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Assessing the Geographic Impact of Higher Food Prices in Guinea

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Abstract

Telling a policy maker that poverty will increase due to the recent increase in food prices is not very useful; telling the policy makers where the impact is likely to be larger is better, so that measures to cope with the impact of the crisis can be targeted to areas that need them the most. This paper shows how to use poverty mapping techniques to assess where higher food prices are likely to hurt the most using Guinea census and survey data as a case study. The results suggest that in the case of a rice price increase, the poorest areas of the country will not be the hardest hit, especially if the potential positive impact of higher food prices on rice producers is taken into account, in which case poverty may decline in some of these areas even if for the country as a whole poverty will increase significantly due to the large share of rice in the household consumption budget.

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Assessing the Geographic Impact of Higher Food Prices in Guinea[1]

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1. Introduction

A key issue confronted by policy makers designing policies to cope with the recent food price crisis is whether policy responses should be geographically targeted or not. As noted by Zaman et al. (2008; see also World Bank, 2008a and 2008b; IMF, 2-008, and Wodon and Zaman, 2008), three main types of policies have been advocated to respond to the crisis. Firstly, economy-wide policies aim to stabilize domestic food prices typically through indirect tax cuts and broad-based subsidies. Secondly, social protection and human development programs aim to help households cope with the shock induced by higher food prices. The third set of policies aims to boost domestic food production through a focus on agricultural productivity with the hope that a food supply response will help reduce food imports, put downward pressure on prices, and at the same time bringing in additional income for domestic food producers.

A recent survey of 118 country teams and country economists carried out by the World Bank in March 2008 suggests that in sub-Saharan Africa, the reduction in foodgrain taxes and the expansion of existing safety nets and social protection programs were the most commonly adopted policies to deal with the crisis. In this paper, our focus is implicitly on safety nets. A substantial body of research has shown that safety nets can be well targeted, but that this is by no way guaranteed (e.g., Subbarao et al., 1997; Braithwaite et al., 2000; Coady et al., 2003 and 2004). One of the easiest ways to achieve good targeting to the poor is to rely on geographic targeting through poverty maps (Elbers et al., 2002, 2003). Poverty maps can be especially useful in countries which have limited capacity to implement proxy-means testing mechanisms, while at the same time being constrained in terms of the likely gains from self-targeting. Many countries in sub-Saharan Africa clearly fall in these categories.

Because of the potential use of poverty maps for targeting purposes, there has been a growing literature on the use of the maps for policy. The World Bank recently came up with a collection of papers showing how poverty maps can be used for policy (Bedi et al., 2007). In this collection, country studies include work on Albania (Carletto et al., 2007), Bolivia (Arias and Robles, 2007), Bulgaria (Gotcheva, 2007), Cambodia (Fujii, 2007), China (Ahmad and Goh, 2007a), Ecuador (Araujo, 2007), Indonesia (Ahmad and Goh, 2007b), Mexico (Lopez-Calva et al., 2007), Morroco (litvack, 2007), Sri Lanka (Vishwanath and Yoshida, 2007), Thailand (Jitsuchon and Richter, 2007), and Vietnam (Swinkels and Turk, 2007). While East Asia, Eastern Europe, Latin America, Northern Africa and South Asia are all represented, sub-Saharan Africa is notably absent. This does not mean that there has not been any work on poverty maps in sub-Saharan Africa. Indeed, poverty maps have been constructed among others for Ghana (Coulombe, 2008), Madagascar (Mistiaen et al., 2002), South Africa (Alderman et al., 2002), as well as Uganda (Emwanu et al., 2006; Hoogeveen and Schipper, 2005). Still, Africa remains under-represented in terms of work done in this area, and this is especially the case for West and Central Africa.

A key reason for the lack of poverty maps available for West and Central African countries has been the fact that good census and survey data were not available until recently. This has now changed, as more data has become available. This has enabled the World Bank's Africa Region unit launched a few years ago a West and Central Africa poverty mapping initiative that has helped in constructing poverty maps in 16 countries (Coulombe and Wodon, 2007). For most of the countries, the poverty map is close to being finalized.

In the context of the recent food price crisis, poverty map can also be used to document the likely impact of the crisis on various regions and areas within a country. Indeed, telling a policy maker that poverty will increase due to the crisis is not very useful. By contrast, telling the policy makers where the impact is likely to be the larger is better, so that measures to cope with the impact of the crisis can be targeted to areas that need them the most. The objective of this paper is to show how to assess where higher food prices are likely to hurt the most with a case study for Guinea and a focus on rice.

The paper is structured as follows. We first provide findings from a new poverty map for Guinea constructed by the authors with a team from the National Statistical office of Guinea. Next, we provide an assessment of the potential geographic impact of the increase in rice prices. As already mentioned, it turns out that the areas hardest hit by the food crisis are typically not the poorest, which may pose a dilemma for policy makers in terms of whether relief should be targeted to the poorest areas or to areas where the increase in poverty is likely to be largest.

2. Poverty Map for Guinea

2.1. Methodology and data

Elbers et al. (2003) have shown how to construct poverty maps by combining census and survey data (see also Mistiaen, 2003 for an application and a useful summary discussion from which this section is inspired). The idea is straightforward. First, a regression of per capita or adult equivalent consumption is estimated using household survey data, limiting the set of explanatory variables to ones common to both the survey and the latest census. Second, the coefficients from that regression are applied to the census data to predict the expenditure level of each household in the census. Third, the predicted household expenditures are used to construct a series of poverty indicators for geographical population subgroups. Although the idea is simple, its implementation requires complex computations due to the need to take into account spatial autocorrelation (expenditure from households within the same cluster or area are often correlated) and heteroskedasticity in the development of the predictive model. Another issue is the need to compute standard errors to assess the degree of precision of poverty estimates. Those standard errors are important since they help assess how far the information can be disaggregated (the smaller the area and the number of observation are, the larger the standard errors of the poverty measures are likely to be).

For Guinea, our poverty map is based on the latest Population and Housing Census conducted in 1996 and the second round of the Household Income and Expenditure Survey (EIBEP in French) implemented in 2002/03. While we have an interval of six years between the two surveys, this was not a period of dramatic change in conditions of living in the country, so that we are confident that the two data sources can indeed be compared and used jointly. The questionnaire of the Census is relatively detailed but does not contain information on household incomes or expenditures. At the individual level, the questionnaire covers demographic variables, as well as the education of household members and their economic activities. At the household level, dwelling characteristics are well covered. The Census includes data on 7.2 million individuals living in slightly more than one million households. The field work was done in 5127 enumeration areas (EAs) of about 200 households each on average. As for the EIBEP survey, apart from a wide range of individual and household characteristics, it includes detailed consumption data that have been used to construct the welfare index (expenditure per capita) used in our regression models. Our poverty estimates were derived jointly with government staff from the national Statistical Office, which ensures consistency between the official poverty profile of the country and our poverty map.

The administrative structure of Guinea is simple. The top tier is composed of 8 regions broken down into 34 prefectures. Those prefectures are further dissagregated into communes (sometimes called sous-prefecture). Table 1 presents descriptive statistics on the size of those different administrative levels. There are 341 communes in the census with a median size of 2,061 households. Although a few communes are rather small, almost all of them have sufficient population size to yield precise-enough poverty estimates.

The first task for the construction of a poverty map consists in making sure that the variables deemed common to both the census data and the household survey are really measuring the same characteristics. To this end, we first compared the questions and modalities in both the census and survey questionnaires to isolate potential common variables. We then compared the means of those (dichotomized) variables and tested whether they were equal using a 95% confidence interval[2]. Restricting ourselves to those variables ensures that the predicted welfare figures in the census should be consistent with the EIBEP-based poverty profile. This comparison exercise was done at the strata level (i.e., separately for each stratum). The two-stage sample design of the EIBEP survey was taken into account for the computation of the standard errors. The results are available on request.

The second step consists in estimating regressions to predict consumption per capita in the EIBEP. In order to maximise accuracy we estimated the model at the lowest geographical level for which the survey is representative. Specifically, we estimated regressions for each of the nine EIBEP sampling strata: Conakry, Lower Guinea, Middle Guinea, Upper Guinea and Forest Guinea. Except for the capital Conakry, all strata were further broken down into urban and rural areas for the estimation. Following Elbers et al. (2002; see also Mistiaen et al. 2002 from which the presentation below is adapted), denote by y_{ch} the household consumption per capita of household *h* in location *c*, by $\mathbf{x_{ch}}$ a set of explanatory variables, and by u_{ch} a residual. We have:

$$\ln y_{ch} = \mathrm{E}[\ln y_{ch} \mid \mathbf{x_{ch}}] + u_{ch} \qquad (1)$$

The locations represent clusters as defined in the first stage of typical household sampling design. The explanatory variables need to be present in both the survey and the

Census, and need to be defined similarly and have similar mean values. The set of potential variables to be used in the model has been defined in the first stage of the procedure outline earlier. If we linearise (1), we model the household's logarithmic per capita expenditure as

$$\ln y_{ch} = \mathbf{x}_{\mathbf{ch}}^{'}\boldsymbol{\beta} + u_{ch}. \qquad (2)$$

The vector of disturbances $\boldsymbol{u}$ is distributed $F(0,\Sigma)$. The model (2) is estimated by Generalised Least Square. To estimate this model we need first to estimate the error variance-covariance matrix Σ in order to take into account possible spatial autocorrelation (expenditure from households within a same cluster tend to be correlated) and heteroskedasticity. To do so we first specify the error terms as:

$$u_{ch} = \eta_c + \varepsilon_{ch} \qquad (3)$$

where η_c is the location effect and ε_{ch} is the individual component of the error term. In practice we first estimate equation (2) by simple OLS and use the residuals as estimate of the overall disturbances, given by $\hat{\mu}_{ch}$. We then decompose those residuals between uncorrelated household and location components:

$$\hat{u}_{ch} = \hat{\eta}_c + e_{ch} \qquad (4)$$

The location term ($\hat{\eta}_c$) is estimated as cluster means of the overall residuals and therefore the household component (e_{ch}) is simply deducted. The heteroskedasticity in the latest error component is modelled by the regressing its squared (e_{ch}^2) on a long list of independent variables from model (2), their squared and interactions as well as the imputed welfare. A logistic model is used for this. Both error computations are used to produce two matrices which are them summed to $\hat{\Sigma}$, the estimated variance-covariance matrix of the original model (2). That matrix is used for the estimation of the final set of coefficients for the main model (2).

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[2] We also deleted or redefined dichotomic variables being less that 0.03 or larger than 0.97 to avoid serious

To complete the poverty map we associate the estimated parameters from the second stage with the corresponding characteristics of each household found in the census. This enables us to predict the log of per capita expenditure and the simulated disturbances. Since the disturbances have a complex structure which makes the computation of the variance of the imputed welfare indices intractable, bootstrapping techniques are used to get a measure of the dispersion of the imputed welfare index in the Census. From the previous stage, a series of coefficients and disturbance terms are drawn from their corresponding distributions. We then, for each household found in the census, simulate a value of the welfare index ($\hat{y}_{ch}^{r}$) based on the predicted values and the disturbance terms:

$$\hat{y}_{ch}^{r} = \exp(\mathbf{x}_{ch}^{'}\tilde{\beta}^{r} + \tilde{\eta}_{c}^{r} + \tilde{\varepsilon}_{ch}^{r}) \qquad (5)$$

That process was repeated 100 times, each time redrawing the full set of coefficients and disturbances terms. The means of the simulated welfare index become our point estimate and the standard deviation of our welfare index is the standard errors of these simulated estimates.

The strata-specific regression results are available upon request. The ultimate choice of the independent variables was based on a backward stepwise selection model. A check of the results confirmed that almost all of the coefficients were of the expected sign. Note that the models are not meant to indicate causality. Instead, they are purely predictive models. The regressions attempt to control for location effects by incorporating the cluster level averages of some of the independent variables. We also ran a series of regressions using the base model residuals as dependant variables to correct for heteroskedasticity.

The R^2s of the main regressions vary from 0.25 to 0.49. Although this may appear to be on the low side, these statistics are typical of survey-based cross-section regressions and can are comparable with results from other poverty maps. The relatively low R^2s for some of

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multicollinearity problems in our econometric models.

the models are mainly due to four important factors. First, in many areas households are fairly homogeneous in terms of observable characteristics even if there consumption varies relatively more. Second, a large number of potential correlates are simply not observable using standard closed-questionnaire data collection methods. Third, some potentially good predictors had to be discarded at the first stage because their distributions did not appear to be identical in the Census and in the EIBEP. Finally, many variables do not account for quality and are only dichotomised.

The implementation of the above procedure and the computation of the welfare indicators in the Census has been greatly eased thanks to PovMap, a software especially written to implement the methodology (we used the version developed by Zhao, 2005).

2.2. Results

Parameter estimates from the EIBEP regressions were applied to the Census data to compute a series of poverty indicators: the headcount ratio (P_0), the poverty gap index (P_1), and the squared poverty gap index (P_2). In addition, inequality measures were estimated as well, including the Gini Index, the mean log deviation and the Theil index.

Table 2 presents estimated poverty measures for each stratum and compares them with measures obtained in the EIBEP. For each stratum and poverty indicators, the equality of the EIBEP and Census-based indicators cannot be rejected at the 95% confidence interval. This suggests that the estimates from the Census are reliable, at least at that level.

The usefulness of the poverty map consists in using estimates at a low disaggregated level. But in order to make an “objective” judgement on the precision of the estimates obtained at such low levels, it is useful to compute the coefficients of variation of the poverty measures for all three administrative levels used in Guinea as well as for the headcount index estimates obtained with the EIBEP. Figure 1 presents the coefficients of variation of the headcount indices obtained from the EIBEP by region, and compares them with the estimates obtained by region, prefecture and commune in the Census. The idea is to use the precision of the EIBEP-based estimates at the regional level as a benchmark for assessing the precision of Census-based estimates. The stepped curve in the Figure represents the coefficients of variation associated with the different strata in the EIBEP. The curves in Figure 1 clearly show that our prefecture and commune-level estimated headcounts are not as precise as the strata-level estimates from the EIBEP, but since almost all of our Census-based estimates have a coefficient of variation below 0.2 (a common benchmark when constructing poverty maps) we feel confident that these estimates are precise enough to guide policy-makers.

A visualization of the headcount indices obtained for each commune in the Census is given in the Figure 2. Since the estimates are based on consumption aggregates derived in large part from the 2002/03 EIBEP, the map can be (loosely) considered as representing the geography of poverty in Guinea in that year (even though the data from the Census dates back to 1996, as already mentioned there were relatively few changes in key household characteristics between the two years). We have thus estimated poverty measures for a total of 341 communes.

3. Impact of the Food Price Crisis

3.1. Methodology

Mistiaen (2003) suggested that the poverty mapping methodology could be used to estimate the impact of a change in the price of rice in Madagascar for example due to a change in taxation on that product. The idea consists in estimating a new poverty maps using a revised consumption aggregate in the survey with the consumption data. This revised consumption aggregate takes into account the impact of the shock. By comparing the initial poverty map with the revised poverty map based on the new consumption aggregate, we obtain estimates at a disaggregated geographical level of the impact on poverty of the shock.

This is also the procedure used here. In the case of a food price shock, the key is to assess impacts on both the consumer side (higher food prices reduce welfare) and the producer side (higher food prices increase incomes for producers), while making sure than when a food item is produced and auto-consumed, neither effects are taken into account since prices are irrelevant. On the literature on how the short term impact of higher prices on poverty is typically measured, see among others Deaton (1989), as well as the applications of Deaton's framework by Barrett and Dorosh (1996) to Madagascar, Budd (1993) to Cote d'Ivoire, and Loening and Oseni (2007) to Ethiopia.

We simulate the impact of an increase in the price of rice of 50%, since rice is the basic staple food in the country. Rice represents 45 percent of the caloric intake of a typical Guinean household, and even more in some urban areas. According to the EIBEP data, urban poor households spent 16 percent of their total consumption on rice, versus 9 percent for nonpoor urban households. In order to construct the revised consumption aggregate in the EIBEP after the price shock, a number of assumptions are used. First, we assume that the cost of an increase in rice prices for a household translates into an equivalent reduction of its consumption in real terms. This means that we do not take into account the price elasticity of demand which for non-marginal changes in prices may lead to substitution effects and thereby help offset part of the negative effect of higher prices for rice. Similarly, an increase for producers in the value of their net sales of rice translates into an increase of their consumption of equivalent size, and we again do not take into account the role that the price elasticity of supply may play here.

As for rice auto-consumed by producers (which represents a substantial share of total rice consumption), it is not taken into account in the simulations since changes in prices do not affect households when rice is auto-consumed. We also do not take into account the potential spill-over effects of the increase in rice prices for other food items. Finally we consider here only the short term impact on poverty of higher rice prices, as estimated by looking at the consumption and production of rice by households. This means that we do not take into account potential medium to long term impacts arising for example from the fact that an increase in rice prices may lead to higher wages for farm workers (findings from studies on medium term impacts suggest that wage gains compensate only in a very limited way only for the initial impact of food price shocks).

A difficult question is whether increases in consumer prices do translate into increases in producer prices. At least two factors may dilute the impact of rising rice prices on the incomes of farmers. First, production costs for farmers as well as transport costs are likely to be rising due to higher costs for oil-related products. Second, market intermediaries may be able in some cases to keep a large share of the increase in consumer prices for themselves without paying farmers much more for their crops. Because it is difficult to assess whether producers will benefit substantially from higher rice prices, especially in the short term, we consider our estimates obtained when considering only the impact on consumers as an upper bound of the impact of the rise in prices on poverty, and we interpret the results obtained when factoring in a proportional increase in incomes for net sellers or producers as a lower bound of the impact.

3.2. Results

Figures 3 and 4 provide the visualization at the commune level of the impact on poverty of a 50% increase in rice prices for respectively the upper and lower bound estimates. With the upper bound estimates, the national poverty headcount could increase by about three percentage points, although the increase could be much higher in some communes, especially in urban areas. These are large effects for a single commodity like rice. The impact is smaller with the lower bound (national increase of about 1.6 percentage point) as a substantial proportion of the rice consumed in Guinea is produced locally, but still important.

We also find that the poorest areas in the country are not the hardest hit by the crisis, with poverty actually decreasing in quite a few predominantly rural communes when potential producer effects are fully taken into account. The relationship between initial poverty and the change in poverty by district is visualized in Figures 5 and 6 for the headcount index of poverty, and in Figures 7 and 8 for the poverty gap. The Figures provide scatter plots with on the horizontal axis the initial level of poverty (still measured through the headcount index or the poverty gap) and on the vertical axis the change in the poverty measure due to the increase in food prices.

When looking at the upper bound impact, we find clear evidence of a negative relationship between the change in poverty and the initial level of poverty. For communes with very low poverty measures, the impact of the price increase for rice is very large, as many households are still fairly poor (urban poverty is higher in Guinea than in many other West African countries) and thereby have difficulty to cope with the large shock that results from the prominent place of rice in the population's diet. For very poor areas, the impact is lower in part because many households in these areas are protected from the increase in prices as they rely for a substantial part of their food consumption on auto-consumption.

The same relationship holds for the lower bound impact, which factors in potential income gains for producers. For quite a few of the poorest communes, factoring in the impact on producers leads poverty to drop versus the baseline poverty estimates before the shock (the bottom value on the vertical axis indicates a reduction in the headcount of poverty of up to five percentage points in some communes).

4. Conclusion

There are often large regional differences in poverty and other social indicators within a country. Geographic poverty profiles based on household surveys tend to be limited to broad areas because survey sample sizes are too small to permit analysts to construct valid estimates of poverty at the local level. At the same time policymakers often need finely disaggregated information at the neighbourhood, town, or village level in order to implement anti-poverty programs. It is for this reason that poverty maps have become popular in developing countries to provide better information for the targeting of various types of public transfers. Yet while most of the work on poverty maps has focused on assessing patterns of poverty at one point in time, the technique of the poverty map can also be used to assess the geographic impact of shocks, and thereby to help inform policy responses to such shocks.

After providing summary data from a new poverty map for Guinea, we have focused in this paper on assessing the geographical impact on poverty of an increase in the price of rice. The impacts differ substantially between areas. In some countries which import most of their rice such as Senegal for example, these differences in impacts between areas pose a difficult dilemma for policy makers. On the one hand, the desire to help households cope with the increase in food prices may lead policy makers to implement projects or provide relief in the hardest hit areas which tend to be urban. On the other hand these hard hit areas may not be among the poorest in the country, and when a country imports essentially all of its consumption of a basic staple, the rural poor suffer as well. In such case, one may wonder if for poverty reduction, interventions should not remain focused to the poorest areas (as measured after the shock), instead of the hardest hit ones by the shock.

In the case of Guinea, the dilemma is perhaps less present than in some other countries in West and Central Africa. Given the substantial production of rice in the country, some of the poorest areas, which are also the rice producing regions, may benefit from the increase in rice prices. Thus these areas may not need larger safety-net types of public interventions to help them cope with the shock, but on the other hand they would benefit (as would the country as a whole) from policies designed to increase rice production. What the data suggests in Guinea is that safety-net types of policy interventions may focus in part on urban and peri-urban areas, and rely on the detailed information available in the poverty map to target those rural areas which are not part of the rice producing economy.

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Table 1: Descriptive Statistics on the Guinean Administrative Structure

Territorial Unit	# of Units	Number of Households: Median	Minimum	Maximum	Number of Individuals: Median	Minimum	Maximum
Region	8	118,746	89,544	203,078	867,355	605,059	1,343,500
Prefecture	34	23,847	11,306	156,326	164,156	82,546	1,084,937
Commune	341	2,061	526	52,964	14,478	3,339	388,916

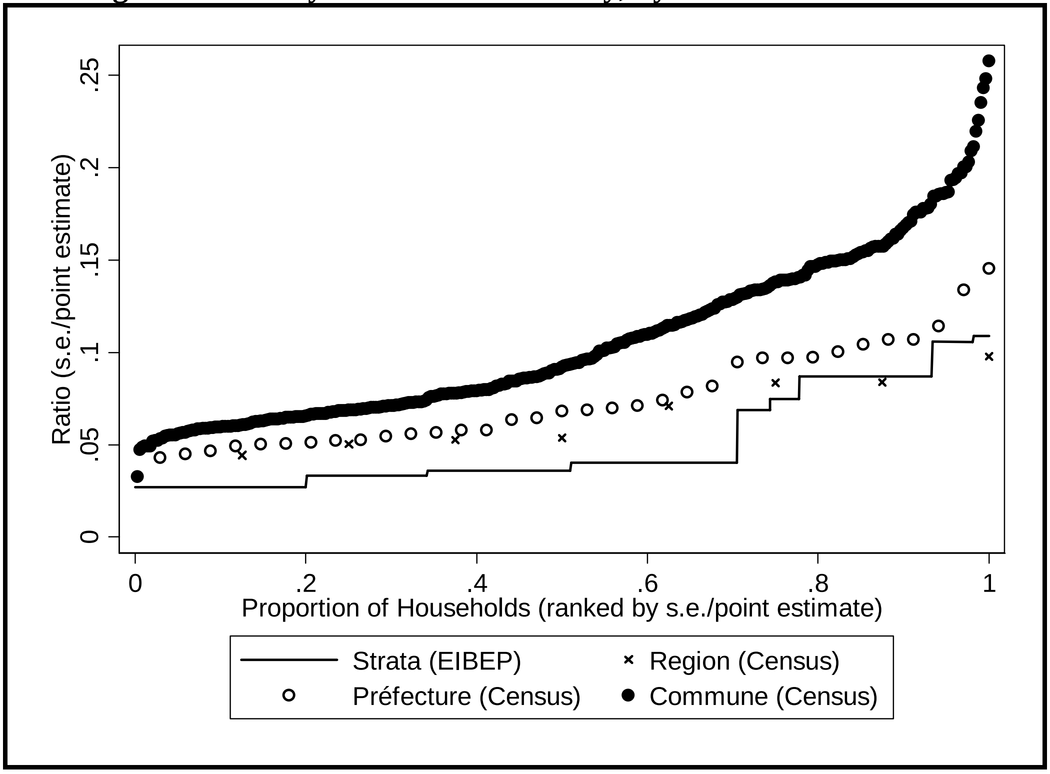
Source: Authors' calculation based on the 1996 Census

Table 2: Poverty Rates based on HIES (actual) and Census 2001 (predicted), by strata

	Headcount Incidence (P_0)		Poverty Gap Index (P_1)		Poverty Severity Index (P_2)	
	Survey (Actual)	Census (Predicted)	Survey (Actual)	Census (Predicted)	Survey (Actual)	Census (Predicted)
Conakry	0.201	0.244	0.049	0.065	0.019	0.025
	(0.026)	*(0.017)*	*(0.011)*	*(0.006)*	*(0.008)*	*(0.003)*
Lower Guinea Urban	0.178	0.226	0.042	0.057	0.015	0.021
	(0.022)	*(0.024)*	*(0.007)*	*(0.008)*	*(0.003)*	*(0.004)*
Lower Guinea Rural	0.485	0.474	0.152	0.173	0.065	0.085
	(0.036)	*(0.037)*	*(0.015)*	*(0.020)*	*(0.008)*	*(0.012)*
Middle Guinea Urban	0.198	0.220	0.049	0.058	0.017	0.023
	(0.026)	*(0.031)*	*(0.009)*	*(0.011)*	*(0.004)*	*(0.005)*
Middle Guinea Rural	0.592	0.599	0.232	0.242	0.122	0.128
	(0.035)	*(0.025)*	*(0.024)*	*(0.016)*	*(0.018)*	*(0.011)*
Upper Guinea Urban	0.319	0.389	0.094	0.132	0.039	0.062
	(0.033)	*(0.033)*	*(0.013)*	*(0.016)*	*(0.007)*	*(0.009)*
Upper Guinea Rural	0.709	0.648	0.280	0.271	0.139	0.146
	(0.030)	*(0.025)*	*(0.021)*	*(0.013)*	*(0.015)*	*(0.009)*
Guinea Forest Urban	0.376	0.362	0.105	0.102	0.042	0.041
	(0.051)	*(0.043)*	*(0.020)*	*(0.016)*	*(0.010)*	*(0.008)*
Guinea Forest Rural	0.603	0.601	0.206	0.230	0.090	0.116
	(0.025)	*(0.026)*	*(0.016)*	*(0.015)*	*(0.010)*	*(0.010)*

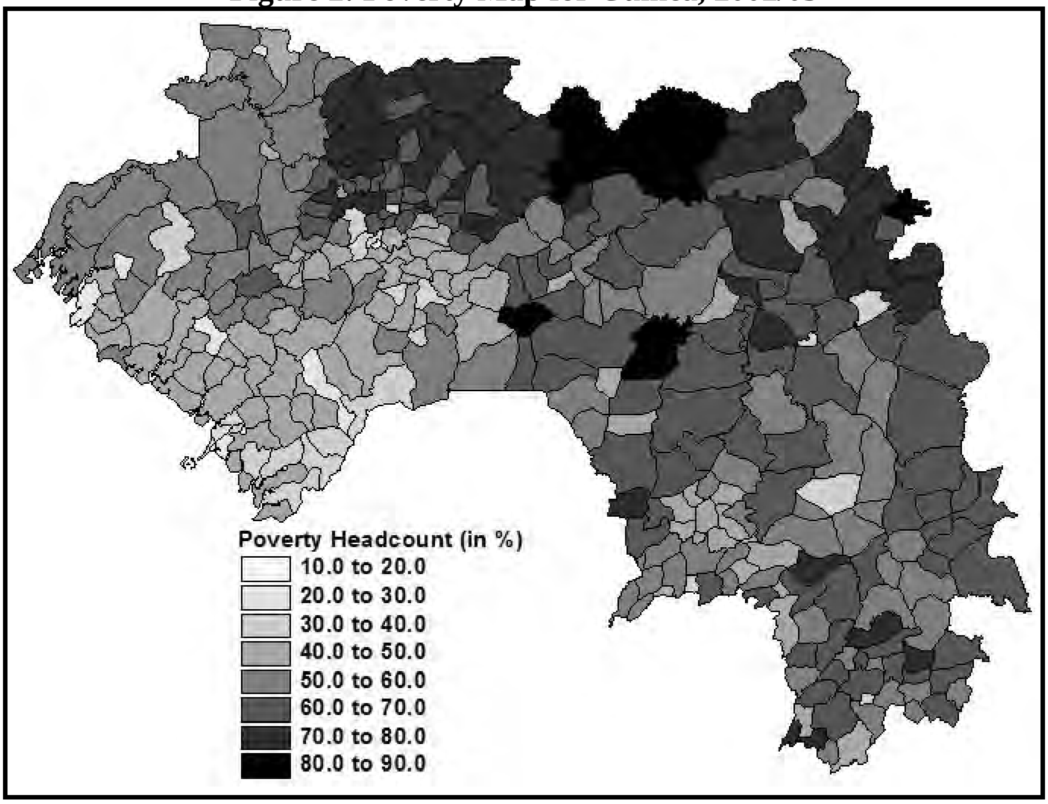
Sources: Authors' calculation based on the 2002/03 EIBEP and the 1996 Census
Note: Robust standard errors are in parentheses.

Figure 1: Poverty Headcount Accuracy, by Administrative Level



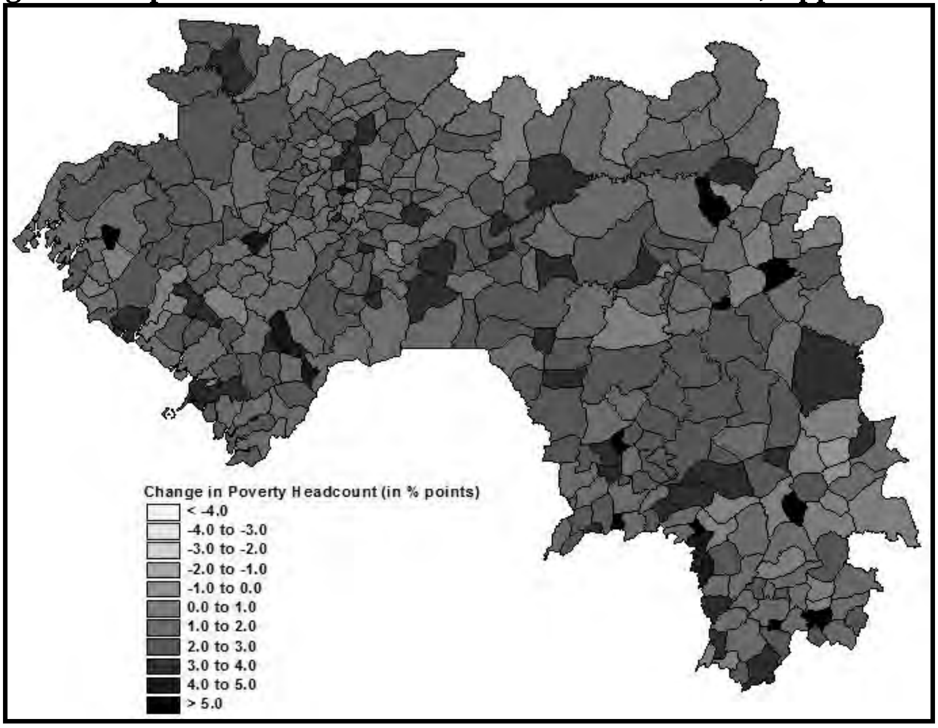
Sources: Authors' calculation based on the 2002/03 EIBEP and the 1996 Census

Figure 2: Poverty Map for Guinea, 2002/03



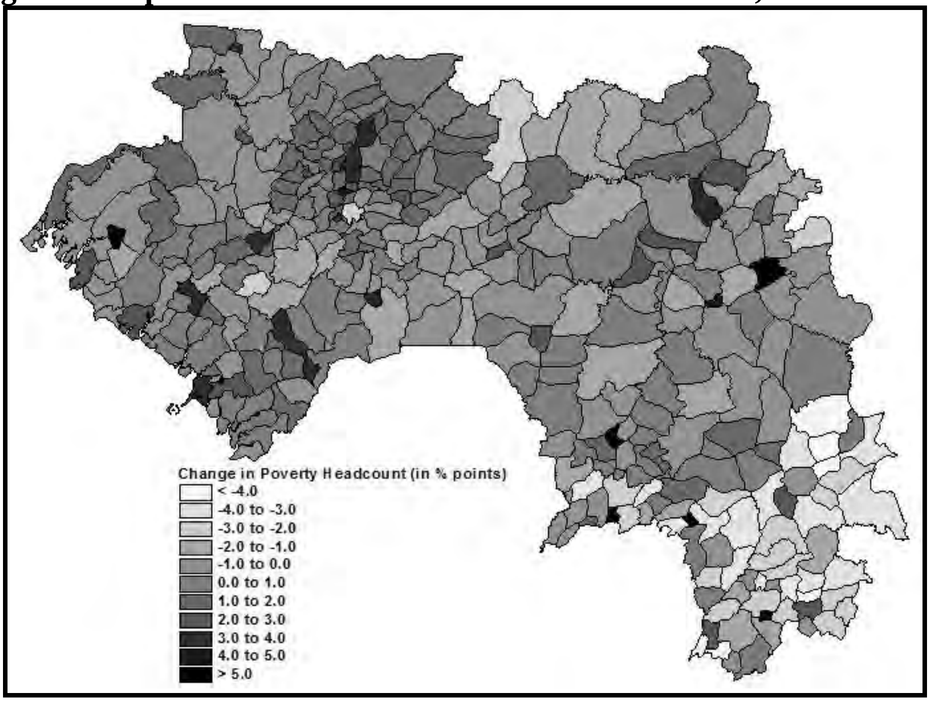
Sources: Authors' calculation based on the 2002/03 EIBEP and the 1996 Census

Figure 3: Impact of a 50 Percent Increase in Price of Rice, Upper Bound



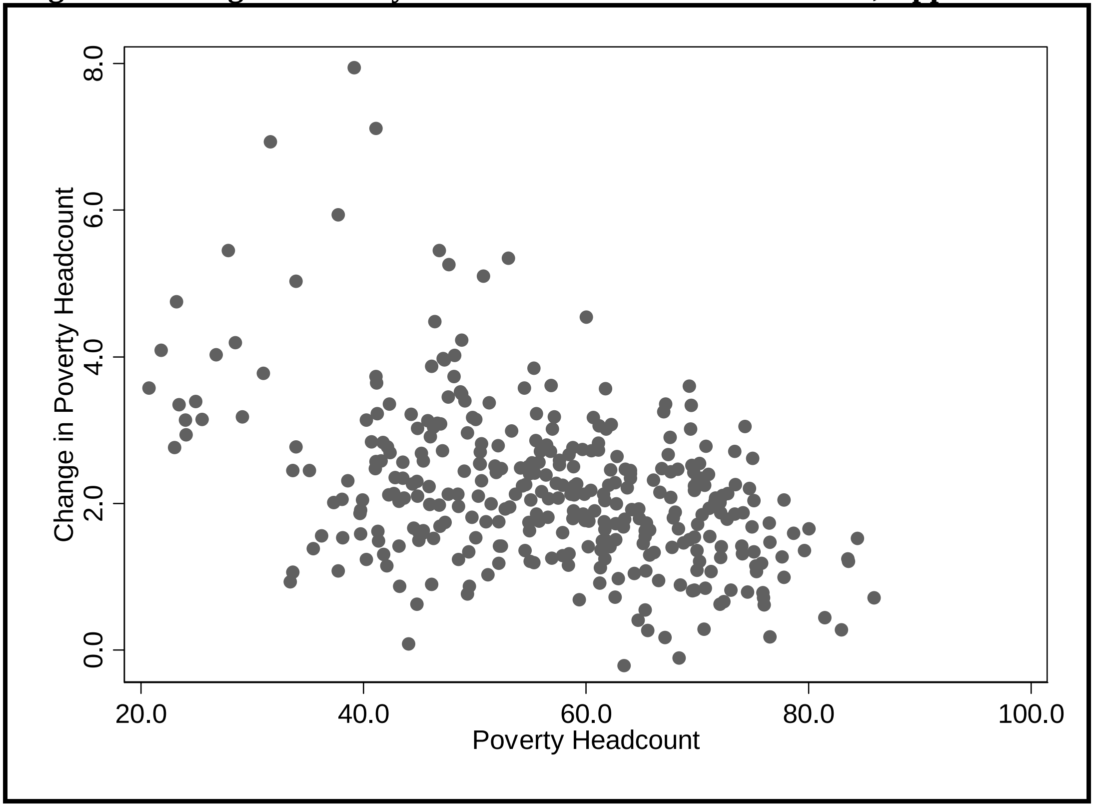
Sources: Authors' calculation based on the 2002/03 EIBEP and the 1996 Census

Figure 4: Impact of a 50 Percent Increase in Price of Rice, Lower Bound



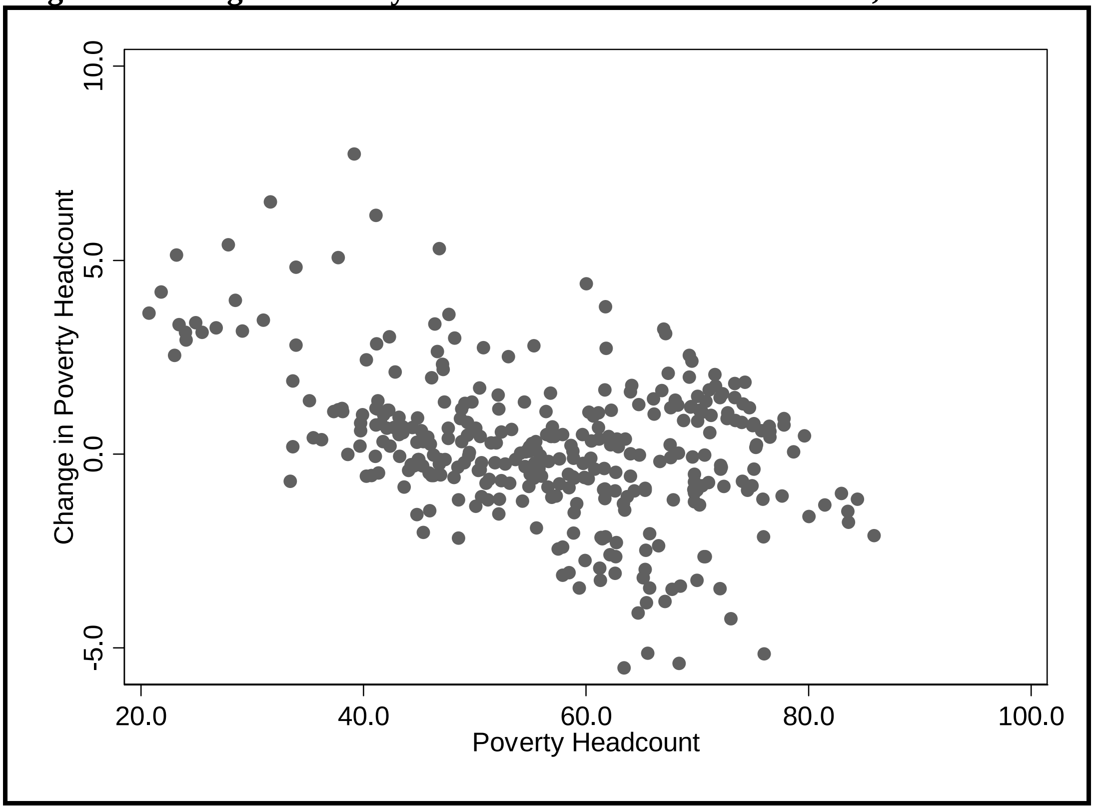
Sources: Authors' calculation based on the 2002/03 EIBEP and the 1996 Census

Figure 5: Change in Poverty Headcount and Initial Headcount, Upper Bound



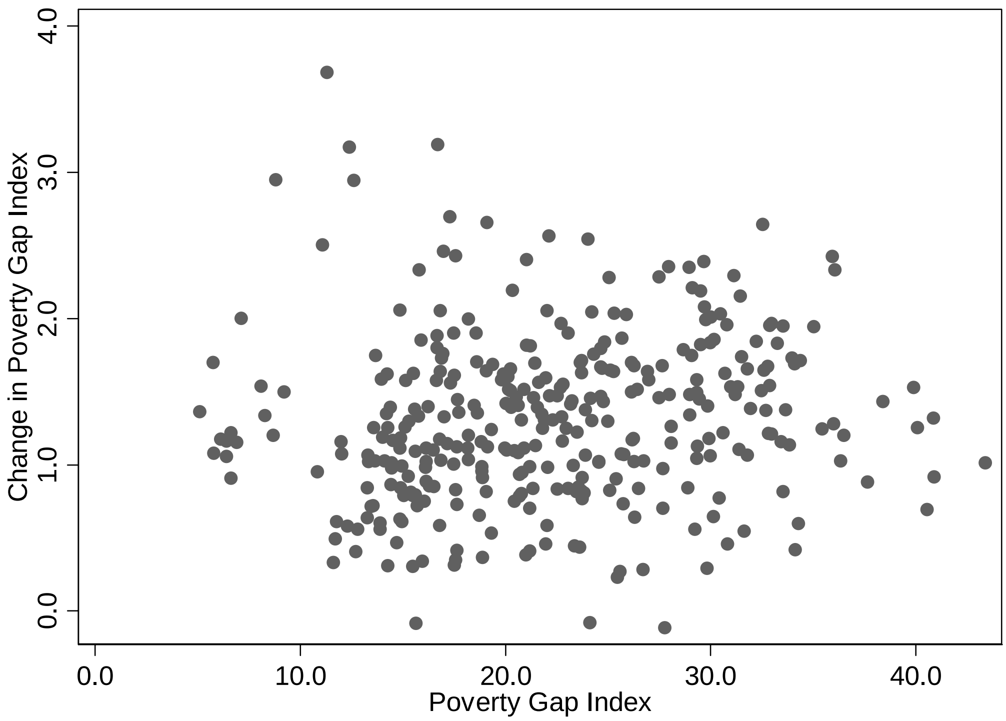
Sources: Authors' calculation based on the 2002/03 EIBEP and the 1996 Census

Figure 6: Change in Poverty Headcount and Initial Headcount, Lower Bound



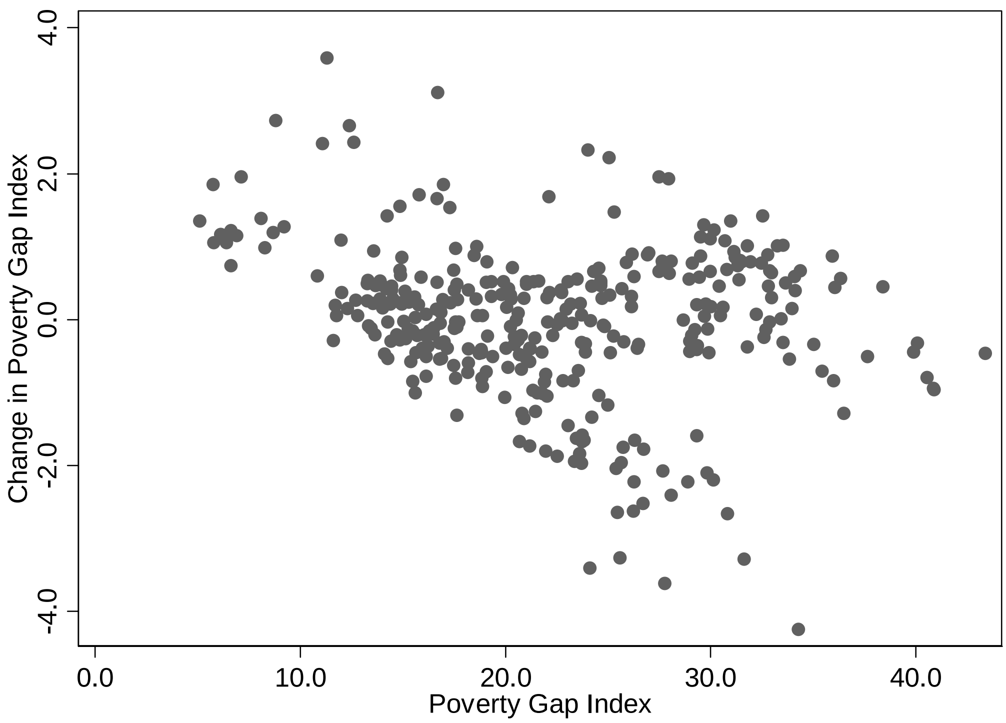
Sources: Authors' calculation based on the 2002/03 EIBEP and the 1996 Census

Figure 7: Change in Poverty Gap and Initial Poverty Gap, Upper Bound



Sources: Authors' calculation based on the 2002/03 EIBEP and the 1996 Census

Figure 8: Change in Poverty Gap and Initial Poverty Gap, Lower Bound



Sources: Authors' calculation based on the 2002/03 EIBEP and the 1996 Census