# Spatial Price Adjustment for Poverty and Inequality Measurement: A Case Study of Ghana

Xiaomeng Chen[†], Rose Mungai[†], Shohei Nakamura[†], Thomas Pearson[‡], Ayago E. Wambile[†], Nobuo Yoshida[†]

† World Bank, ‡ Boston University

## 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.

## Data

Our Ghana case study relies on the following three datasets:
1) the nationally representative official household budget survey data (Ghana Living Standard Survey, GLSS7 [2016/17]) for the calculation of budget shares, poverty and inequality measures, and housing information;
2) the market price survey, which was collected in parallel to the GLSS7, for food prices; and
3) the consumer price index (CPI) raw price data for food and non-food prices.

### Table 1. Summary of data

| Data | Geographic coverage | Information |
|---|---|---|
| GLSS7 | 1,000 EAs in 214 districts in 10 regions | Expenditures on 109 food items<br>Housing rent and characteristics |
| Market price survey | 398 EAs (U209; R189) in 174 districts in 10 regions | Food prices<br>Limited non-food prices |
| CPI price data | 44 markets (U & R) in 10 regions | Food and non-food prices<br>Limited housing prices |

Presenter: Shohei Nakamura, World Bank
(snakamura2@worldbank.org)
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## Research questions

- Is the CPI price data a potential source for spatial price adjustment for poverty measurement?
- How should non-food items (particularly housing) be treated in measuring spatial differentials in costs of living?

## Conclusion

It is essential to have detailed product specification information in price data for the purpose of spatial price adjustment. CPI price data can be a potential source with other supplement data (e.g., housing).

## Analysis 1

To assess the performance of the CPI price data in measuring costs of living across regions, we apply a weighted country product dummy (WCPD) method to the market price survey data and the CPI raw price data (with and without detailed product specification information).

The CPD is estimated as a ordinary least squares (OLS) regression model

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

where $p_{ij}$ is the price of item $i$ in region $j$, $\alpha_i$ is the natural logarithm of the price level of item $i$ relative to other items, $\beta_j$ is the natural logarithm of the price level (or the purchasing power parity) of region $j$ with respect to other regions, $D_i$ and $D_j$ are item and region dummy variables, and $u_{ij}$ is a random disturbance term.

The results in Figure 1 show that regional price index values converge as price data improves from the market price survey to the CPI price data (with item-level information) to the CPI price data (with variety-level information). While the Greater Accra region remains the most expensive region, the gap with other regions become narrower. This reflects a potential bias from omitting quality information in price data, as Accra was originally estimated to be expensive partly because of its high-quality food products in the market.



**Figure 1. Food price indexes based on the CPD method**
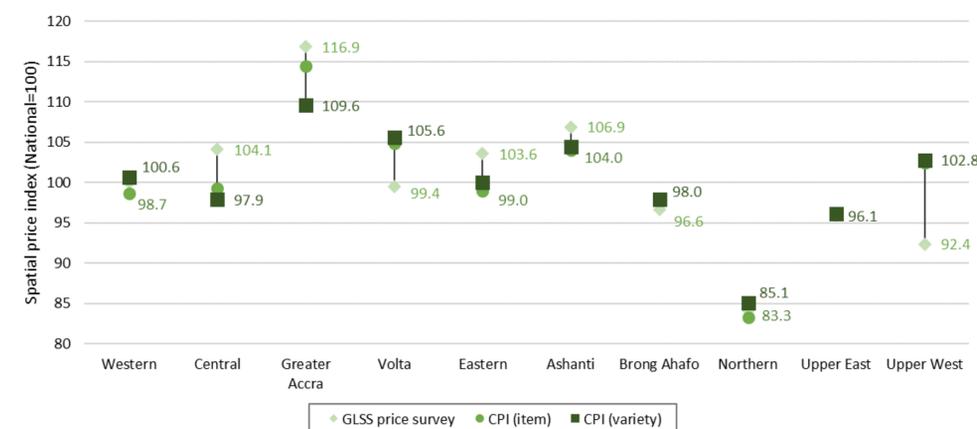
## Analysis 2

In the next analysis, we compare regional price indexes based on different housing price measures. There are two key questions:

- Quality difference of housing units should be taken into account or only the housing values should be considered?

We explore the influence of controlling for quality differences in housing across regions by comparing 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).

- Housing prices of rent-free units (e.g., slum dwellings) should be imputed (imputed rent approach) or only paid rents should be considered (paid rents approach)?

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).

Figure 2 shows food price index (GEKS-Fisher) and food plus housing price indexes. 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.

The treatment of housing prices also affects poverty measures (Table 2). Spatially deflating consumption aggregates by food and housing price index yielded lower national poverty rates (higher urban poverty rates) than the official rates.
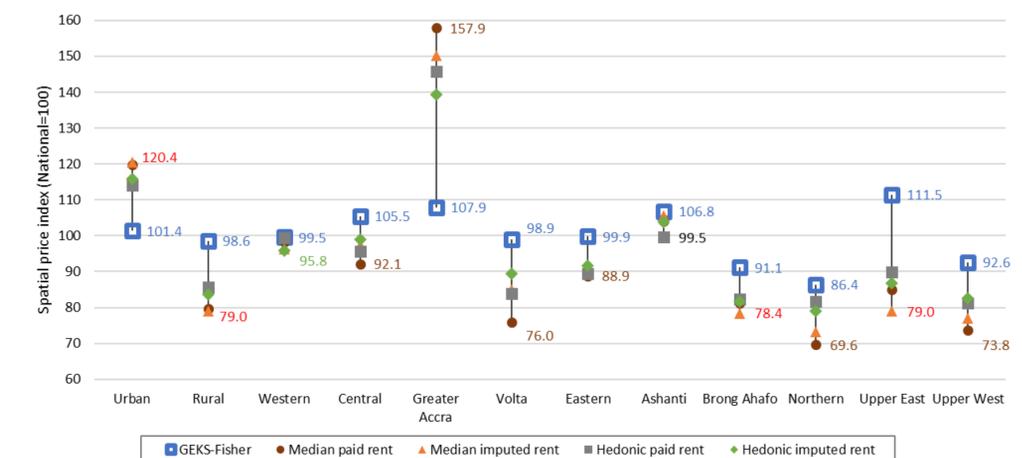


**Figure 2. Food plus housing price indexes**

### Table 2. Poverty rates and Gini coefficients

| | 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 |