Small Area Estimation of Poverty in Rural Bhutan

Technical Report jointly prepared by National Statistics Bureau of Bhutan and the World Bank

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ABBREVIATIONS, ACRONYMS, AND GLOSSARY

BLSS	Bhutan Living Standard Survey
dzongkhag	District
ELL	Elbers et al.
gewog	Sub-district
GIS	Geographical Information System
GNHC	Gross National Happiness Commission
MDGs	Millennium Development Goals
NSB	National Statistics Bureau
RGOB	Royal Government of Bhutan
SAE	Small Area Estimation
WDR	World Development Report (WDR)
WFP	World Food Program

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Executive Summary

The Small Area Estimation (SAE) of Poverty in Rural Bhutan was prepared with an objective to provide a more disaggregated picture of poverty in Bhutan down to the *gewog* level, based on the Bhutan Living Standard Survey (BLSS) 2007 and Population & Housing Census of Bhutan (PHCB) 2005.

The analysis was carried out by the National Statistics Bureau (NSB) and the World Bank in response to the emerging need of the Royal Government of Bhutan (RGOB) especially for effective resource allocation to all the *gewogs*.

The report records the estimation process in detail and describes results of statistical tests for quality checks. According to these tests, the poverty estimates at the *gewog* level are reliable. The report also enhances the transparency of the process and intends to serve as a guide for future updates.

According to the Poverty Analysis Report (PAR) 2007, about one-fourth of the country's population is estimated to be poor with rural poverty as high as 30.9 percent. It also shows that poverty rates are high in Zhemgang, Samtse, Monggar and Lhuntse *dzongkhags*. This report, which presents some results of the SAE, compliments the PAR 2007 by further identifying pockets of poverty in these *dzongkhags* as well as in other *dzongkhags*

The results from the SAE are compared with other geo-referenced database. It is observed that, generally poor *gewogs* tend to have limited access to markets and road networks. Similarly, access to rural electrification is relatively low in poor areas while densely populated but non-poor *gewogs* in Paro, Chukha, Thimphu and Punakha have high rates of rural electrification. Furthermore, the poverty incidence of each *gewog* is highly associated with school attendance of children. For example, poor *gewogs* register lower school attendance compared with non-poor *gewogs*. As such, overlaying a poverty map with other geo-referenced indicators is highly informative, and some of these findings can be used for designing, planning and monitoring poverty alleviation strategies at the *gewog* level.

Section I: Introduction

1. Over the past 10 years, Bhutan has performed remarkably well in reducing poverty. However, vast differences in poverty levels across *dzongkhag* (district) and *gewog* (sub-district) persist. Popular perceptions suggest that the geography of poverty and of economic affluence is accentuated at the local level, and that an understanding of the spatial distribution of economic welfare is needed in order to spread the benefits of growth to lagging regions. In order to fulfill Bhutan's development philosophy of gross national happiness, and poverty reduction, it is essential to understand its geographic and spatial patterns. In the case of Bhutan, its land-locked geography and sparse population pose major challenges for poverty reduction. Poverty maps will help the government and development partners locate pockets of poverty which might otherwise be overlooked.

2. The Royal Government of Bhutan (RGOB) is committed to carrying out various programs to alleviate poverty and deprivation, and to achieve the Millennium Development Goals (MDGs). Although many of these programs are centrally funded, they are frequently carried out at *dzongkhag* and *gewog* levels. However, limited data on poverty and other key human development indicators at the sub-national levels constrain the local and central governments' capability to monitor spending and outcomes. As asserted in the 10th Five Year plan, allocating resources to poor *gewog* is essential to assisting them tackling their residents' poverty.

3. Precise poverty estimates at the *gewog* level will facilitate the implementation of the newly-introduced, formula-based mechanism for resource allocation from the central government to all *gewogs*. Previously, in the absence of poverty maps, all *gewogs* in a *dzongkhag* were assumed to have equal poverty rates. However, following the preparation of the new poverty maps, the block grants can now incorporate *gewog*-level poverty estimates to better reflect ground-level realities. Using poverty maps and other geographic data, local governments can identify key development bottlenecks for their constituencies.

4. The Poverty Mapping was implemented to largely help fill the data gap. It combines existing census and survey data, and produces reliable poverty estimates at lower levels of disaggregation than existing survey data would permit. A more disaggregated picture below the district may help uncover pockets of poverty and deprivation that might otherwise be overlooked, thereby potentially informing the design of targeted interventions. Performance monitoring could also be improved with the availability of poverty maps that permit the tracking of poverty at the local level over multiple time periods.[1] Overlaying a poverty map with other geo-referenced information such as transport infrastructure, public service centers, and information on natural resources, like soil quality, may also help identify the investments necessary to lift such areas out of poverty. Market access maps are examples of this geographical database.

5. In response to the demand from the RGOB, the National Statistics Bureau (NSB) and the World Bank, with support from the Gross National Happiness Commission (GNHC), launched the Small Area Estimation initiative, or so-called Poverty Mapping, in December 2008. A technical working group was formed, comprised of staff members from the NSB, the GNHC, and the World Bank. This task benefited greatly from a feasibility study completed by the World Food Program (WFP) and NSB. In June 2009, the working group discussed the preliminary results and provided comments and suggestions to the World Bank team. After a review by technical committee, the task was completed in September 2009.

[1] An immediate use of a poverty map in India would be to monitor the 200 districts identified as backward areas for implementation of an employment guarantee scheme. Through this scheme, the Government intends to create village-level assets generating future employment and improving other welfare indicators in these regions.

The poverty maps at the *gewog* level will be an effective tool in allocating resources to the target population, enabling not only efficient use of the scarce resources but also carrying out direct interventions to the poor.

6. The Bhutan Poverty Mapping applied a Small Area Estimation (SAE) method developed by Elbers et al. (2003); this methodology has been widely tested and applied around the world. The Elbers et al. approach was carefully implemented in the present project, and considerable efforts were made to avoid or minimize potential bias.

7. Capacity-building has been a very important component of this task; its aim is to ensure that poverty mapping can be used as a regular monitoring instrument. To support this objective, the World Bank provided multiple rounds of training on poverty mapping methodology to the staff from the RGOB. The World Bank's new software, PovMap2, was actively utilized in the estimation process as well as in training sessions. Several staff members from the NSB and the GNHC have actively participated in the training sessions in Bhutan and Bangladesh, to understand and learn the methodology and software used for poverty mapping.

8. The structure of this report is as follows. Section II describes the poverty mapping method, particularly the SAE method and comprehensive detail of validation and quality checks of poverty mapping results. Section III illustrates the results. Section IV shows some uses of poverty maps with other geo-referenced datasets. Section V lists concluding remarks. Technical discussion of other related topics are presented in the Technical Annex I.

Section II: Poverty Mapping Method

9. Historically, poverty has been measured by using sample survey consumption data, in which household per capita expenditures are compared against a poverty line. Under this approach the sampling error of poverty estimates rises rapidly as the target area gets smaller. It therefore precludes analysts from estimating poverty at a disaggregated level.

10. In order to estimate poverty at a disaggregated level, the Bhutan team selected the Small Area Estimation method developed by Elbers et al. (2003) (henceforth referred to as ELL). This method uses the strengths of both the 2005 Population Census and the 2007 BLSS to produce statistically reliable poverty estimates at the *gewog* level. In contrast, traditional approaches of poverty estimation cannot produce reliable estimates below the *dzongkhag* level because these would yield large sampling errors.

Methodology

11. Many poverty mapping methodologies have been proposed in the literature (see for example, Bigman and Deichmann, 2000). These methods have their respective advantages and disadvantages, but recently the ELL method has been gaining popularity among development practitioners worldwide.

12. As mentioned above, the Bhutan poverty mapping applies the ELL methodology. In the ELL method, consumption levels are imputed for each household in the population census based on a consumption model estimated from a household survey. The consumption model must include explanatory variables (household and individual characteristics) that are available in both the census and the survey. By applying estimated coefficients to these same variables in the census data, consumption expenditures can be imputed to each census household. Poverty and inequality statistics for small areas can then be calculated based on this imputed per capita consumption for each census households.

13. One advantage of the ELL method is that it not only sets out to estimate poverty incidence, but also yields estimates of standard errors on the poverty estimates. Since such poverty estimates are

computed based on imputed consumption, they are clearly subject to imputation errors, which are reflected in the standard errors.

14. The standard errors are helpful in guiding analysts about the precision and reliability of the poverty estimates produced with the ELL methodology. In their original studies, Elbers et al. (2002, 2003) analyze the properties of the imputation errors in detail and derive a procedure to compute standard errors of poverty estimates.

Main Data Sources

15. The primary data sources used in the ELL methodology are household survey and population census data. The Bhutan Poverty Mapping uses unit record data from the PHCB 2005 and the BLSS 2007.. As a common practice throughout the world, the Census does not include information on household consumption and income levels. The BLSS, on the other hand, contains detailed information on consumption as well as a wealth of additional information on employment, ownership of assets, housing condition, and access to services such as education and health. This large set of variables is a key to the procedure of imputing household consumption from the survey into the population census. Most variables from BLSS are representative at the *dzongkhag* level. The BLSS was collected by the NSB in 2007 (March-May), while the Census reference date was May 31, 2005.[2]

Box 1: The Small Area Estimation method developed by ELL (2003)

The method proposed by ELL has two stages. In the first stage, a model of log per capita consumption expenditures ($\ln y_{ch}$) is estimated in the survey data:

$$\ln y_{ch} = X_{ch}{}' \beta + Z' \gamma + u_{ch}$$

where $X_{ch}{}'$ is the vector of explanatory variables for household *h* in cluster *c*, β is the vector of associated regression coefficients, Z' is the vector of location specific variables with γ being the associated vector of coefficients, and u_{ch} is the regression disturbances due to the discrepancy between the predicted household consumption and the actual value. This disturbance term is decomposed into two independent components: $u_{ch} = \eta_c + \varepsilon_{ch}$ with a cluster-specific effect, η_c, and a household-specific effect, ε_{ch}. This error structure allows for both a location effect—common to all households in the same area—and heteroskedasticity in the household-specific errors. The location variables can be at any level of disaggregation—district, *gewog*, or *chiwog*—and can be drawn from any data source that includes all the locations in the country. All parameters regarding the regression coefficients (β, γ) and distributions of the disturbance terms are estimated by Feasible Generalized Least Square (FGLS). In the second part of the analysis, poverty estimates and their standard errors are computed. There are two sources of errors involved in the estimation process: errors in the estimated regression coefficients ($\hat{\beta}$, $\hat{\gamma}$) and the disturbance terms, both of which affect poverty estimates and the level of their accuracy. ELL propose a way to properly calculate poverty estimates as well as measure their standard errors while taking into account these sources of bias. A simulated value of expenditures for each census household is calculated with predicted log expenditures $X_{ch}{}' \hat{\beta} + Z' \hat{\gamma}$ and random draws from the estimated distributions of the disturbance terms, η_c and ε_{ch}. These simulations are repeated 100 times. For any given location (such as a *dzongkhag* or a g*ewog*), the mean across the 100 simulations of a poverty statistic provides a point estimate of the statistic, and the standard deviation provides an estimate of the standard error.

[2] See more details in Annex IV.

Technical Challenges

16. The ELL poverty mapping methodology continues to evolve in response to ongoing scrutiny from researchers. To this end, a variety of documents and manuals are available on the World Bank website to inform practitioners of the latest developments and methodological improvements of the SAE method. These improvements are also reflected in the updated versions of the PovMap2 software produced by the World Bank to assist with application of the procedure.

17. The present Bhutan Poverty Mapping faced two main technical challenges: (i) an interval between the PHCB 2005 and the BLSS 2007 and (ii) the Tarrozi and Deaton (2008) critique.

Interval between PHCB 2005 and BLSS 2007

18. The Poverty Mapping Methodology is founded on a consumption model estimated using the BLSS 2007 data, in which household per capita expenditure is regressed on a set of household and individual characteristics. As described earlier, information on these characteristics is available in both the BLSS 2007 and PHCB 2005. It then predicts household expenditure into each census household based on the model.

19. The appeal of this approach is most obvious if the PHCB 2005 reflects the situation of BLSS 2007 well. This assumption is reasonable given the short interval and the seemingly limited change in the socio-economic structure of Bhutan during the period. Moreover, both datasets were collected or referenced at the same time of year. However, it might be possible that consumption patterns changed markedly between the period as a result of structural changes and relative price shifts. The population distribution might also have changed due to migration. Changes in consumption patterns and the population distribution can introduce biases in the poverty estimates and their standard errors derived from the ELL method.[3]

Misspecifications of Consumption Models and Error Structures

20. In a recently published paper, Tarozzi and Deaton (2008) highlight a number of concerns with the ELL methodology that can be summarized as follows.

21. First, differences in consumption patterns within a domain can bias both poverty estimates and the standard errors. The ELL method estimates a consumption model that is assumed to apply to all households within each domain (in the case of Bhutan poverty mapping: large urban, small urban, and rural areas). The implicit assumption is that the relationship between household expenditures and its correlates is the same for all households within the domain, and that all remaining differences are due not to structural factors, but are attributable to errors. This is not a minor assumption and is explicitly acknowledged as such in ELL (2003).

22. Second, misspecification in the error structure can lead to an overstatement of the precision of resultant poverty estimates. In its current configuration, PovMap2, the software developed by the World Bank for the purpose of poverty mapping (freely downloadable from www.iresearch.worldbank.org), can accommodate only two layers of errors: at the level of the household and at the level of some unit of aggregation above the household. In the case of the present study, the two layers of errors were selected

[3] One way to reduce this risk is to focus on common variables that did not change much over time. Such an approach was adopted in Bangladesh, and was found to be effective in reducing bias. This approach is certainly worth being tested in the future.

to be households and the sample clusters (corresponding to "*chiwogs*"[4] in rural areas and "towns" in urban areas). However, as noted by Tarozzi and Deaton (2008), there could be correlation in errors also at some higher level, such as the *gewog* level, which is above the *chiwog* and below the district level (or districts and town/cities in urban areas), and a further correlation can exist at the district level. Tarozzi and Deaton (2008) show that if the ELL method is applied and any existing correlation of errors at these higher levels of aggregation is ignored, then standard errors on poverty estimates can be understated – resulting in an overly optimistic assessment of the precision of the poverty estimates. One apparent solution to this issue is to allow for more than two layers of errors in implementation of the ELL methodology. This, however, is not a feasible solution given the sampling design of most household surveys, including the BLSS.

Production of Poverty Maps and Quality Checks

23. The poverty mapping procedure comprises two main components: (i) selecting sound consumption models and (ii) selecting the level of disaggregation.

24. The explanatory power of the consumption models that were estimated for the Bhutan Poverty Mapping Project was generally quite high. In addition, the unexplained variation in household consumption at the cluster level (*chiwog* for rural areas and city/town for urban areas) appears moderate. These two observations combine to suggest that there is limited scope for the kind of concerns raised by Tarozzi and Deaton (2008). Nonetheless, the issues are real and must be tackled. It is reassuring that district level poverty rates estimated from this exercise match those estimated directly from the BLSS 2007 data.

25. In Bhutan, the primary objective of this exercise was to produce poverty estimates at the *gewog* level for rural areas, and at the town level for urban areas. The report carefully assessed the quality of the poverty estimates that were produced, and concluded that rural poverty maps were sufficiently accurate, while urban poverty maps were not as reliable. This section also explains how the challenges pointed out by Tarrozi and Deaton (2008) were addressed. This section goes on to explain how the levels of disaggregation for producing poverty maps – *gewog* level for rural areas and district level for urban areas – were selected. Final models are listed in Table A-3 of Annex 1.

Model Selection

a) The number of consumption models

26. The Bhutan Poverty Mapping exercise prepared three different consumption models; large urban cities, small/medium sized cities/towns, and rural areas.

27. As mentioned earlier, failure to capture regional differences in consumption patterns could bias poverty estimates produced with the ELL method. Regional differences in consumption pattern can often be substantial. For example, the educational attainment of household heads might be a good predictor of household wealth in urban areas, whereas it might not be as important in rural areas, where the agricultural sector dominates.

28. Despite potential heterogeneity across areas, increasing the number of consumption models does not necessarily improve the statistical performance of poverty mapping. As the number of models rises,

[4] *Chiwog* is commonly translated as "block". It is an administrative level that lies below *gewog* but above village. It usually compose of a few villages.

the sample size in the BLSS 2007 data for each model declines, lowering the accuracy and stability of the consumption model.

29. In order to find a balance between capturing regional heterogeneity and maintaining adequate sample sizes it was decided to create three consumption models (large urban, small urban, and rural areas). Urban areas were split to two domains – large cities and small/medium cities after confirming consumption models of these areas are statistically different.

b) Explanatory Power of Consumption Models

30. The accuracy of poverty estimates depends on the predictive power of consumption models. This predictive power is gauged by R-squared statistics. Both R-squared and Adjusted R-squared statistics provide information on how well a consumption model can predict the actual consumption expenditure of each census household. Specifically, the R-squared is a statistic that indicates how well the predicted expenditure from a consumption model fits the actual household expenditure. The higher the R-squared, the better the predicted expenditure fits the actual household expenditure. Adjusted R-squared is a modification of R-squared that adjusts for the number of regressors in a model. R-squared always increases when a new variable is added to a model, but adjusted R-squared increases only if the new variable improves the model more than would be expected by chance.

c) Share Variance of Residuals at the Cluster Level

31. The consumption models, generally, only capture part of the variation in household expenditures, and the unexplained variation is called residuals (or simply errors). The residuals can be separated into two layers in the present analysis – the household layer and the cluster layer ("c*hiwog*" in rural areas and "town/city" for urban areas). The cluster effect is included since consumption expenditures can be affected by region- specific factors that are common across households, some of which may be observable while others are not.

Table 1: R-squared and Adjusted R-squared of consumption models

Areas	**R-Square**	**Adj. R-Square**
Big Urban	0.53	0.53
Small Urban	0.57	0.56
Rural	0.50	0.49

Source: Authors' estimation

32. Since residual location effects such as cluster effects can reduce the precision of poverty and inequality estimates, Elbers et al. (2002, 2003) recommend applying great effort to capturing variation in consumption by observables as far as possible. If c*hiwog* level error is large, reliability of poverty estimates is low. A rule of thumb is to reduce the share of the variance of the cluster effect to the total variance of residuals to 10 percent or lower. International experience suggests that in rural areas achievement of this goal often remains elusive (see Mistiaen et al., 2002).

33. A strategy for reducing the share of the variance of the cluster effect is to include location-specific variables in the regression models. In the case of the Bhutan Poverty Mapping, the team uses location-specific variables that can be constructed by aggregating data from the Population Census. Such effort has been found to be of great importance also in addressing the concerns raised by Tarozzi and Deaton (2008) regarding the precision of poverty map estimates.

34. The exercise reveals that the error structure is judicious and effects of cluster variance are at minimum. The share of the variance of the cluster effect to the total variance of residuals in the small urban model is 9 percent and in the rural model 12 percent. Judging by the rule of thumb mentioned above, there is still room for improvement for the rural consumption model.

d) *The Impact of Errors at the gewog Level*

35. Datasets used for the Bhutan Poverty Mapping have three layers of administrative units that are below the district level: *gewog; chiwog*, and village (or town/city). Consumption models in the Bhutan Poverty Mapping can control for correlation of errors at the district level, since consumption models include district dummies. However, controlling for correlations at the *gewog* level, as well as the *chiwog* level, was not *possible.*

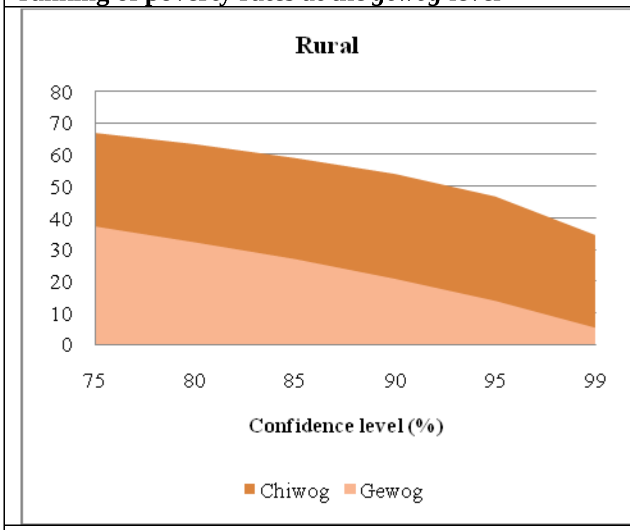
Table 2: Comparison on mean and median of Standard Errors of poverty estimates at the gewog level if the cluster level is changed

Cluster level	Mean	Median
chiwog	0.032	0.035
gewog	0.072	0.083
Ratio (*gewog*/*chiwog*)	2.3	2.4

Source: Authors' estimation

36. As mentioned above, if the variance of errors at the *gewog* level were high relative to the overall variance, then ignoring the *gewog*-level error could lead to a significant underestimation of standard errors (Tarrozi and Deaton, 2007). Elbers et al. (2008) show that if location-specific variables are included in consumption models (particularly at the level of the *gewog*), the risk of underestimating the standard errors of poverty estimates may be attenuated. The Bhutan Poverty Mapping follows this strategy in specifying the consumption models.

Figure 1: Percentage of statistically distinguishable ranking of poverty rates at the *gewog* level



Source: Authors' estimation, using BLSS 2007 and Population Census 2005.

37. Elbers et al. (2008) also propose tests to assess the likelihood of underestimated standard errors of poverty estimates. One approach is to switch the location effect from the cluster level (*chiwog*) to the *gewog* level and to then examine by how much standard errors rise. Switching the location effect from a smaller unit to a larger unit tends to increase standard errors of poverty estimates. Because in reality correlation of errors would likely occur at both the *gewog* and *chiwog* levels, assuming that the entire effect occurs at the *gewog* level would thus likely exaggerate the size of standard errors. The true level of standard errors of poverty estimates must be somewhere in between.

38. Indeed, standard errors rise significantly after switching the level of cluster effect from *chiwog* to *gewog*. Table 2 shows how many times the standard errors increase as a result of switching the cluster from *chiwog* to *gewog*. Irrespective of which is chosen, mean or median, the standard error more than doubles after switching the cluster level from *chiwog* to *gewog*.

Table 3: Variances of different layers

	Two-layer model				One-layer model		
Domain	**Gewog**	***chiwog***	**Household**	**All**	***chiwog***	**Household**	**All**
1: Rural	5.00	8.00	87.00	100.00	12.00	88.00	100.00
2: Large Urban	Not available				convergence not achieved		
3: Small Urban	Not available				9.00	91.00	100.00

Source: World Bank staff estimations using BLSS 2007 and PHCB 2005. Chiwog is the administrative level that only applicable in rural areas; therefore, this switching analysis was not conducted for the urban case.

39. Unsurprisingly, the share of statistically distinguishable rankings among *gewogs* falls if the cluster is shifted from *chiwog* to *gewog*, particularly in rural areas (see Figure 1 above). For example, in rural areas, when the cluster effect and the confidence level are set at the *chiwog* level and at 75 percent respectively, nearly 70 percent of *gewogs* can be ranked with statistical significance. However, if the cluster effect is defined to apply at the *gewog* level, the percentage falls to less than 40 percent. In urban areas, ignoring correlations at the *gewog* level is far less problematic. The share of statistically distinguishable rankings among *gewogs* does not fall much in urban areas.

40. The above test is thus able to provide some reassurance that standard errors reported here for urban areas are reasonable. However, in rural areas, the standard errors reported here could well be overly optimistic. In a further effort to probe whether the location effect should, in fact, be more reasonably applied at the *gewog* level in rural areas than at the cluster level, Elbers et al. (2008) propose another test, based on a mixed-maximum likelihood procedure (STATA command XTMIXED), that allows more than two layers of errors. Here the idea is to explicitly examine what fraction of the location effect occurs at the cluster level, and what fraction at the *gewog* level.

41. Contributions of *gewog*, *chiwog*, and household level errors were estimated for each stratum separately using this STATA command (see Table 3). There is a case for which the procedure could not converge, and for which results are thus not available. Non-convergence seems to occur more frequently if the consumption model includes a large number of explanatory variables, particularly dummy variables.

42. In rural and small urban areas, the contribution of *gewog*-level errors was found to be quite limited: the variance of the *gewog*-level errors constituted no more than five percent of variance of the total errors. The results indicate that most errors apply at the *chiwog* and the household levels, and these are explicitly taken into account by the PovMap2 software.

e) Incidence of Outliers from Simulation

43. Another set of important modeling issues is confronted when handling outliers in the simulated household expenditures of census households. The ELL method simulates household expenditure for all census households by randomly drawing parameters (including both regression coefficients and residuals) from their corresponding distributions, as estimated in the survey-based consumption model. One issue with this method is that random drawing can potentially pick extreme values, albeit with low probability. Simulated household expenditures can thus include a few outlier values. PovMap2 allows for the elimination of such outliers by dropping them before estimating poverty and inequality indicators. Such an adjustment, which is often called 'trimming,' is needed since a few outliers can produce huge biases, especially in inequality statistics. However, trimming is more of a practical solution than one derived from rigorous statistical theory. In this sense, it would always be preferable if a consumption model could be specified from which a need for trimming did not arise.

Table 4: Incidence of outliers and trimming

Percentile	**Ratio of dropped households to all (%)**			**Ratio of trimmed values to all (%)**		
	Stratum	*dzongkhag*	*gewog*	Stratum	*dzongkhag*	*gewog*
P50	0.08	0.05	0	0.05	0.04	0.04
P95	0.08	0.2	0.36	0.1	0.18	0.23
Max.	0.08	1.06	1.32	0.1	0.65	1.29

Source: World Bank staff estimations using BLSS 2007 and PHCB 2005.

44. Table 4 summarizes the incidence of trimming at three different administrative unit levels if the final consumption models were adopted. It shows that all strata, districts, and *gewogs* (or towns in urban areas) involve a very low incidence of trimming. Such results are encouraging, since such outliers can bias poverty estimates.

The Level of Disaggregation

45. As noted above, the ELL method produces standard errors of poverty estimates, which can be useful to practitioners in finding the appropriate level of disaggregation of poverty estimates. Although most statistics of this type are associated with certain margins of error, results of poverty mapping are frequently reported without providing any information about such errors. PovMap2 provides both poverty estimates and their standard errors.

Table 5: Accuracy of poverty estimates (standard error at the *Gewog* level, %)

	Median	95%	Max
urban	1.9	6.6	8.4
rural	4.6	7.4	14.8

Source: World Bank staff estimations using BLSS 2007 and PHCB 2005.

46. Table 5 shows that most standard errors are of reasonable size. For example, a median of standard errors at the *gewog* level is 4.6 percentage points in rural areas, which means the 95 percent confidence interval of the corresponding poverty estimate has a range of only +/- 9 percentage points from the poverty estimate. Even the 95th percentile of standard errors is 7.4 percentage points. The performance at higher levels of aggregation is even better: the maximum standard error is nearly 15 percentage points, which is admittedly large. However, this is only the case when the standard error is beyond 10 percent – all other poverty estimates have less than 10 percentage points of standard error.

47. However, in comparison to other countries' poverty mapping, Bhutan's poverty estimates have slightly higher standard errors. In Bangladesh, the 95th percentile of all standard errors at the Upazila level is at 4 percentage points, while in India the 99th percentile of all standard errors at the Tehsil level is at 7 percentage points. The fact that some *gewogs* have few households is likely to contribute to the higher standard errors than other countries. The *gewog* with low number of households are shown below, and Table 6 shows the 10 least populated *gewog* in Bhutan.

Table 6: *Gewog* with the lowest rural populations

Unit ID	*Dzongkhag*	*Gewog* Name	# of HH	Poverty Rate	SE of Poverty Rate
12110	Samdrup Jongkhar	Samrang	22	0.57	0.15
12409	Thimphu	Soe	37	0.2	0.1
12408	Thimphu	Naro	39	0.18	0.08
12314	Sarpang	Tarythang	45	0.01	0.03
11402	Gasa	Goenkhatoe	48	0	0
11210	Chhukha	Metap	93	0.45	0.08
11312	Dagana	Nichula	94	0.44	0.08
12406	Thimphu	Lingzhi	120	0.1	0.06
12005	Punakha	Lingmukha	124	0.09	0.03

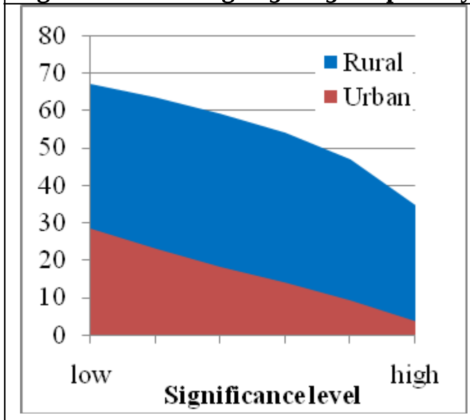
Source: World Bank staff estimations using BLSS 2007 and PHCB 2005.

Ranking *gewogs* with Poverty Estimates from the Bhutan Poverty Mapping

48. The most relevant feature of the poverty map in policy-making is its ability to rank *gewog* by their poverty rates. Such a feature allows policy-makers to prioritize and allocate resources to address the overall poverty reduction policies. Therefore, it is important to study the extent that we can rank *gewogs* according to poverty estimates from the Bhutan Poverty Mapping.

49. Overall, the standard errors of rural poverty estimates at the *gewog* level are low enough to yield a statistically significant ranking. The ability to rank poverty across towns is limited in urban areas.

Figure 2: Percentage of statistical significant ranking of *gewogs* in poverty



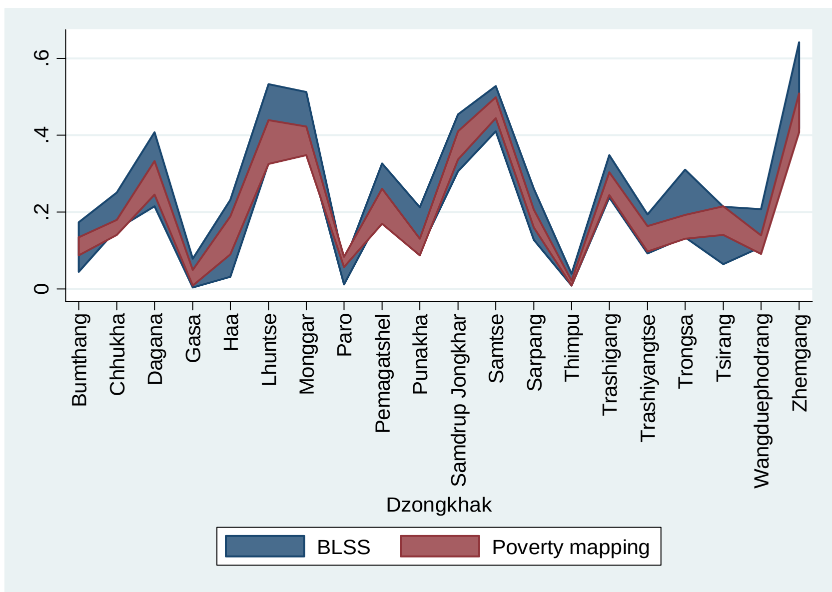
Source: World Bank staff estimations using BLSS 2007 and PHCB 2005.

50. Ranking of <u>true poverty incidence</u> can be different from ranking of <u>poverty estimates</u>. Figure 2 shows the percentage of rankings based on poverty mapping by level of statistical significance. The result suggests that rural poverty maps were sufficiently accurate, while urban poverty maps were not as reliable.[5]

Consistency with Poverty Rates Directly Estimated from the BLSS 2007

51. The reliability of estimates from the ELL method can be verified by comparing with the corresponding numbers estimated directly from the BLSS 2007 data. Key variables in the BLSS 2007 data are representative at the *dzongkhag* (district) level, separately for urban and rural areas. The ELL method can obviously generate estimates at the *dzongkhag* level as well. Presumably, if underlying assumptions of within-region homogeneity and of relative stability between 2005 and 2007 do not hold, there would be little reason to expect estimates based on the ELL method to

Figure 3: Confidence interval of poverty estimates from direct and SAE methods



Source: World Bank staff estimations using BLSS 2007 and PHCB 2005

[5] See Annex V for more details.

be close to those from the BLSS data directly. Conversely, if the ELL method produces a good predictor of true poverty incidence, this should be consistent with that estimated from BLSS 2007 data.

52. Consistency checks are applied using the 95 percent confidence intervals of both estimates. Both poverty estimates are statistics rather than true levels, and their 95 confidence intervals reflect the margins of errors of the poverty estimates. These two estimates can be considered as consistent if the 95 percent confidence intervals are overlapping.

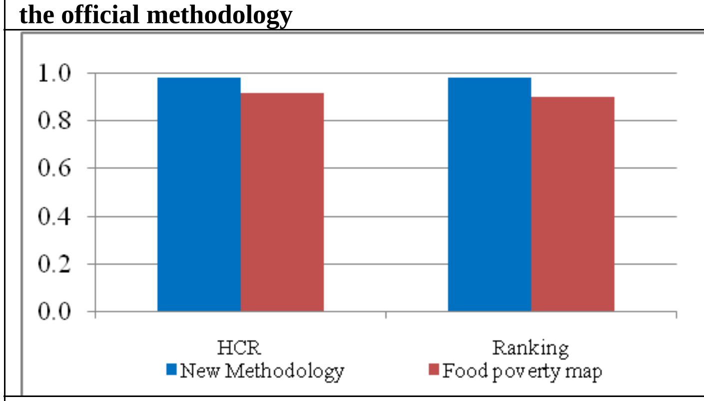
53. Figure 3 shows *dzongkhag*-level poverty rates from poverty mapping and compares them with the official poverty rates from BLSS 2007. The blue band indicates a range where a true poverty rate exists with a probability of 95 % according to BLSS 2007 estimates. The red band indicates the range according to the poverty mapping. For example, for Dagana, the BLSS 2007 estimate suggests the true poverty rate is likely located somewhere between 20 and 40 percent, while poverty mapping suggests it is likely located between 25 and 35 percent.

54. Two observations emerge. First, these two bands are overlapping, which means that predictions of true poverty rates from both BLSS 2007 and poverty mapping are consistent. Second, the red band is smaller than the blue one, indicating that poverty mapping can locate the level of true poverty rates more accurately. This reflects the fact that estimates directly from the BLSS 2007 survey are based on far fewer data points than are those based on the PHCB 2005.

Sensitivity check: Is the poverty map sensitive to choice of poverty line?

55. There are potential concerns on poverty line estimation and data in that (i) some of non-food expenditure appears too lumpy in some rural areas; (ii) differences in consumption patterns in urban and rural areas can be beyond price differences. Note that price differences are properly addressed in the official methodology; but, if the differences in consumption patterns are beyond price differences, the official poverty estimates might be vulnerable to biases.

Figure 4: Correlations with the (rural) poverty map based on the official methodology



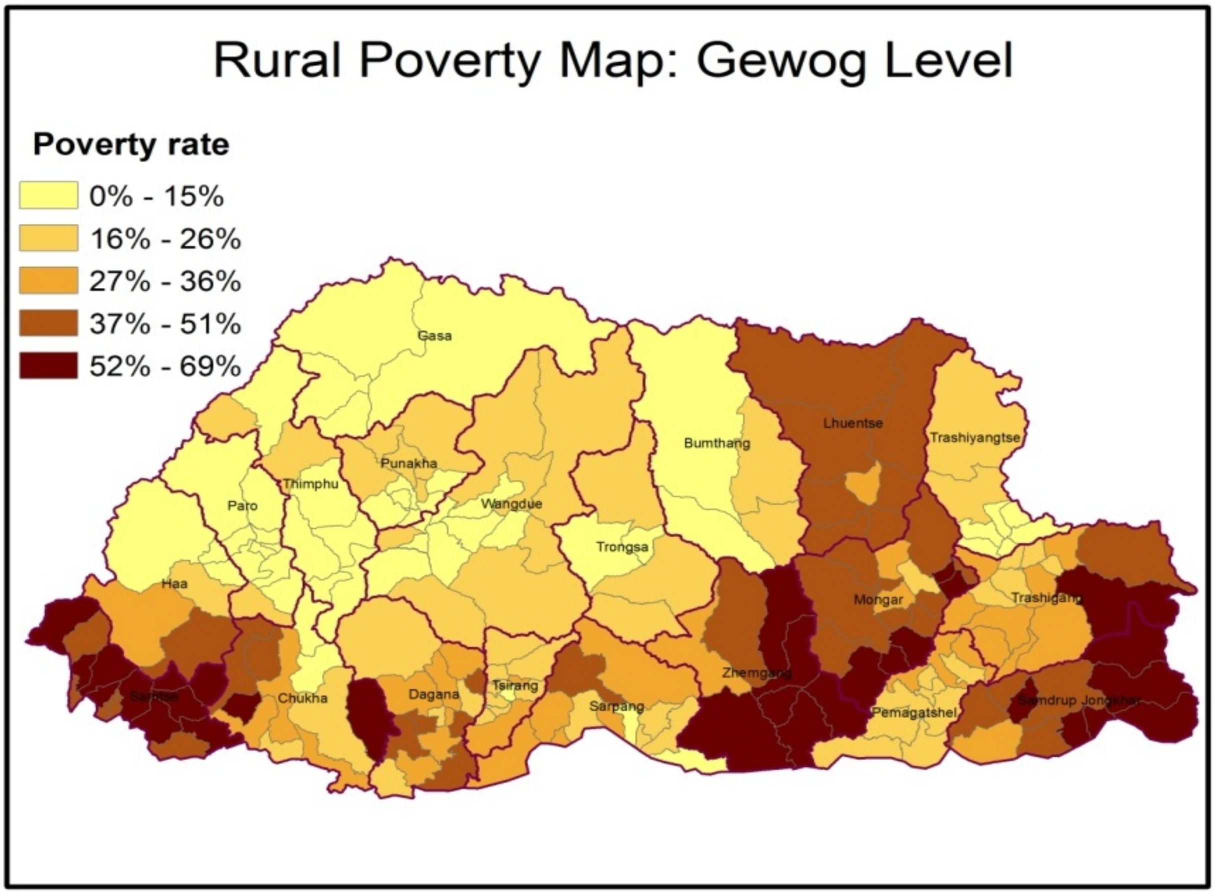
Source: World Bank staff estimations using BLSS 2007 and PHCB 2005.

56. To check robustness against these potential issues, we produce (i) poverty maps using only the food expenditure and food poverty lines ("food poverty map") and (ii) poverty maps using separate cost-of-basic needs poverty lines for urban and rural areas ("new methodology"), and we then compare them with the poverty map based on the official methodology. The results of these poverty maps are very similar to that of the official methodology in terms of poverty estimates and rankings (Figure 4). This suggests the abovementioned potential data and methodological issues are not substantial.

57. Overall, test results confirm the validity of the poverty map. Formulas predict true consumption expenditure well. The error structures are correctly estimated, though there is still room for improvement in rural areas. Simulations methodology is reliable. These facts lead to accurate final results, including in rural areas. Urban results, on the other hand, are less reliable. Overall, the ELL estimates are consistent with the official poverty estimates. In comparison to other countries, formulas are in general better; simulations are more reliable; but final results are less accurate, even for rural areas, due to small sizes of population in some areas.

Section III: Poverty Mapping Results

Figure 5: ***Gewog*** **level rural poverty map**



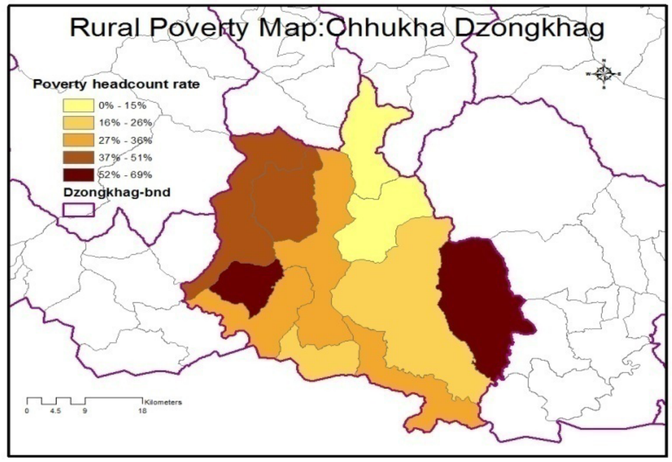
Source: World Bank staff estimations using BLSS 2007 and PHCB 2005.

58. The most prominent result from the poverty mapping exercise of Bhutan is the production of a disaggregated poverty headcount rate at the *gewog* level. The rural poverty map at the *gewog* level is shown in Figure 5 while the poverty numbers are shown in Annex I, Table A-1.

59. Landlocked geography creates many isolated remote areas. National or *dzongkhag*-level poverty estimates hide rich diversity in living standards across *gewogs*. For example, *Chhukha dzongkhag* is an average *dzongkhag* in terms of well-being, its poverty rate at 20.3 percent while the national poverty rate is at 23 percent. However, its *gewogs* vary dramatically in terms of poverty headcount rates. Some *gewog* in Chhukha *dzongkhag* record among the highest poverty incidences in the country, while some record among the lowest. The use of *dzonghag* level poverty estimates cannot reflect the large variation in poverty incidence within a *dzongkhag.* The rural poverty rates range from 6 percent in Bjachho *gewog* to 55 percent in Logchina *gewog* . The map in Figure 6 lucidly depicts the variation in poverty.

60. In terms of policy implications, poverty maps are useful to identify such pockets of poverty and also of wealth. It is useful to fine-tune policies and resource allocation for each small area. For example, providing the same amount of recourses to rich and poor areas is not efficient. Poverty maps allow us to fine-tune policy interventions based on needs. Additionally, the disaggregated data of development indicators enhances the "results-based approach" in the 10th plan.

Figure 6: Benefits of poverty mapping exercise: poverty varies across *Gewogs* in Chhukha *Dzongkhag*

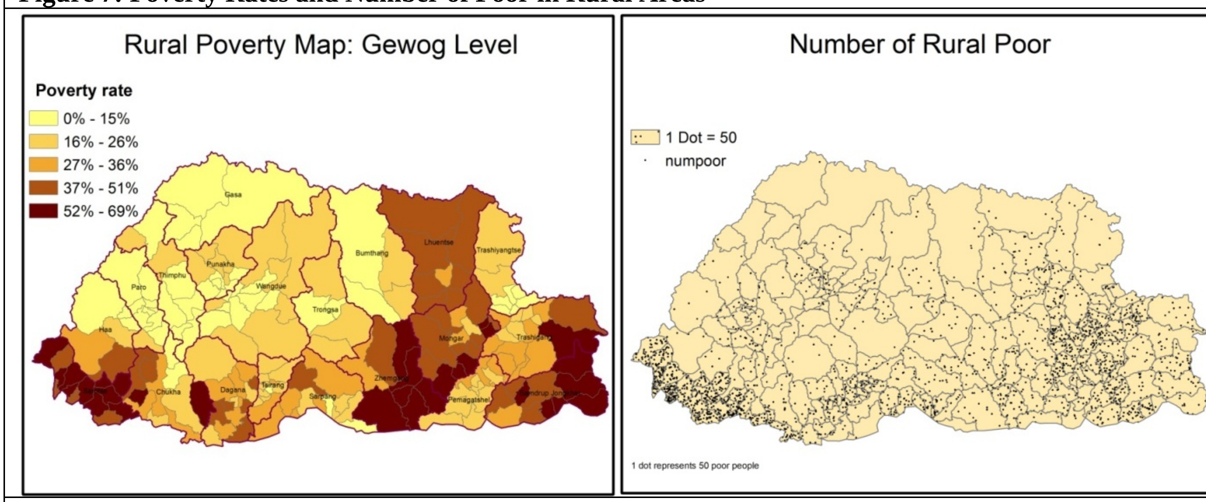


Source: World Bank staff estimations using BLSS 2007 and PHCB 2005.

Poverty Headcount Rate vs. Number of Poor Population

61. The poverty headcount rate refers to the proportion of people who live below the poverty line; it reflects the prevalence of poverty in a specific area. It is the most popular indicator of poverty. In addition, one can also look at the absolute number of the poor population. Poverty maps provide geographical depictions of where the poor are populated (as shown in the upper map of Figure 7) and where the percentage of poor populations is high (as shown in the lower map of Figure 7).

Figure 7: Poverty Rates and Number of Poor in Rural Areas



Source: World Bank staff estimations using BLSS 2007 and PHCB 2005.

62. Geographic patterns of poverty in Bhutan vary by area. Areas in the southwest around Samtse *dzongkhag* have high poverty rates with large number of poor people. On the other hand, *dzongkhag*s in the east have high poverty rates but fewer poor people due to lower population density. These geographic patterns of poverty—showing areas have high poverty rates or where the poor are located—can be used to calibrate poverty alleviation strategies to fit local conditions. A poverty alleviation strategy might need to take into account the geographic patterns of poverty.

Poverty maps with other geo-referenced data

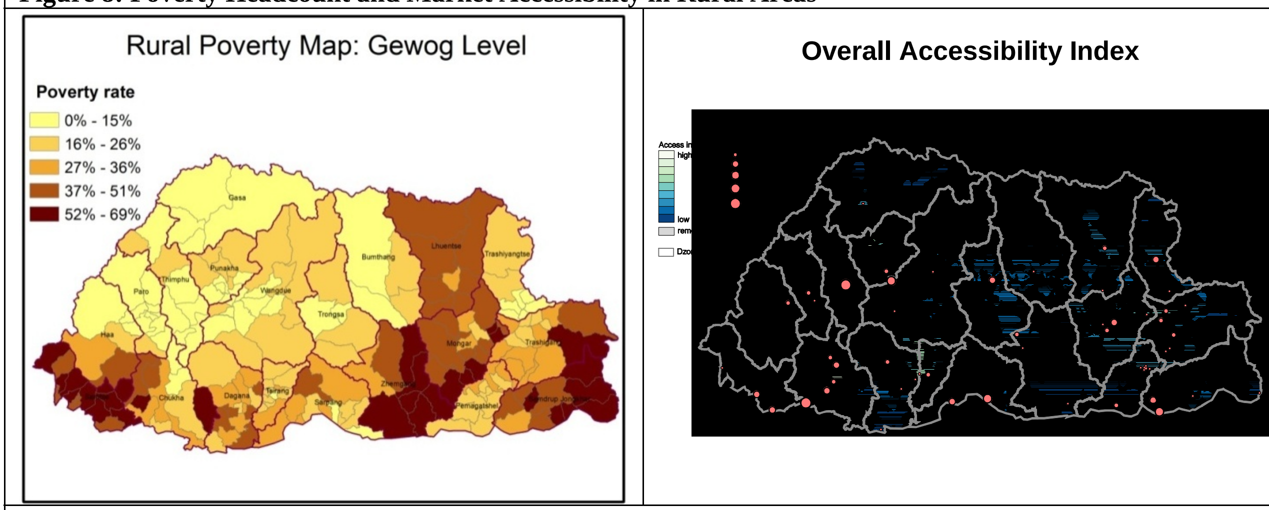
63. Geo-referenced poverty data is useful to locate pockets of severe deprivation, which cannot be identified from poverty estimates at the *dzongkhag* level. However, locating poor areas is not enough. It is important for policy makers to identify what are bottlenecks or constraints limiting economic opportunities in these areas. For this purpose, it is instructive to overlay the poverty map with other geo-referenced data.

64. Despite its apparent advantages, it is important to note such comparisons can only show visual correlations rather causal relationships. For example, even if poverty and market accessibility are highly correlated, this does not necessarily mean improving market access reduces poverty. There is always a possibility that non-poor areas attract road and other infrastructure investment. To understand a causal relationship, a further careful empirical analysis is necessary.

(i) Market Accessiblity and Poverty

65. Market access and connection to road networks are the main drivers of poverty reduction and development in rural areas. The maps in Figure 8 show the relationship between market access and poverty. Access to markets and road network is shown by the Overall Accessibility Indicator, which is measured by the size of markets weighted by travel time, while road network is shown in the bottom map[6]. Travel time was estimated from the road network information using GIS software. This measure works as follows: even when there are many large markets and cities, if they are very far away from a village, the village's accessibility indicator takes a low value. On the other hand, even when there is only one medium-size market, if a village is located near the market, the village's accessibility indicator takes a high value. The accessibility data was plotted only for areas which are populated. Areas with lighter colors have better access to markets. The calculation of market accessibility indicators is explained in detail in Annex III.

Figure 8: Poverty Headcount and Market Accessibility in Rural Areas



Source: World Bank staff estimations using BLSS 2007 and PHCB 2005.

66. Looking at the maps, we can see a pattern between rural poverty and market access. Overall, poor areas tend to have low access to markets and poor connection to road networks. For example, one of the poorest *dzongkhags*, Zhemgang, has very little access to road networks and markets. On the other

[6] Overall accessibility is calculated for each place as the sum of the population of all towns in its vicinity, inversely weighted by the travel time to reach them. It is also often called "population potential".

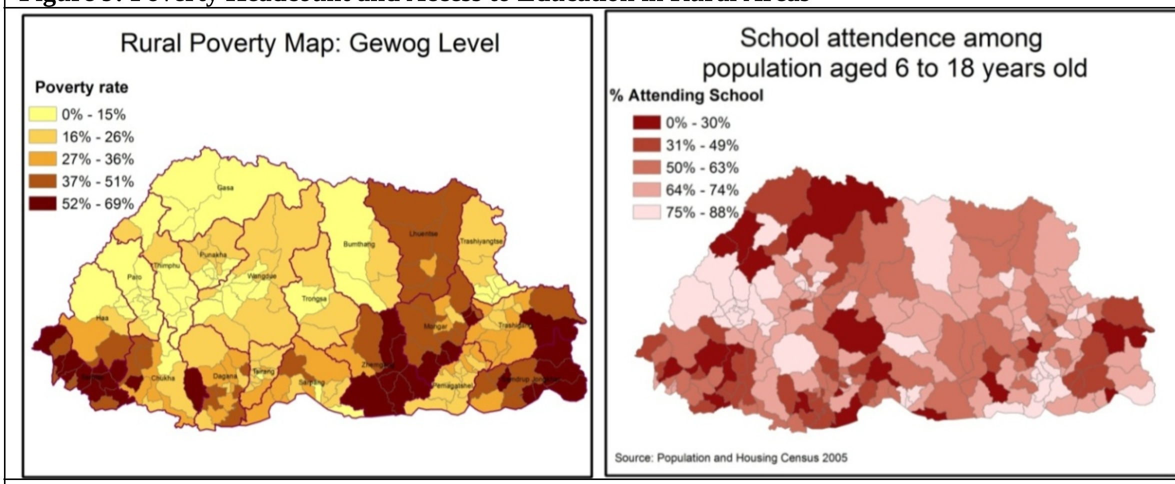
hand, areas in western Bhutan are highly connected to markets and also have the lowest poverty levels. However, it is worth noting that there are some exceptions in the north (Gasa *dzongkhag*), where poverty incidence is low but the market access is also limited.

(ii) Access to Education and Poverty

67. Education is universally agreed to be a factor that can help people out of poverty, by giving them better jobs and higher earnings. Access to education, regardless of children's circumstances and their parent's income, improves economic opportunities for the next generation of Bhutanese, and facilitates growth and poverty reduction for the country as a whole.

68. Bhutan has made tremendous progress in access to education in rural areas; however, several challenges remain. Access to education is shown in the map by the percentage of population aged 6 to 18 years old who are attending school (Figure 9). The map shows that there are many areas where few children attend school, and many of these *gewogs* tend to also have high poverty rates.

Figure 9: Poverty Headcount and Access to Education in Rural Areas



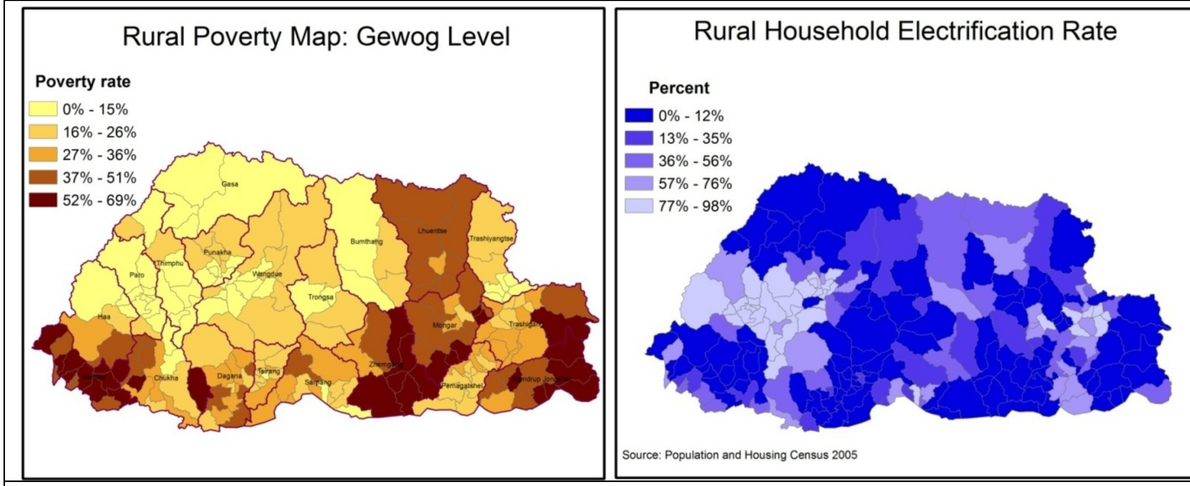
Source: World Bank staff estimations using BLSS 2007 and PHCB 2005.

(iii) Electrification and Poverty

69. Rural electrification is often regarded as a vehicle for rural development, and helps to improve the quality of basic services like education and health. Bringing electricity to the rural population not only improves their quality of life, but also promotes economic activity and increases agricultural production.

70. Rural electrification in Bhutan varies dramatically across the country, ranging from almost full coverage to none. The map on the right shows the percentage of households with an electricity connection in rural areas. The areas with high electrification rates tend to be concentrated in rich and densely populated *gewog* in Paro, Chhukha, Thimphu, and Phunaka. On theother hand, rural eletrification is relatively low in the rest of the country (Figure 10).

Figure 10: Poverty Headcount and Access to Electricity in Rural Areas



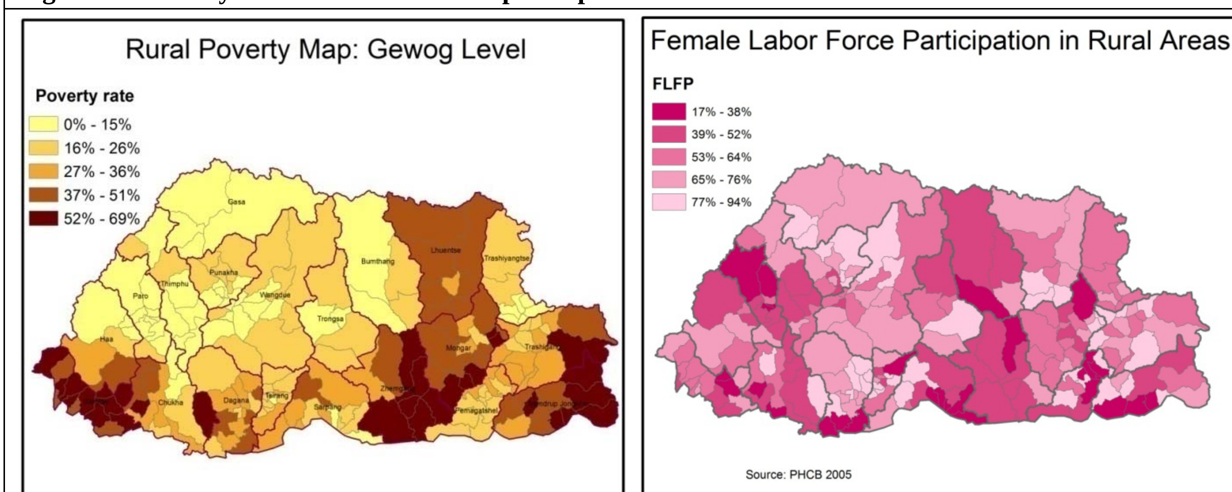
Source: World Bank staff estimations using BLSS 2007 and PHCB 2005.

(iv) Gender and Poverty

71. The linkage between gender and development has gained much attention among development practitioners. Women's engagement in economic activities can bring more income and other resources to households and elevate their living standard. One of the most prominent indicators in women's economic engagement is the female labor force participation, which represents all economic engagements, both paid and unpaid.

72. The spatial relationship between location of poverty and female labor force participation is shown in Figure 11. Overall, there is no clear spatial pattern between rural poverty and female labor force participation. Such results call for additional studies on the relationship between gender and poverty. Gender is generally a complex issue, involving multiple layers of socio-economic variables as well as local culture and traditional practices. Incorporating such factors into the analysis can shed more light onto the gender and development connection in the case of Bhutan.

Figure 11: Poverty and female labor force participation in rural areas



Source: World Bank staff estimations using BLSS 2007 and PHCB 2005.

Section IV: Conclusion

73. Poverty mapping is a powerful tool to illustrate the geography of poverty at the *gewog* level; it can help identify pockets of poverty, as well as pockets of affluence. Its use can be broadened by combining it with other GIS databases such as human development, agriculture, and transportation. Geographical presentation of these development indicators can be valuable for designing and planning poverty alleviation strategies.

Caveats

74. A few caveats apply to the Small Area Estimation of poverty. Like the official poverty estimates, poverty rates from the Bhutan poverty mapping are also estimates, not actual poverty rates. The team employed all techniques available within the poverty mapping literature to improve accuracy of the estimates, but some errors remain. The small population sizes of *gewogs* are concerns. As a result, the Bhutan poverty map has slightly higher standard error than other countries' poverty maps, likely due to the small population sizes of the *gewog*.

Poverty Mapping as a Regular Monitoring Instrument

75. The use of poverty maps will be magnified if they are updated regularly. To ensure that poverty mapping becomes a regular monitoring instrument, capacity-building at the NSB and other stakeholders is essential. The World Bank organized a training course for the NSB and GNHC staff members, to demonstrate the poverty mapping methodology and the use of poverty mapping software. It is hoped that such initiatives will be continued. It will also be critical to ensure the continuity of Population Census and Bhutan Living Standard Surveys, which form key databases for updating poverty maps. Finally, poverty mapping techniques can be applied to other outcomes, such as food security and child nutrition. These indicators can fill the gap where poverty indicators based on consumption expenditure alone may not be the best indicator to gauge the extent of deprivation in remote areas.

Combining Poverty Maps with Geographical Database

76. The variation in poverty at the *gewog* level shows several interesting geographical patterns. As many expected, the western valleys are relatively well-off, while most extreme poor areas are located in the East and part of the South. Such a pattern suggests that poverty maps can be much more powerful if they are combined with other geo-referenced data sets like market accessibility, human development indicators, and agro-climatic information. The combination helps us identify key poverty correlates. These correlations are no doubt useful first steps for identifying effectively policy instruments, but it is also important to note that drawing clear policy implications requires rigorous statistical and econometric analysis. It is also essential to develop a good geographical database for Bhutan.

77. The GIS database is not just useful to identify spatial characteristics that are high correlated with poverty, but also useful to improve the accuracy of poverty estimates. For this round, market accessibility index was produced after the poverty maps were finalized. Given the high correlation, it would be useful to improve the performance of consumption models further. For the next round of poverty mapping, market accessibility and more GIS variables should be included in the consumption models.

78. The poverty mapping methodology is powerful, but it is still evolving and improving. This exercise has benefited from recent methodological improvements to reduce potential biases in estimates.

But, this pilot did also face several data issues and technical challenges; these can be addressed in the future BLSS and Population Census implementation.

Capacity building for the NSB staff

79. The World Bank provided two rounds of hands-on training on how to carry out poverty mapping exercise using PovMap2 software. The result of the capacity building was successful. After the two sessions, the NSB team could produce poverty maps as well as new maps of calorie intake per capita by themselves. Based on this knowledge, when the next rounds of BLSS and Population Census are completed in 2012 and 2015, respectively, the NSB team will be able to produce poverty maps by themselves. However, it might still be useful to continue training so that the core team can replicate the quality checks conducted in this report and also other NSB staff can learn the methodology well.

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Annex I: Results of Rural Poverty Map

Table A-1: Rural Poverty Estimates by *gewog*

Dzongkhag		*Gewog*		Number of households	Poverty headcount rate		Gini coefficient		Number of poor
Code	Name	Code	Name		Estimate	S.E.	Estimate	S.E.	
11	Bumthang	1101	Chhoekhor	798	0.099	0.025	0.293	0.013	377
11	Bumthang	1102	Chhume	622	0.114	0.022	0.304	0.012	338
11	Bumthang	1103	Tang	349	0.245	0.042	0.278	0.013	421
11	Bumthang	1104	Ura	361	0.162	0.035	0.261	0.014	277
12	Chhukha	1201	Balujhora	1431	0.226	0.027	0.297	0.019	1446
12	Chhukha	1202	Bjachho	796	0.063	0.023	0.278	0.017	173
12	Chhukha	1203	Bongo	1326	0.194	0.031	0.296	0.016	1072
12	Chhukha	1204	Chapchha	698	0.123	0.025	0.268	0.013	339
12	Chhukha	1205	Dala	1361	0.313	0.034	0.299	0.013	2131
12	Chhukha	1206	Dungna	127	0.480	0.087	0.241	0.022	338
12	Chhukha	1207	Geling	356	0.313	0.041	0.285	0.019	476
12	Chhukha	1208	Getana	144	0.530	0.074	0.282	0.018	444
12	Chhukha	1209	Logchina	407	0.552	0.055	0.258	0.012	1344
12	Chhukha	1210	Metap	93	0.454	0.080	0.282	0.023	239
12	Chhukha	1211	Phuentsholing	1007	0.362	0.033	0.259	0.017	1836
13	Dagana	1301	Dorona	149	0.440	0.066	0.272	0.012	326
13	Dagana	1302	Drugyelgang	464	0.254	0.052	0.257	0.011	540
13	Dagana	1303	Gesarling	261	0.389	0.068	0.269	0.014	521
13	Dagana	1304	Gozhi	446	0.249	0.038	0.264	0.012	544
13	Dagana	1305	Kalidzingkha	350	0.311	0.054	0.267	0.012	605
13	Dagana	1306	Khipisa	223	0.343	0.058	0.269	0.013	414
13	Dagana	1307	Lajab	165	0.327	0.054	0.272	0.013	282
13	Dagana	1308	Trashiding	307	0.400	0.057	0.261	0.010	642
13	Dagana	1309	Tsendagang	339	0.274	0.053	0.263	0.013	465
13	Dagana	1310	Tsangkha	257	0.390	0.058	0.269	0.016	506
13	Dagana	1311	Tseza	217	0.161	0.036	0.285	0.024	175
13	Dagana	1312	nichula	94	0.440	0.085	0.281	0.016	211
13	Dagana	1313	deorali	251	0.328	0.053	0.253	0.013	426
13	Dagana	1314	lhamoyzingkha	320	0.241	0.050	0.264	0.014	371
14	Gasa	1401	Goenkhame	197	0.038	0.014	0.261	0.015	30
14	Gasa	1402	Goenkhatoe	48	< 0.001*	0.004	0.245	0.029	<5**
14	Gasa	1403	Laya	229	0.043	0.018	0.229	0.014	38
14	Gasa	1404	Lunana	169	0.018	0.019	0.224	0.015	13
15	Ha	1501	Bji	660	0.085	0.049	0.226	0.010	241
15	Ha	1502	Uesu	468	0.086	0.031	0.252	0.016	184
15	Ha	1503	Katsho	247	0.073	0.040	0.246	0.012	78

15	Ha	1504	Sama	301	0.227	0.067	0.263	0.019	328
15	Ha	1505	Sombeykha	173	0.305	0.071	0.230	0.015	240
15	Ha	1506	Gakiling	224	0.377	0.061	0.253	0.018	412
16	Lhuentse	1601	Gangzur	490	0.468	0.046	0.256	0.012	1188
16	Lhuentse	1602	Jarey	216	0.466	0.063	0.254	0.015	493
16	Lhuentse	1603	Khoma	391	0.385	0.047	0.262	0.014	649
16	Lhuentse	1604	Kurtoe	186	0.397	0.072	0.238	0.017	347
16	Lhuentse	1605	Menbi	487	0.283	0.042	0.274	0.016	609
16	Lhuentse	1606	Minjay	291	0.452	0.058	0.239	0.011	615
16	Lhuentse	1607	Metsho	243	0.452	0.055	0.241	0.012	528
16	Lhuentse	1608	Tsenkhar	461	0.402	0.057	0.231	0.010	849
17	Monggar	1701	Balam	227	0.515	0.064	0.233	0.014	559
17	Monggar	1702	Chhali	345	0.396	0.065	0.236	0.016	633
17	Monggar	1703	Chaskhar	457	0.420	0.059	0.222	0.011	974
17	Monggar	1704	Drametse	431	0.542	0.061	0.225	0.010	1152
17	Monggar	1705	Drepung	240	0.395	0.064	0.243	0.014	432
17	Monggar	1706	Gongdue	267	0.530	0.064	0.229	0.013	687
17	Monggar	1707	Jurmey	285	0.654	0.064	0.223	0.012	939
17	Monggar	1708	Khengkhar	423	0.625	0.054	0.231	0.010	1247
17	Monggar	1709	Mongar	704	0.338	0.052	0.245	0.011	1086
17	Monggar	1710	Ngatshang	384	0.242	0.067	0.252	0.015	434
17	Monggar	1711	Saleng	439	0.441	0.051	0.250	0.012	900
17	Monggar	1712	Shermung	383	0.472	0.052	0.260	0.016	857
17	Monggar	1713	Silambi	289	0.465	0.062	0.239	0.011	596
17	Monggar	1714	Thangrong	369	0.440	0.068	0.227	0.014	785
17	Monggar	1715	Tsakaling	374	0.327	0.056	0.239	0.011	500
17	Monggar	1716	Tsamang	218	0.403	0.068	0.248	0.018	420
17	Mongar	1717	Narang	279	0.465	0.075	0.217	0.013	576
18	Paro	1801	Doga	338	0.141	0.032	0.262	0.014	242
18	Paro	1802	Doteng	190	0.086	0.030	0.299	0.018	75
18	Paro	1803	Hungrel	173	0.036	0.023	0.291	0.019	29
18	Paro	1804	Lamgong	706	0.037	0.015	0.269	0.014	121
18	Paro	1805	Lungnyi	567	0.043	0.016	0.287	0.017	108
18	Paro	1806	Naja	553	0.257	0.035	0.282	0.013	761
18	Paro	1807	Shapa	903	0.058	0.016	0.274	0.015	241
18	Paro	1808	Shari	619	0.061	0.021	0.285	0.014	189
18	Paro	1809	Tsento	905	0.081	0.019	0.296	0.018	326
18	Paro	1810	Wangchang	1341	0.022	0.008	0.278	0.010	129
19	Pemagatshel	1901	Chhimung	176	0.278	0.064	0.245	0.013	209
19	Pemagatshel	1902	Chongshing	228	0.250	0.054	0.251	0.015	233
19	Pemagatshel	1903	Dungmin	355	0.261	0.060	0.245	0.016	365
19	Pemagatshel	1904	Khar	411	0.228	0.049	0.263	0.013	393

19	Pemagatshel	1905	Shumar	720	0.263	0.043	0.266	0.012	937
19	Pemagatshel	1906	Yurung	318	0.160	0.066	0.251	0.017	197
19	Pemagatshel	1907	Zobel	367	0.183	0.051	0.239	0.012	263
19	Pemagatshel	1908	Nanong	532	0.274	0.038	0.242	0.009	613
19	Pemagatshel	1909	Dechenling	502	0.251	0.053	0.232	0.011	502
19	Pemagatshel	1910	Norbugang	432	0.235	0.070	0.227	0.016	403
19	Pemagatshel	1911	Choekharling	299	0.228	0.079	0.218	0.014	218
20	Punakha	2001	Chhubu	350	0.204	0.045	0.292	0.019	337
20	Punakha	2002	Goenshari	129	0.239	0.065	0.295	0.022	145
20	Punakha	2003	Guma	816	0.048	0.016	0.286	0.016	176
20	Punakha	2004	Kabjisa	447	0.177	0.039	0.265	0.014	396
20	Punakha	2005	Lingmukha	124	0.093	0.034	0.289	0.022	55
20	Punakha	2006	Shenga Bjimi	284	0.111	0.028	0.273	0.015	137
20	Punakha	2007	Talo	368	0.087	0.029	0.276	0.015	131
20	Punakha	2008	Toewang	285	0.191	0.047	0.264	0.014	254
20	Punakha	2009	Zomi	257	0.229	0.049	0.280	0.016	309
20	Punakha	2010	Barp	723	0.047	0.016	0.286	0.014	151
20	Punakha	2011	Toep	454	0.067	0.017	0.287	0.012	128
21	Samdrup Jongkhar	2101	Phuntshothang	599	0.458	0.060	0.245	0.013	1404
21	Samdrup Jongkhar	2102	Pemathang	297	0.559	0.079	0.236	0.013	810
21	Samdrup Jongkhar	2104	Gomdar	621	0.439	0.050	0.264	0.014	1161
21	Samdrup Jongkhar	2105	Lauri	697	0.606	0.053	0.236	0.010	1619
21	Samdrup Jongkhar	2106	Martshala	475	0.453	0.053	0.258	0.014	986
21	Samdrup Jongkhar	2108	Orong	639	0.424	0.042	0.279	0.012	1194
21	Samdrup Jongkhar	2109	Langchhenphu	171	0.550	0.070	0.242	0.020	482
21	Samdrup Jongkhar	2110	Samrang	22	0.570	0.148	0.252	0.045	60
21	Samdrup Jongkhar	2111	Serthig	421	0.539	0.052	0.241	0.012	952
21	Samdrup Jongkhar	2112	Wangphu	339	0.561	0.064	0.256	0.013	1077
21	Samdrup Jongkhar	2113	Deothang	653	0.300	0.040	0.292	0.014	899
22	Samtse	2201	Bara	606	0.655	0.036	0.272	0.011	2172
22	Samtse	2202	Biru	573	0.589	0.042	0.263	0.012	1744
22	Samtse	2203	Chargharay	640	0.533	0.040	0.288	0.017	1649
22	Samtse	2204	Chengmari	763	0.535	0.043	0.278	0.015	2019
22	Samtse	2205	Denchhukha	384	0.683	0.040	0.272	0.014	1544
22	Samtse	2206	Dorokha	891	0.616	0.039	0.269	0.012	2649
22	Samtse	2207	Dungtoe	235	0.691	0.058	0.263	0.015	894
22	Samtse	2208	Ghumaunay	541	0.507	0.044	0.273	0.013	1391
22	Samtse	2209	Laherene	475	0.609	0.044	0.277	0.013	1667
22	Samtse	2211	Nainital	315	0.486	0.063	0.267	0.018	714
22	Samtse	2212	Pagli	1018	0.489	0.038	0.318	0.016	2470
22	Samtse	2213	Samtse	599	0.578	0.037	0.283	0.011	1827
22	Samtse	2214	Sipsu	504	0.390	0.047	0.286	0.014	939

22	Samtse	2215	Tading	790	0.596	0.040	0.266	0.012	2437
22	Samtse	2216	Tendu	877	0.486	0.047	0.280	0.015	2148
23	Sarpang	2301	Bhur	289	0.313	0.062	0.279	0.012	463
23	Sarpang	2302	Chhuzagang	483	0.253	0.041	0.251	0.011	599
23	Sarpang	2303	Dekiling	732	0.210	0.040	0.264	0.015	740
23	Sarpang	2305	Doban	397	0.386	0.056	0.242	0.012	781
23	Sarpang	2306	Gelephu	784	0.093	0.033	0.246	0.013	341
23	Sarpang	2307	Hiley	473	0.321	0.050	0.261	0.012	774
23	Sarpang	2308	Jigmechhoeling	688	0.328	0.057	0.259	0.011	1129
23	Sarpang	2311	Shompangkha	215	0.304	0.049	0.262	0.014	334
23	Sarpang	2312	Serzhong	394	0.170	0.038	0.264	0.012	311
23	Sarpang	2313	Senge	126	0.266	0.069	0.226	0.017	157
23	Sarpang	2314	Taklai	45	0.009	0.026	0.265	0.036	<5**
23	Sarpang	2315	Umling	348	0.191	0.044	0.245	0.014	279
24	Thimphu	2402	Chang	722	0.041	0.026	0.324	0.026	122
24	Thimphu	2403	Dagala	247	0.080	0.043	0.279	0.025	85
24	Thimphu	2404	Genye	184	0.099	0.041	0.290	0.023	85
24	Thimphu	2405	Kawang	591	0.068	0.029	0.335	0.021	147
24	Thimphu	2406	Lingzhi	120	0.105	0.056	0.269	0.027	39
24	Thimphu	2407	Mewang	1101	0.059	0.020	0.325	0.021	304
24	Thimphu	2408	Naro	39	0.184	0.085	0.235	0.033	32
24	Thimphu	2409	Soe	37	0.203	0.098	0.269	0.037	29
25	Trashigang	2501	Bartsham	424	0.170	0.033	0.251	0.011	298
25	Trashigang	2502	Bidung	391	0.243	0.038	0.240	0.011	404
25	Trashigang	2503	Kanglung	1064	0.213	0.050	0.263	0.012	985
25	Trashigang	2504	Kangpara	518	0.342	0.040	0.241	0.009	698
25	Trashigang	2505	Khaling	655	0.299	0.048	0.253	0.010	884
25	Trashigang	2506	Lumang	952	0.346	0.031	0.262	0.011	1424
25	Trashigang	2507	Merak	270	0.579	0.072	0.242	0.013	938
25	Trashigang	2509	Phongme	599	0.325	0.043	0.255	0.012	773
25	Trashigang	2510	Radi	720	0.252	0.036	0.247	0.013	748
25	Trashigang	2511	Sakten	546	0.403	0.048	0.242	0.010	823
25	Trashigang	2512	Samkhar	632	0.231	0.034	0.251	0.014	602
25	Trashigang	2513	Shongphu	716	0.275	0.033	0.275	0.013	752
25	Trashigang	2514	Thrimshing	537	0.272	0.037	0.253	0.010	609
25	Trashigang	2515	Udzorong	624	0.343	0.037	0.248	0.011	993
25	Trashigang	2516	Yangnyer	507	0.356	0.043	0.247	0.013	805
26	Yangtse	2601	Bumdeling	390	0.209	0.046	0.257	0.015	408
26	Yangtse	2602	Jamkhar	313	0.108	0.034	0.270	0.015	132
26	Yangtse	2603	Khamdang	671	0.131	0.031	0.258	0.016	389
26	Yangtse	2604	Ramjar	301	0.086	0.030	0.244	0.012	107
26	Yangtse	2605	Toetsho	474	0.112	0.034	0.236	0.011	223

26	Yangtse	2606	Tomzhangtshen	349	0.128	0.041	0.254	0.010	191
26	Yangtse	2607	Yalang	402	0.120	0.037	0.246	0.012	191
26	Yangtse	2608	Trashiyangtse	323	0.178	0.042	0.267	0.013	273
27	Trongsa	2701	Drakteng	516	0.136	0.046	0.278	0.018	338
27	Trongsa	2702	Korphu	210	0.221	0.068	0.274	0.019	221
27	Trongsa	2703	Langthil	556	0.227	0.037	0.273	0.011	576
27	Trongsa	2704	Nubi	485	0.245	0.033	0.287	0.012	578
27	Trongsa	2705	Tangsibji	438	0.130	0.037	0.288	0.015	217
28	Tsirang	2801	Barzhong	148	0.219	0.051	0.298	0.022	166
28	Tsirang	2802	Beteni	218	0.269	0.072	0.239	0.016	320
28	Tsirang	2803	Dunglegang	224	0.237	0.057	0.256	0.015	269
28	Tsirang	2804	Gosaling	277	0.184	0.045	0.276	0.019	257
28	Tsirang	2805	Kikorthang	529	0.078	0.024	0.286	0.021	200
28	Tsirang	2806	Mendrelgang	301	0.176	0.043	0.254	0.014	264
28	Tsirang	2807	Patakla	259	0.235	0.056	0.260	0.015	314
28	Tsirang	2808	Phuentenchhu	231	0.193	0.044	0.245	0.012	222
28	Tsirang	2809	Rangthangling	284	0.213	0.055	0.250	0.013	303
28	Tsirang	2810	Semjong	233	0.272	0.061	0.252	0.013	354
28	Tsirang	2811	Tsholingkhar	353	0.170	0.052	0.241	0.012	283
28	Tsirang	2812	Tsirangtoe	221	0.222	0.056	0.263	0.015	256
29	Wangdue Phodrang	2901	Athang	152	0.248	0.043	0.282	0.018	172
29	Wangdue Phodrang	2902	Bjena	521	0.116	0.037	0.250	0.013	221
29	Wangdue Phodrang	2903	Daga	261	0.211	0.046	0.287	0.015	257
29	Wangdue Phodrang	2904	Dangchhu	266	0.195	0.057	0.258	0.018	249
29	Wangdue Phodrang	2905	Gangte	355	0.138	0.074	0.248	0.017	200
29	Wangdue Phodrang	2906	Gasetsho gom	349	0.093	0.027	0.296	0.022	152
29	Wangdue Phodrang	2907	Gasetsho Om	148	0.080	0.040	0.255	0.018	56
29	Wangdue Phodrang	2908	Kazhi	297	0.206	0.044	0.258	0.015	265
29	Wangdue Phodrang	2909	Nahi	152	0.208	0.056	0.261	0.019	137
29	Wangdue Phodrang	2910	Nysho	467	0.127	0.034	0.271	0.018	270
29	Wangdue Phodrang	2911	Phangyuel	236	0.094	0.036	0.258	0.016	94
29	Wangdue Phodrang	2912	Phobji	346	0.182	0.040	0.217	0.014	346
29	Wangdue Phodrang	2913	Ruepisa	353	0.147	0.035	0.251	0.014	250
29	Wangdue Phodrang	2914	Sephu	413	0.165	0.040	0.258	0.016	313
29	Wangdue Phodrang	2915	Thedtsho	453	0.064	0.026	0.268	0.020	138
30	Zhemgang	3001	Bardo	373	0.612	0.055	0.256	0.013	1129
30	Zhemgang	3002	Bjoka	155	0.598	0.068	0.237	0.016	521
30	Zhemgang	3003	Gozhing	298	0.605	0.071	0.228	0.014	873
30	Zhemgang	3004	Nangkor	492	0.479	0.061	0.259	0.013	1085
30	Zhemgang	3005	Ngangla	368	0.612	0.051	0.240	0.012	1188
30	Zhemgang	3006	Pangkhar	220	0.642	0.081	0.236	0.016	786
30	Zhemgang	3007	Shingkhar	325	0.576	0.055	0.248	0.014	749

30	Zhemgang	3008	Trong	597	0.333	0.047	0.313	0.023	926
Source: Authors' estimations using BLSS 2007 and Census 2005. ***Note***: * "<0.001" refers to "less than 1 percent". ** "<5" refers to "less than 5".									

Annex II: Results of Consumption Models

Small Urban - Final Model

Variables	Coefficient	Description of the variable
intercept	8.1957	Constant term used in the model
CHLD0YRP	-0.6283	Proportion of children 0 yr in the household
CHLD1_4P	-0.3747	Proportion of children of age 0-4 yr in the household
DFLUSH_NSH_1	0.121	Household with flush toilet but not shared
DFRIDGE_1	0.1287	Household owned a fridge
DGRA_EDU_1	0.3266	Head with graduate education in the household
DHD_MARIED_1	-0.1133	Married head in the household
DHD_OWNENT_1	0.1633	Head working in own enterprise
DHD_WIDOW_1	-0.3029	Head is widowed in the household
DHH_2ROOM_1	-0.0678	Household with two rooms
DHSEC_EDU_1	0.1283	Head with higher secondary education in the household
DMSEC_EDU_1	0.0678	Head with middle secondary education
DPRI_EDU_1	-0.0552	Head with primary education
DTV_VEDIO_1	0.1496	Household owned Television/video
HHSIZE	-0.2736	Size of the household
HHSIZE2	0.0117	Size of the household squared
LIT_RATE	0.2445	Literacy rate in the household
PGTCH0YR	4.0511	Proportion of children 0 yr at the *gewog*/town level
PGTCOMPUTR	3.2596	Proportion of household owning computer at *gewog* level
PGTHAPPY	0.58	Proportion of household reporting being happy at *gewog* level
PGTMOBILE	-0.3241	Proportion of household owning a mobile phone at *gewog* level
_DZ_CODE#18$HHSIZE2	0.0174	
_DZ_CODE$DGRA_EDU_120	0.276	District=12 and head with not graduate education
_DZ_CODE$DGRA_EDU_200	0.6119	District=20 and head with not graduate education
_DZ_CODE$DGRA_EDU_210	-0.1976	District=21 and head with not graduate education
_DZ_CODE$DGRA_EDU_231	-0.3798	District=23 and head with graduate education
_DZ_CODE$DGRA_EDU_270	0.1966	District=27 and head with not graduate education
_DZ_CODE$DGRA_EDU_290	0.3516	District=29 and head with not graduate education
_DZ_CODE$DHD_LIT_281	0.2573	District=28 and literate head in the household

Big Urban - Final Model

Variables	Coefficient	Description of the variables
intercept	-8.498	Constant used in the model
DD30_60M_1	0.9074	Time taken 30-60 minutes to reach the facility from household
DDLESS30M_1	0.9615	Time taken less than 30 minutes to reach the facility from household
DFLUSH_NSH_1	0.1368	Household with flush toilet but not shared
DFLUSH_SH_1	0.1246	Household with flush toilet but shared
DFRIDGE_1	0.1537	Household owning a fridge
DHD_EDUCAT_1	-0.1993	Head working in the education sector
DHH_1ROOM_1	-0.2423	Household with 1 room
DHH_2ROOM_1	-0.088	Household with 2 rooms
DMOBILE_1	0.1262	Household owning a mobile
DPRI_EDU_1	-0.1251	Head of the household with primary education
DVEHICLE_1	0.1219	Household owning a vehicle
DWASHING_1	0.2099	Household owning washing machine
EMPLOYEEP	-0.3532	Proportion of employees in the household
HHSIZE	-0.3764	Size of the household
HHSIZE2	0.0218	Size of the household squared
LIT_RATE	0.2488	Literacy rate in the household
PCBFLUSH	-0.4163	Proportion of households with flush toilet at *chiwog* level
PCBHH1ROOM	-0.3866	Proportion of households with 1 room at *chiwog* level
PGTTELE	36.8715	Proportion of households with access to telephone at *gewog* level
POP15_64P	0.3513	Proportion of 15-64 yr (working age) population in the household

Rural - Final Model

Variables	Coefficient	Description of the variables
intercept	8.2814	Constant used in the model
CHLD0YRP	-0.4306	Proportion of children 0 yr in the household
CHLD1_4P	-0.5735	Proportion of children 1-4 yr in the household
DD30_60M_1	-0.0404	Time taken 30-60 minutes to reach the facility from household
DD6PLUS_1	-0.0814	Time taken 6 hours or more to reach the facility from household
DHD_EDUCAT_1	0.4233	Head working in the education sector
DHD_EGW_1	0.2503	Head working in the Electricity, gas and water sector
DHD_HEALTH_1	0.2819	Head working in the Health sector
DHD_MARIED_1	-0.0306	Head of the household married
DHSEC_EDU_1	0.3733	Head of the household with higher secondary education
DMSEC_EDU_1	0.2406	Head of the household with middle secondary education
DZ_CODE_14	0.394	*dzongkhag*=14
DZ_CODE_25	-0.2282	*dzongkhag*=25
HHSIZE2	-0.0061	Household size squared
PCBELECTR	0.0728	Proportion of households having electricity at the *chiwog* level
PCBHH1ROOM	-0.1754	Proportion of households having 1 room in the household
PCBOWNDHH	-0.3486	Proportion of households owning the house
PCBTELE	0.2667	Proportion of households having a telephone at *chiwog* level
PGTHDCPRI	-0.5456	Proportion of households with head completed primary education at *gewog* level
PGTTELE	0.6046	Proportion of households having a telephone at *gewog* level
POP0_14P	-0.4157	Proportion of under-15 children in the household
POP65PLUSP	-0.211	Proportion of elderly people (65+) in the household
_DZ_CODE#13$HHSIZE2	-0.0042	*dzongkhag*=13 & household size squared
_DZ_CODE#13$PCBHAPPY	0.2361	*dzongkhag*=13 & proportion of household happy at *chiwog* level
_DZ_CODE#15$PCBHAPPY	-0.3675	*dzongkhag*=15 & proportion of household happy at *chiwog* level
_DZ_CODE#21$PCBHAPPY	0.2341	*dzongkhag*=21 & proportion of household happy at *chiwog* level
_DZ_CODE#23$HHSIZE2	-0.0013	*dzongkhag*=23 & household size squared
_DZ_CODE#30$HHSIZE2	0.003	*dzongkhag*=30 & household size squared
_DZ_CODE$DHD_REMIT_111	0.7369	*dzongkhag*=11 and household receiving remitance
_DZ_CODE$DHD_REMIT_161	-0.3562	*dzongkhag*=16 and household receiving remittance
_DZ_CODE$DHD_REMIT_190	-0.0973	*dzongkhag*=19 and household not receiving remittance
_DZ_CODE$DHD_REMIT_221	0.2243	*dzongkhag*=22 and household receiving remittance
_DZ_CODE$DHD_REMIT_301	-0.4588	*dzongkhag*=30 and household receiving remittance
_DZ_CODE$DHSEC_EDU_170	-0.3237	*dzongkhag*=17 and head with not higher secondary education
_DZ_CODE$DHSEC_EDU_210	-0.4116	*dzongkhag*=21 and head with not higher secondary education
_DZ_CODE$DHSEC_EDU_260	0.0655	*dzongkhag*=26 and head with not higher secondary education

_DZ_CODE$DHSEC_EDU_280	0.1329	*dzongkhag*=28 and head with not higher secondary education
_DZ_CODE$DMSEC_EDU_120	-0.1589	*dzongkhag*=12 and head with not middle secondary education
_DZ_CODE$DMSEC_EDU_160	-0.2491	*dzongkhag*=16 and head with not middle secondary education
_DZ_CODE$DMSEC_EDU_220	-0.367	*dzongkhag*=22 and head with not middle secondary education
_DZ_CODE$DMSEC_EDU_240	0.1721	*dzongkhag*=24 and head with not middle secondary education
_DZ_CODE$DMSEC_EDU_300	-0.4833	*dzongkhag*=30 and head with not middle secondary education

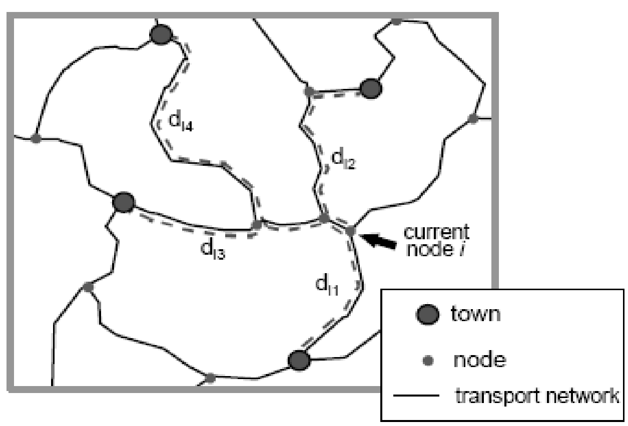
Annex III: Accessibility Indicators

This annex explains technical details related to the derivation of the accessibility index mentioned in the main text of this report. The annex covers the concept of market accessibility, the calculation of the index, and the compilation of Bhutan's road network database. The explanations are designed to be concise; more comprehensive discussions may be found in *Accessibility indicators in GIS* (UN Statistics Division, 1997). The mimeo discusses details about access indicator formula, other types of access indicators, as well we computer programs to calculate the index.

Concept of market accessibility

The market accessibility index rates the potential of villages to reach markets in cities. It tells us how easy it is for someone in rural area to reach markets. The indicator relies on two factors: travel time to nearby cities and size of markets or cities. The *potential accessibility index* is an "all-purpose" measure that gives an indication of how well a particular area is integrated with respect to urban centers, services, markets or employment opportunities. An indicator of general accessibility is useful as a summary measure of the degree of integration of a network consisting of roads and towns or facilities.

Figure AIII-1: Shortest distance from a node to towns



Source: *Accessibility indicators in GIS* (UN Statistics Division, 1997)

Calculation of the index

The "market accessibility index" is constructed by measuring potential to access markets in major cities and towns from any populated area in Bhutan. The index I can be described as

$I_c^i = \sum_j \frac{S_j}{d_{ij}^b}$, where I_c^i is the accessibility indicator, *Sj* is a size indicator at town *j* (for example, population), *dij* is the distance between origin *i* and town *j*, and *b* is the distance exponent which is two in the original formulation. The index simply is a weighted average of population of nearby cities/towns, weighted by travel time. The indicator is created for all rural settlements in Bhutan. Travel time is estimated from a detailed road network. The method of finding the shortest distance can be seen from Figure AII-1. Considering only surface distance, the shortest route to each town is depicted by the dotted lines. However, the shortest route may change if one use the concept of travel time and consider road conditions. GIS software automatically finds the shortest route to targets, and calculates travel time from distance and condition of roads. In the case of Bhutan where many areas are not populated, we only calculate access for populated areas.

For a given location we assume that the probability of market size and customer base is larger where there is a higher urban population in the vicinity. Since travel time and transportation cost increase with distance, locations located further away tend to be less important than those close by. A simple accessibility indicator can thus be derived by summing the number of people living in towns in the vicinity whereby each town's population total is adjusted downward using an inverse measure of the travel time between the point of origin and the target towns.

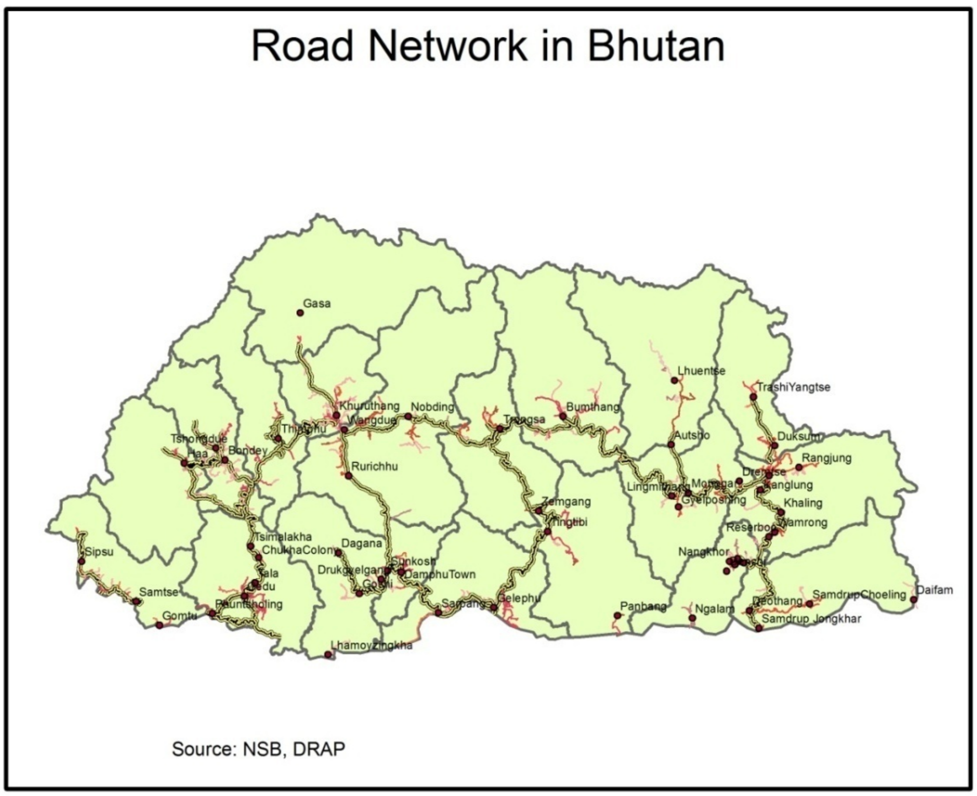
The accessibility indicator based on the *classical* potential model is simply the sum of the masses of the target locations divided by the squared distance between the point of origin and each target location – although an exponent other than two can also be used. The target locations may represent towns, villages, or employment opportunities, and their masses could indicate total population.

Compilation of road network data

We constructed a new consolidated road network database for Bhutan. The road network database was compiled based on road data from the NSB and *Dzongkhag* Rural Access Project (DRAP). The final road network layer consists primarily of DRAP roads, with supplemental information from the NSB data. Overall, the position and topological accuracy of the DRAP database was superior. Where NSB was determined to be superior, the DRAP road segment was deleted and replaced with the NSB counterpart. During the data complication process, roads segments are categorized into three types: highway, farm road, and feeder road. Because the NSB data use the projection *Everest-Def 1962 Lambert Conformal Conic*, all other road data (mostly from DRAP) was re-projected to be consistent with the NSB projection.

At the end, the clean DRAP data is merged with the NSB road data to create the final road network. A topology layer was also created in ArcMap, in order to identify dangles/breaks/overlap between the two sources of road network data—DRAP and NSB. During the manual cleaning, nodes that appeared as though they "should be joined", were joined only if they were within .1 miles of each other. This criterion was maintained for validations. The created topology is visually validated in Google Earth. Visual validation was used to determine which source to maintain in the final cut.

Figure AIII-2: Road network of Bhutan



Source: World Bank staff estimations using BLSS 2007 and PHCB 2005.

Annex IV: Descriptions of national poverty line, specifics of BLSS data, and Census

Poverty Line

The poverty line, the minimum acceptable standard of per capita consumption needed to assure a minimum standard of living, is obtained using the Cost of Basic Needs (CBN) approach, a commonly used methodology in many countries for constructing the poverty line. This approach estimates the food component of the poverty line as the cost of a food bundle attaining a pre-determined minimum food energy requirement (of 2,124 Kcal per person per day), and then adds some non-food requirements to the food component in order to yield the total poverty line.

Poverty Analysis Report 2007 established the Poverty line at Nu. 1,096.94 per person per month. The poverty line is obtained by adding the estimated food and non-food requirements of Nu. 688.96 and Nu. 407.98 respectively.

An estimated 23.2 percent of the population is found to be poor (about 146,000 persons from the extrapolated surveyed population of 629,000 persons). Poverty in rural areas (30.9 percent) is significantly higher than urban areas (1.7 percent). Only 5.9 percent of the population is subsistence poor (i.e., persons belonging to households with per capita consumption below food requirements of Nu. 688.96).

BLSS 2007

A stratified two-stage sampling of households was adopted for BLSS 2007 with *dzongkhag* as the Primary stratum while urban and rural areas as the Secondary stratum.

Samples were drawn independently within each level of the secondary stratum. The primary sampling units were blocks for urban (towns) areas and *chiwogs* for rural areas while the secondary sampling units were the households within the selected blocks/*chiwogs*.

The BLSS 2007 collected information from 9,798 sample households against the targeted households of 10,000. It covered all *gewogs* and key variables including poverty estimates are representative at the *dzongkhag* level.

Following are the information collected for the BLSS 2007:

a) Individual:

1) Demographic characteristics

2) Education

2) Health

4) Employment

b) Household:

1) Housing

2) Asset ownership

3) Access and distances

4) Remittances

5) Priorities, opinions on govt. infrastructures/services

6) Main source of income

7) Food consumption

8) Non-food consumption

9) Home-produced non-food items

Census (2005) data

Bhutan's first Population & Housing Census, based on international standards was conducted in May 2005. It collected information for every individual living in the country based on the de-facto method. It also collected information for all households.

Following are the information collected for the Census:

a) Individual:

1) Population characteristics

2) Migration

2) Health

4) Education

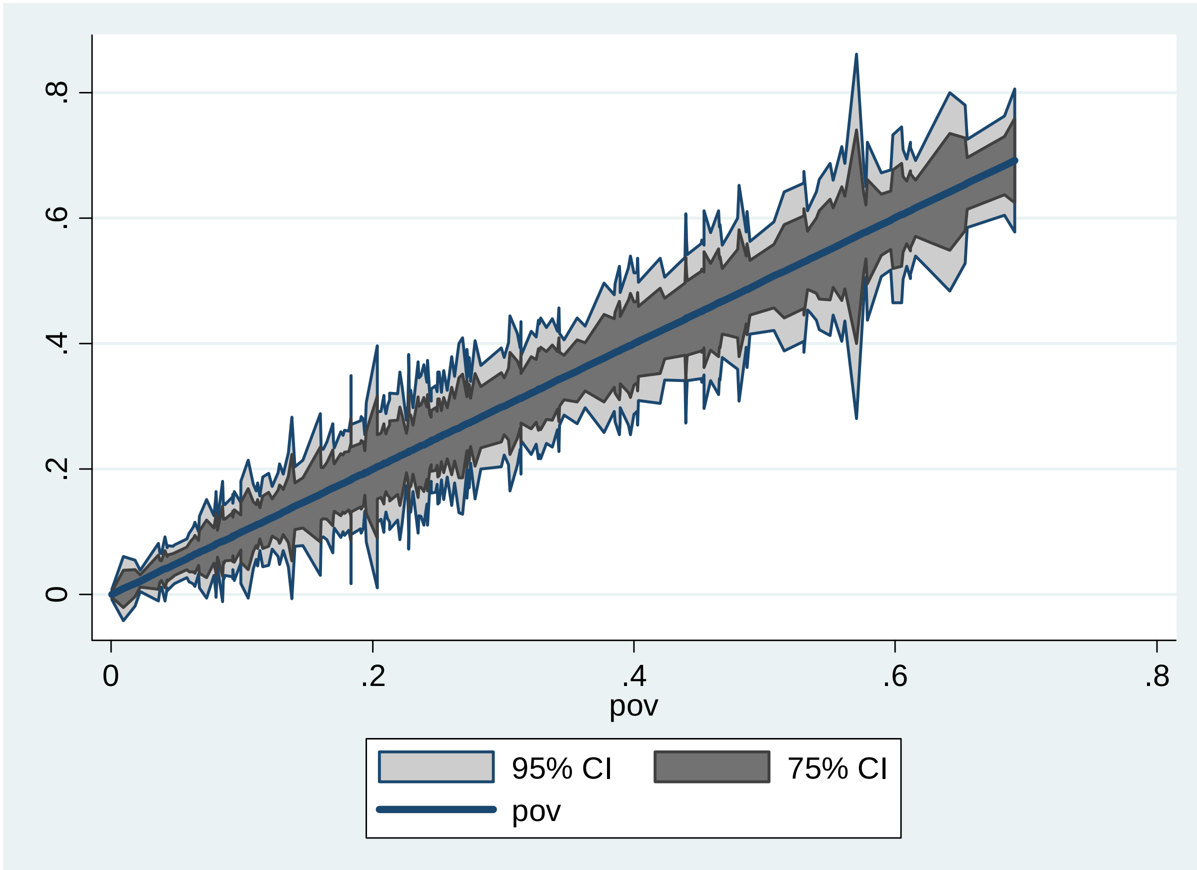
5) Labor & Employment

b) Household:

1) Household and Housing Characteristics

Annex V: Standard errors and statistically distinguishable rankings

Figure V.1: Poverty rates and the 75% and 95% confidence intervals at the Gewog level for rural areas



Source: World Bank staff estimations using the results of the rural poverty map

The results of the rural poverty map are not true numbers but they are estimates and include errors. Figure V.1 visualize the margin of error for the poverty estimate of each *gewog*. The 95 percent confidence interval (95% CI) includes a true level of poverty incidence with a probability of 95 percent and the 75 percent confidence interval includes it with a probability of 75 percent. The figure clearly shows that the 95% CI is bigger than the 75% CI and includes the latter. In general, both 95% and 75% CIs become larger as the poverty estimate becomes larger, but there are many clear exceptions.

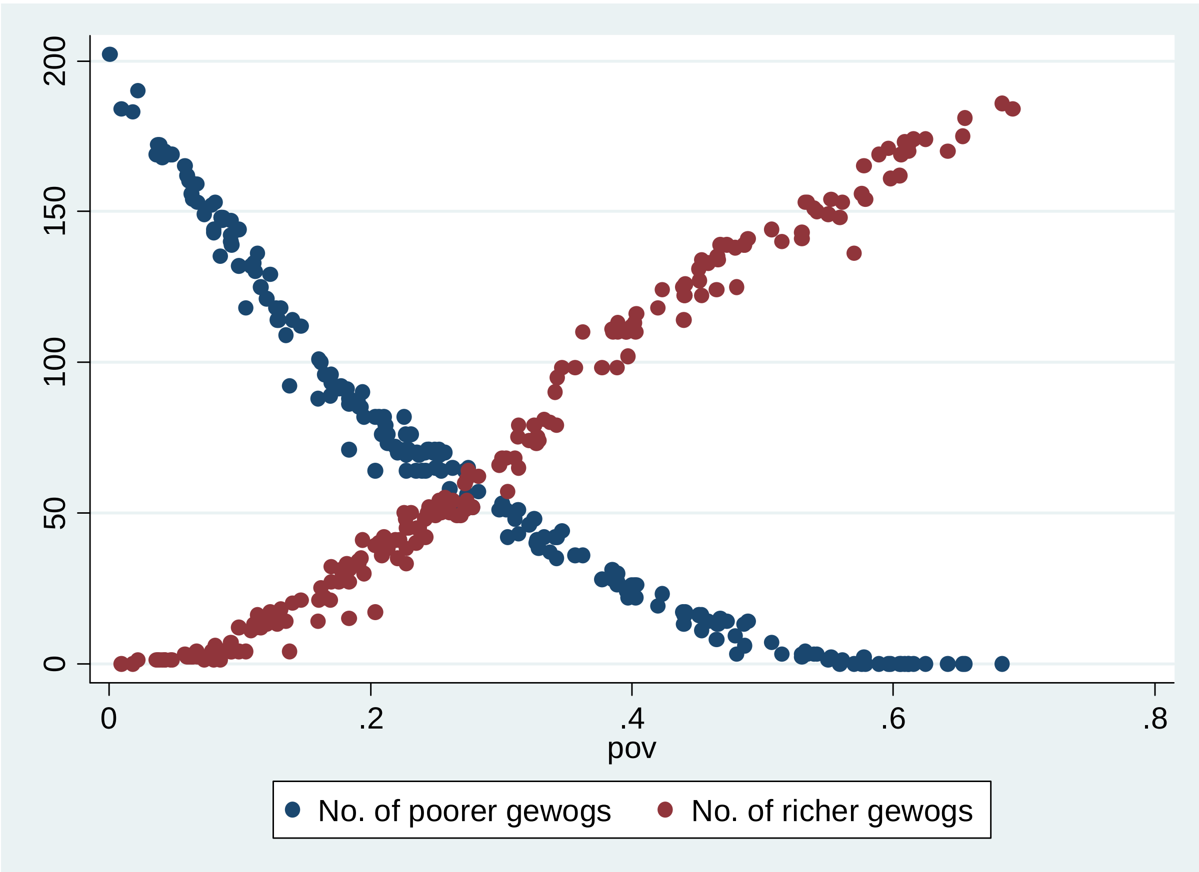
If a gewog's 75% CI overlaps with another *gewog*'s 75% CI, the ranking of these two *gewogs* in poverty incidence is not distinguishable with 75 percent of probability. Given the fact that a 95% CI is larger than a 75% CI, the ranking is more difficult to be statistically significant if the 95% CI is used. Figure V.1 shows rankings of many *gewogs* are not statistically distinguishable although it is clear that the ranking between the poorest and the richest *gewogs* is statistically significant in both probabilities of 95% and 75%.

Figure V.2 shows how many *gewogs* are poorer or richer than a particular *gewog* with a probability of 75 percent. For example, *gewog* Bara's poverty headcount rate is estimated to be 65.5 percent. The ranking of this *gewog* is the third poorest *gewogs* in the country according to the poverty estimate (out of 205 *gewogs* with poverty estimates). But, only 181 *gewogs* are poorer than Bara *gewog* with a probability of

75 percent. This means 21 *gewogs* are less poor than Bara *gewog* but the differences in poverty estimates are not statistically significant. Also, there are two *gewogs* that have poorer poverty estimates than Bara *gewog*, but they were not statistically significantly poorer. According to Figure 2 in the main text, nearly 70 percent of all possible rankings are statistically significant with a probability of 75 percent.

It is important to acknowledge some rankings are not statistically significant when using the results of poverty mapping for resource allocations. If the amount of resource is limited and only part of *gewogs* can receive the resource, then it might be reasonable to focus on *gewogs* that are clearly poorer than a certain number of *gewogs*.

Figure V.2: The number of statistically significantly poorer *gewogs* and that of statistically significantly richer *gewogs* for rural areas (with a probability of 75 percent)



Source: The World Bank staff estimations using the results of the rural poverty map.