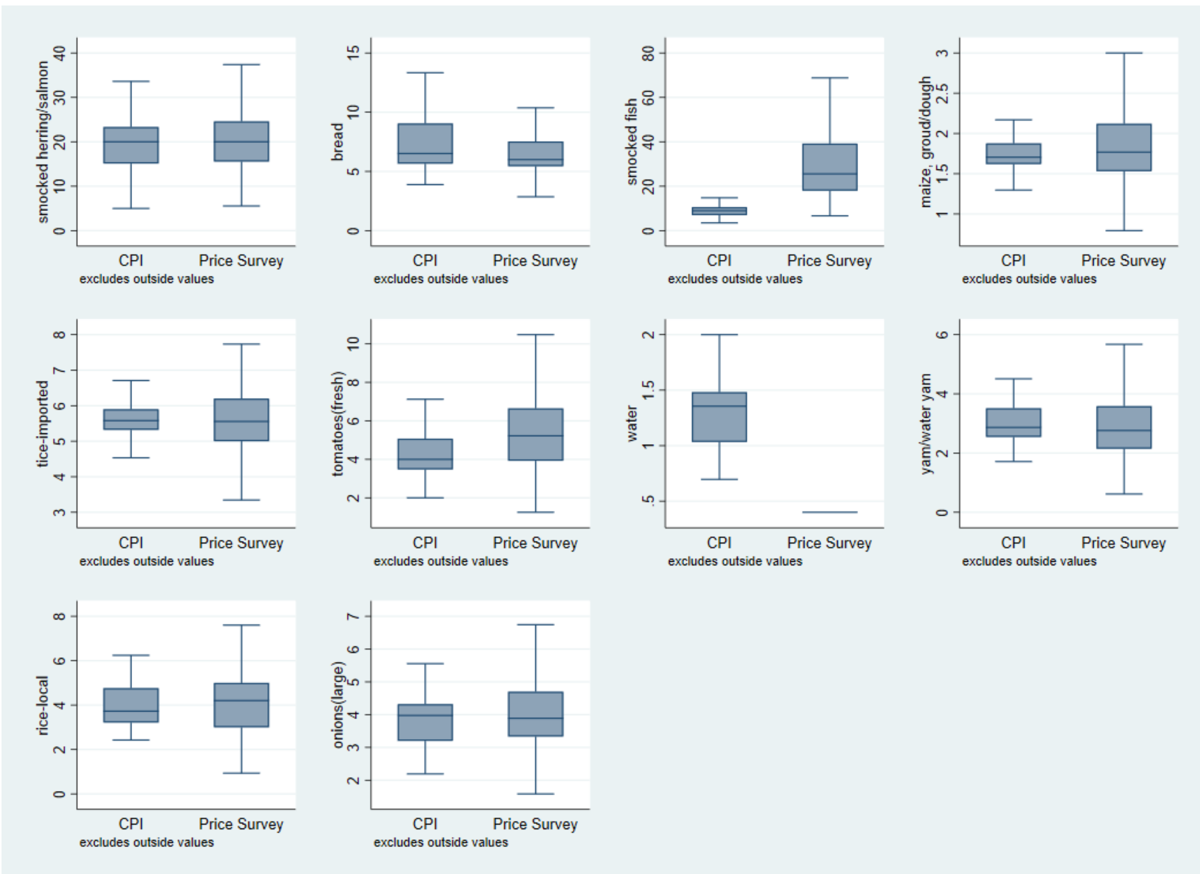
For this study, the main price datasets we use are the market price survey data from the GLSS7 and CPI price data. Survey unit values cannot be calculated based on the GLSS7 consumption module due to the prevalence of non-standard units and lack of conversion factors. The market price survey was collected from 398 clusters (or EAs in the GLSS7 data collection), of which 209 clusters are located in urban areas and 189 clusters are located in rural areas (Table 3). Those clusters cover 174 districts in the all the 10 regions of the country. Out of 109 food items found in the GLSS consumption module, the market price survey has price information for 96 food items. The CPI price data are regularly collected from 44 markets, covering all the 10 regions of the country. Table A3 and Table A4 in Appendix A show detailed information about the list of goods and services considered for our study and associated budget shares (calculated based on the GLSS7).

Table 3. Price data in Ghana

	GLSS7 consumption module	Market price survey	CPI price data
Geographic coverage	• 1,000 clusters • 214 districts • 10 regions	• 398 clusters (U209; R189) • 174 districts • 10 regions	• 44 markets • 10 regions
Food items	109 items	96 items in consumption module matched	67 items in consumption module matched
Non-food items	Paid rents and imputed rents available with quality information	Limited housing information	Limited housing information

We compare price distributions of major food items in the market price survey and CPI price data. Figure 3 shows price distributions of the following food items: smoked herring and salmon, bread, smoked fish, maize (ground or dough), imported rice, fresh tomatoes, water, yam and water yam, local rice, and large onions. Median price values between the market price survey and the CPI database are overall similar with smoked fish and water as exceptions.

Figure 3. Comparison of prices in the GLSS and CPI price data



Source: Authors' calculations based on the GLSS7 market price survey and the CPI price database.

For housing information, we rely on the GLSS7. Table 4 lists housing rent information in the GLSS7. In urban areas, 2,138 out of 3,880 households (35.5 percent) paid rents. In rural areas, only 9 percent of households pay rents, which clearly demonstrates the challenge of imputing rents based on such a small size of rental markets in rural areas.

Table 4. Housing rent information in the GLSS7

	Urban		Rural	
	Observed	Not observed	Observed	Not observed
Western	213	316	86	716
Central	215	406	144	553
Greater Accra	505	766	34	93
Volta	171	302	82	812
Eastern	197	392	91	715
Ashanti	425	617	112	581
Brong Ahafo	208	365	95	650
Northern	76	354	28	951
Upper East	63	216	19	1,073
Upper West	65	146	31	1,125
Total	2,138	3,880	722	7,269

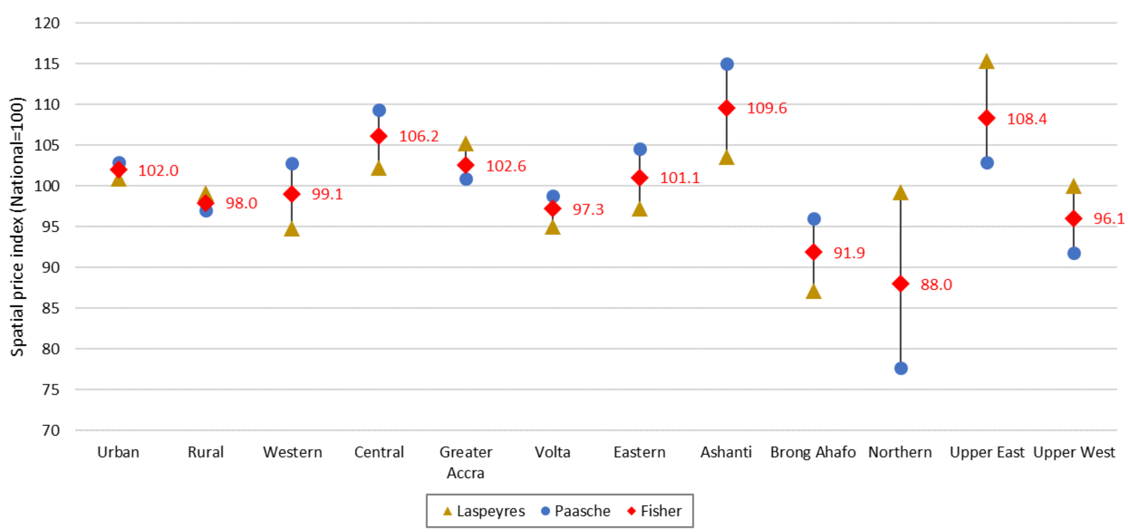
Note: Sampling weights are not applied. 'Observed' indicates the number of households who actually paid rents (including subsidized rents); 'Not observed' indicates the number of households who did not pay any rent.
Source: Authors' calculations based on the GLSS7.

4. Results

4.1. Food price index

We first focus on food prices based on the GLSS7 price survey. Figure 4 summarizes the results of spatial price measurement based on Paasche, Laspeyres, and Fisher indexes. Each price index is normalized so that the national-level prices equal to 100. As expected, the gap between Paasche and Laspeyres indexes is relatively wide in poorly connected and/or poor regions, such as the Northern region and Upper East region. In the Northern region, Paasche and Laspeyres index values are different by 20 points, as Paasche index and Laspeyres index are 77.6 and 99.3, respectively. In the Upper East region, Paasche and Laspeyres index values are 103.0 and 115.4, respectively. The variation in food prices across regions is wider than the variation between urban and rural areas. The price ratio between the most expensive region (Ashanti, 109.6) and the least expensive region (Northern region, 88.0) is 1.24. Urban food prices (102.0) are only marginally higher than rural food prices (98.0). Greater Accra's food prices (102.6 based on Fisher index) are higher than the national average, yet it is not the most expensive region.

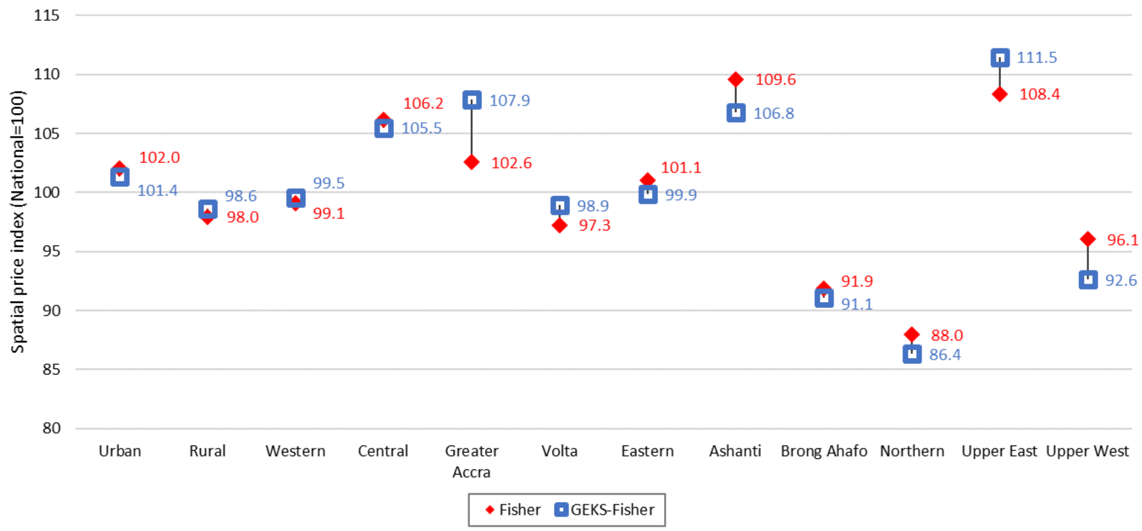
Figure 4. Food price index based on bilateral price index approaches



Source: Authors' calculations based on the GLSS7 market price survey.

We then compare the results of regional food price estimations based on Fisher index and GEKS-Fisher index to see the difference between bilateral and multilateral price indexes. In theory, the latter provides a more accurate measure of spatial price comparisons satisfying transitivity. As illustrated in Figure 5, they overall show similar price patterns, except for the Greater Accra region. Based on GEKS-Fisher index, food prices in Greater Accra are 8 percent higher than the national average, which makes Greater Accra one of the most expensive regions in Ghana in terms of food prices. By contrast, Fisher index indicates only 3 percent higher food prices in the capital region.

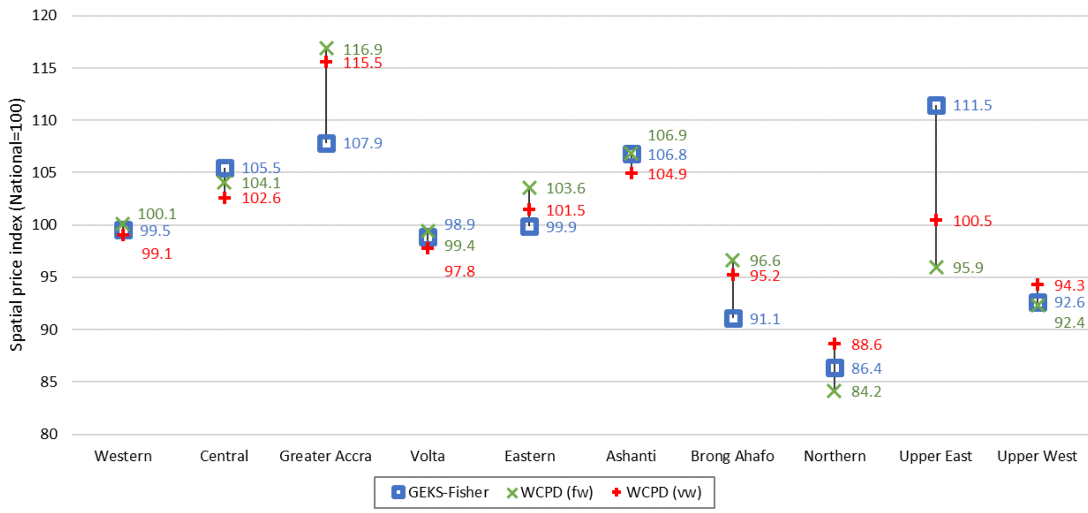
Figure 5. Food price index based on multilateral price index approaches



Source: Authors' calculations based on the GLSS7 market price survey.

Another important comparison is the results of CPD approaches and the GEKS-Fisher method. Figure 6 shows the results of WCPD with fixed weights and variables weights, as well as GEKS-Fisher price index values across regions. Compared to GEKS-Fisher index, the WCPD-based price indexes estimate the Greater Accra region as the most expensive (15 percent more expensive than the national average). Another profound difference between the WCPD results and GEKS-Fisher price index is found in the Upper East region. GEKS-Fisher price index indicates the Upper East is the most expensive region in Ghana in terms of food prices. The price levels, however, become moderate in the WCPD results. The regional price index values based on fixed-weight and variable weight WCPD approaches are overall similar.

Figure 6. Food price index based on WCPD approaches (market price survey)



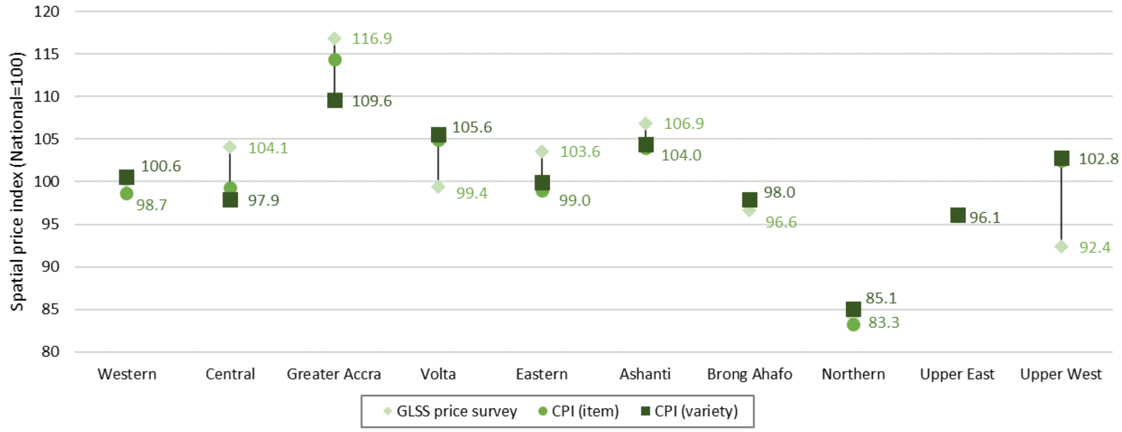
Source: Authors' calculations based on GLSS market price survey.

Next, we examine how the choice of data, instead of the choice of index calculation methods, influences the estimation of spatial price patterns (Figure 7). We compare the regional price indexes calculated by the WCPD method (variable weights in Panel A and fixed weights in Panel B) using the market price survey data and the CPI database. We first exploit only item-level price information in the CPI price database. The regional price index values are overall similar, as Greater Accra and North regions are the most and least expensive regions, respectively. However, CPI-based values are substantially higher than GLSS-based values in the Upper West region and (to a lesser extent) Volta region. For the Upper West region, CPI-and GLSS-based index values are 102.8 and 92.4, respectively.

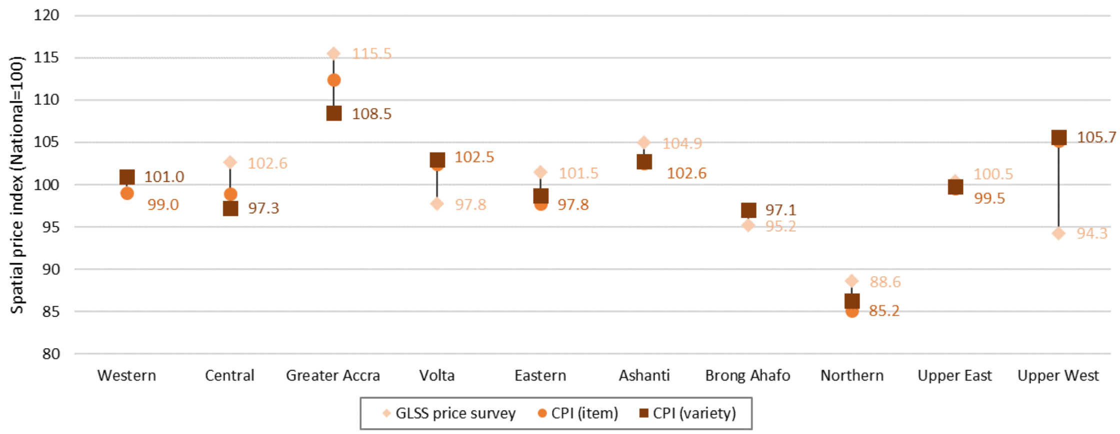
Figure 7 shows another important CPI-based price index that is calculated based on a WCPD regression with a control of variety information. The comparison of regional price index values based on the CPI-based WCPD approach with and without control for variety information points to the impact of potential bias due to the lack of product quality information. Regional price dispersion is estimated to be smaller when variety-level information is controlled for in the WCPD regression. While remaining as the most expensive region, Greater Accra's price level falls considerably. This is probably because Greater Accra was originally estimated to be expensive due to the prevalence of high-quality goods and services.

Figure 7. Food price index based on CPD approaches (GLSS and CPI price data)

(A) Variable weights



(B) Fixed weights



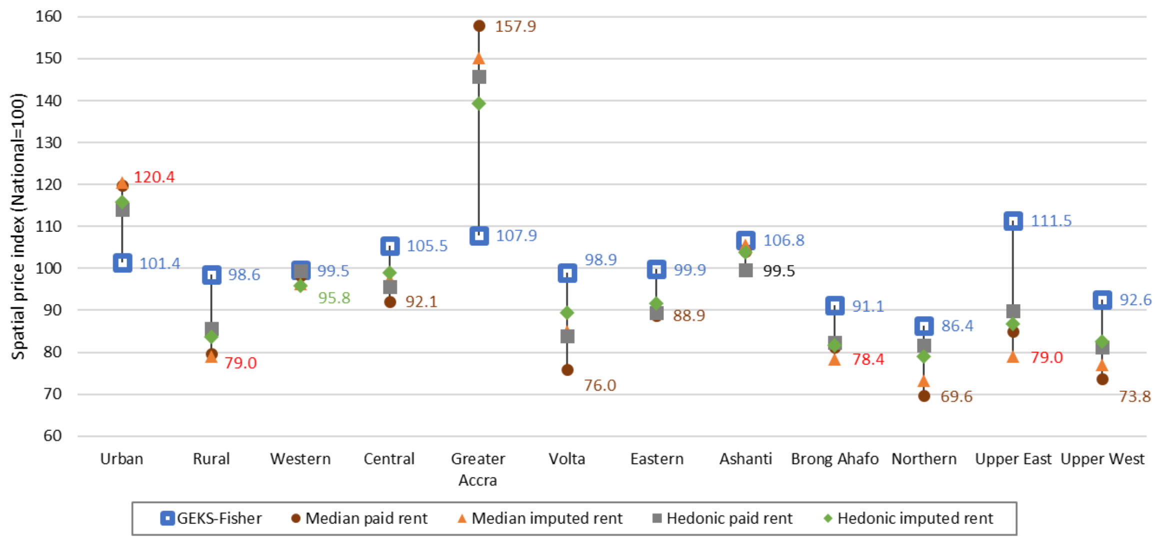
Source: Authors' calculations based on the GLSS 7 market price survey and CPI price data.

4.2. Food plus non-food price index

As the GLSS market price survey data does not allow us to calculate non-food price index, we only add the housing price index to it. After reporting the results, we analyze the CPI price data [This will be added in the next revision].

Adding housing prices to spatial price index calculation completely changes the estimated spatial pattern of prices. As explained in Section 3.1, we employ several approaches to analyze housing prices. Figure 8 summarizes the results. Table A5 in Appendix A reports the results of hedonic regression estimations. When we consider both urban and rural rents, a wide gap is observed between the median value approach and the hedonic approach. The median value approach makes urban areas expensive, particularly in Accra (150 to 160). By contrast, rural regions, such as Volta and other northern regions, are found relatively less expensive, with their price index values ranging from 70 to 80. The gap between urban and rural areas shrinks when we use the hedonic approach.

Figure 8. Food + housing price index



Source: Authors' calculations based on the GLSS7 and the GLSS7 market price survey data.

The treatment of housing prices also affects poverty measures. Spatially deflating consumption aggregates by food and housing price index yielded lower national poverty headcount ratio than the official rate. Particularly, the median value approach results in a low poverty rate (around 19 percent) because rural areas are estimated to be less expensive and thereby rural poverty is estimated to be lower (about 10 percentage points lower than official rural poverty rate). By contrast, urban poverty is estimated to be 2-3 percentage points higher than the official rate (7.8 percent). Greater Accra's poverty rate also becomes higher (around 7.0 percent as opposed to the official rate of 2.5 percent).

Gini coefficients also become lower than the official ones. The median value approach reduces the Gini coefficients because of the reduction in rural poverty and the increase in urban poverty. In addition, Gini coefficients drop within urban and rural areas.

Table 5. poverty and inequality measures based on different treatments of housing prices

	Poverty rate				Gini coefficient		
	National	Urban	Rural	Accra	National	Urban	Rural
Official	23.4	7.8	39.5	2.5	41.6	36.5	40.5
Food + median paid rent	18.9	9.5	28.6	7.3	37.2	34.0	39.2
Food + hedonic paid rent	20.5	8.5	32.8	4.8	38.1	34.2	39.9
Food + median imputed rent	19.4	10.1	29.1	6.5	37.3	34.1	39.7
Food + hedonic imputed rent	20.3	9.0	32.0	4.2	38.0	34.3	40.1
Food + median paid urban rent	20.0	8.0	32.4	5.2	41.3	37.6	41.3
Food + hedonic paid urban rent	22.0	7.4	36.9	4.4	39.0	34.3	39.3
Food + median imputed urban rent	20.6	8.2	33.4	4.7	38.0	34.1	38.7
Food + hedonic imputed urban rent	22.4	7.8	37.4	3.8	39.1	34.4	39.2

Source: Authors' calculations based on the GLSS7.

In the next revision, we will add the results of the WCPD regression applied to both food and non-food items in the CPI raw price data.

5. Discussion and conclusion

The preliminary findings are summarized as follows. We find a wider gap between Paasche and Laspeyres indexes in poor regions, suggesting that Fisher index is better. Our results also demonstrate that considering only food prices may create a substantial bias in spatial price measurement as non-food prices (housing) vary widely across regions. This is particularly true in the regions with major urban markets, such as Greater Accra. Proper account of housing costs raises estimated poverty levels in urban Ghana and Greater Accra. We also find that the CPD works well when missing price observations exist across regions and detailed variety product or item-level information is available. Controlling for detailed quality information in the application of the CPD to the CPI data results in the falling price level of Greater Accra.

CPI price data appear to be useful for constructing a spatial deflator poverty measurement, conditional on its availability and quality. The key conditions include the geographic coverage of price data collection and the detailed product specification list that guides data collection in a consistent manner across regions. For the primary purpose of the CPI, price data collection from rural areas is not necessary. In fact, many developed countries collect price information only from urban areas. However, using the CPI price data for spatial price adjustment requires rural areas to be well covered. While expanding the geographic coverage of the CPI price data collection is costly, a few African countries already collect price data from rural areas, such as Ghana, Rwanda, Ethiopia, and Zimbabwe. Importantly, these countries also already use the CPI price data for spatial price adjustment for official poverty measurement. South Africa is the most recent case that updated its CPI price database so that subnational PPPs can be calculated from it. While we agree that improving market price surveys is important, our research sheds light on the potential of the CPI price data for spatial price adjustment for poverty and inequality analysis.

References

Almas, I. 2012. "International Income Inequality: Measuring PPP Bias by Estimating Engel Curves for Food." *American Economic Review* 102 (1): 1093–1117.

Almas, I., T. K. M. Beatty, and T. F. Crossley. 2018. "Lost in Translation: What Do Engel Curves Tell Us About the Cost of Living?" CESifo Working Papers.

Almas, I., and A. Kjelsrud. 2017. "Rags and Riches: Why Consumption Patterns Matter for Inequality." *World Development* 97 (C): 102–121.

Almas, I., A. Kjelsrud, and R. Somanathan. 2019. "A Behavior-based Approach to the Estimation of Poverty in India." *Scandinavian Journal of Economics* 121 (1): 182–224.

Almas, I., and A. Johnsen. 2018. "The Cost of a Growth Miracle: Reassessing Poverty and Inequality Trends in China." *Review of Economic Dynamics* 30:239–264.

Aten, B. H. 2017. "Regional Price Parities and Real Regional Income for the Unites States." *Social Indicators Research* 131:123–143.

Atkin, D., B. Faber, T. Fally, and M. Gonzales-Navarro. 2018. "A New Engel on the Gains from Trade." Unpublished manuscript.

Balcazar, C. F., L. Ceriani, S. Olivieri, and M. Ranzani. 2017. "Rent Imputation for Welfare Measurement: A Review of Methodologies and Empirical Findings." *Review of Income and Wealth* 63 (4): 881–898

Balk, B. M. 2008. *Price and Quantity Index Numbers: Models for Measuring Aggregate Change and Difference.* New York: Cambridge University Press.

Berry, F., B. Graf, M. Stanger, and M. Ylä-Jarkko. 2019. "Price Statistics Compilation in 196 Economies: The Relevance for Policy Analysis." IMF Working Paper WP/19/163.

Biggeri, L., and L. Tiziana. 2014. "Sub-national PPPs: Methodology and Application by Using CPI Data." Paper prepared for the IARIW 33rd General Conference.

Chakrabarty, M., A. Majumder, and R. Ray. 2015. "Preferences, Spatial Prices and Inequality." *Journal of Development Studies* 51 (11): 1488–1501.

CPI Manual. 2004. "Consumer Price Index Manual: Theory and Practice." Published for ILO, IMF, OECD, UN, Eurostat, and The World Bank by ILO, Geneva.

Dabalen, A., I. Gaddis, N. T. V. Nguyen. 2019. "CPI Bias and Its Implications for Poverty Reduction in Africa." *The Journal of Economic Inequality*: 1–32.

Deaton, A. 1986. "Quality, Quantity, and Spatial Variation of Price." *The American Economic Review* 78 (3): 418–30.

Deaton, A., and A. Heston. 2010. "Understanding PPPs and PPP-based National Accounts." *American Economic Journal: Macroeconomics* 2 (4): 1–35.

Deaton, A., and J. Muellbauer. 1980. "An Almost Ideal Demand System." *American Economic Review* 70 (3): 312–326.

Deaton, A., and S. Zaidi. 2002. "Guidelines for Constructing Consumption Aggregates for Welfare Analysis." Living Standards Measurement Study Working Paper 135.

Diewert, W. E. 1976. "Exact and Superlative Index Numbers and Consistency in Aggregation." *Journal of Econometrics* 4: 115–45.

———. 2005. "Weighted Country Product Dummy Variable Regressions and Index Number Formulae." *Review of Income and Wealth* 51 (4): 561–570.

Dikhanov, Y., N. Hamadeh, W. Vigil-Oliver, T. B. Degefu, and I. Song. 2017. "Poverty-specific Purchasing Power Parities in Africa." World Bank Policy Research Working Paper 8150.

Dikhanov, Y., C. Palanyandy, and E. Capilit. 2011. "Subnational Purchasing Power Parities toward Integration of International Comparison Program and Consumer Price Index: The Case of the Philippines." ADB Economics Working Paper Series.

Feenstra, R. C., R. Inklaar, and M. P. Timmer. 2015. "The Next Generation of the Penn World Table." *American Economic Review* 105 (1): 3150–3182.

Feenstra, R. C., M. Xu, and A. Antoniades. 2017. "What Is the Price of Tea in China? Towards the Relative Cost of Living in Chinese and U.S. Cities." NBER Working Paper 23161.

Ferreira, F. H. G., S. Chen, A. Dabalen, Y. Dikhanov, N. Hamadeh, D. Jolliffe, A. Narayan, E. B. Prydz, A. Revenga, P. Sangraula, U. Serajuddin, and N. Yoshida. 2016. "A Global Count of the Extreme Poor in 2012: Data Issues, Methodology and Initial Results." *Journal of Economic Inequality* 14 (2): 141–172.

Gaddis, I. 2016. "Prices for Poverty Analysis in Africa." World Policy Research Working Paper 7652.

GSS (Ghana Statistical Service). 2018. "Ghana Living Standards Survey Round 7 (GLSS 7): Poverty Trends in Ghana 2005–2017."

Gibson, J. n.d. "A Guide to Using Prices in Poverty Analysis."

Gibson, J., and B. Kim. 2015. "Hicksian Separability Does Not Hold over Space: Implications for the Design of Household Surveys and Price Questionnaires." *Journal of Development Economics* 114:34–40.

———. 2019. "Quality, Quantity, and Spatial Variation of Price: Back to the Bog." *Journal of Development Economics* 137:66–77.

Gibson, J., and T. Le. 2018. "Improved Modeling of Spatial Cost of Living Differences in Developing Countries: A Comparison of Expert Knowledge and Traditional Price Surveys." Working Paper in Economics 8/18.

Gibson, J., T. Le, and B. Kim. 2017. "Prices, Engel Curves, and Time-Spatial Deflation: Impacts on Poverty and Inequality in Vietnam." *World Bank Economic Review* 31 (2): 504–530.

Gibson, J., S. Stillman, and T. Le. 2008. "CPI Bias and Real Living Standards in Russia during the Transition." *Journal of Development Economics* 87:140–160.

Handbury, J. 2013. "Are Poor Cities Cheap for Everyone? Non-Homotheticity and the Cost of Living across U.S. Cities." Kilts Booth Marketing Series, Paper No. 1-054.

Handbury, J., and D. E. Weinstein. 2015. "Goods Prices and Availability in Cities." *Review of Economic Studies* 82:258–296.

Hill, R. J., and I. A. Syed. 2015. "Improving International Comparisons of Prices at Basic Heading Level: An Application to the Asia-Pacific Region." *Review of Income and Wealth* 61 (3): 515–539.

Laureti, T., and D. S. P. Rao 2018. "Measuring Spatial Price Level Differences within a Country: Current Status and Future Developments." *Estudios de Economia Aplicada* 36 (1): 119–148.

Majumder, A., R. Ray, and K. Sinha. 2015. "Spatial Comparisons of Prices and Expenditure in a Heterogeneous Country: Methodology with Application to India." *Macroeconomic Dynamics* 19: 931–989.

McKelvey, C. 2011. "Price, Unit Values, and Quality Demanded." *Journal of Development Economics* 95:157–169.

Melser, D., and R. Hill. 2007. *Methods for Constructing Spatial Cost of Living Indexes.* Official Statistics Research Series vol. 1.

Moretti, E. 2013. "Real Wage Inequality." *American Economic Journal: Applied Economics* 5 (1): 65–103.

Moulton, B. R. 1995. "Interarea Indexes of the Cost of Shelter Using Hedonic Quality Adjustment Techniques." *Journal of Econometrics* 68:181–204.

Nakamura, E., J. Steinsson, and M. Liu. 2016. "Are Chinese Growth and Inflation Too Smooth? Evidence from Engel Curves." *American Economic Journal: Macroeconomics* 8 (3): 113–144.

Navamuel, E. L., F. R. Morollon, and E. F. Vazquez. 2018. "Does the Urban Population Pay More for Food? Implications in Terms of Poverty." *Applied Spatial Analysis* 2 (3): 547–566.

National Institute of Statistics of Rwanda. 2016. *Poverty Trend Analysis Report 2010/11-2013-14*.

Office for National Statistics. 2018. "Relative Regional Consumer Price Levels of Goods and Services, UK: 2016."

Rao, P. 2004. *The Country-Product-Dummy Method: A Stochastic Approach to the Computation of Purchasing Power Parities in the ICP*. University of Queensland, Australia.

———. 2005. "On the Equivalence of Weighted Country-Product Dummy (CPD) Method and the Rao-System for Multilateral Price Comparisons." *Review of Income and Wealth* 51 (4): 571–580.

Ravallion, M. 2008. "Poverty Lines." In *The New Palgrave Dictionary of Economics*, 2nd edition, edited by Larry Blume and Steven Durlauf. London: Palgrave Macmillan. 556–561.

Ravallion, M., and S. Chen. 2015. "Rising Food Prices in Poor Countries: A New Clue to Those Puzzling PPP Revisions." Center for Global Development Blog. Retrieved on October 15, 2019 from https://www.cgdev.org/blog/rising-food-prices-poor-countries-new-clue-those-puzzling-ppp-revisions

Ravallion, M., and D. van de Walle. 1991. "Urban-Rural Cost-of-Living Differentials in a Developing Economy." *Journal of Urban Economics* 29:113–127.

Summers, R. 1973. "International Price Comparisons Based upon Incomplete Data." *Review of Income and Wealth* 19 (1): 1–16.

United Nations Statistics Division. 2005. *Handbook on Poverty Statistics: Concepts, Methods and Policy Use*.

Weinand, S., and L. von Auer. 2019. "Anatomy of Regional Price Differentials: Evidence from Micro Price Data." Universität Trier Research Papers in Economics No. 3/19.

World Bank. 2015a. *Purchasing Power Parities and the Real Size of World Economies: A Comprehensive Report of the 2011 International Comparison Program.* Washington, DC: World Bank.

———. 2015b. *Operational Guidelines and Procedures for Measuring the Real Size of the World Economy: 2011 International Comparison Program (ICP).* Washington, DC: World Bank.

Appendix A. Additional tables and figures

Table A1. List of price surveys in Sub-Saharan African countries

No.	Country	Survey	Year
1.	Burkina Faso	EMC2014	2014
2.	Central Africa Republic	ECASEB2008	2008
3.	Gabon	EGEPII-2017	2017
4.	Ghana	GLSS3, GLSS4, GLSS5, GLSS6, and GLSS7	1991, 1998, 2005, 2012/13, and 2016/17
5.	Guinea	EIBEP2002, ELEP	2002, 2012
6.	Gambia	IHS2015	2015
7.	Guinea Bissau	ILAP2010	2010
8.	Kenya	KIHBS2015	2015
9.	Liberia	HIES2014 and HIES2016	2014, and 2016
10.	Mauritania	EPCV2004. EPCV2008, EPCV2014	2004, 2008, and 2014
11.	Niger	ECVMA2014	2014
12.	Nigeria	NLSS2003-04, NLSS2008-09	2003/04 and 2008/09
13.	Sierra Leone	SLIHS2003	2003
14.	Uganda	UNHS2005, UNHS2012	2005, 2012
15.	Zambia	LCMS2010	2010
16.	Zimbabwe	PICES2017	2017

Table A2. List of CPI price data in Sub-Saharan African countries

No.	Country	Geographic coverage of data collection
1	Burkina Faso	Urban
2	Cameroon	Urban
3	Congo, DR	Urban
4	Côte d'Ivoire	Urban
5	Ethiopia	Urban and rural
6	Ghana	Urban and rural
7	Madagascar	Urban
8	Mauritius	Urban
9	Mozambique	Urban
10	Nigeria	Urban and rural
11	Rwanda	Urban and rural
12	Senegal	Urban
13	South Africa	Urban and rural
14	Tanzania	Urban
15	Togo	Urban
16	Uganda	Urban
17	Zimbabwe	Urban and rural

Source: Authors' work building on "Consumer Price Indices," Laborsta Internet, International Labour Organization, Geneva, as cited by Dabalen, Gaddis, and Nguyen 2019.

Table A3. Food items and budget shares in the GLSS7

Consumption Survey Group	Budget Share	Price Survey Item
Rice - local	0.032	Rice - local
Rice - imported	0.048	Rice - imported
Guinea corn	0.004	Guinea corn/sorghum red grains
		Guinea corn/sorghum white grains
Maize grains (white/yellow)	0.025	Maize (dried, white grains)
		Maize (dried, yellow grains)
		Maize, new dried grains
Millet	0.003	Millet
Millet flour	0.002	Millet flour
Wheat flour	0.000	Takoradi flour mill
		GMG
		Wheat semolina, suji
Maize, ground/dough	0.048	Maize, ground (flour)
		Corn dough
Cerelac (baby food)	0.003	Cerelac made from maize
		Cerelac made from millet
		Cerelac made from rice
		Cerelac made from wheat
Oats	0.001	White oats
Cassava - kokonte	0.007	Cassava - kokonte
Cassava - dough	0.009	Cassava - dough
Gari (yellow/white)	0.008	Cassava - gari
Bread	0.064	Sugar bread
		Whole wheat bread
		Butter bread
		Tea bread
Biscuits	0.007	Picadilly biscuit
		Kings crackers
		Malt and milk biscuit
		Cream crackers
		Digestive biscuit
		Jack and Jill
		Other (specify) _ _ _ _ _ _ _ _ _ _
Other cereals	0.002	Cornflakes (Kellogg's)
Meat	0.028	Beef with bones
		Beef without bones
		Cow leg, local
		Cow leg, imported
Pork	0.003	Pork meat
		Pork - ribs
		Pork - fillet
		Pork - feet

Table A3. Food items and budget shares in the GLSS7 (continued)

Consumption Survey Group	Budget Share	Price Survey Item
Mutton	0.001	Mutton chop
		Mutton mixed cut
Goat	0.005	Sheep - live
		Goat - live
		Goat meat
Chicken	0.005	Live chicken (local)
		Live chicken (broiler)
		Live chicken (layers)
Frozen chicken	0.018	Chicken parts (thighs) - frozen
		Chicken parts (wings)
Guinea fowl	0.001	Guinea fowl - live
Corned beef	0.001	Exeter corned beef
		Corned beef (other brands)
Sausage (all types)	0.000	Sausage
Grasscutter	0.002	Bushmeat (grasscutter)
Game bird	0.000	(a)
Other meat	0.001	(b)
Fresh/frozen fish	0.015	Kpala (starvids) frozen
		Fresh river fish
		Tilapia - fresh /frozen
Shrimps	0.000	Shrimps
Snails	0.001	Snails
Crab	0.001	Crabs
Smoked fish	0.058	Smoked river fish
Smoked herring/salmon	0.091	Herrings - smoked
Fried fish	0.013	(c)
Dried fish	0.004	Dried fish - koobi
Other fish	0.009	Fish (salted)
Sardines/tuna in vegetable oil	0.004	Titus
		Princess
		Obaapa
		Gino
		Starkist
		Other (specify) _ _ _ _ _ _ _ _ _ _
Mackerel in tomato sauce	0.004	Geisha
		African queen
		Geisha
		Ena pa
		Obaapa
		Delay
		Other (specify) _ _ _ _ _ _ _ _ _ _
Fresh milk	0.001	Fresh milk
		Baby milk (lactogen)
		Fan milk

Table A3. Food items and budget shares in the GLSS7 (continued)

Consumption Survey Group	Budget Share	Price Survey Item
Powdered milk	0.004	Nido milk (sachet)
		Peak milk (sachet)
		Cowbell (sachet)
		Ideal milk (sachet)
		Nunu milk (sachet)
		Loya milk (sachet)
		Miksi milk (sachet)
		Vega milk (sachet)
		Other (specify) _ _ _ _ _ _ _ _ _ _
Evaporated milk	0.007	Evaporated milk - ideal
		Evaporated milk - peak
		Evaporated milk - nunu
		Evaporated milk - vega
		Evaporated milk - carnation
Condensed milk	0.000	Condensed milk, tin - peak
Other milk products	0.005	Other (specify) _ _ _ _ _ _ _ _ _ _
Chicken eggs	0.009	Chicken eggs (fresh, single)
Margarine	0.000	Margarine
Coconut oil	0.000	Coconut oil
Groundnut oil	0.002	Groundnut oil
Palm oil (red oil)	0.008	Palm oil (red oil)
Shea butter	0.005	Shea butter
Palm kernel oil	0.000	Palm kernel oil
Other oils	0.021	Vegetable oil - frytol
		Vegetable oil - gino
		Vegetable oil - obaapa
		Vegetable oil (other, specify)
Coconut (fresh/dried)	0.002	Coconut (fresh)
Banana	0.005	Banana
Oranges	0.003	Oranges
Pineapple	0.001	Pineapple
Mango	0.001	Mango (local)
		Mango (grafted)
Watermelon	0.003	Watermelon
Avocado pear	0.001	Avocado pear
Apples/sweet apple	0.001	Apples (foreign)
		Sweet apple
Grapes	0.000	Grapes
Lime	0.000	Lime
Cashew	0.000	(d)
Pawpaw	0.001	Pawpaw
Other fruits	0.000	(e)
Canned fruit	0.000	Canned (processed) fruits

Table A3. Food items and budget shares in the GLSS7 (continued)

Consumption Survey Group	Budget Share	Price Survey Item
Cocoyam leaves (kontomire)	0.007	Cocoyam leaves (kontomire) or Alefu
Sweet pepper	0.000	Sweet pepper
Carrot	0.001	Local carrot
		Carrot
Garden eggs	0.009	Garden eggs
Okro (fresh)	0.017	Okro (fresh)
Pepper (fresh)	0.017	Pepper (fresh)
Powder pepper	0.002	Powder pepper
Onions (large)	0.028	Onions (large)
Tomatoes (fresh)	0.040	Tomatoes (fresh)
Other vegetables	0.005	(f)
Tomato paste	0.020	Gino
		Obaapa
		Pomo
		Other (specify) _ _ _ _ _ _ _ _ _ _
White beans (cowpea)	0.007	White beans (cowpea)
Palm nut (fruits)	0.003	Palm fruits
Groundnuts (shelled)	0.005	Groundnuts (shelled)
Groundnut (paste)	0.006	Groundnuts (roasted)
Agushie seeds (or milled)	0.001	(g)
Plantain	0.025	Plantain (green)
Cassava (fresh)	0.026	Cassava (fresh)
Cocoyam	0.004	Cocoyam
Yam/water yam	0.038	Yam - puna
		Water yam
Taro	0.000	(h)
Potatoes	0.000	(i)
Other tubers	0.000	(j)
Sugar	0.013	Cube sugar (Saint Louis)
		Granulated sugar
Honey	0.000	Honey (bottle)
Chocolate bar	0.000	Kings bite
		Golden tree chocolate
		Other (specify) _ _ _ _ _ _ _ _ _ _
Chewing gum	0.001	Chewing gum
		Trident
		PK
		Mentos
		Other (specify) _ _ _ _ _ _ _ _ _ _
Garlic	0.001	Garlic
Ginger	0.002	Ginger
Vinegar	0.000	Vinegar

Table A3. Food items and budget shares in the GLSS7 (continued)

Consumption Survey Group	Budget Share	Price Survey Item
Dawadawa	0.007	(k)
Curry powder	0.000	(l)
Black/dried red pepper	0.007	Pepper (dried)
		Chilli powder(black pepper)
Other spices	0.000	(m)
Other condiments	0.013	Royco
		Onga cube
		Benny
		Other (specify) _ _ _ _ _ _ _ _ _ _
Salt	0.010	Salt (iodized - local)
		Anapuna iodated salt
		U2 iodated salt
Coffee (nescafe)	0.000	Nescafe - tin
Pure cocoa powder	0.000	Pure cocoa powder (for example, Brown Gold)
Tea	0.002	Tea bags (for example, Lipton)
Cocoa with milk powder	0.012	Cocoa with milk powder
		Bournvita
		Cow bell (coffee, choco, and so on)
		This way chocolate drink
		Country milk - chocolate
Water	0.038	Sachet water
Soft drinks	0.006	Coca Cola/Fanta (bottle)/Sprite (bottle)
Malt	0.012	Malta Guinness
		Magic malt
		Other (specify) _ _ _ _ _ _ _ _ _ _
Fruit juice	0.005	Don Simon
		Frutelli
		Blue skies
		Pure Heaven
		Kalipo
		Healthy live
		Ceres
		Other (specify) _ _ _ _ _ _ _ _ _ _

Note: Average budget shares is each item's household expenditure share on average. For items with multiple prices per consumption survey group, the price relativities are averaged before mapping to the budget shares. Items with () use prices of similar items as follows: (a) guinea fowl - live; (b) average of the meat group (exclude sausage and corned beef); (c) dried fish; (d) groundnuts (shelled) and groundnuts (roasted); (e) average of the fruit group; (f) average of the vegetable group; (g) ½ price of groundnuts (shelled); (h) yam - puna and water yam; (i) cassava (fresh); (j) average of the tuber group; (k) white beans (cowpea); (l) pepper (dried) and chilli powder(black pepper); (m) royco, onga cube, benny and other condiments.

Table A4. Food items and budget shares in CPI price database

Consumption Survey Group	Budget Share	CPI Item
Rice - local	0.032	Rice - local
Rice - imported	0.048	Rice - imported
Guinea corn	0.004	Soghum white grains
		Soghum red grains
Maize grains (white/yellow)	0.025	Maize grains
Millet	0.003	Millet
Millet flour	0.002	Millet flour
Wheat flour	0.000	Wheat flour
Maize, ground/dough	0.048	Corn dough
		Corn flour (Akpele)
Cerelac (baby food)	0.003	Cerelac (baby food)
		Cerelac (tin)
		Yumvita
Oats	0.001	White oats (other cereals)
		Quaker
Cassava - kokonte	0.007	Cassava - kokonte
Cassava dough	0.009	Cassava - processed
Gari (yellow/white)	0.008	Yellow gari
		Gari
Bread	0.064	Bread
		Other bread
Biscuits	0.007	Biscuit (simple cookie)
		Jack and Jill
		Ginger biscuits
Other cereals	0.002	Indomie or instant noodles
		Spaghetti
		Other cereal products
		Other spaghetti
Meat	0.028	Cow meat
		Beef without bones
		Cow leg, local
		Cow leg, imported
Pork	0.003	Pork meat
		Pork, ribs
		Pork, shoulder
Mutton	0.001	Mutton
Goat	0.005	Goat meat
Chicken	0.005	Live chicken
		Live chicken, local
Frozen chicken	0.018	Frozen chicken
Guinea fowl	0.001	Guinea fowl - live
Corned beef	0.001	Corned beef
		Exeter corned beef

Table A4. Food items and budget shares in CPI price database (continued)

Consumption Survey Group	Budget Share	CPI Item
Sausage (all types)	0.000	Sausage
Grasscutter	0.002	Bushmeat
Game bird	0.000	(a)
Other meat	0.001	Dog meat
Fresh/frozen fish	0.015	Frozen fish
Shrimps	0.000	Shrimps
Snails	0.001	Snails
Crab	0.001	Crab
Smoked fish	0.058	Smoked river fish
Smoked herring/salmon	0.091	Fish and seafood
Fried fish	0.013	Fish fried
Dried fish	0.004	Dried fish - koobi
Other fish	0.009	Fish (salted)
Sardines/tuna in vegetable oil	0.004	Tuna in vegetable oil
		Tuna, canned, starkist
		Tuna, canned, geisha
		Sardines in vegetable oil
Mackerel in tomato sauce	0.004	Mackerel in tomato sauce
Fresh milk	0.001	Milk (fresh)
Powdered milk	0.004	Powdered milk
		Peak (sachet)
		Powdered milk (sachet)
Evaporated milk	0.007	Evaporated milk
		Cowbell (sachet)
Condensed milk	0.000	(b)
Other milk products	0.005	Fan milk products
Chicken eggs	0.009	Chicken eggs (fresh, single)
Margarine	0.000	Margarine
Coconut oil	0.000	Coconut oil
Groundnut oil	0.002	Oils and fats (ND)
Palm oil (red oil)	0.008	Palm oil (red oil)
Shea butter	0.005	Oils and fats (ND)
Palm kernel oil	0.000	Cooking oil
Other oils	0.021	Oils and fats (ND)
Coconut (fresh/dried)	0.002	Coconut (fresh)
Banana	0.005	Banana
Oranges	0.003	Oranges
Pineapple	0.001	Pineapple
Mango	0.001	Mango
Watermelon	0.003	Watermelon
Avocado pear	0.001	Avocado pear
Apples/sweet apple	0.001	Apples (foreign)
		Sweet apple

Table A4. Food items and budget shares in CPI price database (continued)

Consumption Survey Group	Budget Share	CPI Item
Grapes	0.000	Grapes
Lime	0.000	Lemon/lime
Cashew	0.000	(c)
Pawpaw	0.001	Pawpaw
Other fruits	0.000	(d)
Canned fruit	0.000	(e)
Cocoyam leaves (kontomire)	0.007	Cocoyam leaves (kontomire)
Sweet pepper	0.000	Fresh pepper
Carrot	0.001	Local carrot
		Foreign carrot
Garden eggs	0.009	Garden eggs
Okro (fresh)	0.017	Okro
Pepper (fresh)	0.017	Fresh pepper
		Pepper
Powder pepper	0.002	Powder pepper
Onions (large)	0.028	Onion
Tomatoes (fresh)	0.040	Tomatoes
Other vegetables	0.005	Fresh vegetables (ND)
Tomato paste	0.020	Gino
		Lele
		Tomato paste
White beans (cowpea)	0.007	White beans (cowpea)
Palm nut (fruits)	0.003	Palm nut
Groundnuts (shelled)	0.005	Groundnuts
Groundnut (paste)	0.006	Oils and fats (ND)
Agushie seeds (or milled)	0.001	(f)
Plantain	0.025	Plantain (green)
Cassava (fresh)	0.026	Cassava
Cocoyam	0.004	Cocoyam
Yam/water yam	0.038	Yam
Taro	0.000	(g)
Potatoes	0.000	(h)
Other tubers	0.000	(i)
Sugar	0.013	Sugar/honey
Honey	0.000	Sugar/honey
Chocolate bar	0.000	Chocolate bar
Chewing gum	0.001	Chewing gum
Garlic	0.001	Garlic
Ginger	0.002	Ginger
Vinegar	0.000	Vinegar
Dawadawa	0.007	(j)
Curry powder	0.000	(k)
Black/dried red pepper	0.007	(l)

Table A4. Food items and budget shares in CPI price database (continued)

Consumption Survey Group	Budget Share	CPI Item
Other spices	0.000	Cube spices
		Benny
		Maggi cube (crevette)
Other condiments	0.013	(m)
Salt	0.010	Salt - iodized
Coffee (nescafe)	0.000	Coffee
Pure cocoa powder	0.000	Pure cocoa powder (for example, Brown Gold)
Tea	0.002	Tea bag
Cocoa with milk powder	0.012	Cocoa with milk powder
Water	0.038	Mineral water (bottled)
		Bottle water
		Sachet water
Soft drinks	0.006	Soft drink
		Fanta (can)
		Sprite (bottle)
		Coca Cola (can)
Malt	0.012	Malt drinks(bottle)
		Malt drinks (can)
Fruit juice	0.005	Fruit juice

Note: Average budget shares is each item's household expenditure share on average. For items with multiple prices per consumption survey group, the price relativities are averaged before mapping to the budget shares. Items with () use prices of similar items as follows: (a) guinea fowl - live; (b) evaporated milk; (c) groundnuts; (d) average of the fruit group; (e) half average price of the fruit group; (f) half price of groundnuts (shelled); (g) yam; (h) cassava; (i) average of the tuber group; (j) white beans (cowpea); (k) powder pepper; (l) powder pepper; (m) cube spices, benny and maggi cubes.

Table A5. Estimation results of hedonic regression models

	All areas		Urban areas only	
	Paid rent (1)	Imputed rent (2)	Paid rent (3)	Imputed rent (4)
Number of bed rooms	0.355***	0.00756***	0.426***	0.391***
	(16.30)	(4.23)	(17.80)	(83.42)
Dwelling type: separate house	0.464***	-0.110***	0.558***	0.246***
	(3.63)	(-5.17)	(4.29)	(5.99)
Dwelling type: semi-detached house	0.448**	-0.0411	0.582***	0.312***
	(3.29)	(-1.75)	(4.19)	(6.73)
Dwelling type: flat	0.809***	-0.0444	0.896***	0.454***
	(5.81)	(-1.78)	(6.35)	(9.57)
Dwelling type: compound house	0.324**	-0.158***	0.413**	0.0964*
	(2.60)	(-7.53)	(3.29)	(2.41)
Dwelling type: huts	0.0950	-0.205***	0.365	0.0619
	(0.48)	(-8.69)	(1.27)	(0.97)
Dwelling type: tent and others (reference)				
Wall materials: high quality	0.306***	0.130***	0.245***	0.130***
	(6.98)	(19.51)	(4.39)	(6.79)
Wall materials: wood	-0.0428	0.0640***	-0.0606	-0.109**
	(-0.48)	(3.40)	(-0.64)	(-2.77)
Wall materials: high quality	0.349**	0.181***	0.488**	0.422***
	(3.26)	(12.85)	(3.03)	(8.49)
Wall materials: mud and others (reference)				
Floor materials: tiles	-0.152	-0.00462	0.0336	-0.0387
	(-1.60)	(-0.48)	(0.22)	(-0.83)
Floor materials: mud (reference)				
Roof materials: wood	-0.348	-0.0236	-0.545	-0.198
	(-1.24)	(-0.60)	(-1.83)	(-1.87)
Roof materials: metal sheet	-0.0355	-0.0129	-0.186	-0.148**
	(-0.23)	(-1.15)	(-0.94)	(-2.81)
Roof materials: asbestos	0.0144	0.0436**	-0.112	-0.0878
	(0.09)	(3.19)	(-0.56)	(-1.61)
Roof materials: concrete	0.0594	0.0731***	-0.0952	-0.0373
	(0.36)	(3.79)	(-0.46)	(-0.63)
Roof materials: mud bricks and others (reference)				
Toilet type: pit or bucket	0.203***	0.00543	0.284***	0.0378
	(3.41)	(0.66)	(3.33)	(1.37)
Toilet type: public toilet	0.0602	0.0291***	0.122	0.0549*
	(1.09)	(3.60)	(1.54)	(2.21)
Toilet type: WC	0.444***	0.154***	0.489***	0.378***
	(7.90)	(17.60)	(6.12)	(14.50)
Toilet type: no facility (reference)				
Water type: pipe inside	0.111	0.0749***	0.0440	0.111***
	(1.92)	(6.33)	(0.75)	(4.92)
Water type: pipe outside	-0.0549	-0.0187**	-0.0735*	-0.0400**
	(-1.85)	(-3.11)	(-2.30)	(-3.05)
Water type: Borehole and others (reference)				
National grid connection (1 = connected; 0 = none)	0.145**	0.0715***	0.278***	0.241***
	(2.93)	(10.69)	(4.58)	(11.64)
Region: Western (urban)	-0.356***	-0.287***	-0.334***	-0.345***
	(-6.33)	(-21.54)	(-6.15)	(-15.27)
Region: Western (rural)	-0.765***	-0.941***		
	(-8.77)	(-74.74)		
Region: Central (urban)	-0.511***	-0.355***	-0.486***	-0.316***
	(-8.61)	(-26.40)	(-8.51)	(-13.92)
Region: Central (rural)	-0.981***	-0.901***		
	(-13.71)	(-67.26)		
Region: Greater Accra (urban)	0.591***	0.534***		
	(10.11)	(40.81)		
Region: Greater Accra (rural)	-0.0940	-0.480***		
	(-1.14)	(-24.01)		

Table A5. Estimation results of hedonic regression models (continued)

	All areas		Urban areas only	
	Paid rent (1)	Imputed rent (2)	Paid rent (3)	Imputed rent (4)
Region: Volta (urban)	-0.664***	-0.488***	-0.656***	-0.500***
	(-9.37)	(-31.07)	(-9.46)	(-18.50)
Region: Volta (rural)	-1.135***	-0.905***		
	(-10.03)	(-67.46)		
Region: Eastern (urban)	-0.591***	-0.534***	-0.571***	-0.558***
	(-10.11)	(-40.81)	(-10.09)	(-24.94)
Region: Eastern (rural)	-1.109***	-0.910***		
	(-15.36)	(-71.83)		
Region: Ashanti (urban)	-0.545***	-0.375***	-0.515***	-0.453***
	(-13.17)	(-37.96)	(-12.74)	(-26.62)
Region: Ashanti (rural)	-0.997***	-0.955***		
	(-15.23)	(-83.76)		
Region: Brong Ahafo (urban)	-0.848***	-0.783***	-0.813***	-0.726***
	(-13.81)	(-57.05)	(-13.63)	(-30.90)
Region: Brong Ahafo (rural)	-0.931***	-0.933***		
	(-11.47)	(-70.02)		
Region: Northern (urban)	-1.092***	-0.871***	-1.069***	-0.827***
	(-10.19)	(-53.12)	(-10.22)	(-27.14)
Region: Northern (rural)	-0.739***	-0.880***		
	(-3.69)	(-61.37)		
Region: Upper East (urban)	-0.565**	-0.872***	-0.517**	-0.730***
	(-3.26)	(-32.52)	(-3.06)	(-14.93)
Region: Upper East (rural)	-0.981***	-0.893***		
	(-3.60)	(-51.19)		
Region: Upper West (urban)	-0.666***	-0.810***	-0.633***	-0.791***
	(-3.84)	(-22.59)	(-3.78)	(-13.14)
Region: Upper West (rural)	-1.075**	-0.901***		
	(-2.99)	(-48.97)		
Constant	5.476***	6.401***	5.118***	5.663***
	(25.37)	(245.85)	(17.60)	(69.02)
Observations	2860	14008	2138	6018
Adjusted R^2	0.502	0.731	0.512	0.761

Note: t statistics in parentheses. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. Dependent variables are the natural logarithm of paid housing rents (columns 1 and 3) or imputed rents (columns 2 and 4).

Appendix B. Is the Engel curve approach a promising alternative?

Some studies developed and applied several Engel curve approaches to construct a spatial price index. The most common use of the Engel curve approach is motivated by temporal focus (rather than spatial), estimating and correcting a CPI bias.[16] For example, Dabalen, Gaddis, and Nguyen (2019) use this method and find a substantial impact of CPI bias on poverty estimates among several African countries. Other examples of the use of Engel curve methods for temporal analysis include Nakamura, Steinsson, and Liu (2016), which argues that China's economic growth is overestimated due to CPI bias (that is, underestimation of inflation).

More relevant uses of Engel curve approaches for our study are those from spatial (or spatiotemporal) perspectives. Almas (2012) uses an Engel curve method to correct PPP bias across countries, finding that the income of poorer countries tends to be overestimated. Almas and Kjelsrud (2017) incorporate the expenditure-specific cost of living in Engel curve model to measure income inequality in India. They find that the relative price changes were pro-poor during the study period and thus growing income inequality was overestimated further. Almas and Johnsen (2018) estimate an Engel curve model to measure poverty comparable across time and space in China. They find that inflation was mild in urban/rich areas and thus poverty reduction has been more moderate than previously assumed. Most importantly, Gibson, Le, and Kim (2017) compare the performance of Engel curve methods as a tool for spatial price adjustment with other methods. Their analysis based on Vietnam's detailed price data concludes that the Engel curve approach is not suitable for spatial adjustment.[17]

This line of approaches assumes that households with the same expenditure share for food have the same level of utilities across space. In other words, the difference in nominal income (or expenditure) among households with the same expenditure share for food reflects spatial cost-of-living differentials. However, it is possible that many other unobserved factors affect food budget shares. As Gibson, Le, and Kim (2017) argue, however, this assumption may not hold across space (discussed later in this Annex).

Engel curve method with no price data. A great advantage of the Engel curve method for spatial price adjustment is that price data are not necessary in some cases. Almas, Kjelsrud, and Somanathan (2019) applied such a method to estimate poverty in India. In a standard Engel curve model, the relative (aggregated) prices of food and non-food are required. They, however, argue that a restricted version of the Engel curve model below can be used by assuming that the budget share for food is not influenced by relative prices.

$$w_{ijt} = a + b\left(\ln y_{ijt} - \ln P_{jt}\right) + \theta X_{ijt} + \varepsilon_{ijt}, \tag{15}$$

where w_{ijt} indicates the budget share for food of household *i* in region *j* (or urban/rural) at time *t*; $\left(\ln y_{ijt} - \ln P_{jt}\right)$ is the real income for household *i* (nominal expenditure y_{ijt} divided by the overall price level of region *j*, P_{jt}); X_{ijt} is a vector of household-specific control variables; and ε_{ijt} is an error term. Given that P_{jt} varies only at the region/time, it can be identified through region- and time-specific dummies (D_{jt}):

[16] It is noted that even in case of temporal analysis as the primary purpose, the Engel curve method requires regional price index to identify CPI bias (discussed later).

[17] Other studies that construct spatial price index and estimate poverty/inequality using an Almost Ideal Demand System (AIDS)-type demand system include Chakrabarty, Majumder, and Ray (2015); Majumder, Ray, and Sinha (2015); Navamuel, Morollon, and Vazquez (2018); and Ravallion and van de Walle (1991).

$$w_{ijt} = a + b\ln y_{hst} + \theta X_{ijt} + \sum d_{j1} D_{j1} + \sum d_{j2} D_{j2} + \varepsilon_{ijt}. \tag{16}$$

The region dummy coefficient d_{jt} is a function of the overall region price level P_{jt} and the coefficient for the logarithm of household expenditure b,

$$d_{jt} = -b\ln P_{jt}, \tag{17}$$

and thus regional price level at time t can be obtained as follows:

$$P_{jt} = e^{-\frac{d_{jt}}{b}}. \tag{18}$$

While the no-price approach above is attractive, the assumption may be too restrictive.[18]

Engel curve method with price data. Most Engel curve methods instead require food and non-food price relatives as follows:

$$w_{ijt} = a + b\left(\ln y_{ijt} - \ln P_{jt}\right) + \gamma(\ln P_{jt}^{f} - \ln P_{jt}^{n}) + \theta X_{ijt} + \varepsilon_{ijt}, \tag{19}$$

where P_{jt}^{f} is a regional price index for food and P_{jt}^{n} is a regional price index for non-food (at time *t*). However, to identify this model, the relative price of food $(\ln P_{jt}^{f} - \ln P_{jt}^{n})$ needs to be calculated at a more geographically disaggregated level, such as districts to avoid perfect collinearity.[19] This requires prices or unit values for food and non-food items.[20]

It is common to group items (for example, rice instead of white rice, brown rice) when estimating an AIDS-type demand system (Deaton and Muellbauer 1980), including the Engel curve method above. Such aggregation can be done by either taking the mean or median of items under the same commodity groups, calculating a standard price index (for example, Laspeyres), or estimating a CPD regression (for example, Almas, Kjelsrud, and Somanathan 2019). Since prices in the same commodity groups tend to vary widely across space (Gibson and Kim 2015), it is important to ensure the variety of goods included in the groups.[21]

Results

Figure B1 shows Engel curves for three different regions (Greater Accra, Upper West, and Eastern). It is worth noting that the shifts in the Engel curves across regions are not parallel—a violation of the

[18] Almas, Kjelsrud, and Somanathan (2019) justify this assumption by stating "the evidence on the effect of relative prices on food shares in mixed but most studies find insignificant or small effects." See also a study of Russia by Gibson, Stillman, and Le (2008), which reports similar CPI bias in Engel curve models with and without relative food prices.

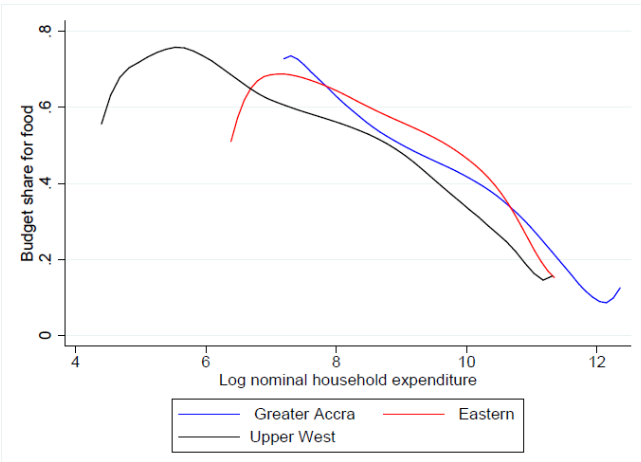
[19] If we simply distinguish price levels between urban and rural sectors (instead of regional levels), then price relatives need to be calculated at the regional level (instead of district levels). In this case, regional CPI may be used if available.

[20] Allowing the budget share for food to depend on relative prices in the demand model above means that the cost of living is income specific (that is, non-homothetic). In other words, estimated cost of living represents one reference household income level, which is not necessarily the same for the reference in CPI. It is well known that as a plutocratic price index, CPI measures changes in cost-of-living for households in the upper end of income distribution (Gaddis 2016). Some recent studies attempt to estimate cost of living for different points of income distribution. For example, Almas, Beatty, and Crossley (2018) propose a new method, the translated Engel curve (TEC) method, to estimate expenditure-specific CPI bias.

[21] This is called 'Hicksian separability': relative prices of elementary goods within a commodity group are constant, allowing the price of a single representative good to proxy for the group price level (Gibson and Kim 2015).

assumptions implicit in our Engel curve specifications. This is also one of the two facts documented in India in Atkin et al. (2018) which motivate their alternative approach. These authors also find the Engel curves in India are not linear. Figure B1 does not show any striking evidence of a nonlinear relationship between the budget share for food and the natural log of household expenditure for most expenditure levels across the three regions. There appears to be some evidence of a nonlinear relationship for low levels of household expenditure; however, this is likely because there are relatively few observations and the local polynomial predictions are noisy at both tails for the three Engel curves.

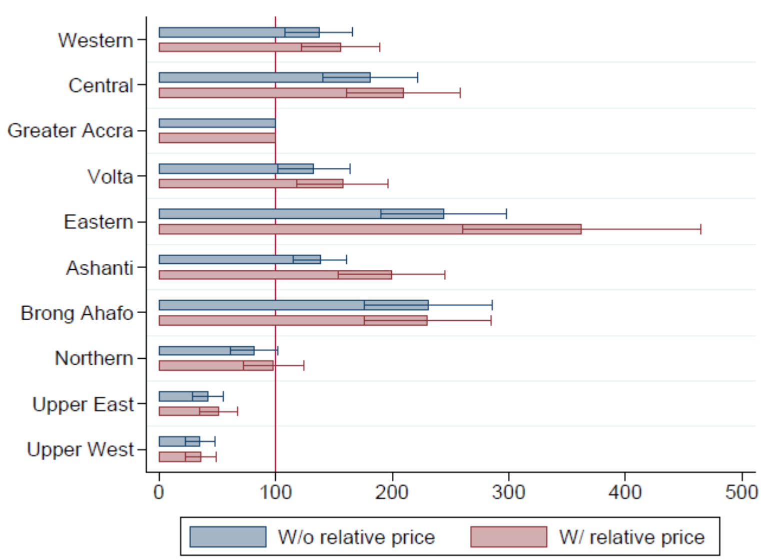
Figure B1. Engel curves over different regions



Source: Authors' calculations based on the GLSS7.

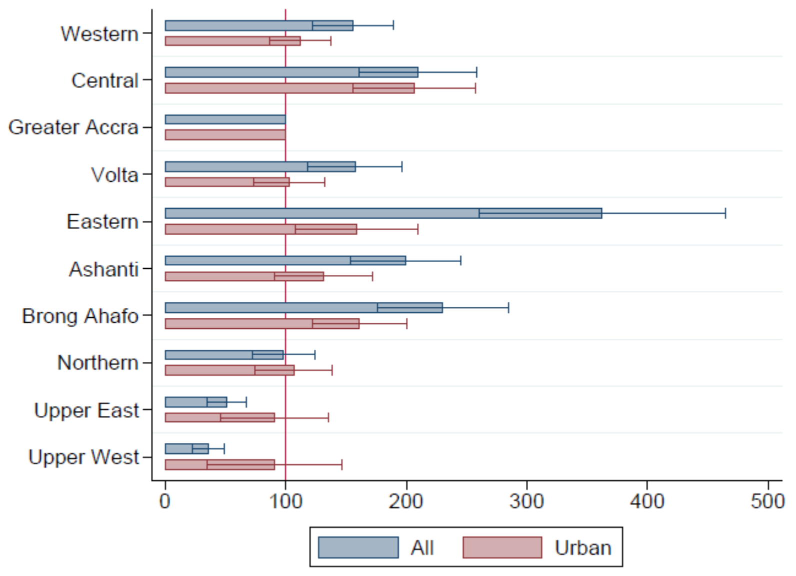
Figure B2 and Figure B3 summarize the spatial price index estimated by the Engel curve method with and without food/non-food price relatives. The intuition behind the Engel approach is that regions with positive and significant fixed effects are relatively more expensive than Greater Accra. A positive and significant fixed effect estimate suggests that a household devotes a larger share of its household expenditure on food than a comparably similar household in the Greater Accra region.

Figure B2. Spatial price index based on the Engel curve method (with and without price relatives)



Note: Spatial price index is normalized so that Greater Accra equals to 100.
Source: Authors' calculations based on the GLSS7.

Figure B3. Spatial price index based on the Engel curve method (all sample and urban subsample)



Note: Spatial price index is normalized so that Greater Accra equals to 100.
Source: Authors' calculations based on the GLSS 7.