POVERTY MAP OF BANGLADESH 2022

Small Area Estimation
District and Upazila Results

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BANGLADESH BUREAU OF STATISTICS
Statistics and Informatics Division, Ministry of Planning
Government of the People's Republic of Bangladesh

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December 2024, Dhaka

Report Writing:
Poverty and Livelihood Statistics (PLS) Cell, BBS,
The World Bank (WB), and
The World Food Programme (WFP)

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For further information on the report, please contact:

Director General
Bangladesh Bureau of Statistics
E-27/A Agargaon, Sher-e-Bangla Nagar, Dhaka-1207.
Email: dg@bbs.gov.bd Tel: +88-0255007056

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ACRONYMS

BBS	Bangladesh Bureau of Statistics
CAFE	Computer Assisted Filed Entry
CAPI	Computer Assisted Personal Interviewing
CensusEB	Census-Empirical Best
COICOP	Classification of Individual Consumption According to Purpose
CV	Coefficient of variation
EB	Empirical Best
ELL	Elbers, Lanjouw and Lanjouw
GIS	Geographic Information System
GLS	Generalized Least Squares
HIES	Household Income and Expenditure Survey
ICMS	Integrated Census Management System
LL	Lower Limit
LPL	Lower Poverty Line
MSE	Mean Squared Errors
NOC	Network Operations Centre
PAPI	Paper-and-Pencil Interviewing
PHC	Population and Housing Census
PLS	Poverty and Livelihood Statistics Cell
Q1	First Quintile
Q2	Second Quintile
Q3	Third Quintile
Q4	Fourth Quintile
Q5	Fifth Quintile
SAE	Small Area Estimation
SDGs	Sustainable Development Goals
SE	Standard Error
UL	Upper Limit
UPL	Upper Poverty Line
WB	The World Bank
WFP	The World Food Programme

FOREWORD

Poverty Maps serve as a pivotal instrument for accurately identifying underserved and impoverished areas, thereby informing policymakers, planners, researchers, and development partners to gain a nuanced understanding of geographical variation and spatial inequality in growth and poverty. The 'Poverty Map of Bangladesh 2022' utilize model-based indirect estimation techniques to address the increasing demand for updated and disaggregated poverty estimates at granular levels, such as district and upazila levels. While direct poverty estimates are available at the division level through the Household Income and Expenditure Survey (HIES) 2022, conducted by BBS, the Poverty Maps provide further insights by offering more localized data.

The Bangladesh Bureau of Statistics (BBS), in collaboration with the World Bank (WB) and the World Food Programme (WFP), initiated this comprehensive exercise to produce and disseminate the Bangladesh Poverty Maps 2022. This initiative involved the rigorous review of data by the Poverty Mapping Working Group, and Technical and Steering Committees, both composed of professionals and subject matter experts. The BBS, WB and WFP jointly estimated poverty and necessary maps for key sub-national administrative units of Districts and Upazilas of Bangladesh. These estimates are derived using the Household Income and Expenditure Survey 2022 and the Population and Housing Census (PHC) 2022, alongside applying the latest guideline of the World Bank on Small Area Estimation (SEA) methodology (CensusEB).

These latest poverty maps are expected to significantly enhance the targeting of policy interventions and programs by providing a more precise understanding of the local context. With strong commitment, sound policies, and effective coverage, we are well-positioned to work towards a brighter future for the people of Bangladesh. Our enhanced knowledge and data-driven insights will enable us to implement targeted and impactful interventions to reduce poverty and promote equity and sustainable development.

As we present the 'Poverty Map of Bangladesh 2022', we extend our gratitude to all the professionals, experts, and partners who contributed to this gigantic effort. We look forward to continuing and expanding this collaboration to explore the poverty situation of the country to overcome the development challenges and eradicate poverty in all its forms. We appreciate BBS, WB, and WFP officials who are engaged to accomplish this huge task by reducing the time significantly compared to earlier exercises.

Together, we can build a more equitable and prosperous Bangladesh.

Abdoulaye Seck
Country Director
World Bank, Bangladesh

Mohammed Mizanur Rahman
Director General
Bangladesh Bureau of Statistics

Domenico Scalpelli
Country Director
World Food Programme, Bangladesh

ACKNOWLEDGEMENTS

Bangladesh Bureau of Statistics (BBS) published the first 'Poverty Maps of Bangladesh 2000' in 2004 to display the poverty situation of the country at district and upazila levels based on HIES 2000 and the 5% sample dataset of the Population & Housing Census 2001. Later on, after completion of each HIES i.e. HIES 2005, HIES 2010 and HIES 2016, BBS prepared the poverty maps accordingly. The World Food Program (WFP) and the World Bank (WB) are two very important long-standing partners in these tasks.

The HIES and the Population & Housing Census datasets are the basis of preparing poverty maps at the district and upazila levels by using the Small Area Technique (SAE). It is important to mention that poverty pictures are highly demanded by the stakeholders at the granular level. However, BBS has conducted the HIES 2022 from 01 January to 31 December 2022 and the Population & Housing Census 2022 during 15-21 June 2022 which is a coincidence for preparing 'Poverty Map of Bangladesh 2022'. This year BBS has followed the CensusEB method according to the World Bank's latest guideline of SAE.

I would like to extend my gratitude to Dr. Wahiduddin Mahmud, Honorable Adviser, Ministry of Planning, and Mr. Md. Mahbub Hossain, Secretary, Statistics and Informatics Division (SID), Ministry of Planning for their kind support and guidance. Special thanks to Mr. Mohammed Mizanur Rahman, Director General, Bangladesh Bureau of Statistics (BBS), for his invaluable suggestions. Our gratefulness to all respected members of the Working Committee, Editors Forum, Technical Committee, Report Review Committee, Report Scrutiny Committee, and Steering Committee for their valuable comments, suggestions, and directives to accomplish this effort efficiently.

I must convey my heartfelt thanks to the WFP for their financial and technical support, particularly in generating the poverty maps and valuable contributions to this report. We are indebted to the Poverty and Equity Global Practice, WB team for providing necessary technical support, hands-on training and valuable contribution to preparing this report. My sincere appreciation to the members of the PLS Cell, BBS, relevant officials of BBS and SID for their persistent hard work to do this highly technical task successfully by reducing the time remarkably compared to all previous poverty map exercises done by BBS.

I believe this effort will be meaningful if the 'Poverty Map of Bangladesh 2022' report would somehow be useful to policy-makers, development partners, researchers, NGOs and other users. BBS would appreciate it if you could provide any valuable comments, suggestions or opinions to improve our future endeavors.

Mohiuddin Ahmed *MPH*
Deputy Director, BBS &
Focal Point Officer
Poverty Map of Bangladesh 2022
Email: mohiuddin.bbs@gmail.com

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INTRODUCTION

1.1. BACKGROUND

Bangladesh Bureau of Statistics (BBS) conducted the first round of Household Expenditure Survey (HES) in 1973. The latest i.e. the 17th round of HIES was held in 2022. National and Divisional level (rural and urban) poverty Head Count Rates (HCR) are generated directly from the HES/HIES survey datasets. However, the District and Upazila level poverty rates are highly demanded by the policy makers, development partners and the researcher's community too. To meet the stakeholder's high expectations, BBS started publishing the District and Upazila poverty pictures by using the Small Area Estimation (SAE) technique with the collaboration of WFP and WB since 2000. However, the survey figures show that the poverty has undergone a profound shift from a high 48.9 percent in 2000, the poverty rate plummeted to 18.7 percent by 2022.[1] Despite these strides, marked disparities persist across different geographical areas and communities. Understanding these spatial disparities is crucial for formulating effective policies tailored to address these multifaceted challenges. The 'Poverty Map of Bangladesh 2022' provides a detailed poverty distribution across the country, embodying Bangladesh's enduring commitment to poverty alleviation. It is worth to mention here that the only exception was HIES 2016 where the National, Divisional and also the District HCRs were given directly from the survey and the Upazila level figures were produced through SAE method.

The traditional household surveys are invaluable for assessing poverty at national or large regional levels.[2] Yet, their capacity to capture the nuanced disparities in smaller or more specific areas often falls short due to many reasons including limitations in sample size. In areas where only a few households are surveyed, the results may not accurately reflect the broader local conditions, leading to a potentially skewed understanding of

[1] While earlier HIES rounds are not directly comparable to HIES 2022 due to significant improvements made in the latter, they still offer useful insights into poverty trends.

[2] For the 2022 HIES survey the data is representative at the national, division, and rural and urban levels. Previous surveys were also representative at the division levels apart from 2016 HIES which was representative at the Zila level.

poverty and its distribution. The SAE techniques are specifically developed to address these shortcomings by enhancing the precision of poverty estimates for smaller geographic areas or specific demographic subgroups, that traditional surveys cannot capture due to smaller sample size.

The SAE achieves this enhanced accuracy by integrating detailed survey data with auxiliary information including census data, administrative records, and potentially satellite imagery or mobile data. This methodology allows for 'borrowing strength' from related areas or groups, significantly increasing the reliability of the estimates where direct survey data is sparse. For instance, SAE leverages demographic and economic patterns identified in the census—which includes every household in the country—to refine and adjust poverty estimates derived from survey data.

In the development of the 'Poverty Map of Bangladesh 2022', SAE techniques were utilized, capitalizing on data from the Household Income and Expenditure Survey (HIES) 2022 and the Population and Housing Census (PHC) 2022. This approach facilitates the estimation of poverty levels down to the district and upazila levels, offering a granularity that surpasses the division-level estimates typically provided by HIES 2022. The Bangladesh Bureau of Statistics (BBS), in collaboration with two international partners i.e. the World Bank (WB) and the World Food Programme (WFP), played a vital role in spearheading the production of the 2022 poverty maps.

Such detailed mapping of poverty at lower sub-national administrative units is crucial for both government and non-government organizations to allocate resources and taking interventions more effectively. By pinpointing areas of acute need and monitoring progress over time, these maps serve as a foundational tool for targeted poverty alleviation strategies. This ensures that efforts are concentrated where they are most important, promoting equitable development across diverse communities. Furthermore, these detailed measures provide policymakers with a robust mechanism to assess the effectiveness of their policies, particularly in tracking and monitoring the Sustainable Development Goals (SDGs) to be achieved by 2030.

1.2. OBJECTIVES

The overall objective of the 'Poverty Map of Bangladesh 2022' is to provide policy support to the policymakers, planners, researchers, and development partners with precise and disaggregated data on poverty, thereby enabling more effective targeting of interventions and resources.

The specific objectives are:

- To provide disaggregated poverty estimates for key sub-national administrative units.
- To enhance the understanding of spatial inequality and geographical variations in poverty.
- To support the design and targeting of policies and programs aimed at poverty reduction.
- To foster informed decision-making and resource allocation by government agencies and development partners.

1.3. HISTORY OF POVERTY MAPPING EXERCISES IN BANGLADESH

The genesis of poverty mapping in Bangladesh is rooted in the late 1990s and early 2000s, a period characterized by an increasing international and local interest in precise poverty alleviation strategies. During these formative years, the initiative was primarily driven by international development organizations such as WFP and the World Bank, alongside the BBS. These initial maps were somewhat basic, relying primarily on census data and lacked integration with detailed household survey data. The first significant attempt was the production of the 2000 poverty maps, developed with technical support from Massey University, New Zealand, using data from HIES 2000 and a 5 percent sample of the Population Census 2001.

The methodology of poverty mapping saw transformative changes in the mid-2000s with the advent of Geographic Information Systems (GIS) technology. This technology change facilitated the merging of socioeconomic data with spatial characteristics, enhancing the visualization of poverty distribution across the regions of Bangladesh. During this period, there was increased collaboration between governmental and academic institutions to improve the precision and usefulness of these maps. The poverty maps of 2005, which utilized full census data from 2001 and HIES 2005 data, exemplify this evolution and collaboration with academia. In the late 2000s, more comprehensive poverty maps began to emerge under the auspices of the Government of Bangladesh and development partners. A notable achievement was the 2010 Poverty Map, developed by the BBS with technical assistance from the World Bank and the WFP, utilizing SAE techniques. This map provided detailed insights into poverty rates at the district and upazila levels, significantly enhancing the targeting of social safety net programs and national resource allocation and planning.

The sophistication of these methodologies continued to evolve with the 2016 poverty map, which incorporated the full population census data from 2011 and HIES data from 2016, despite the challenges posed by the significant time interval between the census and survey years which may have affected the relevance of some socio-demographic characteristics. The most recent iteration, the ‘Poverty Map of Bangladesh 2022’, represents a significant milestone, incorporating data from both the full Population and Housing Census 2022 and the HIES 2022, thus perfectly aligning the census and survey years. This edition adheres closely to the World Bank latest guidelines on SAE techniques, specifically the Census-Empirical Best (CensusEB) method, demonstrating a matured approach to capturing the complexities of poverty in Bangladesh.[3]

The poverty maps have become essential tools not only for guiding development initiatives but also for monitoring progress towards the SDGs, showcasing the advanced statistical methods and diverse data sources that now define poverty mapping in the country.

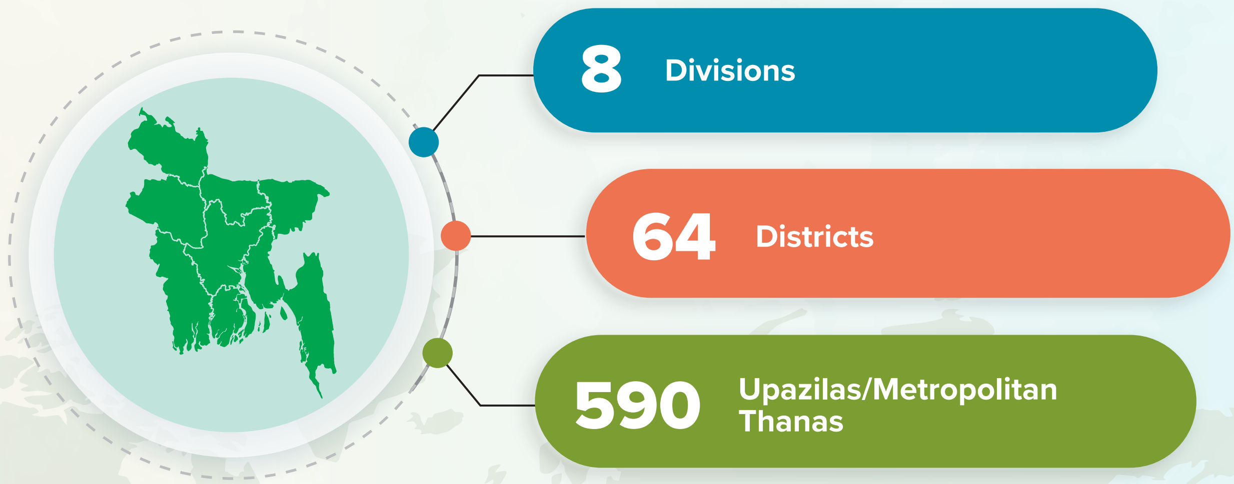
Figure 1: History of Poverty Mapping Exercise in Bangladesh

[3] Guidelines to Small Area Estimation for Poverty Mapping (Report): https://openknowledge.worldbank.org/server/api/core/bitstreams/1d1fcadc-43e3-541b-8949-fea45dd2a528/content

1.4. GEOGRAPHIC AND ADMINISTRATIVE UNITS 2022

The 2022 poverty maps offer extensive coverage, encompassing all 8 divisions, and extending it through SAE methodology to the 64 districts, 590 upazilas and metropolitan thanas across Bangladesh. This comprehensive coverage ensures a thorough and detailed geographical representation of poverty within the country.

Figure 2: Geographic and Administrative Units, 2022



2

POVERTY MAPPING METHODOLOGY

The Poverty Map 2022 for Bangladesh leverages the timely release of the Population and Housing Census 2022 and the Household Income and Expenditure Survey 2022. Additionally, it incorporates the most updated techniques on small-area estimation. Utilizing microdata from both sources, a comprehensive set of common variables is constructed to develop the poverty maps through a unit-level modeling approach. Finally, it utilizes the geospatial and Geographic Information System (GIS) mapping information collected during the PHC 2022 to produce the maps.

2.1. DATA DESCRIPTION

The HIES 2022 is representative at the national, division, rural, and urban levels. BBS implemented rigorous upgradation in survey design and fieldwork operation for this round, which affected the comparability of consumption and poverty over time.[4] The introduction of the Classification of Individual Consumption According to Purpose (COICOP) expanded the number of food and non-food items from 149 to 263 and 261 to 441, respectively. The data collection method moved from Computer Assisted Field Entry (CAFE) to Computer Assisted Personal Interviewing (CAPI). The prices were directly collected instead of deriving unit values from household total expenditure values and quantities, and weighing scales were implemented to ensure the accuracy of household consumed food items.

[4] As technology and survey design methods evolve, enhancements should be implemented. For instance, Argentina improved its survey instrument and periodicity of data collection in 2003 and most of the countries in Latin America have adopted and report their poverty estimates annually, India made several changes in the late 1990s, Peru and Ecuador made significant changes in their household surveys in 2004 and 2007, and, more recently, Zambia and Bhutan in their 2022 survey round. In the ideal situation, a proper way to implement these changes is to simultaneously conduct old and new methods and then clearly identify their differences to maintain comparability over time. However, this process could be costly, challenging, and complex, leaving most countries with two options: break trends or find an analytical way to tackle this issue after implementing the survey.

Furthermore, a more rigorous fieldwork monitoring system was implemented, residential training and refresher training were conducted for the enumerators/ supervising officers throughout the year.

The Population and Housing Census of 2022, while maintaining its main objectives and characteristics, has embraced digitalization in its data collection process. The utilization of the CAPI method, alongside a web-based Integrated Census Management System (ICMS) and a Network Operations Centre (NOC), has not only streamlined census activities but also allowed for real-time monitoring of data collection progress, thereby ensuring data quality. It further allowed BBS to prepare and release the census preliminary report within a month after the completion of fieldwork and the main report within one year. The modernization effort, complemented by traditional census campaigns and social media engagements, underscores BBS's commitment to remaining at the forefront of data collection methods.

2.2. IMPLEMENTATION OF SMALL AREA ESTIMATION FOR POVERTY MAPPING

The first step in constructing the poverty map involves creating a set of potential indicators that are common to both the census database (target) and the household welfare survey, e.g., HIES. For the 2022 Bangladesh poverty mapping, a total of 119 potential variables were carefully harmonized and constructed in both sources (see Annex 3). These variables encompass household demographic characteristics (such as household size, age, age composition of household members, religion, marital status, disabilities, and members living abroad), education characteristics (including literacy, educational attainment, the composition of educational attainment of household members), labor characteristics (such as labor status, and working sector), and dwelling characteristics (like ownership, toilet type, source of drinking water, access to electricity, cooking fuel source, and roof and wall material of dwelling units, remittances, access to financial services, and access to information technology and communication).

From this initial set of potential variables, only those variables that have a close distribution from the census and survey were selected.[5] Census variables lying either within the survey's 95 percent confidence interval or within a normalized distance of 0.05 from the confidence interval are considered eligible variables

Table 1: Selection of Eligible Variables by Domain

Domain		No. variables	No. of eligible variables by normalized distance to HIES 95% C. I			
			0	0.05	0.1	0.15
Barishal	Rural	119	72	85	94	99
	Urban	119	66	80	89	93
Chattogram	Rural	119	74	91	96	100
	Urban	119	73	89	97	104
Dhaka	Rural	119	69	85	97	103
	Urban	119	74	90	98	103

[5] Corral, Molina, Cojocaru, and Segovia (2022, pp. 33) suggest that "Ideally, the mean and distribution of the covariates should be comparable..."

Table 1: Selection of Eligible Variables by Domain (*continued*)

Domain		No. variables	No. of eligible variables by normalized distance to HIES 95% C. I			
			0	0.05	0.1	0.15
Khulna	Rural	119	75	94	100	106
	Urban	119	68	85	97	103
Mymensingh	Rural	119	65	77	88	94
	Urban	119	66	81	92	97
Rajshahi	Rural	119	64	81	90	92
	Urban	119	76	90	101	107
Rangpur	Rural	119	67	86	95	99
	Urban	119	50	70	82	92
Sylhet	Rural	119	64	82	89	97
Sylhet	Urban	119	61	82	92	100
Average			68	84	94	99

Source: Estimations based on HIES 2022 and Population and Housing Census of 2022, BBS

for the modeling procedure discussed below.[6] Table 1 illustrates that, on average, 68 variables from the census lie within the HIES 95 percent confidence interval. This number increases to 84 if a tolerance of 0.05 of normalized distance to the confidence interval is allowed. Annex 4 provides details of this alignment exercise by variable and domain.

Small area estimates for constructing the 2022 poverty map for Bangladesh adhere to the most recent guidance from the World Bank on techniques to achieve the best unbiased empirical estimates (Corral, Molina, Cojocaru, and Segovia, 2022). Previous poverty mapping exercises in Bangladesh utilized the method developed by Elbers, Lanjouw, and Lanjouw (2003), widely known as the ELL method. Over time, enhancements to the ELL method have been made to improve precision and reduce the bias of small area estimates. Recently, Corral, Molina, and Nguyen (2021) expanded upon the ELL method by introducing a new approach that incorporates Monte Carlo simulation and bootstrapping techniques to estimate point estimates and mean squared errors (MSE), respectively. This new approach is referred to as the Census-Empirical Best (CensusEB) method.[7] The next section provides a brief overview of the CensusEB methodology and its key difference from the ELL method.[8] Accordingly, for the current 2022 poverty exercise, the latest edition of the SAE Stata code available was applied (Nguyen, Corral, Azevedo, and Zhao, 2018).[9, 10] The BBS team followed the guidance decision tree to decide on the modeling approach (Corral, Molina, Cojocaru, and Segovia, 2022 p.13). Based on the decision tree and taking advantage of the access to same-year census and household survey microdata, the team chose a unit-level modeling approach for the estimation of small areas. Unit-level models rely on detailed household-level data on consumption from the household survey and a common set of household-level characteristics in both census and survey to simulate household-level consumption in the census data.

[6] There is not a general rule in the guidelines for the selection of eligible variables. BBS applied a rule of thumb approach to accomplish this step.

[7] In the SAE literature, there is a distinction between the Empirical-Best (EB) and the Census-Empirical Best (CensusEB) methods. While the former can only be applied if the households can be identified in both the census and survey datasets, the latter only requires identifying the locations in both data sources.

[8] For a full explanation of the CensusEB method refers to Corral, Molina and Nguyen (2021).

[9] The most updated SAE Stata package for small area estimates has been acceded on Feb 15, 2024 from https://github.com/pcorralrodas/SAE-Stata-Package. It includes all modules referenced in Corral, Molina and Nguyen (2020).

[10] An older version of SAE Stata package is obtained when users type in Stata “ssc install sae”

2.3. SELECTION OF CONSUMPTION MODEL

Once the set of eligible common balanced variables was defined and the modeling approach for producing small area estimates was selected, the next step involved specifying the level at which location effects are incorporated into the modeling process. Since the objective is to report poverty estimates at the upazila level (administrative level 3), the upazila-level clustering was chosen (administrative level 3) for the estimation procedure.[11]

The selected one-fold nested-error model for the small area estimation follows Molina and Rao (2010).[12] This method assumes that the transformed consumption y_{ch} for household h in location c is linearly related to a vector of household characteristic x_{ch}, location η_c and household-specific idiosyncratic errors e_{ch}. Both errors are assumed to be normal, independent, and identically distributed. Thus, variation in consumption y_{ch} across the population is determined by three components: the variation in household characteristics, the variation in location-specific non-observables effects, and the variation in household-specific non-observables.[13]

$$y_{ch} = x_{ch}\beta + \eta_c + e_{ch} \qquad (1)$$

Where, $h = 1, \ldots N_c$, $c = 1, \ldots, C$

$$\eta_c \sim N(0, \sigma_\eta^2), \quad e_{ch} \sim N(0, \sigma_e^2)$$

The estimation of small areas follows a two-stage procedure. In the first stage, equation (1) is fitted according to guidelines for each of the 16 defined domains in the survey data. In the second stage, the parameters obtained in the first stage are used to simulate the welfare metric target data. For the fitting/modeling stage, the Generalized Least Squares (GLS) approach with Henderson's method III was chosen for the estimation of the variance parameters. This approach accommodates heteroskedasticity and the inclusion of survey weights.[14] The method will produce CensusEB small area estimates, which are more accurate and make more efficient use of the survey information in the simulation process, as shown in Corral, Molina, and Nguyen (2021). The extended coverage of 410 out of 590 upazilas during the HIES survey makes Bangladesh a suitable candidate to fully benefit from the advantages of the CensusEB estimation method.

The CensusEB method shares many advantages with the ELL method. Additionally, it corrects the synthetic ELL estimator by accounting for location effects using survey data (Corral, Molina, and Nguyen 2021).[15] The magnitude of this correction depends on an adjustment factor, which measures the proportion of between-location heterogeneity variance (σ_η^2) to the total variance in the location ($\sigma_\eta^2 + \sigma_e^2/n_c$). The correction will be stronger in highly heterogeneous locations and minimal when all the heterogeneity is fully explained by auxiliary variables. If ELL fully controls existing location heterogeneity, the CensusEB reduces to the ELL estimator. Consequently, CensusEB makes more efficient use of the survey data and relies less heavily on auxiliary location-level variables. Furthermore, the CensusEB is an optimal predictor in the sense that it minimizes the MSE under the model.

For each domain, the World Bank guidelines were meticulously followed to take care of factors that may bias estimates, as described in sequential order below:

a) Define a set of eligible variables (xvars) that include only those from the census and survey with a close distribution. Census variables within the survey's 95% confidence interval or a normalized distance of 0.05 from the confidence interval are considered eligible variables.

b) Remove extremely low values of the dependent variable by trimming the lower 0.5%.

c) Generate a shift transformation variable of the dependent variable to approximate normality to get less bias and less noisy estimates and better align to the model assumptions.

d) Reduce the set of eligible variables via LASSO to address potential problems of multicollinearity and overfitting (postlasso).

---

[11] Corral, Molina and Nguyen (2021) show that specifying the random effect at a level of aggregation lower than the reporting level results in noisier estimates, though have minimal impact on bias.

[12] Two-folded nested-error models in SAE are available but do not accommodate survey weights or heteroskedasticity.

[13] The normality assumption does not imply that y_ch is normally distributed. It implies that conditional on observables, the residuals are normally distributed (Corral, Molina, Cojocaru, and Segovia 2022).

[14] The alternative fitting approach using Restricted Maximum Likelihood (REML) does not accommodate survey weights or heteroskedasticity.

[15] This prevents the simulation stage from giving two households with identical observable characteristics but residing in two different locations the same welfare level as it does with the ELL method.

e) Remove non-significant covariates sequentially (postsign)

f) Model diagnostic of residuals and influential observations: Cook's distance, Leverage, and Influence based on rule of thumb criteria.[16]

g) Define an alpha model for GLS estimation: i) exclude from eligible variables (xvars) those variables already included in (postsign); ii) remove non-significant ones (alfa_postsign)

h) Fit model (1) includes an alpha model with (postsign) and (alfa_postsign) sets of variables.

i) Finally, remove non-significant variables (postalfa).

The second stage of producing small area estimates consists of simulating consumption for each household in the census data through Monte Carlo simulation. The procedure first calculates the point estimates with 100 repetitions. Then, it estimates MSE through bootstrap simulation with 50 replications.[17]

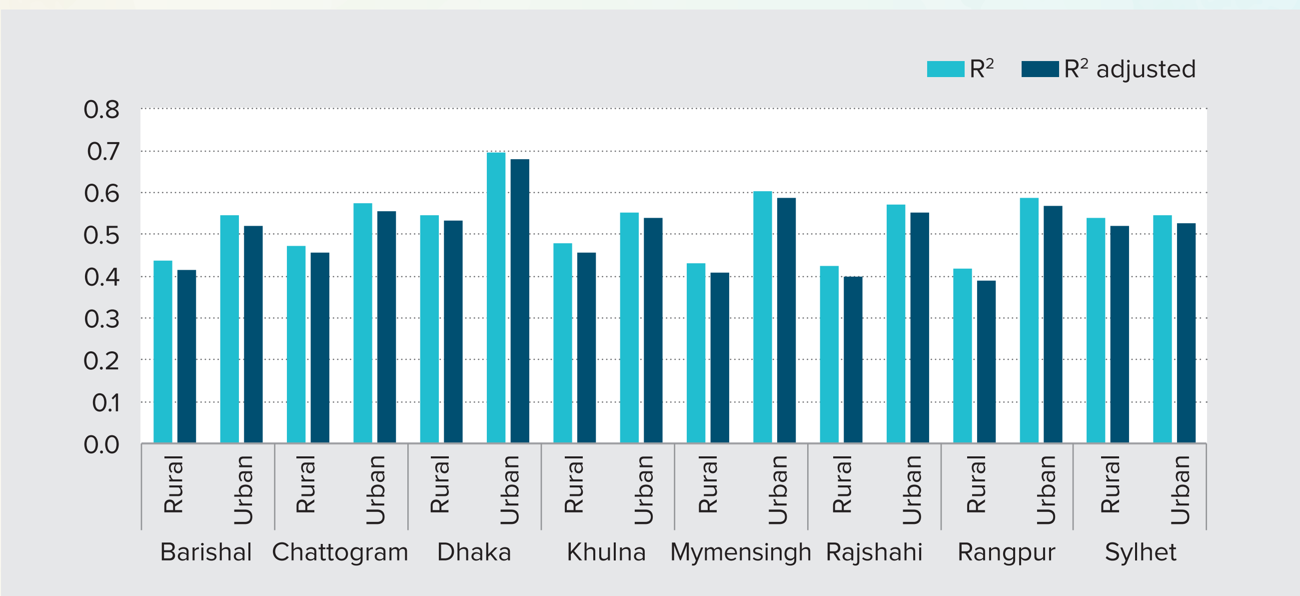
2.4 MODEL FITNESS

Regardless of the clustering selection, the model fitness results in Figure 3 indicate a relatively good fit for most of the domains, explaining between 40 to 70 percent of the variance of the transformed consumption metric, with urban Dhaka stands at the highest adjustment. The normality of the transformed dependent variable cannot be rejected across estimated domains as shown in Annex 5. The underlying assumptions regarding the random effects in nested model (1) are assessed by evaluating the normality of residuals and location effects. Overall, the normal Q-Q plots in Annex 6 and 7 show no dramatic deviations from normality across domains, suggesting no major departures from the nested model's assumption.[18, 19]

2.4.1. Comparisons between Point Estimates from HIES and CensusEB

Poverty headcount estimates from the 2022 HIES, conducted at domain and division levels, serve as reliable "ground truth" benchmarks. These benchmarks are essential for comparing and validating the accuracy

Figure 3: CensusEB Model Fitness by Domain, Upazila Clustering Level, 2022



Source: Estimations based on HIES 2022 and PHC 2022, BBS

[16] Influential data points are excluded as per guidelines if $|stud.res|>2$ and $Cook's\ distance>\frac{4}{N}$ and $leverage>\frac{2k+2}{N}$.

[17] The simulation process tends to be computationally slow, contingent upon the processing power and available RAM, particularly when handling census microdata as extensive as that of Bangladesh.

[18] A normal Q-Q plots the quantiles of the sample data against the quantiles of a theoretical normal distribution.

[19] Keep in mind that Marhuenda et at (2017) acknowledges that achieving perfect normality is very hard when working with real census and survey data.

of poverty estimates derived from the SAE technique. Table 2 reports this comparison at the national level for rural and urban areas. The results demonstrate a reasonable alignment between HIES and CensusEB estimates once confidence intervals are considered.

Table 3 reports this comparison at the division level, albeit at a more disaggregated level. Once confidence intervals are taken into account in the assessment, the results also show a reasonable alignment between HIES and CensusEB estimates.

Finally, Table 4 reports the correspondence between HIES and CensusEB poverty estimates at the domain level. When considering the confidence intervals, the results exhibit a relatively strong alignment. Furthermore, Figure 4 illustrates a straightforward scatter plot of HIES and CensusEB point estimates, revealing a correlation close to 0.94.

Table 2: Direct (HIES) and Indirect (SAE) Poverty Estimates (%) by National, Rural and Urban (UPL), 2022

	HIES				SAE, CensusEB			
	Mean	SE	Confidence limits		Mean	SE	Confidence limits	
			LL	UL			LL	UL
Bangladesh	18.7	0.8	17.0	20.3	19.2	0.4	18.4	20.0
Bangladesh, rural	20.5	1.1	18.3	22.6	20.3	0.5	19.3	21.3
Bangladesh, urban	14.7	1.2	12.4	17.1	16.5	0.6	15.3	17.7

Note: CensusEB estimates with heteroskedasticity and sample weights. Mean=point estimate, SE= √MSE, LL=lower limit, UL=upper limit.
Source: Estimations based on HIES 2022 and PHC 2022, BBS

Table 3: Direct (HIES) and Indirect (SAE) Poverty Estimates (%) by Division (UPL), 2022

	HIES				SAE, CensusEB			
	Mean	SE	Confidence limits		Mean	SE	Confidence limits	
			LL	UL			LL	UL
Barishal	26.9	2.6	21.7	32.1	26.6	1.1	24.3	28.8
Chattogram	15.8	2.2	11.5	20.1	15.2	1.2	12.8	17.7
Dhaka	17.9	2.0	13.9	21.9	19.6	0.9	17.9	21.3
Khulna	15.1	1.6	11.9	18.2	17.1	0.8	15.4	18.7
Mymensingh	24.2	2.6	19.0	29.5	22.6	0.9	20.8	24.4
Rajshahi	16.7	1.9	12.8	20.5	16.3	1.0	14.4	18.1
Rangpur	24.7	1.9	21.0	28.5	25.0	1.3	22.4	27.6
Sylhet	17.3	2.0	13.2	21.3	18.5	0.9	16.8	20.2

Note: CensusEB estimates with heteroskedasticity and sample weights. Mean=point estimate, SE= √MSE, LL=lower limit, UL=upper limit.
Source: Estimations based on HIES 2022 and PHC 2022, BBS

Table 4: Direct (HIES) and Indirect (SAE) Poverty Estimates (%) by Domain (UPL), 2022

		HIES				SAE, CensusEB			
		Mean	SE	Confidence limits		Mean	SE	Confidence limits	
				LL	UL			LL	UL
Barishal	Rural	28.4	3.2	21.9	34.8	28.1	1.4	25.3	31.0
	Urban	21.3	2.4	16.5	26.2	21.7	1.3	19.2	24.2
Chattogram	Rural	17.9	3.0	11.8	23.9	17.8	1.7	14.4	21.3
	Urba	11.3	2.2	6.8	15.8	9.9	1.1	7.7	12.0

Table 4: Direct (HIES) and Indirect (SAE) Poverty Estimates (%) by Domain (UPL), 2022 (*continued*)

		HIES				SAE, CensusEB			
		Mean	SE	Confidence limits		Mean	SE	Confidence limits	
				LL	UL			LL	UL
Dhaka	Rural	21.7	3.4	15.0	28.5	21.4	1.1	19.2	23.6
	Urban	14.3	2.3	9.7	19.0	17.4	1.3	14.8	20.0
Khulna	Rural	16.5	2.0	12.6	20.5	18.7	1.1	16.6	20.8
	Urban	9.9	1.7	6.4	13.4	11.9	0.9	10.2	13.6
Mymensingh	Rural	26.2	3.2	19.7	32.7	24.0	1.1	21.8	26.2
	Urban	16.0	2.8	10.5	21.6	17.8	1.1	15.6	20.0
Rajshahi	Rural	17.2	2.4	12.3	22.2	17.2	1.2	14.8	19.5
	Urban	14.9	2.2	10.5	19.3	13.3	0.9	11.5	15.0
Rangpur	Rural	23.6	2.2	19.2	28.0	22.4	1.6	19.3	25.6
	Urban	29.9	2.9	24.0	35.8	34.5	1.7	31.2	37.9
Sylhet	Rural	17.9	2.4	13.0	22.7	18.4	1.0	16.4	20.3
	Urban	14.3	2.5	9.2	19.5	19.2	1.5	16.3	22.2

Note: CensusEB estimates with heteroskedasticity and sample weights. Mean=point estimate, SE= √MSE, LL=lower limit, UL=upper limit.
Source: Estimations based on HIES 2022 and PHC 2022, BBS

Figure 4: HIES and CensusEB Poverty Estimates Alignment at the Domain Level, 2022

Note: CensusEB estimates with heteroskedasticity and sample weights.
Source: Estimations based on HIES 2022 and PHC 2022, BBS

Table 5: CensusEB Standard Error (%) of Poverty Estimates (UPL), 2022

	Min	Mean	p50	p95	p99	Max
Domain	0.9	1.3	1.2	1.7	1.7	1.7
Zila	0.7	2.1	1.9	4.0	5.0	5.9
Upazila	0.7	4.6	3.8	10.9	15.1	19.2

Note: 1. CensusEB estimates with heteroskedasticity and sample weights. Standard errors are computed as √MSE through bootstrap simulation.
2. Upazila Clustering (UPL),
Source: Estimations based on HIES 2022 and PHC 2022, BBS

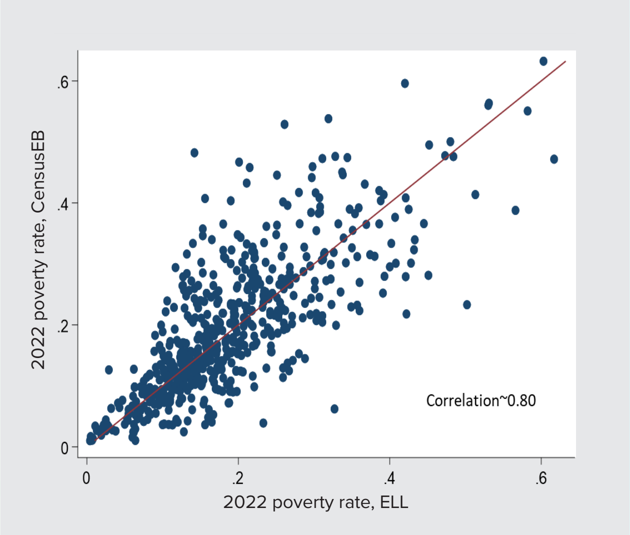
2.4.2. CensusEB standard error estimates

As evidenced in Table 5, small-area standard errors of poverty estimates are reasonable for the majority of upazilas. Comparing these estimates to those from the prior poverty mapping exercise conducted in 2016 (ELL method) reveals that CensusEB estimates are lower and exhibit less noise. Given the large standard error for about 5% of the reporting upazilas, a robust ranking is suggested to account for this issue.

2.4.3. Empirical Comparison of ELL and CensusEB Methodologies

To ensure the robustness of 2022 poverty maps, the poverty rates were calculated using the traditional ELL method for comparison. The analysis shows a high degree of correlation (0.8) between the ELL and CensusEB estimates. As depicted in the scatter plot (Figure 5), both methods align closely, validating the reliability of the estimates. Both methods consistently identify regions with higher and lower poverty rates, confirming the spatial distribution of poverty. While both provide close estimates, the CensusEB method guarantees unbiased estimates and aligns with the new empirical developments in small area estimation.

Figure 5: Comparison of 2022 Poverty Rates by ELL and CensusEB



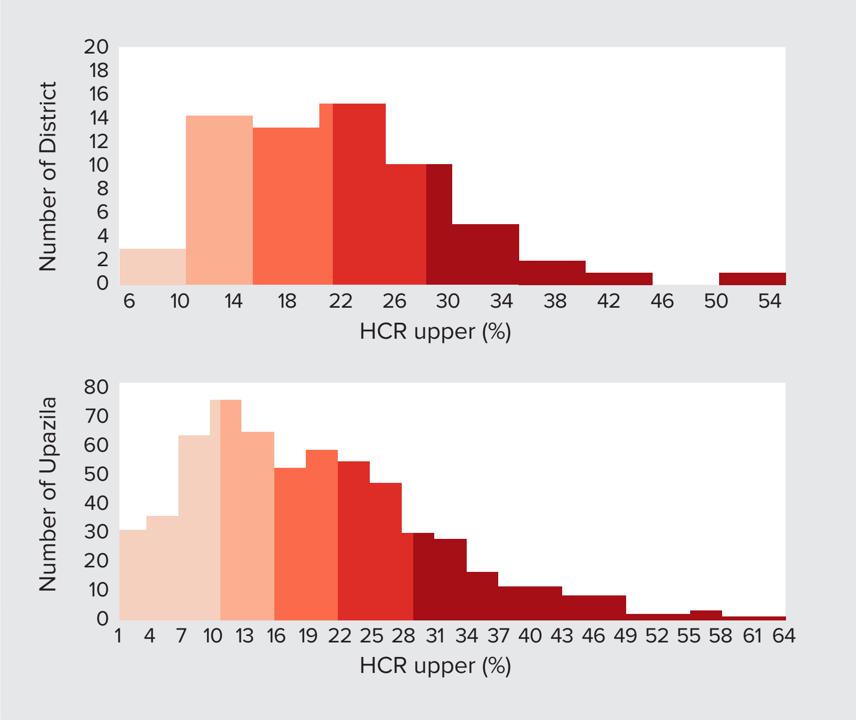
Source: Estimations based on HIES 2022 and PHC 2022, BBS

3

MAPPING POVERTY (UPL)

The histograms presented in Figure 6 depict the distribution of poverty rates across districts and upazilas in Bangladesh. Utilizing SAE to generate point estimates, the poverty rates at the district and upazila levels range from 1 to 54 percent and 1 to 63 percent, respectively. Both distributions exhibit a rightward skew, indicating a concentration of most districts and upazilas within a poverty rate range of 10 to 30 percent. This pattern suggests that while moderate levels of poverty predominate, there exists a smaller number of districts and upazilas experiencing significantly higher poverty rates. This skewness highlights the presence of substantial disparities in economic conditions across different regions, emphasizing the need for targeted poverty alleviation efforts in areas with acute poverty.

Figure 6: Distribution of Poverty Rates across Districts and Upazilas in Bangladesh, 2022



Source: Estimations based on HIES 2022 and PHC 2022, BBS

3.1. GROUPING OF DISTRICTS AND UPAZILAS: QUINTILE-BASED STRATIFICATION

When employing poverty rates of districts and upazilas for ranking and comparison, reliance solely on point estimates may lead to misleading interpretations due to variability reflected in confidence intervals and standard errors. For instance, minimal differences in poverty rates between two upazilas could lead to an inaccurate representation of their comparative standings if these differences are not statistically significant, potentially resulting in an erroneous inverse ranking under rigorous statistical analysis.

To enhance reliability in comparisons, it is prudent to categorize districts and upazilas into distinct groups based on their poverty levels. A quantile-based stratification system has been adopted that classifies upazilas into five categories, from the First to the Fifth Quintile.[20] Each category encompasses an equal number of upazilas. Districts are then categorized using the cutoffs from each quintile. Table 6 provides a summary of this categorization. The categorization ensures that the analysis and interpretation of poverty distributions are both simplified and statistically robust, accurately reflecting significant disparities in poverty levels.

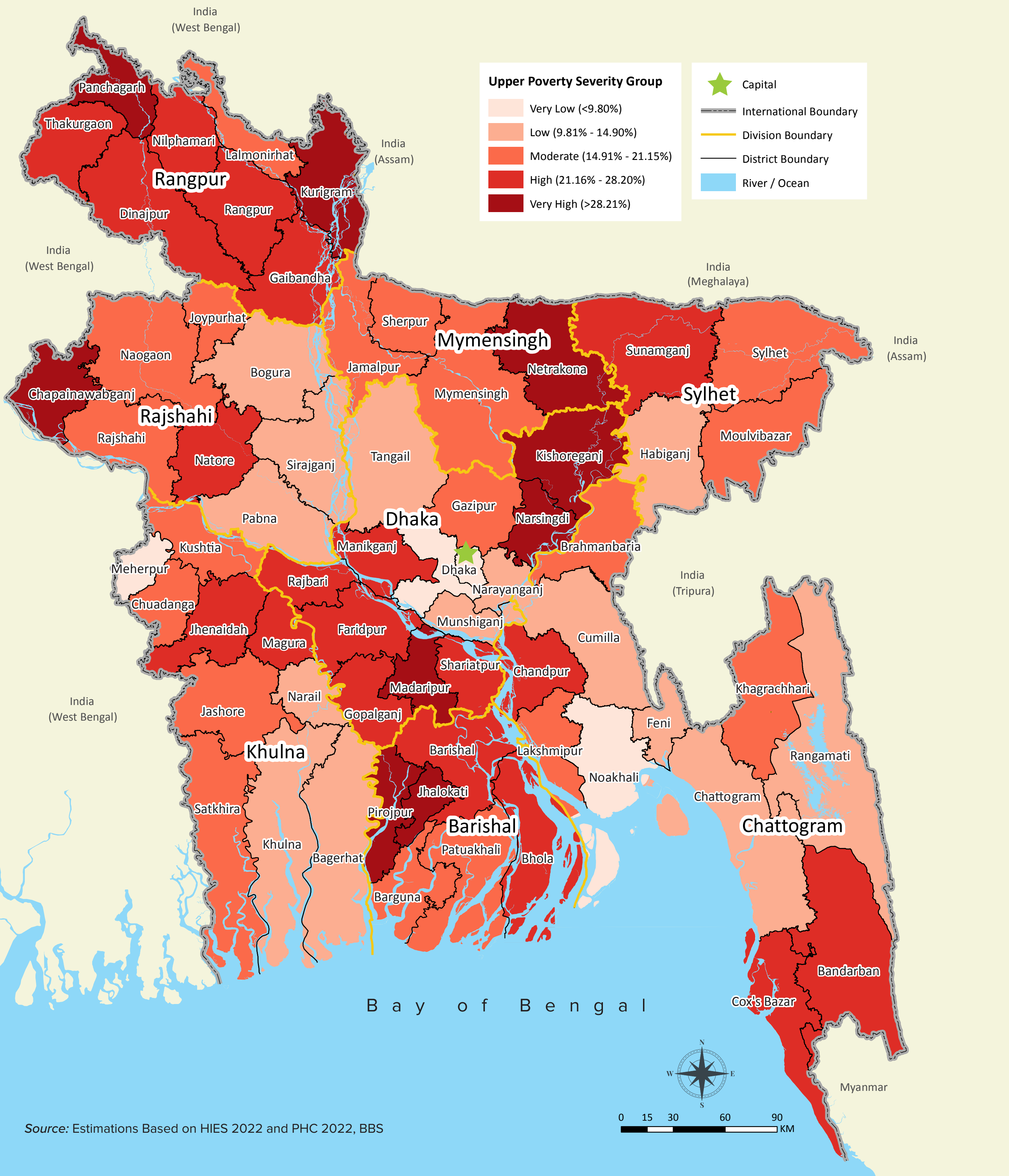
Table 6: Number of Upazilas/Thanas within Each Category of Poverty Level, 2022

Quantile	Poverty Rate Range	Number of Upazilas/ Thanas
First (Very Low)	<9.80	118
Second (Low)	9.80-14.90	118
Third (Moderate)	14.91-21.15	118
Fourth (High)	21.16-28.20	118
Fifth (Very High)	>28.20	118

[20] The Upazilas in the First Quintile are the wealthiest, with a gradual shift towards the poorest in the Fifth Quintile

3.2. POVERTY ESTIMATES AT DISTRICT LEVEL (UPL), 2022 [CensusEB]

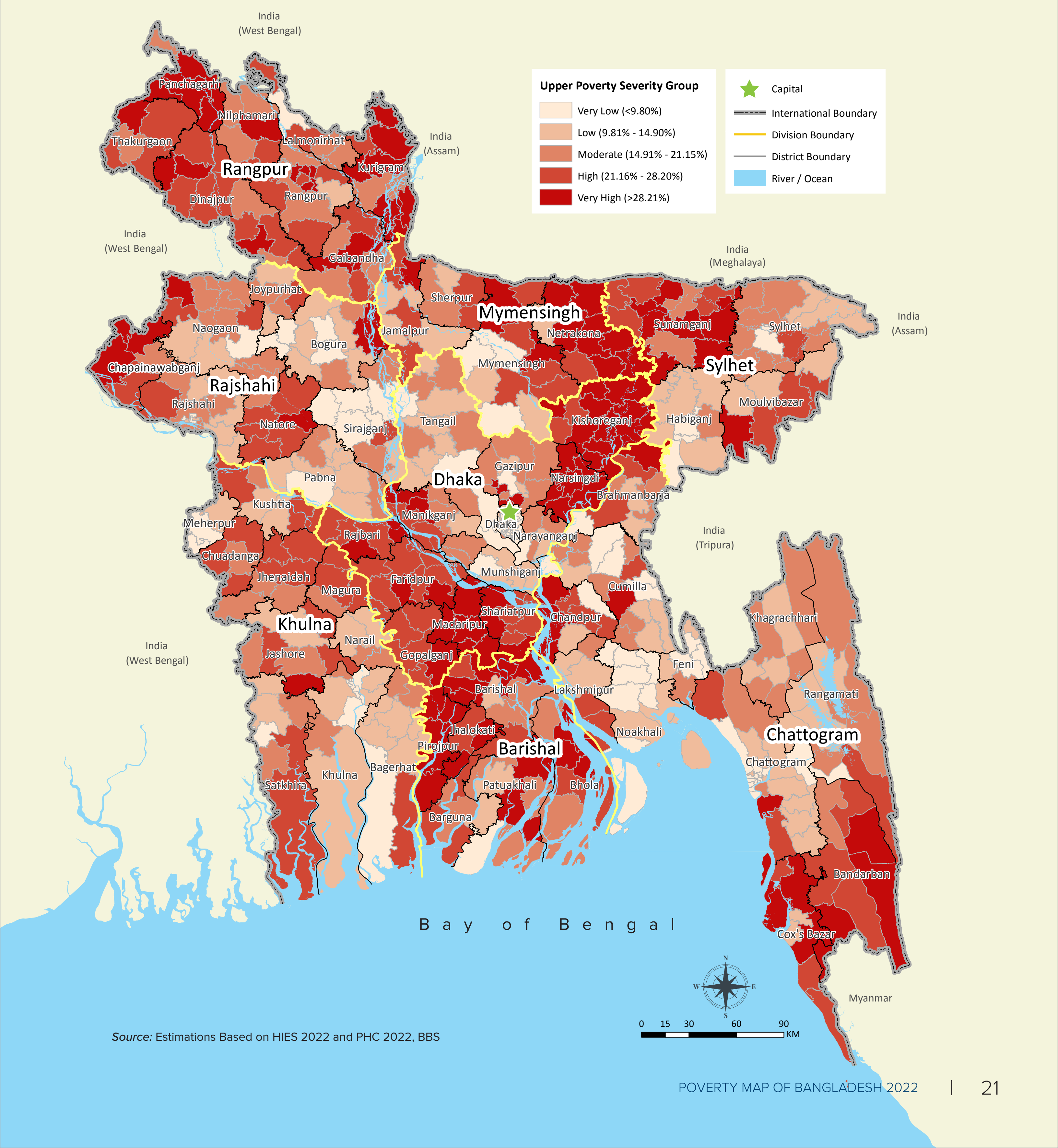
Map 1: Poverty Estimates at District Level (Upper Poverty Line), 2022 [CensusEB]



Source: Estimations Based on HIES 2022 and PHC 2022, BBS

3.3. POVERTY ESTIMATES AT UPAZILA LEVEL (UPL), 2022 [CensusEB]

Map 2: Poverty Estimates at Upazila Level (Upper Poverty Line), 2022 [CensusEB]



Source: Estimations Based on HIES 2022 and PHC 2022, BBS

3.4. POVERTY LEVEL BY DIVISION

Table 7 outlines the distribution of districts within each of Bangladesh's eight divisions according to five designated poverty quantiles. Notably, divisions such as Chattogram, Khulna, and Rajshahi exhibit a substantial number of districts classified within the 'First' and 'Second' quantiles, indicating lower levels of poverty. Conversely, divisions like Rangpur and Barishal show a concentration of districts in the 'Fifth' and 'Fourth' quantiles, suggesting higher poverty rates and presenting significant economic challenges that could benefit from intensified development initiatives. Meanwhile, division such as Dhaka displays a wide distribution across all quantiles, reflecting a heterogeneous mix of economic conditions within each division.

This pattern of economic disparity is further mirrored at the upazila level as detailed in Table 8, which underscores both the regional economic disparities and the potential for targeted interventions. Chattogram again stands out with a balanced distribution across all quantiles and notably fewer upazilas in the 'Fifth' quantile, suggesting better overall economic conditions. Conversely, Barishal and Rangpur display a significant clustering of upazilas within the 'Fifth' quantile, marking these areas as particularly vulnerable and in need of targeted poverty alleviation efforts. Dhaka, despite its economic importance and having the largest number of upazilas/metro thanas at 147, exhibits significant internal economic contrasts, with a considerable number of upazilas in both the 'First'

Table 7: Distribution of Districts Across Different Poverty Levels, 2022

Division	Number of Districts					
	Very low (Q1) (<9.80)	Low (Q2) (9.81-14.90)	Moderate (Q3) (14.91-21.15)	High (Q4) (21.16-28.20)	Very high (Q5) (>28.20)	Total
Barishal	0	0	2	2	2	6
Chattogram	1	4	3	3	0	11
Dhaka	1	3	1	5	3	13
Khulna	1	3	4	2	0	10
Mymensingh	0	0	3	0	1	4
Rajshahi	0	3	3	1	1	8
Rangpur	0	0	1	5	2	8
Sylhet	0	1	2	1	0	4
Total	3	14	19	19	9	64

Source: Estimations based on HIES 2022 and PHC of 2022, BBS

Table 8: Distribution of Upazilas/Thanas Across Different Poverty Levels, 2022

Division	Number of Upazila/Thana					
	Very low (Q1) (<9.80)	Low (Q2) (9.81-14.90)	Moderate (Q3) (14.91-21.15)	High (Q4) (21.16-28.20)	Very high (Q5) (>28.20)	Total
Barishal	1	3	10	9	19	42
Chattogram	32	33	24	17	13	119
Dhaka	48	21	20	21	37	147
Khulna	11	19	15	18	1	64
Mymensingh	3	7	2	11	12	35

Table 8: Distribution of Upazilas/Thanas Across Different Poverty Levels, 2022 (*continued*)

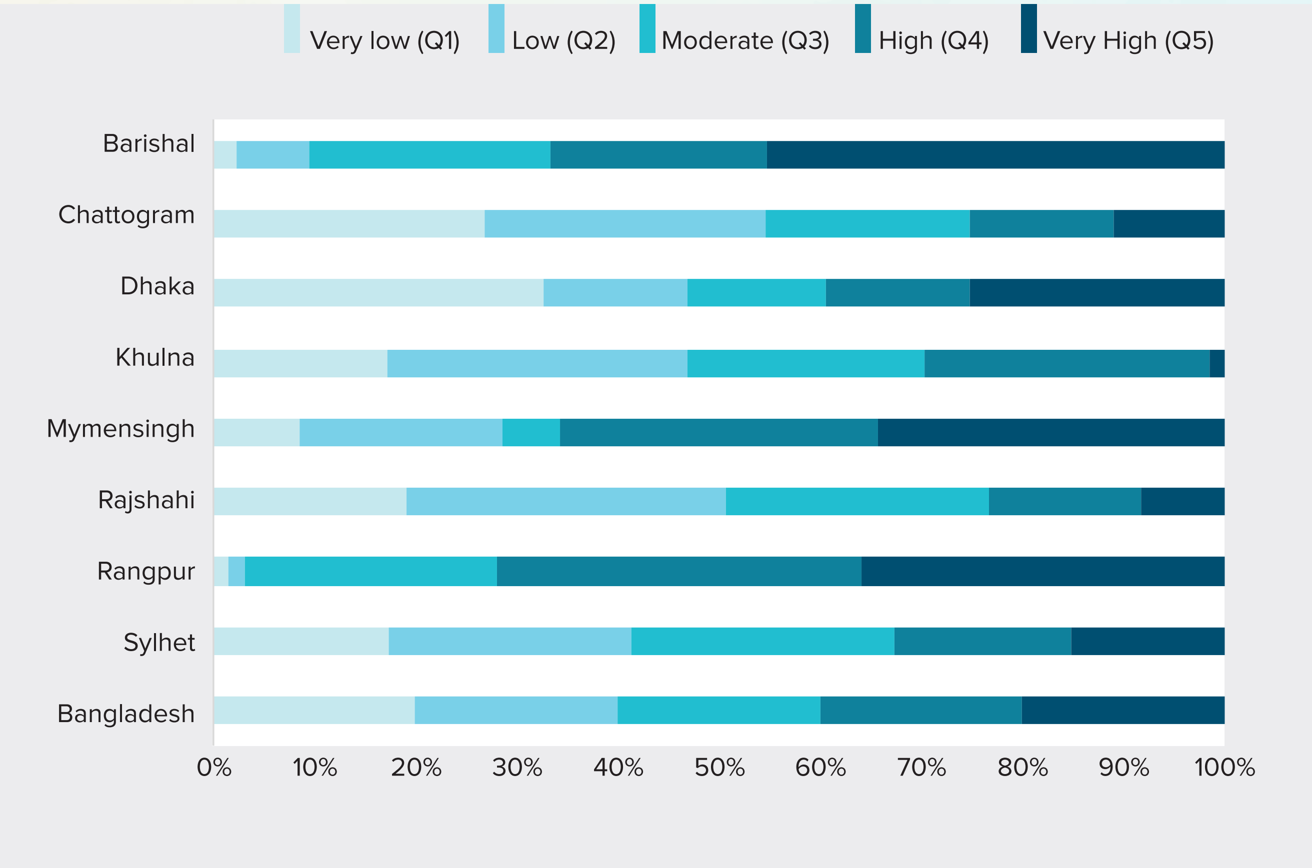
Division	Number of Upazila/Thana					
	Very low (Q1) (<9.80)	Low (Q2) (9.81-14.90)	Moderate (Q3) (14.91-21.15)	High (Q4) (21.16-28.20)	Very high (Q5) (>28.20)	Total
Rajshahi	14	23	19	11	6	73
Rangpur	1	1	16	23	23	64
Sylhet	8	11	12	8	7	46
Total	118	118	118	118	118	590

Source: Estimations based on HIES 2022 and PHC 2022, BBS

and 'Fifth' quantiles, highlighting the need for nuanced policy approaches that can address such disparities. Similarly, Khulna and Rajshahi, with their strengths in the third quantiles, indicate a level of economic stability that could potentially be leveraged to enhance further economic growth.

Figure 7 offers a visual representation of the distribution of poverty across the divisions of Bangladesh, effectively complementing the data presented in the previous tables. This diagram provides an immediate and clear insight into the regional disparities in poverty levels, highlighting the need for precisely targeted local policies. To address these complexities effectively, policy interventions must be customized both at the divisional level and within individual divisions, ensuring that strategies are specifically tailored to meet the unique challenges and opportunities present in each district and upazila.

Figure 7: Distribution of Upazila/Thana Level Poverty Groups by Division, 2022



Source: Estimations based on HIES 2022 and PHC 2022, BBS

3.5. POVERTY LEVEL BY DISTRICT

Table 9 shows the variability in poverty levels within Districts. This distribution reflects the diverse economic conditions prevalent across the country's districts, with some districts showing a concentration of upazilas in the 'First' quantile, such as Dhaka, which has a notably high number of upazilas in the wealthiest quantile. In contrast, districts like Kishoreganj, Kurigram, Pirojpur, and Netrakona have a significant number of upazilas in the 'Fifth' quantile, highlighting regions with acute economic challenges. This varied landscape of economic conditions necessitates a deeper understanding and continual monitoring of district-level data to better inform development strategies and resource allocation.

Table 9: Distribution of Upazilas/Thanas Across Different Poverty Levels by District, 2022

District	Number of Upazilas/Thanas					
	Very low (Q1) (<9.80)	Low (Q2) (9.81-14.90)	Moderate (Q3) (14.91-21.15)	High (Q4) (21.16-28.20)	Very high (Q5) (>28.20)	Total
Bagerhat	1	5	2	1	0	9
Bandarban	0	0	1	3	3	7
Barguna	0	1	2	3	0	6
Barishal	0	1	2	2	5	10
Bhola	0	0	2	2	3	7
Bogura	4	5	2	0	1	12
Brahmanbaria	1	2	3	2	1	9
Chandpur	1	1	0	3	3	8
Chapainawabganj	0	0	1	1	3	5
Chattogram	15	10	2	2	1	30
Chuadanga	0	0	1	3	0	4
Cox's Bazar	0	2	0	3	4	9
Cumilla	4	4	7	1	1	17
Dhaka	42	8	5	0	0	55
Dinajpur	0	0	2	8	3	13
Faridpur	0	0	0	7	2	9
Feni	3	2	1	0	0	6
Gaibandha	0	0	3	2	2	7
Gazipur	1	1	6	0	5	13
Gopalganj	0	0	0	4	1	5
Habiganj	3	5	1	0	0	9
Jamalpur	0	3	0	3	1	7
Jashore	0	2	2	3	1	8
Jhalokati	0	0	0	2	2	4
Jhenaidah	0	0	3	3	0	6
Joypurhat	0	2	2	1	0	5
Khagrachhari	0	4	5	0	0	9
Khulna	7	5	2	0	0	14

Table 9: Distribution of Upazilas/Thanas Across Different Poverty Levels by District, 2022 (*continued*)

District	Number of Upazilas/Thanas					
	Very low (Q1) (<9.80)	Low (Q2) (9.81-14.90)	Moderate (Q3) (14.91-21.15)	High (Q4) (21.16-28.20)	Very high (Q5) (>28.20)	Total
Kishoreganj	0	0	0	2	11	13
Kurigram	0	0	1	1	7	9
Kushtia	0	2	1	3	0	6
Lakshmipur	0	2	1	2	0	5
Lalmonirhat	1	0	2	2	0	5
Madaripur	0	0	0	0	5	5
Magura	0	0	1	3	0	4
Manikganj	0	1	2	2	2	7
Meherpur	2	1	0	0	0	3
Moulvibazar	0	3	0	3	1	7
Munshiganj	2	4	0	0	0	6
Mymensingh	3	2	0	5	3	13
Naogaon	1	2	5	2	1	11
Narail	0	2	1	0	0	3
Narayanganj	1	1	3	0	0	5
Narsingdi	0	0	0	0	6	6
Natore	0	0	1	5	1	7
Netrakona	0	1	0	1	8	10
Nilphamari	0	0	3	2	1	6
Noakhali	7	2	0	0	0	9
Pabna	1	6	2	0	0	9
Panchagarh	0	0	1	0	4	5
Patuakhali	1	1	4	0	2	8
Pirojpur	0	0	0	0	7	7
Rajbari	0	0	0	3	2	5
Rajshahi	3	7	4	1	0	15
Rangamati	1	4	4	1	0	10
Rangpur	0	1	3	5	5	14
Satkhira	1	2	2	2	0	7
Shariatpur	0	0	0	3	3	6
Sherpur	0	1	2	2	0	5
Sirajganj	5	1	2	1	0	9
Sunamganj	0	0	2	4	6	12
Sylhet	5	3	9	1	0	18
Tangail	2	6	4	0	0	12
Thakurgaon	0	0	1	3	1	5
Total	**118**	**118**	**118**	**118**	**118**	**590**

Source: Estimations based on HIES 2022 and PHC 2022, BBS

4

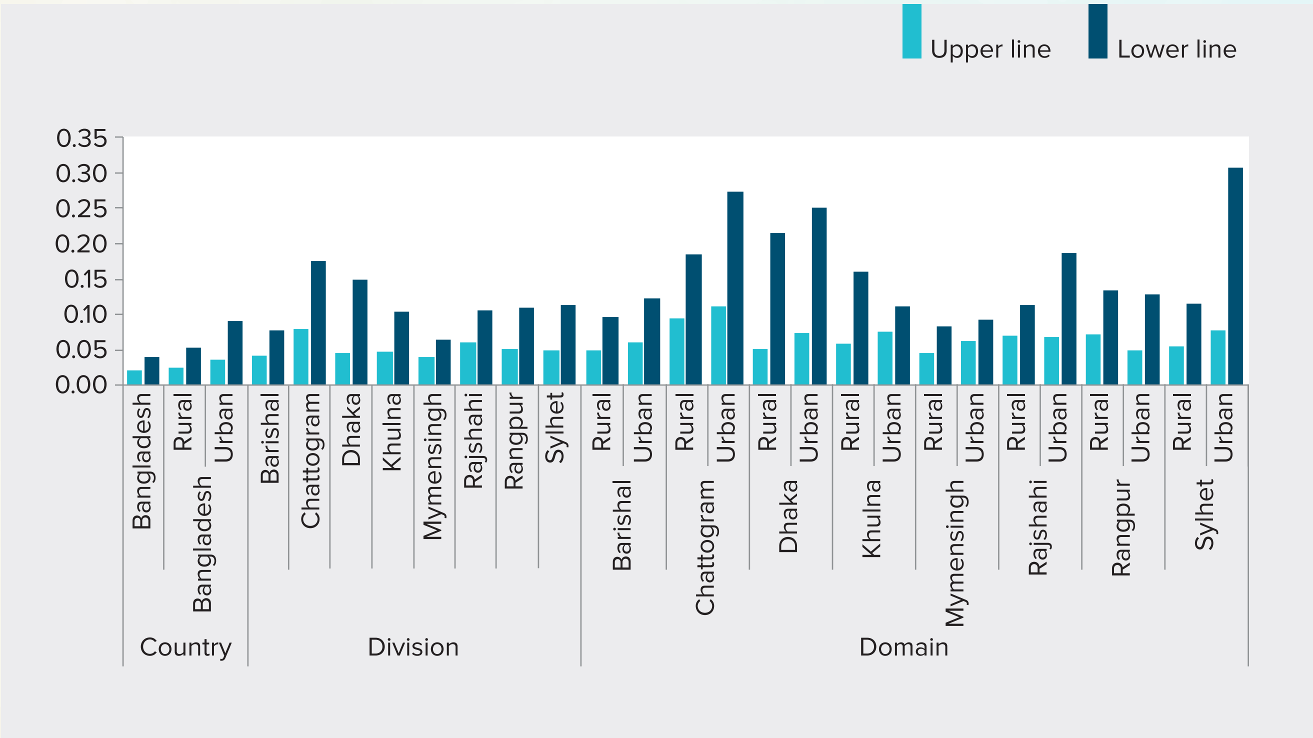
MAPPING EXTREME POVERTY (LPL)

There is a high demand of portraying the extreme poverty pictures at granular level by the stakeholders. The mapping of the extreme poverty using the SAE method has significant challenges, particularly at disaggregated levels.

The coefficient of variation (CV), which combines mean estimates and standard errors, is a critical metric for comparing populations with substantial variation in their mean values, such as poverty levels. A CV threshold of 15% is suggested by established survey sampling standards (Groves, 2009; Lohr, 2019; Rao & Molina, 2015). Estimates exceeding this threshold are generally considered less precise and unsuitable for robust analysis and reporting. However, in our case, at finer reporting levels, SAE extreme poverty estimates frequently exceed the 15% CV threshold, whereas estimates for the upper poverty rates remain below 15% (Figure 8). This discrepancy further underscores the lower reliability of extreme poverty estimates compared to those based on the upper poverty line."

Disclaimer: The challenges arise from the relatively low national extreme poverty rate of 5.6%, which is even lower in urban areas at 3.8%. This low prevalence leads to higher coefficients of variation (CV) and wider confidence intervals compared to estimates based on the upper poverty line. In some cases, the high CV results in confidence intervals that include negative values which are somehow impractical and statistically less reliable.

Figure 8: Coefficient of variation of poverty estimates by poverty lines, 2022



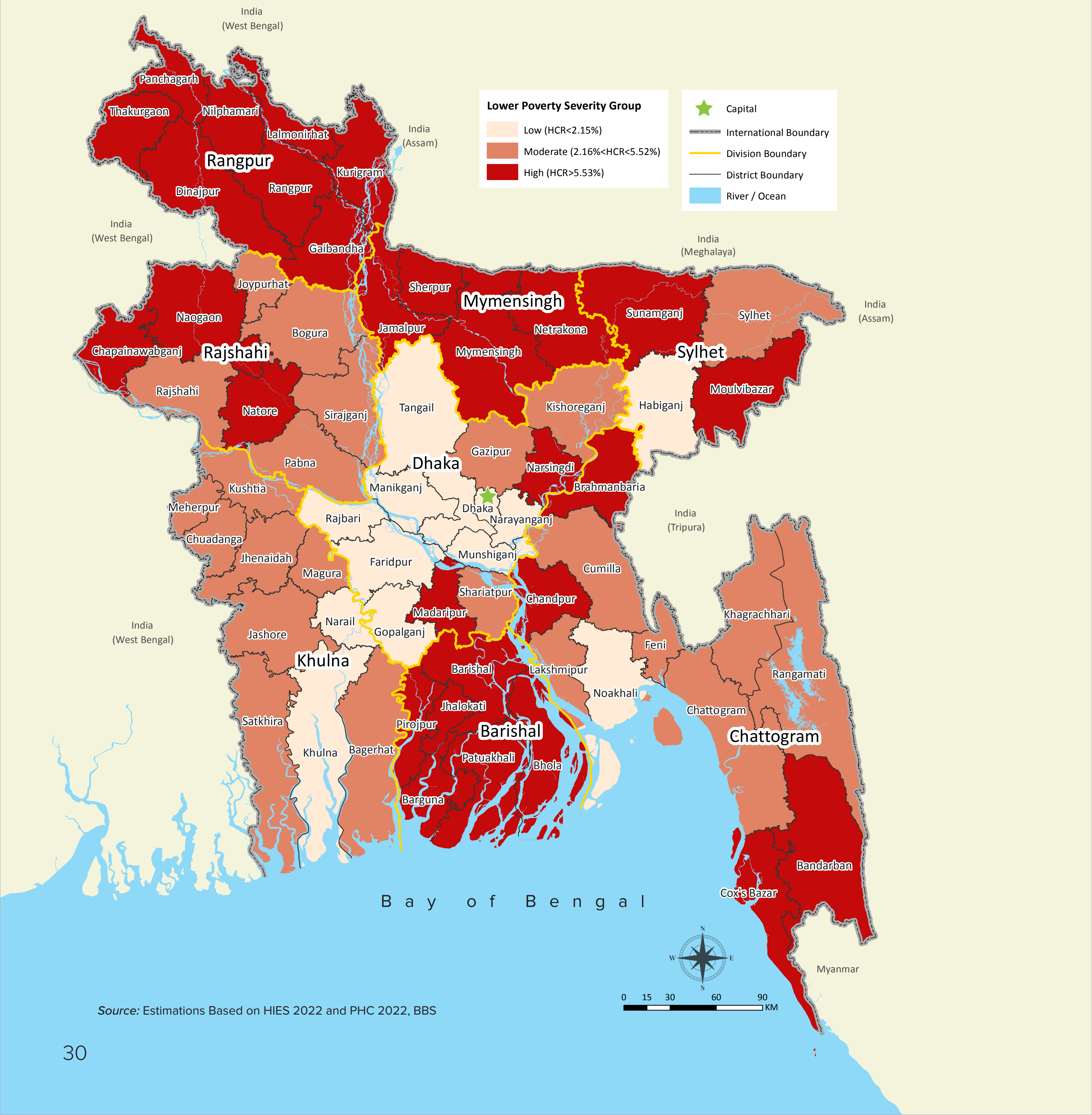
Source: Estimations based on HIES 2022 and Population and Housing Census of 2022, BBS

Given these challenges, we recommend focusing on estimates based on the upper poverty line for more dependable data interpretation and policy formulation. Nevertheless, to derive some insights into extreme poverty, the report categorizes upazilas and districts into three groups based on upazila-level poverty quantiles. Each category contains an equal number of upazilas, with thresholds defined as low (below 2.15%), moderate (2.16% to 5.52%), and high (above 5.53%). These groupings offer a broader view of spatial disparities in extreme poverty while acknowledging the limitations of precision. By focusing on patterns rather than specific point estimates, this approach provides a practical framework for identifying areas of acute need and guiding targeted interventions.

4.1. EXTREME POVERTY ESTIMATES AT DISTRICT LEVEL (LPL), 2022 [CensusEB]

The map reveals that extreme poverty is the most concentrated in divisions such as Rangpur, Mymensingh and Barishal District. In contrast, the districts in Dhaka Division are predominantly categorized in the low level of extreme poverty.

Map 3: Extreme Poverty Estimates at District Level (Lower Poverty Line), 2022 [CensusEB]

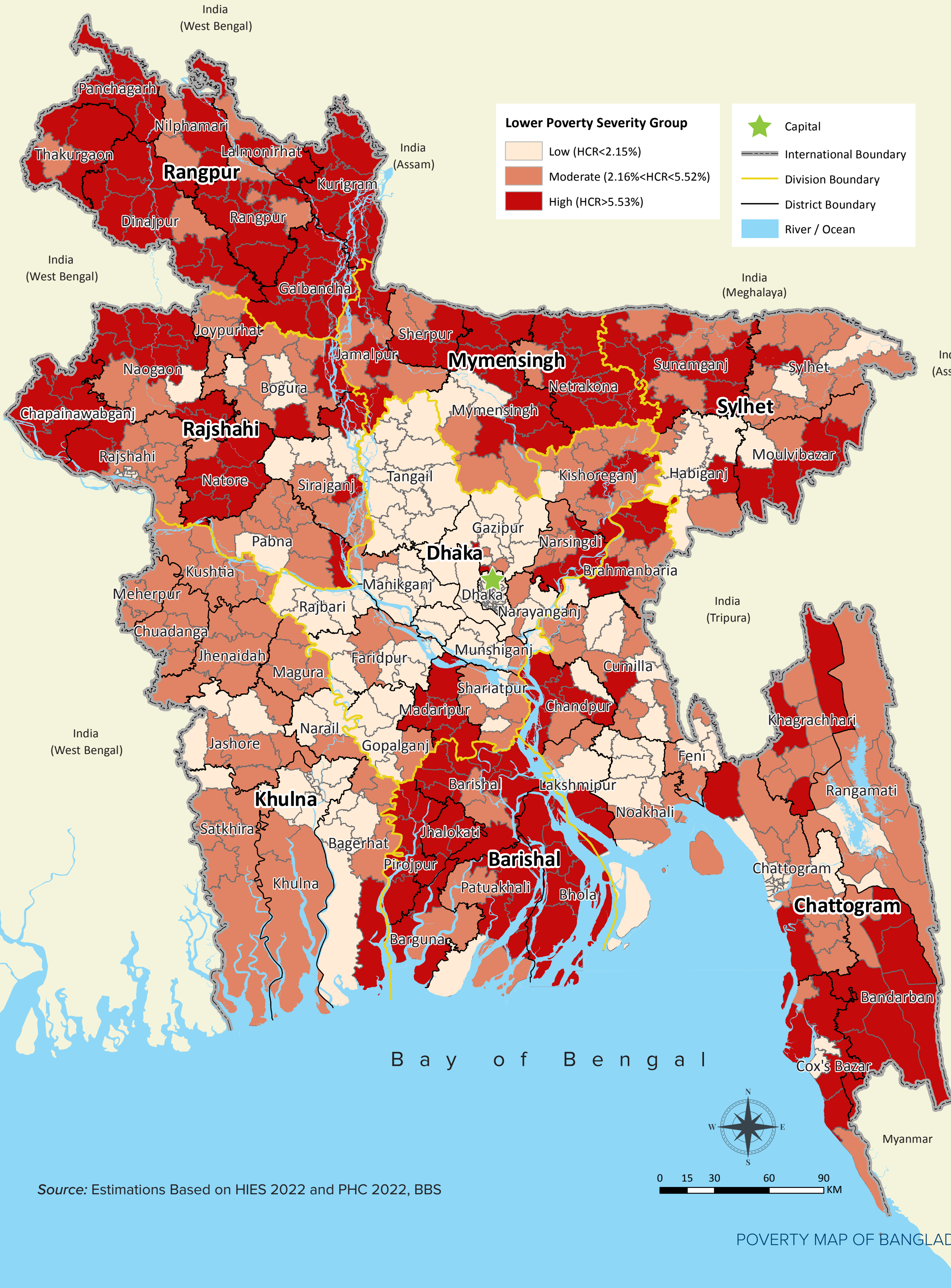


Source: Estimations Based on HIES 2022 and PHC 2022, BBS

4.2. EXTREME POVERTY ESTIMATES AT UPAZILA LEVEL (LPL), 2022 [CensusEB]

The Upazila-level CensusEB poverty map provides a more granular perspective on extreme poverty, revealing localized pockets of deprivation that might otherwise be obscured within broader district-level analyses. By aligning thresholds with the district-level analysis, the map ensures comparability while capturing the heightened variability of poverty at this finer scale. For instance, in Rangpur district—generally classified as "high poverty"—the upazila-level map pinpoints specific areas where poverty is especially acute.

Map 4: Extreme Poverty Estimates at Upazila Level (Lower Poverty Line), 2022 [CensusEB]



Source: Estimations Based on HIES 2022 and PHC 2022, BBS

5

A COMPARATIVE ANALYSIS OF POVERTY: A DECADAL SNAPSHOT (2010-2022)

Comparing poverty estimates over time presents significant challenges due to several key enhancements introduced in the HIES 2022. As previously mentioned, the 2022 round implemented improvements in survey design and fieldwork operation, which affected the comparability of the consumption aggregate with earlier rounds. Additionally, poverty lines were also re-estimated in 2022 to reflect new consumption patterns, further complicating longitudinal comparisons of poverty incidence.

Other methodological changes also hinder comparability. The 2022 maps used the CensusEB method instead of the ELL method used in previous years. CensusEB provides more accurate and precise estimates by effectively integrating auxiliary information and incorporating advanced techniques. Furthermore, the number of upazilas has increased over time, with more upazilas in 2022 compared to 2010, affecting the geographic granularity of the estimates. Another significant issue is the change in sample size.

To measure trends accurately, it is necessary to adjust the consumption aggregate of previous rounds to 2022 standards, use the same poverty lines as in 2022, align the previous upazila maps to the 2022 map, and employ the same poverty map methodology. Despite these challenges, the BBS reconstructed the national poverty trend from 2010 to 2022 and published comparable figures in the HIES 2022 report. In this report, an effort was made to reconstruct comparable SAE CensusEB poverty estimates for 2010 to enable a longitudinal comparison.

5.1. ALIGNING THE POVERTY MAP 2010 WITH THE POVERTY MAP 2022

To enable meaningful comparisons between the 2010 and 2022 poverty maps, critical adjustments were made to align methodologies and standards. These included revisions to consumption aggregates, poverty lines, administrative boundaries, and estimation methods.

First, adjustments to consumption aggregates and poverty lines were necessary due to significant changes in the 2022 HIES. Using a survey-to-survey imputation method (BBS, 2023b), the 2010 consumption aggregates were recalibrated, and poverty lines were revised to ensure compatibility with 2022 standards.

Second, upazila-level boundary harmonization addressed administrative changes over time. The 2022 upazila boundaries were overlaid with the 2011 mouza-level shapefile to identify comparable units. Mouza centroids from 2011 were matched to their corresponding 2022 upazila boundaries, and a geocode bridge was constructed to link 2011 and 2022 geocodes.

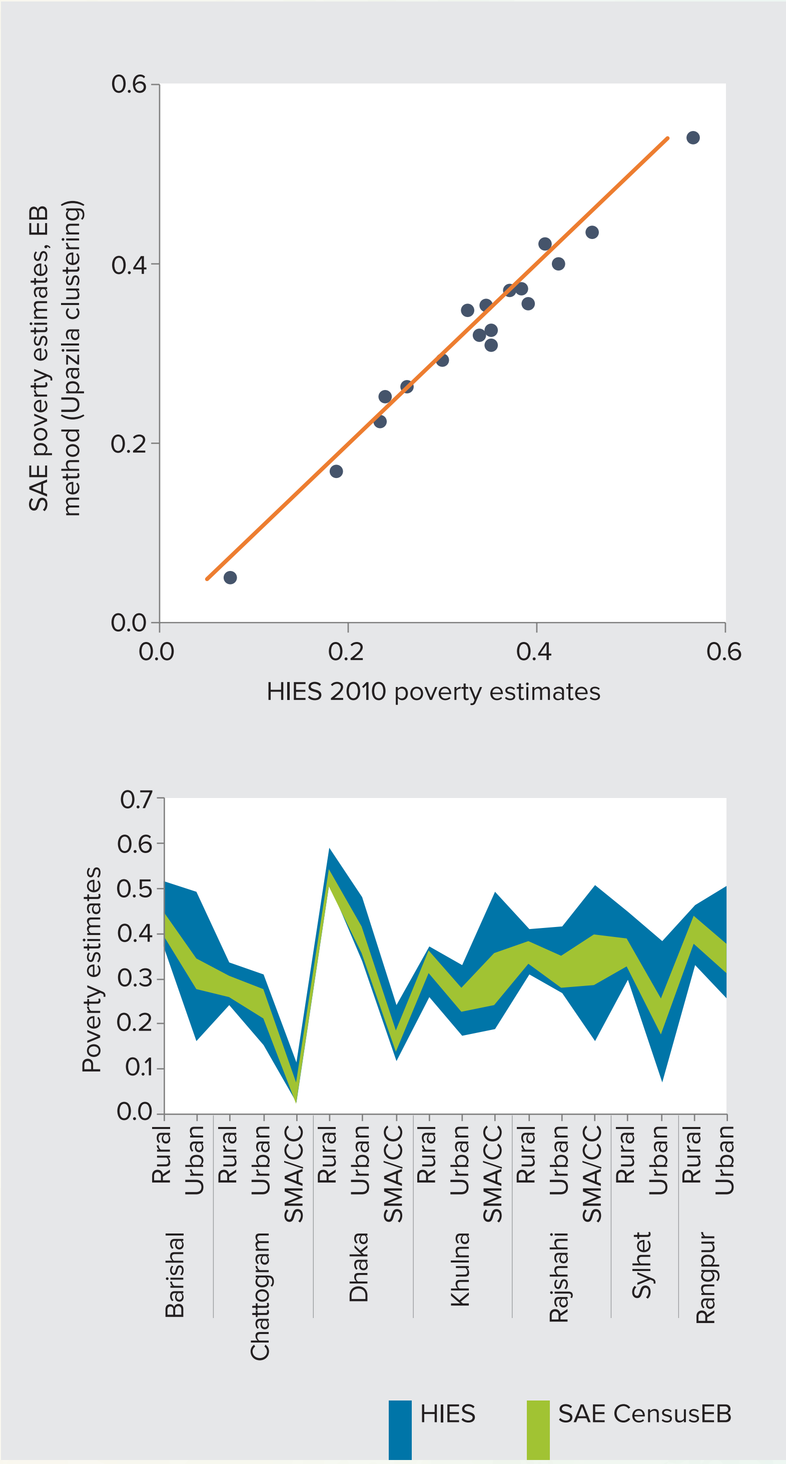
Lastly, the estimation methodology was updated. The 2010 maps, initially created using the ELL method, were re-estimated using the CensusEB method, as described in Chapter 2, (Corral et al., 2022). These updated estimates align well with 2010 HIES poverty headcounts at national, divisional, and domain levels, providing a reliable benchmark. Tables 10 and Figure 9 illustrate this alignment and confirm the reliability of these adjustments.

Table 10: Small area poverty estimates at national and division level, upazila clustering (UPL), 2010

	HIES				SAE, CensusEB			
	Mean	SE	LL	UL	Mean	SE	LL	UL
National	0.371	0.009	0.353	0.388	0.377	0.004	0.369	0.385
Rural	0.244	0.016	0.213	0.274	0.239	0.006	0.228	0.250
Urban	0.416	0.011	0.395	0.437	0.411	0.005	0.401	0.421
Barishal	0.438	0.033	0.372	0.505	0.422	0.013	0.397	0.446
Chattogram	0.257	0.019	0.218	0.295	0.262	0.011	0.240	0.284
Dhaka	0.433	0.017	0.400	0.466	0.450	0.009	0.431	0.468
Khulna	0.321	0.023	0.275	0.368	0.338	0.012	0.315	0.361
Mymensingh	0.368	0.022	0.324	0.413	0.363	0.012	0.341	0.386
Rajshahi	0.406	0.031	0.345	0.467	0.415	0.015	0.387	0.444
Rangpur	0.362	0.033	0.294	0.429	0.355	0.015	0.327	0.384
Sylhet	0.438	0.033	0.372	0.505	0.422	0.013	0.397	0.446

Note: CensusEB estimates with heteroskedasticity and sample weights. Mean=point estimate, SE=√MSE, LL=lower limit, UL=upper limit.
Source: Estimations based on HIES 2010 and PHC 2011, BBS

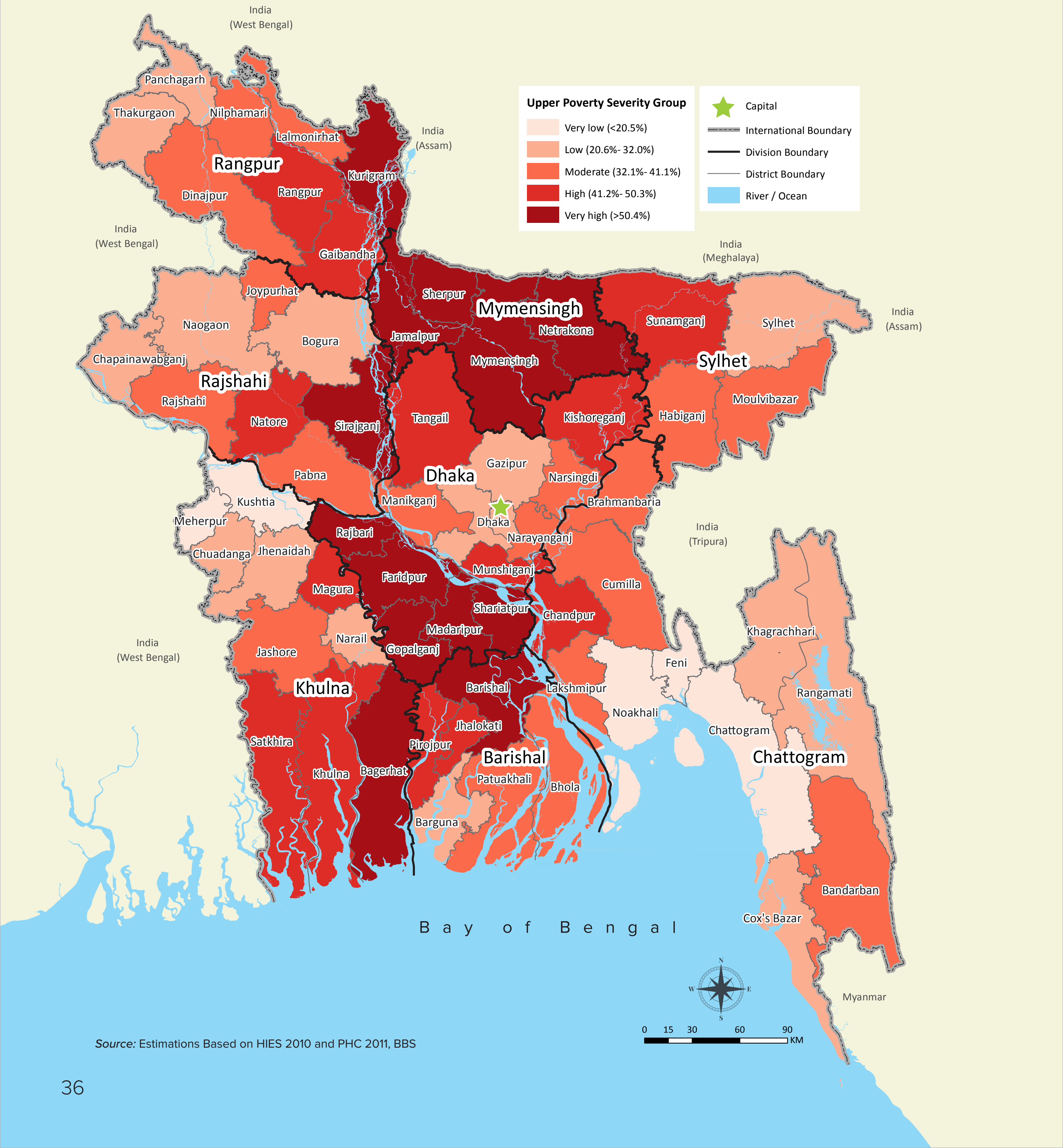
Figure 9: HIES and CensusEB Poverty Estimates Alignment at the Domain Level, Upazila Clustering, 2010



Note: CensusEB estimates with heteroskedasticity and sample weights
Source: Estimations based on HIES 2010 and PHC 2011, BBS

5.2. POVERTY ESTIMATES AT DISTRICT LEVEL (UPL), 2010 [CensusEB]

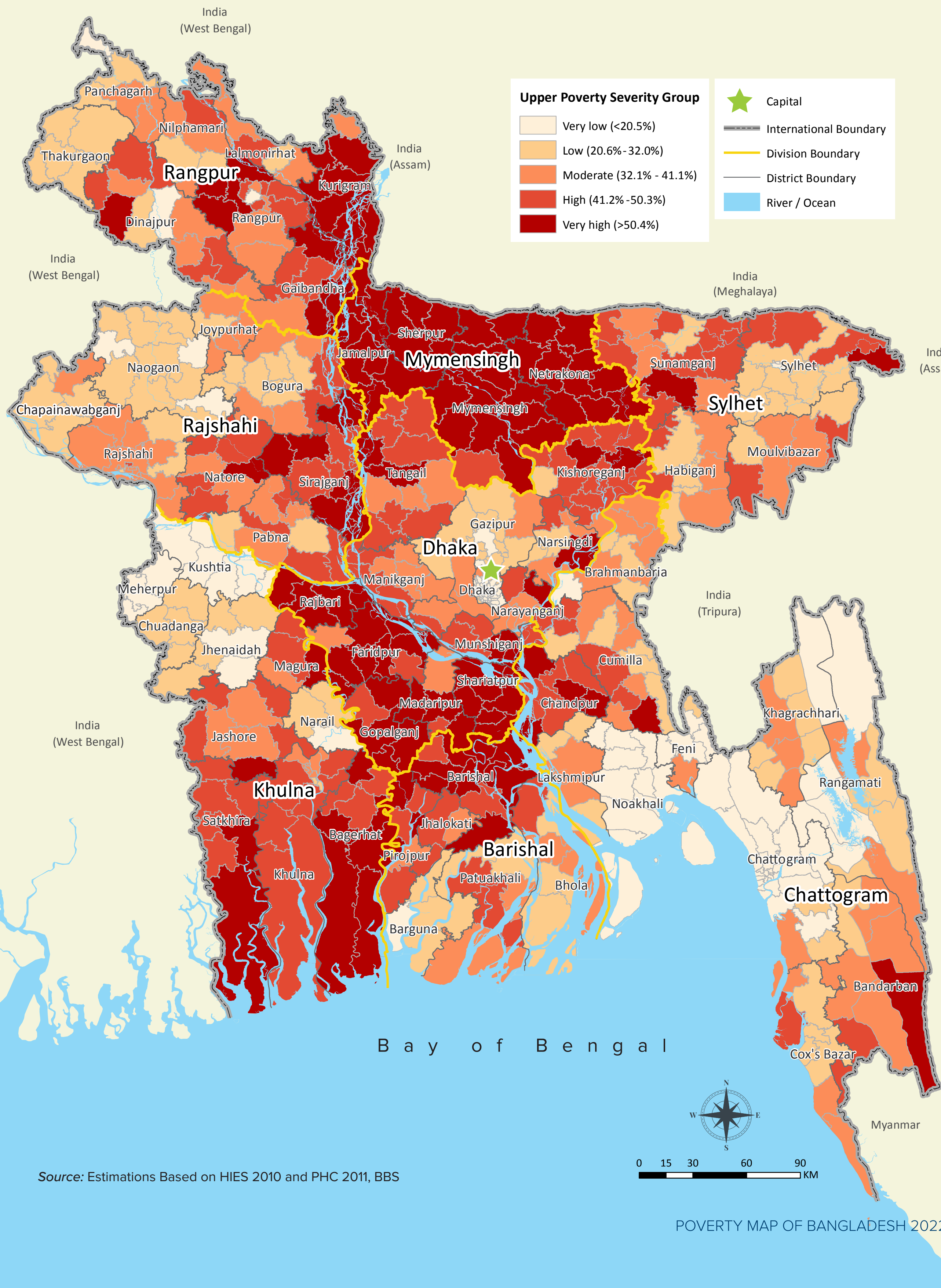
Map 5: Poverty Estimates at District Level (Upper Poverty Line), 2010 [CensusEB]



Source: Estimations Based on HIES 2010 and PHC 2011, BBS

5.3. POVERTY ESTIMATES AT UPAZILA LEVEL (UPL), 2010 [CensusEB]

Map 6: Poverty Estimates at Upazila Level (Upper Poverty Line), 2010 [CensusEB]

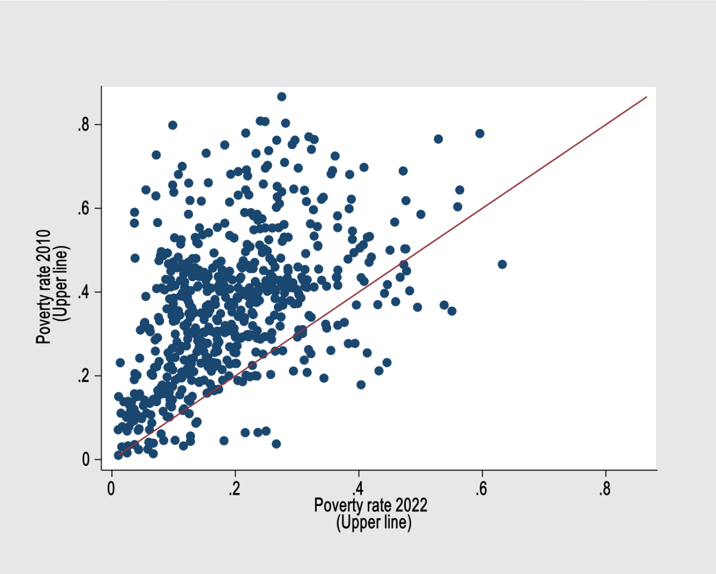


Source: Estimations Based on HIES 2010 and PHC 2011, BBS

5.4. CHANGE IN POVERTY 2010 TO 2022 AT UPAZILA LEVEL

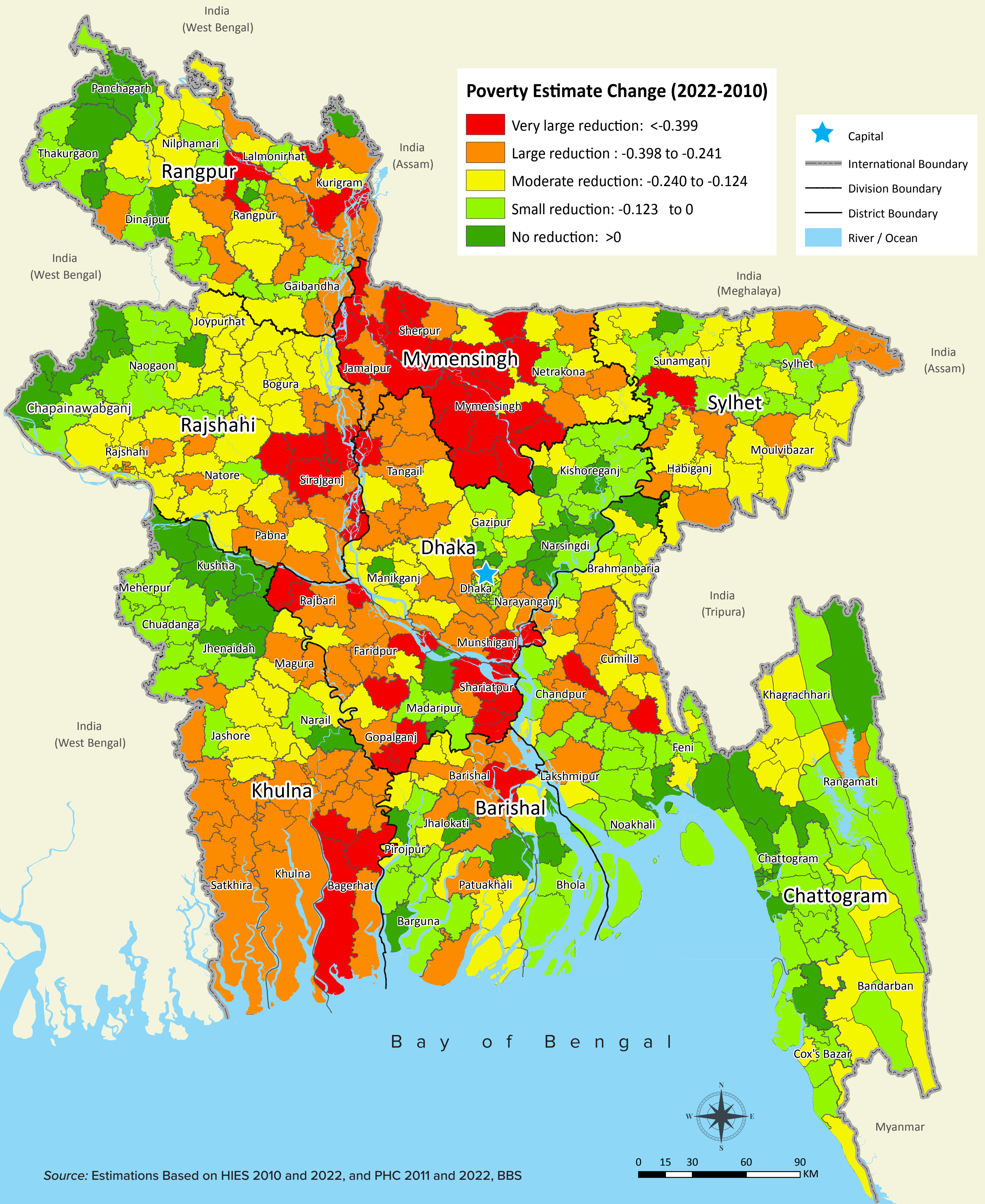
Between 2010 and 2022, poverty at the upazila level declined significantly, with nearly 90% of upazilas experiencing a reduction in poverty incidence. This progress is evident in a median reduction of 15 percentage points and an average reduction of 17 percentage points. The largest reductions occurred in upazilas with the highest poverty rates in 2010, indicating a convergence effect where areas with initially higher poverty levels made the most substantial gains. Regionally, western upazilas saw greater reductions in poverty headcounts compared to those in the eastern region, reflecting geographic variations in poverty alleviation (Figure 10).

Figure 10: Poverty Estimates Change 2010-2022



Source: Estimations based on HIES 2010 and 2022, and PHC 2011 and 2022

Map 7: Change in Poverty 2010 to 2022 at Upazila Level



Source: Estimations Based on HIES 2010 and 2022, and PHC 2011 and 2022, BBS

6

CONCLUDING REMARKS

The Poverty Map of Bangladesh 2022 reflect on the strides made in enhancing our understanding of poverty across Bangladesh. This year's report, backed by robust data from the HIES 2022 and the PHC 2022, provides a comprehensive view of poverty at granular levels, extending our insights down to the upazila level. The meticulous application of the CensusEB method has significantly improved the accuracy and reliability of poverty estimates, enabling us to pinpoint areas of critical need with higher precision.

The findings from this iteration of poverty maps underscore the persistent geographic and demographic disparities in poverty levels across Bangladesh.

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While some areas show promising signs of economic stability and even prosperity, others remain entrenched in cycles of poverty that demand urgent and targeted intervention. The stratification of districts and upazilas into quantiles of poverty has revealed both the broad regional patterns of wealth distribution and the nuanced intra-regional variations that complicate the task of poverty alleviation.

This nuanced understanding of poverty distribution is crucial for the effective allocation of resources and the strategic planning of development initiatives. By identifying specific areas where poverty is most acute, policymakers, development partners, and stakeholders are better equipped to tailor their interventions to meet the distinct needs of these communities. Moreover, the alignment of our poverty estimates with SDGs provides a clear pathway toward achieving more equitable development outcomes across the nation.

The insights gained from this report should serve as a cornerstone for ongoing and future efforts to reduce poverty in Bangladesh. The use of advanced statistical techniques and detailed data analysis should continue to evolve, reflecting our commitment to refining our understanding of poverty and improving the lives of the most vulnerable populations. These efforts must remain dynamic and responsive to Bangladesh’s changing socio-economic landscape.

In conclusion, the "Poverty Map of Bangladesh 2022" not only highlight the progress made but also illuminate the challenges that lie ahead. With the continued commitment of the Bangladesh Bureau of Statistics, in collaboration with international partners and local stakeholders, we can look forward to making significant strides in the fight against poverty. By harnessing the power of detailed, accurate data and innovative analysis techniques, we can ensure that our development efforts are both impactful and inclusive, steering Bangladesh towards a future where prosperity is shared by all.

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ANNEX

ANNEX 1
DIVISION, DISTRICT AND UPAZILA LEVEL POVERTY RATES OF 2022 AND 2010

Name	Population[20]	2022			2010[21]		
		Quintile	HCR Upper (%)	Standard Error (%)	Quintile	HCR Upper (%)	Standard Error (%)
Barishal Division	**8900160**		**26.6**	**1.1**		**43.8**	**3.3**
Barguna District	**992721**	**Moderate (Q3)**	**19.8**	**2.9**	**Low**	**24.4**	**2.5**
Amtali	211015	Low (Q2)	14.9	5.0	Low (Q2)	25.8	4.2
Bamna	77419	Moderate (Q3)	20.2	10.5	Low (Q2)	22.9	8.5
Barguna Sadar	288426	Moderate (Q3)	18.6	3.0	Low (Q2)	23.7	4.3
Betagi	124379	High (Q4)	22.3	10.2	Low (Q2)	29.8	4.5
Patharghata	175873	High (Q4)	23.5	2.2	Very Low (Q1)	20.0	5.3
Taltali	115609	High (Q4)	23.3	9.6	Low (Q2)	25.7	5.9
Barishal District	**2496625**	**High (Q4)**	**25.7**	**1.7**	**Very high**	**56.1**	**2.5**
Agailjhara	153523	High (Q4)	24.9	4.7	High (Q4)	42.7	5.5
Babuganj	150640	Low (Q2)	13.7	5.0	Very High (Q5)	51.9	12.1
Bakerganj	346151	High (Q4)	27.1	3.4	Very High (Q5)	61.1	5.7
Banaripara	167200	Very High (Q5)	38.4	4.1	Very High (Q5)	59.9	5.1
Gaurnadi	202870	Very High (Q5)	33.3	4.0	Very High (Q5)	55.6	3.9
Hijla	148102	Very High (Q5)	35.7	13.3	Very High (Q5)	69.0	9.8
Barishal Sadar	617993	Moderate (Q3)	18.5	1.4	High (Q4)	43.5	2.7
Mehendiganj	280553	Moderate (Q3)	19.2	3.8	Very High (Q5)	68.1	4.4
Muladi	178483	Very High (Q5)	31.2	5.4	Very High (Q5)	64.2	4.9
Ujirpur	251110	Very High (Q5)	32.2	3.7	Very High (Q5)	56.3	10.7
Bhola District	**1904358**	**High (Q4)**	**27.0**	**2.0**	**Moderate**	**35.3**	**3.4**
Bhola Sadar	434440	Moderate (Q3)	20.7	3.3	High (Q4)	43.1	4.0
Borhanuddin	261842	Very High (Q5)	44.2	5.1	Moderate (Q3)	39.7	6.4
Charfasson	514341	Moderate (Q3)	19.8	3.3	Low (Q2)	31.3	5.4
Daulatkhan	180248	Very High (Q5)	39.4	5.0	Low (Q2)	27.7	4.8
Lalmohan	292169	High (Q4)	23.5	5.7	Low (Q2)	30.8	5.1
Monpura	88973	High (Q4)	27.6	6.1	Moderate (Q3)	38.0	12.6
Tazumuddin	132345	Very High (Q5)	32.3	8.2	Moderate (Q3)	34.0	10.9

[20] General Household Population includes individuals in private households and excludes those in institutions (e.g., dormitories, hospitals, prisons) and the floating population (e.g., those without permanent housing or in temporary shelters).
[21] The 2010 figures have been re-estimated using the CensusEB method and comparable consumption aggregates, and therefore differ from the original 2010 poverty maps published by BBS in 2014.

Name	Population[20]	2022			2010[21]		
		Quintile	HCR Upper (%)	Standard Error (%)	Quintile	HCR Upper (%)	Standard Error (%)
Jhalokati District	**647167**	**Very High (Q5)**	**33.5**	**2.6**	**High**	**42.2**	**3.5**
Jhalokati Sadar	209894	High (Q4)	21.9	3.4	High (Q4)	46.5	3.3
Kanthalia	110496	Very High (Q5)	31.2	5.4	High (Q4)	41.3	10.2
Nalchhity	184777	Very High (Q5)	53.8	4.1	Moderate (Q3)	36.9	4.2
Rajapur	142000	High (Q4)	26.0	5.2	High (Q4)	43.7	6.6
Patuakhali District	**1687450**	**Moderate (Q3)**	**20.8**	**1.4**	**Moderate**	**36.0**	**2.7**
Bauphal	322609	Very High (Q5)	35.5	4.3	Low (Q2)	26.1	3.7
Dashmina	128549	Moderate (Q3)	20.4	3.8	Moderate (Q3)	38.5	10.2
Dumki	78579	Moderate (Q3)	18.8	3.4	Low (Q2)	30.7	11.0
Galachipa	295095	Very High (Q5)	28.5	3.9	High (Q4)	45.0	5.3
Kalapara	277035	Very Low (Q1)	7.7	2.6	Moderate (Q3)	33.1	4.1
Mirzaganj	124976	Moderate (Q3)	17.1	3.4	Low (Q2)	30.7	8.9
Patuakhali Sadar	343505	Low (Q2)	14.0	2.4	High (Q4)	41.5	4.7
Rangabali	117102	Moderate (Q3)	17.5	4.1	Moderate (Q3)	40.2	10.5
Pirojpur District	**1171839**	**Very High (Q5)**	**37.9**	**2.6**	**High**	**47.1**	**3.3**
Bhandaria	160364	Very High (Q5)	30.1	4.2	Moderate (Q3)	37.3	6.1
Pirojpur Sadar	69085	Very High (Q5)	41.4	14.3	High (Q4)	45.1	7.2
Mathbaria	272481	Very High (Q5)	39.2	5.3	High (Q4)	49.4	6.9
Nazirpur	185143	Very High (Q5)	33.4	5.7	Very High (Q5)	51.1	6.5
Pirojpur Sadar	176647	Very High (Q5)	47.7	3.8	High (Q4)	45.1	7.2
Nesarabad (Swarupkathi)	224752	Very High (Q5)	36.6	5.8	High (Q4)	45.2	5.1
Indurkani	83367	Very High (Q5)	38.9	6.2	Very High (Q5)	52.6	10.2
Chattogram Division	**32162688**	**Moderate (Q3)**	**15.2**	**1.2**	**Low (Q2)**	**25.7**	**1.9**
Bandarban District	**450692**	**High (Q4)**	**25.0**	**5.9**	**Moderate**	**39.0**	**3.6**
Alikadam	59162	High (Q4)	27.7	13.9	Moderate (Q3)	36.9	5.8
Bandarban Sadar	100447	Moderate (Q3)	18.3	6.6	Low (Q2)	30.3	7.0
Lama	133515	High (Q4)	23.7	15.2	Moderate (Q3)	40.5	5.7
Naikkhongchhari	74509	Very High (Q5)	30.8	4.2	High (Q4)	43.6	5.4
Rowangchhari	26069	High (Q4)	23.4	14.9	Moderate (Q3)	37.5	9.6
Ruma	30065	Very High (Q5)	28.7	13.7	Moderate (Q3)	41.1	7.6
Thanchi	26925	Very High (Q5)	32.8	15.6	Very High (Q5)	53.4	12.8
Brahmanbaria District	**3227902**	**Moderate (Q3)**	**20.2**	**2.7**	**Moderate**	**32.1**	**2.6**
Akhaura	164102	Moderate (Q3)	16.8	9.0	Moderate (Q3)	37.1	3.8
Banchharampur	327327	Very Low (Q1)	3.6	2.9	Very Low (Q1)	15.7	5.4
Bijoynagar	286164	Moderate (Q3)	19.7	14.7	Moderate (Q3)	37.0	9.1
Brahmanbaria Sadar	645099	Low (Q2)	13.8	3.0	Low (Q2)	25.7	3.9
Ashuganj	203505	Moderate (Q3)	17.3	9.6	Low (Q2)	28.1	4.3

ANNEX 1: DIVISION, DISTRICT AND UPAZILA LEVEL POVERTY RATES OF 2022 AND 2010 (*Continued*)

Name	Population[20]	2022			2010[21]		
		Quintile	HCR Upper (%)	Standard Error (%)	Quintile	HCR Upper (%)	Standard Error (%)
Kasba	352248	Low (Q2)	13.9	10.1	Low (Q2)	28.4	9.3
Nabinagar	546739	High (Q4)	26.1	3.8	Moderate (Q3)	41.0	4.8
Nasirnagar	344111	Very High (Q5)	45.9	6.0	Moderate (Q3)	37.7	7.1
Sarail	358607	High (Q4)	22.7	13.7	Moderate (Q3)	38.6	4.9
Chandpur District	**2580728**	**High (Q4)**	**24.6**	**3.5**	**High**	**48.9**	**2.6**
Chandpur Sadar	516696	Very High (Q5)	34.0	2.2	High (Q4)	42.8	5.1
Faridganj	426082	Low (Q2)	14.0	3.6	High (Q4)	43.8	5.4
Haimchar	123584	Very High (Q5)	36.5	4.6	Very High (Q5)	58.2	13.7
Hajiganj	351981	High (Q4)	24.0	14.9	Very High (Q5)	55.1	4.8
Kachua	396813	Very Low (Q1)	7.6	4.3	High (Q4)	47.5	5.5
Matlab Dakkhin	221770	High (Q4)	25.2	11.9	High (Q4)	49.8	9.1
Matlab Uttar	292872	Very High (Q5)	40.7	4.7	Very High (Q5)	51.3	5.2
Shahrasti	250930	High (Q4)	26.0	14.7	Very High (Q5)	55.3	5.1
Chattogram District	**8813087**	**Low (Q2)**	**12.0**	**1.3**	**Very low**	**18.2**	**1.9**
Akbarshah	146436	Low (Q2)	12.7	1.7	Very Low (Q1)	4.4	2.3
Anwara	311458	Very High (Q5)	34.3	4.4	Very Low (Q1)	19.4	9.1
Bayejid Bostami	373753	Very Low (Q1)	8.9	3.1	Very Low (Q1)	10.2	1.8
Banshkhali	526717	High (Q4)	21.4	5.3	Moderate (Q3)	33.0	4.0
Bakalia	218922	Low (Q2)	12.7	3.1	Very Low (Q1)	5.6	3.9
Boalkhali	253856	Low (Q2)	11.5	5.3	Very Low (Q1)	11.7	5.3
Chalk Bazar	107160	Very Low (Q1)	2.5	1.3	Very Low (Q1)	1.6	1.3
Chandanaish	246282	Low (Q2)	13.3	7.7	Low (Q2)	21.0	4.1
Chandgaon	297492	Very Low (Q1)	8.0	1.5	Very Low (Q1)	6.1	1.4
Chattogram Port	166861	Very Low (Q1)	6.7	1.4	Very Low (Q1)	3.9	2.9
Double Mooring	236454	Very Low (Q1)	1.1	1.6	Very Low (Q1)	1.0	1.1
EPZ	237441	Very Low (Q1)	2.6	1.1	Very Low (Q1)	3.3	0.7
Fatikchhari	621041	Moderate (Q3)	17.3	9.2	Very Low (Q1)	16.8	4.1
Halishahar	223012	Very Low (Q1)	6.0	1.5	Very Low (Q1)	4.1	1.2
Hathazari	470083	Low (Q2)	13.6	2.4	Very Low (Q1)	8.7	4.6
Karnaphuli	198192	Moderate (Q3)	15.4	6.8	Very Low (Q1)	15.9	7.8
Kotwali	206959	Very Low (Q1)	6.7	1.4	Very Low (Q1)	1.4	1.1
Khulshi	193239	Very Low (Q1)	5.8	2.1	Very Low (Q1)	2.5	2.2
Lohagara	318359	Low (Q2)	13.2	3.5	Low (Q2)	24.3	4.2
Mirsarai	458898	High (Q4)	25.0	3.9	Very Low (Q1)	6.8	3.3
Pahartali	184488	Very Low (Q1)	8.4	2.3	Very Low (Q1)	4.6	4.1
Panchlaish	199014	Very Low (Q1)	1.6	1.9	Very Low (Q1)	3.0	3.2
Patiya	387531	Low (Q2)	12.5	3.0	Very Low (Q1)	20.3	3.5
Patenga	155542	Very Low (Q1)	4.3	1.8	Very Low (Q1)	2.4	1.4
Rangunia	382940	Very Low (Q1)	4.1	3.1	Very Low (Q1)	15.0	6.5

Name	Population[20]	2022			2010[21]		
		Quintile	HCR Upper (%)	Standard Error (%)	Quintile	HCR Upper (%)	Standard Error (%)
Raozan	383740	Low (Q2)	9.8	5.3	Very Low (Q1)	14.3	2.8
Sadarghat	102931	Very Low (Q1)	3.7	2.1	Very Low (Q1)	3.6	2.6
Sandwip	324425	Low (Q2)	10.8	3.5	Very Low (Q1)	19.5	3.6
Satkania	440129	Low (Q2)	14.1	7.3	Very Low (Q1)	18.4	3.4
Sitakunda	439732	Very Low (Q1)	5.3	3.0	Very Low (Q1)	14.2	6.2
Cumilla District	**6017180**	**Low (Q2)**	**13.4**	**2.0**	**Moderate**	**37.4**	**2.1**
Barura	443946	Very High (Q5)	28.4	3.7	High (Q4)	43.4	5.6
Brahmanpara	228514	Moderate (Q3)	15.9	10.1	Moderate (Q3)	35.8	5.5
Burichang	339299	High (Q4)	21.5	3.5	Moderate (Q3)	33.9	11.3
Chandina	387382	Moderate (Q3)	15.2	11.0	High (Q4)	42.9	5.7
Chauddagram	492696	Low (Q2)	12.3	3.4	Low (Q2)	30.6	6.0
Sadar Dakkhin	319134	Very Low (Q1)	6.0	2.4	Low (Q2)	31.0	8.0
Daudkandi	386757	Low (Q2)	14.8	10.4	Low (Q2)	30.4	5.5
Debidwar	459951	Very Low (Q1)	6.1	2.8	Low (Q2)	31.3	5.6
Homna	222303	Moderate (Q3)	18.1	10.6	High (Q4)	41.7	8.7
Adarsha Sadar	629199	Very Low (Q1)	7.0	1.8	Low (Q2)	28.6	2.8
Laksam	324287	Moderate (Q3)	16.3	12.0	High (Q4)	45.7	4.6
Lalmai	211912	Low (Q2)	10.3	2.9	Moderate (Q3)	33.2	11.3
Manoharganj	270903	Moderate (Q3)	16.1	10.9	Moderate (Q3)	40.9	11.5
Meghna	116211	Moderate (Q3)	17.5	13.6	High (Q4)	42.9	10.2
Muradnagar	565030	Very Low (Q1)	9.3	3.9	Moderate (Q3)	38.4	5.8
Nangalkot	420035	Low (Q2)	10.1	3.3	Very High (Q5)	53.0	5.0
Titas	199621	Moderate (Q3)	15.4	12.9	High (Q4)	41.4	9.5
Cox's Bazar District	**2740161**	**High (Q4)**	**27.8**	**5.0**	**Low**	**31.6**	**3.2**
Chakaria	557613	Very High (Q5)	43.3	4.2	Low (Q2)	21.2	4.1
Cox's Bazar Sadar	389067	Low (Q2)	10.3	4.6	Low (Q2)	30.0	3.2
Eidgaon	146687	Low (Q2)	11.7	5.1	Low (Q2)	23.8	9.5
Kutubdia	142012	Very High (Q5)	31.9	13.5	Moderate (Q3)	34.4	12.6
Maheshkhali	381522	Very High (Q5)	32.7	15.8	High (Q4)	41.2	5.2
Pekua	210325	High (Q4)	25.5	4.9	Moderate (Q3)	33.2	12.3
Ramu	326071	Very High (Q5)	30.3	15.8	Low (Q2)	31.0	6.0
Teknaf	328551	High (Q4)	21.2	5.6	Moderate (Q3)	40.2	13.3
Ukhia	258313	High (Q4)	27.4	16.9	Moderate (Q3)	34.1	12.3
Feni District	**1589784**	**Low (Q2)**	**10.5**	**3.2**	**Very low**	**20.0**	**2.8**
Chhagalnaiya	201576	Very Low (Q1)	8.0	5.2	Very Low (Q1)	16.1	6.4
Daganbhuiyan	271383	Low (Q2)	11.7	2.2	Very Low (Q1)	12.1	2.4
Feni Sadar	599797	Very Low (Q1)	9.4	5.6	Very Low (Q1)	17.3	3.5
Fulgazi	121600	Very Low (Q1)	4.1	3.1	Very Low (Q1)	20.1	10.5
Parashuram	110357	Low (Q2)	11.3	7.4	Low (Q2)	20.9	3.6
Sonagazi	285071	Moderate (Q3)	15.6	10.3	Moderate (Q3)	35.0	5.1

ANNEX 1: DIVISION, DISTRICT AND UPAZILA LEVEL POVERTY RATES OF 2022 AND 2010 (*Continued*)

Name	Population[20]	2022			2010[21]		
		Quintile	HCR Upper (%)	Standard Error (%)	Quintile	HCR Upper (%)	Standard Error (%)
Khagrachhari District	**690804**	**Moderate (Q3)**	**15.9**	**4.5**	**Low**	**27.5**	**3.2**
Dighinala	111170	Moderate (Q3)	17.9	10.5	Very Low (Q1)	18.9	4.4
Guimara	51700	Low (Q2)	12.9	7.1	Moderate (Q3)	36.3	11.5
Khagrachhari Sadar	129429	Low (Q2)	12.9	6.0	Low (Q2)	22.9	6.9
Lakkhichhari	26394	Moderate (Q3)	20.5	13.6	Moderate (Q3)	34.2	14.5
Mahalchhari	47695	Moderate (Q3)	16.6	10.1	Low (Q2)	30.3	5.6
Manikchhari	74971	Moderate (Q3)	15.0	7.9	Low (Q2)	30.3	10.9
Matiranga	123878	Moderate (Q3)	19.4	11.9	Moderate (Q3)	32.3	4.3
Panchhari	67200	Low (Q2)	14.1	8.3	Low (Q2)	26.9	9.0
Ramgarh	58367	Low (Q2)	14.7	6.7	Low (Q2)	28.1	5.2
Lakshmipur District	**1894560**	**Moderate (Q3)**	**15.6**	**3.2**	**Moderate**	**32.6**	**3.0**
Kamalnagar	213870	High (Q4)	22.7	15.0	Moderate (Q3)	35.1	7.4
Lakshmipur Sadar	792380	Low (Q2)	10.0	2.3	Moderate (Q3)	38.6	4.5
Raipur	307672	Low (Q2)	14.4	7.0	Low (Q2)	23.0	4.3
Ramganj	305344	Moderate (Q3)	17.0	2.8	Low (Q2)	27.3	6.4
Ramgati	275294	High (Q4)	25.9	15.1	Low (Q2)	30.3	4.7
Noakhali District	**3541700**	**Very Low (Q1)**	**6.1**	**1.9**	**Very low**	**9.8**	**2.3**
Begumganj	590796	Very Low (Q1)	2.5	1.4	Very Low (Q1)	6.8	2.0
Chatkhil	252207	Very Low (Q1)	3.6	3.5	Very Low (Q1)	9.3	2.2
Companiganj	296351	Low (Q2)	13.8	2.1	Very Low (Q1)	9.0	5.7
Hatiya	532493	Very Low (Q1)	3.9	5.3	Very Low (Q1)	10.9	3.7
Kabirhat	236512	Very Low (Q1)	7.2	5.7	Very Low (Q1)	13.8	7.1
Senbag	305673	Very Low (Q1)	4.3	5.8	Very Low (Q1)	7.0	4.0
Sonaimuri	357940	Very Low (Q1)	6.1	1.6	Very Low (Q1)	7.1	3.8
Subarnachar	352355	Low (Q2)	14.2	11.4	Very Low (Q1)	18.7	8.9
Noakhali Sadar	617373	Very Low (Q1)	4.8	2.1	Very Low (Q1)	9.8	2.2
Rangamati District	**616090**	**Low (Q2)**	**14.3**	**5.6**	**Low**	**20.6**	**2.8**
Baghaichhari	102413	Moderate (Q3)	16.6	9.2	Very Low (Q1)	16.5	4.3
Barkal	47544	Moderate (Q3)	15.3	11.5	Low (Q2)	24.5	11.6
Kawkhali	63366	Low (Q2)	12.5	3.6	Very Low (Q1)	11.0	3.5
Belaichhari	27773	High (Q4)	26.3	12.2	Moderate (Q3)	34.5	13.4
Kaptai	51897	Moderate (Q3)	16.4	7.3	Very Low (Q1)	16.8	3.9
Jurachhari	25942	Moderate (Q3)	15.6	11.9	Low (Q2)	22.1	10.9
Langadu	88254	Low (Q2)	12.5	13.9	Moderate (Q3)	37.5	5.4
Naniarchar	47947	Low (Q2)	12.9	10.2	Very Low (Q1)	18.9	9.4
Rajasthali	25927	Very Low (Q1)	9.5	8.8	Low (Q2)	22.4	8.5
Rangamati Sadar	135027	Low (Q2)	12.4	3.3	Very Low (Q1)	14.3	2.0

ANNEX 1: DIVISION, DISTRICT AND UPAZILA LEVEL POVERTY RATES OF 2022 AND 2010 (*Continued*)

Name	Population[20]	2022			2010[21]		
		Quintile	HCR Upper (%)	Standard Error (%)	Quintile	HCR Upper (%)	Standard Error (%)
Dhaka Division	**42041851**	**Moderate (Q3)**	**19.6**	**0.9**		**43.3**	**1.7**
Dhaka District	**13514349**	**Very Low (Q1)**	**8.6**	**0.7**	**Low**	**21.5**	**1.7**
Adabar	198174	Low (Q2)	9.8	2.0	Very Low (Q1)	17.5	5.7
Badda	342175	Very Low (Q1)	7.4	1.9	Very Low (Q1)	16.5	6.8
Bangshal	141268	Very Low (Q1)	4.2	2.6	Very Low (Q1)	15.4	3.8
Bimanbandar	5787	Very Low (Q1)	1.4	1.0	Low (Q2)	23.1	2.5
Banani	155737	Low (Q2)	11.3	4.1	Very Low (Q1)	19.5	6.3
Cantonment	121394	Very Low (Q1)	2.9	1.4	Very Low (Q1)	12.8	4.0
Chawkbazar	103441	Very Low (Q1)	7.5	3.1	Very Low (Q1)	15.2	5.0
Dakkhinkhan	373870	Low (Q2)	9.8	1.7	Low (Q2)	26.5	10.0
Darussalam	193718	Low (Q2)	11.0	5.0	Very Low (Q1)	15.5	6.5
Demra	264541	Low (Q2)	13.0	2.3	Very Low (Q1)	15.1	2.8
Dhamrai	497575	Moderate (Q3)	18.3	3.4	Low (Q2)	32.0	4.2
Dhanmondi	86965	Very Low (Q1)	1.5	0.9	Very Low (Q1)	11.1	3.2
Dohar	242900	Moderate (Q3)	15.6	5.2	High (Q4)	43.7	4.8
Bhasantek	113348	Moderate (Q3)	16.2	4.9	Very Low (Q1)	16.8	7.8
Bhatara	281518	Very Low (Q1)	4.5	2.3	Very Low (Q1)	15.7	2.8
Gendaria	126731	Very Low (Q1)	2.4	1.5	Very Low (Q1)	10.1	5.0
Gulshan	93066	Very Low (Q1)	3.2	2.0	Very Low (Q1)	13.7	3.6
Hatirjheel	72061	Very Low (Q1)	5.6	2.9	Very Low (Q1)	11.1	4.8
Hazaribag	187043	Very Low (Q1)	6.3	3.8	Low (Q2)	20.5	2.4
Jatrabari	452493	Very Low (Q1)	9.4	1.5	Very Low (Q1)	14.3	5.9
Kafrul	305702	Very Low (Q1)	7.2	3.3	Very Low (Q1)	14.0	4.2
Kadamtali	400295	Very Low (Q1)	8.3	1.8	Very Low (Q1)	15.7	6.8
Kalabagan	95247	Very Low (Q1)	3.4	1.7	Very Low (Q1)	11.9	4.0
Kamrangichar	352807	Moderate (Q3)	19.1	3.3	Low (Q2)	22.8	3.3
Khilgaon	358729	Very Low (Q1)	6.1	1.9	Very Low (Q1)	13.4	5.3
Khilkhet	157142	Very Low (Q1)	7.7	3.8	Low (Q2)	23.4	6.4
Keraniganj	953448	Very Low (Q1)	8.1	2.1	Moderate (Q3)	41.0	12.4
Kotwali	36413	Very Low (Q1)	2.9	1.9	Very Low (Q1)	11.2	2.6
Lalbag	168410	Very Low (Q1)	8.9	1.8	Very Low (Q1)	19.7	2.8
Mirpur	500942	Low (Q2)	12.6	1.5	Very Low (Q1)	13.9	2.4
Mohammadpur	469673	Very Low (Q1)	4.6	1.8	Very Low (Q1)	10.2	2.8
Motijheel	61101	Very Low (Q1)	3.6	2.2	Very Low (Q1)	19.1	2.8
Mugda	196074	Very Low (Q1)	6.7	4.1	Very Low (Q1)	14.4	6.0
Nawabganj	342963	Moderate (Q3)	18.3	3.1	Moderate (Q3)	40.4	4.5
Newmarket	39372	Very Low (Q1)	1.7	1.0	Very Low (Q1)	7.9	2.5
Pallabi	562094	Very Low (Q1)	6.6	1.6	Very Low (Q1)	20.1	2.2
Paltan	43063	Very Low (Q1)	1.0	1.1	Very Low (Q1)	7.1	1.9
Ramna	178049	Very Low (Q1)	4.4	1.3	Very Low (Q1)	7.4	2.2

ANNEX 1: DIVISION, DISTRICT AND UPAZILA LEVEL POVERTY RATES OF 2022 AND 2010 (*Continued*)

Name	Population[20]	2022			2010[21]		
		Quintile	HCR Upper (%)	Standard Error (%)	Quintile	HCR Upper (%)	Standard Error (%)
Rampura	146398	Very Low (Q1)	6.3	2.5	Very Low (Q1)	10.7	3.8
Sabujbag	247294	Very Low (Q1)	5.1	2.0	Very Low (Q1)	12.9	5.4
Rupnagar	168599	Low (Q2)	11.3	4.8	Very Low (Q1)	16.7	7.1
Savar	2186852	Very Low (Q1)	7.6	1.1	Moderate (Q3)	33.9	7.3
Shahjahanpur	104866	Very Low (Q1)	3.6	2.2	Very Low (Q1)	12.0	4.5
Shah Ali	141522	Very Low (Q1)	8.2	2.7	Very Low (Q1)	16.1	5.9
Shahbag	31108	Very Low (Q1)	1.9	1.2	Very Low (Q1)	13.8	2.7
Shyampur	157327	Very Low (Q1)	9.4	4.4	Very Low (Q1)	13.0	2.1
Sher-E-Bangla Nagar	131262	Very Low (Q1)	2.7	1.4	Very Low (Q1)	13.9	3.3
Sutrapur	70805	Very Low (Q1)	2.8	1.9	Very Low (Q1)	7.9	3.3
Tejgaon	101421	Very Low (Q1)	6.5	2.9	Very Low (Q1)	8.8	1.5
Tejgaon Shilpa Elaka	84440	Low (Q2)	9.9	2.5	Low (Q2)	21.4	5.0
Turag	243751	Low (Q2)	11.7	6.6	Moderate (Q3)	38.9	10.2
Uttara Pashchim	159728	Very Low (Q1)	1.1	0.9	Very Low (Q1)	15.0	3.1
Uttara Purba	30309	Very Low (Q1)	2.7	1.3	Very Low (Q1)	10.7	2.6
Uttarkhan	121029	Very Low (Q1)	8.1	4.4	Very Low (Q1)	17.8	6.7
Wari	112309	Very Low (Q1)	3.3	1.2	Very Low (Q1)	9.1	3.7
Faridpur District	**2103804**	**High (Q4)**	**27.0**	**2.2**	**Very high**	**55.2**	**2.6**
Alfadanga	117076	High (Q4)	24.3	6.8	Very High (Q5)	50.6	10.1
Bhanga	288007	Very High (Q5)	28.5	3.8	High (Q4)	45.7	5.0
Boalmari	263237	High (Q4)	27.6	6.3	Very High (Q5)	52.1	5.3
Char Bhadrasan	69039	High (Q4)	26.6	6.2	Very High (Q5)	60.2	12.0
Faridpur Sadar	540415	High (Q4)	27.0	3.7	Very High (Q5)	55.4	5.2
Madhukhali	228342	High (Q4)	24.4	6.6	Moderate (Q3)	41.0	5.1
Nagarkanda	217717	High (Q4)	26.8	8.7	Very High (Q5)	65.2	5.8
Sadarpur	197185	High (Q4)	24.9	4.0	Very High (Q5)	69.6	5.4
Saltha	182786	Very High (Q5)	31.2	9.3	Very High (Q5)	64.3	9.5
Gazipur District	**4983154**	**Moderate (Q3)**	**20.7**	**1.8**	**Low**	**28.1**	**2.5**
Basan	248269	Very High (Q5)	30.9	8.9	Low (Q2)	30.1	9.9
Gachha	371985	Moderate (Q3)	15.5	4.5	Low (Q2)	27.8	9.8
Gazipur Sadar	326460	Low (Q2)	11.3	2.8	Low (Q2)	27.0	8.8
Kaliakair	670497	Moderate (Q3)	16.0	3.9	Low (Q2)	30.7	4.3
Kaliganj	300548	Moderate (Q3)	19.1	5.9	Low (Q2)	26.9	5.0
Kapasia	367153	Moderate (Q3)	19.4	4.6	Moderate (Q3)	36.3	4.9
Kashimpur	365270	Moderate (Q3)	20.9	6.2	Low (Q2)	29.0	8.1
Konabari	274149	Very High (Q5)	34.8	6.2	Low (Q2)	31.4	11.9
Pubail	101250	Very High (Q5)	31.1	5.7	Low (Q2)	23.7	8.4
Sreepur	807297	Moderate (Q3)	17.1	3.2	Low (Q2)	28.8	3.9

ANNEX 1: DIVISION, DISTRICT AND UPAZILA LEVEL POVERTY RATES OF 2022 AND 2010 (*Continued*)

Name	Population[20]	2022			2010[21]		
		Quintile	HCR Upper (%)	Standard Error (%)	Quintile	HCR Upper (%)	Standard Error (%)
Tongi Pashchim	292180	Very High (Q5)	40.4	4.9	Very Low (Q1)	17.9	4.1
Tongi Purba	422338	Very High (Q5)	30.0	4.9	Low (Q2)	29.3	3.8
Joydebpur	435758	Very Low (Q1)	9.1	4.4	Very Low (Q1)	17.6	4.0
Gopalganj District	**1251723**	**High (Q4)**	**25.7**	**3.2**	**Very high**	**66.6**	**2.3**
Gopalganj Sadar	377396	High (Q4)	23.7	6.5	Very High (Q5)	57.2	3.3
Kashiani	222582	High (Q4)	27.4	3.4	High (Q4)	48.1	4.9
Kotalipara	239436	Very High (Q5)	29.2	8.2	Very High (Q5)	75.2	5.7
Muksudpur	301921	High (Q4)	24.0	4.4	Very High (Q5)	80.9	4.8
Tungipara	110388	High (Q4)	26.7	7.8	Very High (Q5)	76.3	5.7
Kishoreganj District	**3201295**	**Very High (Q5)**	**35.3**	**2.7**	**High**	**43.2**	**3.1**
Austagram	150455	Very High (Q5)	40.8	10.9	High (Q4)	42.5	5.7
Bajitpur	264987	Very High (Q5)	36.3	7.6	High (Q4)	43.5	9.2
Bhairab	350749	Very High (Q5)	39.6	3.3	Moderate (Q3)	36.9	4.0
Hossainpur	199122	Very High (Q5)	28.4	7.1	High (Q4)	42.0	9.4
Itna	167396	Very High (Q5)	45.0	9.9	High (Q4)	50.0	10.8
Karimganj	323638	Very High (Q5)	41.7	5.1	Very High (Q5)	53.3	4.5
Katiadi	346608	Very High (Q5)	31.6	7.2	High (Q4)	42.9	10.7
Kishoreganj Sadar	485082	High (Q4)	26.4	4.2	High (Q4)	46.0	4.7
Kuliarchar	198422	Very High (Q5)	33.5	7.4	High (Q4)	45.5	4.3
Mithamain	123910	Very High (Q5)	47.4	8.7	Very High (Q5)	50.3	11.1
Nikli	144400	Very High (Q5)	47.3	7.6	High (Q4)	46.6	12.8
Pakundia	277847	High (Q4)	26.5	3.9	Low (Q2)	25.9	4.4
Tarail	168679	Very High (Q5)	36.6	8.4	High (Q4)	41.6	12.9
Madaripur District	**1259062**	**Very High (Q5)**	**54.4**	**4.6**	**Very high**	**52.9**	**2.7**
Dasar	72243	Very High (Q5)	63.2	10.6	High (Q4)	46.6	11.5
Kalkini	215564	Very High (Q5)	56.3	4.4	Very High (Q5)	64.4	4.8
Madaripur Sadar	385852	Very High (Q5)	50.0	8.0	Very High (Q5)	58.6	4.8
Rajoir	241539	Very High (Q5)	56.0	9.0	Very High (Q5)	60.4	6.2
Shibchar	343864	Very High (Q5)	55.1	4.7	Moderate (Q3)	35.5	2.9
Manikganj District	**1526711**	**High (Q4)**	**22.2**	**2.7**	**Moderate**	**39.2**	**3.2**
Daulatpur	166375	Very High (Q5)	31.4	8.6	High (Q4)	49.2	9.3
Ghior	159852	Very High (Q5)	34.6	3.6	Moderate (Q3)	32.3	5.5
Harirampur	154342	High (Q4)	23.8	8.3	High (Q4)	41.3	10.2
Manikganj Sadar	350775	Moderate (Q3)	20.9	6.2	Moderate (Q3)	35.7	5.0
Saturia	190219	Moderate (Q3)	17.6	3.6	Moderate (Q3)	34.8	5.9
Shibalay	185720	High (Q4)	25.6	8.2	High (Q4)	48.1	4.6
Singair	319428	Low (Q2)	12.6	3.6	Moderate (Q3)	37.0	4.7
Munshiganj District	**1563778**	**Low (Q2)**	**11.3**	**2.2**	**High**	**50.1**	**4.4**
Gazaria	175861	Very Low (Q1)	8.0	4.2	High (Q4)	49.7	9.0

ANNEX 1: DIVISION, DISTRICT AND UPAZILA LEVEL POVERTY RATES OF 2022 AND 2010 (*Continued*)

Name	Population[20]	2022			2010[21]		
		Quintile	HCR Upper (%)	Standard Error (%)	Quintile	HCR Upper (%)	Standard Error (%)
Louhajang	171256	Low (Q2)	12.8	4.1	High (Q4)	45.5	6.3
Munshiganj Sadar	417880	Low (Q2)	14.2	3.0	Very High (Q5)	55.4	5.1
Sirajdikhan	305545	Low (Q2)	10.7	5.1	High (Q4)	48.3	5.2
Sreenagar	286464	Very Low (Q1)	9.1	3.5	High (Q4)	46.7	7.0
Tongibari	206772	Low (Q2)	11.1	2.2	Very High (Q5)	51.5	14.1
Narayanganj District	**3740835**	**Low (Q2)**	**13.7**	**1.4**	**Moderate**	**40.0**	**2.4**
Araihazar	454760	Moderate (Q3)	19.1	5.8	Very High (Q5)	53.5	4.4
Sonargaon	522461	Low (Q2)	12.2	2.4	Moderate (Q3)	38.8	5.1
Bandar	399643	Moderate (Q3)	17.1	4.6	Moderate (Q3)	33.2	4.7
Narayanganj Sadar	1691248	Very Low (Q1)	8.9	1.6	Moderate (Q3)	36.0	5.4
Rupganj	672723	Moderate (Q3)	21.1	2.2	High (Q4)	45.8	4.3
Narsingdi District	**2499690**	**Very High (Q5)**	**43.7**	**3.5**	**Moderate**	**38.5**	**2.4**
Belabo	211270	Very High (Q5)	49.5	11.2	Moderate (Q3)	36.4	6.8
Manohardi	293145	Very High (Q5)	40.4	5.6	High (Q4)	43.4	5.4
Narsingdi Sadar	807445	Very High (Q5)	43.1	4.5	Moderate (Q3)	37.0	4.5
Palash	237799	Very High (Q5)	38.3	7.7	Low (Q2)	27.7	5.6
Raipura	602531	Very High (Q5)	47.6	4.5	Very High (Q5)	50.3	3.1
Shibpur	347500	Very High (Q5)	41.4	11.1	Low (Q2)	25.5	6.1
Rajbari District	**1169673**	**High (Q4)**	**27.8**	**3.9**	**Very high**	**66.6**	**3.3**
Baliakandi	226764	Very High (Q5)	40.8	4.0	Very High (Q5)	69.8	6.1
Goalanda	127252	Very High (Q5)	32.3	10.0	Very High (Q5)	74.1	8.1
Kalukhali	170266	High (Q4)	21.8	10.4	Very High (Q5)	69.2	10.8
Pangsha	270222	High (Q4)	25.2	4.8	Very High (Q5)	70.2	3.3
Rajbari Sadar	375169	High (Q4)	23.0	7.4	Very High (Q5)	58.2	3.8
Shariatpur District	**1271446**	**High (Q4)**	**27.1**	**3.7**	**Very high**	**72.9**	**3.1**
Bhedarganj	275042	High (Q4)	21.7	4.7	Very High (Q5)	78.0	4.0
Damudya	121584	High (Q4)	22.0	9.6	Very High (Q5)	67.7	10.6
Gosairhat	172163	Very High (Q5)	31.9	9.6	Very High (Q5)	77.1	4.8
Naria	256101	High (Q4)	21.7	8.1	Very High (Q5)	64.4	4.1
Shariatpur Sadar	233540	Very High (Q5)	36.2	3.4	Very High (Q5)	72.5	4.3
Zajira	213016	Very High (Q5)	29.6	8.9	Very High (Q5)	76.3	9.0
Tangail District	**3956331**	**Low (Q2)**	**13.3**	**2.0**	**High**	**43.8**	**2.0**
Basail	187434	Low (Q2)	11.4	4.0	Moderate (Q3)	39.8	7.8
Bhuanpur	214250	Very Low (Q1)	7.1	2.5	Very High (Q5)	63.0	4.8
Delduar	215610	Low (Q2)	11.8	4.2	High (Q4)	44.6	9.2
Dhanbari	185144	Low (Q2)	12.1	4.1	High (Q4)	45.4	7.1
Ghatail	442113	Low (Q2)	11.9	4.2	High (Q4)	45.8	3.8
Gopalpur	267817	Moderate (Q3)	15.0	3.8	High (Q4)	44.4	8.3
Kalihati	440553	Low (Q2)	14.0	4.8	Very High (Q5)	51.5	5.7

ANNEX 1: DIVISION, DISTRICT AND UPAZILA LEVEL POVERTY RATES OF 2022 AND 2010 (*Continued*)

Name	Population[20]	2022			2010[21]		
		Quintile	HCR Upper (%)	Standard Error (%)	Quintile	HCR Upper (%)	Standard Error (%)
Madhupur	330527	Moderate (Q3)	17.3	3.3	High (Q4)	41.5	4.3
Mirzapur	462991	Very Low (Q1)	8.7	3.0	High (Q4)	43.0	5.4
Nagarpur	316524	Low (Q2)	13.5	5.4	High (Q4)	45.8	5.3
Sakhipur	315037	Moderate (Q3)	18.9	2.7	Moderate (Q3)	36.8	5.6
Tangail Sadar	578331	Low (Q2)	14.9	4.4	Moderate (Q3)	33.4	4.5
Khulna Division	**17091200**	**Moderate (Q3)**	**17.1**	**0.8**		**32.1**	**2.3**
Bagerhat District	**1582590**	**Low (Q2)**	**13.7**	**1.8**	**Very high**	**51.7**	**3.8**
Bagerhat Sadar	282229	Low (Q2)	14.3	2.3	High (Q4)	43.7	7.9
Chitalmari	152338	Low (Q2)	14.9	6.4	High (Q4)	44.7	5.9
Fakirhat	157097	Low (Q2)	11.4	2.8	High (Q4)	46.7	5.8
Kachua	106532	Low (Q2)	14.7	5.4	Very High (Q5)	53.7	9.9
Mollahat	141170	Moderate (Q3)	17.1	5.8	Very High (Q5)	55.4	9.2
Mongla	153932	Very Low (Q1)	7.4	2.1	Very High (Q5)	56.6	4.9
Morelganj	301874	Low (Q2)	11.2	3.4	Very High (Q5)	52.5	6.3
Rampal	168597	Low (Q2)	12.6	5.3	Very High (Q5)	61.9	6.5
Sharankhola	118821	High (Q4)	24.3	2.7	Very High (Q5)	57.5	9.1
Chuadanga District	**1219036**	**Moderate (Q3)**	**20.9**	**2.7**	**Low**	**28.4**	**3.2**
Alamdanga	365195	High (Q4)	24.8	3.8	Low (Q2)	29.4	4.3
Chuadanga Sadar	344072	Moderate (Q3)	15.5	2.7	Low (Q2)	24.3	3.7
Damurhuda	314172	High (Q4)	21.2	6.9	Low (Q2)	29.3	5.3
Jibannagar	195597	High (Q4)	22.8	4.5	Low (Q2)	32.0	5.5
Jashore District	**3004239**	**Moderate (Q3)**	**20.0**	**1.5**	**Moderate**	**41.0**	**2.5**
Abhaynagar	283395	High (Q4)	27.2	3.4	High (Q4)	42.8	5.3
Bagharpara	236314	High (Q4)	24.6	6.5	High (Q4)	45.2	8.3
Chaugachha	246548	Low (Q2)	11.8	3.8	High (Q4)	41.1	5.0
Jhikargachha	327869	High (Q4)	26.4	3.0	Moderate (Q3)	38.5	5.6
Keshabpur	277655	Very High (Q5)	33.4	4.6	Very High (Q5)	50.9	5.4
Jashore Sadar	804026	Low (Q2)	13.2	2.9	Moderate (Q3)	34.9	5.3
Manirampur	445492	Moderate (Q3)	20.4	2.9	Moderate (Q3)	41.0	6.0
Sharsha	382940	Moderate (Q3)	15.5	3.1	High (Q4)	44.2	5.1
Jhenaidah District	**1969715**	**High (Q4)**	**21.2**	**2.0**	**Low**	**23.6**	**2.3**
Harinakundu	216994	High (Q4)	21.9	7.0	Low (Q2)	29.8	4.6
Jhenaidah Sadar	528242	High (Q4)	21.7	2.4	Very Low (Q1)	20.1	3.6
Kaliganj	305392	Low (Q2)	14.9	3.0	Very Low (Q1)	19.0	4.1
Kotchandpur	155335	Moderate (Q3)	16.1	4.7	Low (Q2)	21.1	5.4
Maheshpur	367678	Moderate (Q3)	20.3	4.5	Low (Q2)	27.2	3.6
Shailkupa	396074	High (Q4)	27.7	4.4	Low (Q2)	26.0	4.9
Khulna District	**2535569**	**Low (Q2)**	**10.2**	**1.5**	**High**	**44.8**	**2.6**
Batiaghata	226308	Very Low (Q1)	9.5	2.8	High (Q4)	45.0	6.6
Dacope	158167	Low (Q2)	12.8	4.9	High (Q4)	45.3	4.6

ANNEX 1: DIVISION, DISTRICT AND UPAZILA LEVEL POVERTY RATES OF 2022 AND 2010 (*Continued*)

Name	Population[20]	2022			2010[21]		
		Quintile	HCR Upper (%)	Standard Error (%)	Quintile	HCR Upper (%)	Standard Error (%)
Daulatpur	97544	Very Low (Q1)	5.2	1.4	Moderate (Q3)	32.3	9.1
Dumuria	338760	Low (Q2)	9.9	2.8	High (Q4)	47.2	6.4
Dighalia	161129	Very Low (Q1)	8.5	2.9	Moderate (Q3)	40.5	6.7
Khalishpur	150929	Very Low (Q1)	5.5	0.7	Moderate (Q3)	39.0	3.6
Khan Jahan Ali	6229	Very Low (Q1)	5.3	2.7	Moderate (Q3)	32.6	8.9
Khulna Sadar	231396	Very Low (Q1)	4.6	0.7	Low (Q2)	30.9	4.2
Koyra	219343	Low (Q2)	13.1	6.1	High (Q4)	48.0	6.2
Paikgachha	284525	Moderate (Q3)	17.0	3.1	High (Q4)	46.7	5.8
Phultala	144063	Moderate (Q3)	15.8	2.1	Moderate (Q3)	36.5	6.6
Rupsa	204055	Low (Q2)	11.8	4.4	High (Q4)	42.4	6.5
Sonadanga	185025	Very Low (Q1)	3.7	0.7	Low (Q2)	20.5	5.4
Terokhada	128096	Low (Q2)	10.6	3.8	High (Q4)	45.8	5.5
Kushtia District	**2119248**	**Moderate (Q3)**	**18.0**	**1.7**	**Very low**	**4.8**	**1.4**
Bheramara	222524	Moderate (Q3)	18.2	5.7	Very Low (Q1)	4.5	2.7
Daulatpur	479263	High (Q4)	23.7	2.9	Very Low (Q1)	6.5	1.9
Khoksa	142999	High (Q4)	21.6	7.1	Very Low (Q1)	6.4	3.0
Kumarkhali	371800	High (Q4)	26.6	3.2	Very Low (Q1)	3.7	2.4
Kushtia Sadar	543631	Low (Q2)	10.2	2.5	Very Low (Q1)	4.6	1.4
Mirpur	359031	Low (Q2)	11.6	2.4	Very Low (Q1)	3.3	1.7
Magura District	**1017133**	**High (Q4)**	**22.8**	**3.2**	**High**	**48.1**	**3.5**
Magura Sadar	417455	High (Q4)	21.3	3.9	High (Q4)	47.5	4.2
Mohammadpur	240505	High (Q4)	24.8	8.4	Very High (Q5)	55.3	5.1
Shalikha	176615	Moderate (Q3)	20.4	3.4	Moderate (Q3)	41.0	7.1
Sreepur	182558	High (Q4)	26.0	7.6	High (Q4)	47.2	6.8
Meherpur District	**699477**	**Low (Q2)**	**9.8**	**1.7**	**Very low**	**14.6**	**2.7**
Gangni	320627	Low (Q2)	10.3	2.1	Very Low (Q1)	19.0	3.6
Mujibnagar	104180	Very Low (Q1)	9.7	2.2	Very Low (Q1)	12.6	3.7
Meherpur Sadar	274670	Very Low (Q1)	9.3	3.1	Very Low (Q1)	10.2	2.9
Narail District	**774876**	**Low (Q2)**	**14.9**	**2.9**	**Low**	**24.5**	**2.3**
Kalia	239764	Moderate (Q3)	20.4	2.7	Very Low (Q1)	18.9	4.3
Lohagara	244063	Low (Q2)	10.5	2.9	Low (Q2)	28.1	3.2
Narail Sadar	291049	Low (Q2)	14.0	6.1	Low (Q2)	26.1	3.2
Satkhira District	**2169317**	**Moderate (Q3)**	**17.3**	**1.8**	**High**	**46.4**	**2.4**
Ashashuni	279404	High (Q4)	22.4	4.1	Very High (Q5)	50.8	4.9
Debhata	131972	Very Low (Q1)	9.5	2.5	High (Q4)	42.9	7.4
Kalaroa	259539	Low (Q2)	12.7	5.9	High (Q4)	45.0	4.8
Kaliganj	302056	Moderate (Q3)	17.8	2.9	High (Q4)	45.3	5.5
Satkhira Sadar	511808	Low (Q2)	13.0	3.0	High (Q4)	43.7	3.6
Shyamnagar	361034	High (Q4)	25.4	3.5	Very High (Q5)	52.5	4.6
Tala	323504	Moderate (Q3)	17.2	3.6	High (Q4)	43.7	5.7

ANNEX 1: DIVISION, DISTRICT AND UPAZILA LEVEL POVERTY RATES OF 2022 AND 2010 (*Continued*)

Name	Population[20]	2022			2010[21]		
		Quintile	HCR Upper (%)	Standard Error (%)	Quintile	HCR Upper (%)	Standard Error (%)
Mymensingh Division	**11976372**	**High (Q4)**	**22.6**	**0.9**		**-**	**-**
Jamalpur District	**2475535**	**Moderate (Q3)**	**18.8**	**1.5**	**Very high**	**66.1**	**2.6**
Bakshiganj	238190	Very High (Q5)	29.5	6.0	Very High (Q5)	64.6	5.0
Dewanganj	286519	High (Q4)	24.8	3.7	Very High (Q5)	80.7	5.0
Islampur	317720	Low (Q2)	11.4	3.5	Very High (Q5)	70.0	8.6
Jamalpur Sadar	656989	Low (Q2)	9.8	2.7	Very High (Q5)	65.6	4.0
Madarganj	284981	Low (Q2)	12.4	3.6	Very High (Q5)	66.0	4.7
Melandaha	350023	High (Q4)	26.8	4.1	Very High (Q5)	62.7	5.2
Sarishabari	341113	High (Q4)	27.9	3.2	Very High (Q5)	56.1	5.3
Mymensingh District	**5737380**	**Moderate (Q3)**	**20.4**	**1.0**	**Very high**	**70.9**	**1.5**
Bhaluka	556443	Very Low (Q1)	9.0	1.6	High (Q4)	49.3	3.6
Dhobaura	214858	High (Q4)	28.1	4.5	Very High (Q5)	80.3	7.3
Fulbaria	488207	Low (Q2)	9.9	4.0	Very High (Q5)	79.8	3.2
Gafargaon	455687	Low (Q2)	10.0	2.5	Very High (Q5)	63.8	4.3
Gouripur	350958	Very High (Q5)	52.9	3.7	Very High (Q5)	76.5	3.7
Haluaghat	312807	Very High (Q5)	59.6	3.5	Very High (Q5)	77.9	5.6
Ishwarganj	398271	High (Q4)	27.5	3.6	Very High (Q5)	86.7	4.1
Mymensingh Sadar	935481	Very Low (Q1)	5.5	2.3	Very High (Q5)	64.4	2.9
Muktagachha	446165	Very Low (Q1)	7.2	2.8	Very High (Q5)	72.7	3.6
Nandail	416623	High (Q4)	25.4	2.8	Very High (Q5)	73.8	3.8
Fulpur	345021	Very High (Q5)	32.8	4.1	Very High (Q5)	76.4	6.8
Tarakanda	335104	High (Q4)	23.3	5.0	Very High (Q5)	73.1	3.4
Trishal	481755	High (Q4)	22.2	3.1	Very High (Q5)	63.2	3.6
Netrakona District	**2281021**	**Very High (Q5)**	**33.9**	**3.0**	**Very high**	**59.7**	**2.8**
Atpara	142125	Very High (Q5)	34.0	12.5	Very High (Q5)	62.2	6.3
Barhatta	180071	Very High (Q5)	36.6	17.2	Very High (Q5)	55.4	5.2
Durgapur	237111	Very High (Q5)	47.6	4.7	Very High (Q5)	61.8	11.3
Khaliajuri	95533	Very High (Q5)	47.2	19.2	Very High (Q5)	68.9	8.6
Kalmakanda	268277	Very High (Q5)	32.6	3.2	Very High (Q5)	59.7	6.1
Kendua	312852	High (Q4)	23.5	5.8	Very High (Q5)	58.6	5.5
Madan	147946	Very High (Q5)	38.8	15.9	Very High (Q5)	62.2	5.5
Mohanganj	164212	Very High (Q5)	34.2	4.2	Very High (Q5)	62.6	10.3
Netrakona Sadar	407278	Very High (Q5)	45.8	3.9	Very High (Q5)	56.7	4.3
Purbadhala	325616	Low (Q2)	12.4	4.4	Very High (Q5)	58.6	11.1
Sherpur District	**1482436**	**Moderate (Q3)**	**19.9**	**1.9**	**Very high**	**69.9**	**2.5**
Jhenaigati	175800	Low (Q2)	10.8	4.1	Very High (Q5)	68.1	10.2
Nakla	206798	High (Q4)	28.0	9.7	Very High (Q5)	70.9	4.7
Nalitabari	268656	High (Q4)	27.5	4.9	Very High (Q5)	64.0	4.6

ANNEX 1: DIVISION, DISTRICT AND UPAZILA LEVEL POVERTY RATES OF 2022 AND 2010 (*Continued*)

Name	Population[20]	2022			2010[21]		
		Quintile	HCR Upper (%)	Standard Error (%)	Quintile	HCR Upper (%)	Standard Error (%)
Sherpur Sadar	553264	Moderate (Q3)	18.3	2.4	Very High (Q5)	75.1	3.2
Sreebardi	277918	Moderate (Q3)	15.6	4.2	Very High (Q5)	66.1	4.6
Rajshahi Division	**19925109**	**Moderate (Q3)**	**16.3**	**1.0**		**36.8**	**2.2**
Bogura District	**3651917**	**Low (Q2)**	**12.0**	**1.5**	**Low**	**30.9**	**2.0**
Adamdighi	203653	Very Low (Q1)	9.4	4.8	Low (Q2)	24.3	4.2
Bogura Sadar	619584	Very Low (Q1)	6.9	1.1	Low (Q2)	22.0	2.9
Dhunat	305280	Low (Q2)	11.1	3.7	High (Q4)	42.7	5.6
Dupchachia	191034	Very Low (Q1)	7.0	5.5	Low (Q2)	25.9	5.7
Gabtali	340500	Low (Q2)	14.5	3.5	Low (Q2)	30.2	4.4
Kahaloo	232354	Low (Q2)	10.2	2.4	Low (Q2)	24.4	4.7
Nandigram	197429	Low (Q2)	12.2	6.9	Moderate (Q3)	32.6	5.5
Sariakandi	274313	Very High (Q5)	30.1	4.2	High (Q4)	46.0	4.5
Shajahanpur	321601	Very Low (Q1)	4.5	2.0	Low (Q2)	24.2	5.6
Sherpur	377535	Moderate (Q3)	17.0	4.3	Moderate (Q3)	33.6	7.1
Shibganj	397401	Low (Q2)	10.0	2.9	Moderate (Q3)	33.0	4.4
Sonatala	191233	Moderate (Q3)	15.6	9.7	Moderate (Q3)	34.9	4.1
Joypurhat District	**938110**	**Moderate (Q3)**	**15.1**	**2.6**	**Moderate**	**34.8**	**2.3**
Akkelpur	142453	Low (Q2)	11.0	3.3	Moderate (Q3)	34.5	5.8
Joypurhat Sadar	305288	Moderate (Q3)	15.7	5.6	Low (Q2)	31.6	3.7
Kalai	144692	High (Q4)	22.3	2.8	Moderate (Q3)	41.0	3.5
Khetlal	110148	Moderate (Q3)	15.3	7.5	Moderate (Q3)	35.4	7.4
Panchbibi	235529	Low (Q2)	12.5	3.5	Moderate (Q3)	34.9	4.6
Naogaon District	**2731917**	**Moderate (Q3)**	**16.2**	**2.1**	**Low**	**22.2**	**2.3**
Atrai	199340	Moderate (Q3)	16.7	9.4	Low (Q2)	25.6	4.0
Badalgachhi	205188	High (Q4)	25.7	3.6	Very Low (Q1)	20.3	5.3
Dhamoirhat	191550	Moderate (Q3)	15.3	8.2	Low (Q2)	23.7	3.9
Manda	377730	Low (Q2)	12.2	2.5	Low (Q2)	21.7	3.5
Mahadebpur	303069	Moderate (Q3)	16.5	9.2	Low (Q2)	23.2	4.4
Naogaon Sadar	431886	Very Low (Q1)	7.3	2.7	Low (Q2)	22.2	4.0
Niamatpur	267524	Low (Q2)	12.7	4.1	Low (Q2)	23.4	2.8
Patnitala	246650	Moderate (Q3)	17.9	3.5	Low (Q2)	21.5	6.6
Porsha	141195	High (Q4)	23.2	8.9	Very Low (Q1)	20.0	6.7
Raninagar	188634	Moderate (Q3)	16.6	8.5	Very Low (Q1)	16.7	4.1
Sapahar	179151	Very High (Q5)	32.2	4.7	Low (Q2)	25.3	6.1
Natore District	**1828058**	**High (Q4)**	**24.4**	**4.0**	**High**	**45.2**	**2.7**
Bagatipara	137075	High (Q4)	21.6	10.1	High (Q4)	49.6	4.6
Baraigram	305580	High (Q4)	23.7	4.6	Moderate (Q3)	39.9	4.7
Gurudaspur	229210	Very High (Q5)	40.2	5.8	Very High (Q5)	50.5	6.6
Lalpur	303782	High (Q4)	23.1	11.4	High (Q4)	47.1	5.1
Naldanga	134133	Moderate (Q3)	16.5	4.8	High (Q4)	49.3	4.6

ANNEX 1: DIVISION, DISTRICT AND UPAZILA LEVEL POVERTY RATES OF 2022 AND 2010 (*Continued*)

Name	Population[20]	2022			2010[21]		
		Quintile	HCR Upper (%)	Standard Error (%)	Quintile	HCR Upper (%)	Standard Error (%)
Natore Sadar	343908	High (Q4)	22.2	11.4	Moderate (Q3)	40.5	4.2
Singra	374370	High (Q4)	22.4	4.0	High (Q4)	45.6	6.0
Chapainawabganj District	**1816475**	**Very High (Q5)**	**34.7**	**3.7**	**Low**	**28.2**	**3.1**
Bholahat	112715	Very High (Q5)	31.9	5.5	Low (Q2)	26.3	7.2
Gomastapur	300418	Very High (Q5)	36.6	14.2	Moderate (Q3)	32.1	4.8
Nachole	165910	Moderate (Q3)	19.9	6.0	Low (Q2)	29.8	7.5
Chapainawabganj Sadar	573178	High (Q4)	27.2	3.3	Low (Q2)	31.9	4.0
Shibganj	664254	Very High (Q5)	44.6	4.9	Moderate (Q3)	33.0	4.4
Pabna District	**2852250**	**Low (Q2)**	**12.1**	**1.9**	**Moderate**	**39.1**	**2.2**
Atgharia	176663	Low (Q2)	11.6	6.3	High (Q4)	44.3	4.6
Bera	298608	Moderate (Q3)	17.7	3.4	High (Q4)	47.4	6.2
Bhangura	134879	Low (Q2)	13.9	7.3	High (Q4)	41.2	6.9
Chatmohar	329279	Moderate (Q3)	15.3	3.2	Moderate (Q3)	36.6	5.5
Faridpur	139141	Low (Q2)	12.3	4.0	Moderate (Q3)	37.9	7.1
Ishwardi	378350	Low (Q2)	11.9	4.7	Low (Q2)	31.7	4.0
Pabna Sadar	685156	Very Low (Q1)	7.2	1.9	Moderate (Q3)	40.8	3.8
Santhia	407301	Low (Q2)	12.3	3.5	Low (Q2)	30.3	4.7
Sujanagar	302873	Low (Q2)	13.6	7.4	High (Q4)	48.0	5.9
Rajshahi District	**2816532**	**Moderate (Q3)**	**15.5**	**1.6**	**Moderate**	**35.0**	**2.2**
Bagha	194242	Low (Q2)	12.7	3.9	Moderate (Q3)	33.9	4.0
Bagmara	371140	Low (Q2)	13.5	3.4	Low (Q2)	30.0	4.8
Boalia	177894	Very Low (Q1)	5.3	1.2	Moderate (Q3)	32.7	4.6
Chandrima	58144	Low (Q2)	10.8	5.8	Moderate (Q3)	35.5	5.5
Charghat	222754	Low (Q2)	13.1	7.2	Moderate (Q3)	35.5	6.6
Durgapur	196570	Moderate (Q3)	15.4	2.9	Moderate (Q3)	40.1	4.2
Godagari	372994	High (Q4)	23.9	3.8	Moderate (Q3)	38.0	3.6
Kashiadanga	42410	Very Low (Q1)	9.7	2.4	Moderate (Q3)	34.4	6.3
Matihar	59116	Moderate (Q3)	15.7	2.7	Moderate (Q3)	37.0	4.7
Mohanpur	185120	Low (Q2)	14.4	8.9	Moderate (Q3)	35.0	4.4
Paba	361328	Moderate (Q3)	19.3	3.7	Moderate (Q3)	37.5	4.3
Puthia	222489	Low (Q2)	13.5	7.6	Low (Q2)	31.4	6.3
Rajpara	106376	Low (Q2)	12.7	1.8	Low (Q2)	24.0	4.6
Shah Makhdum	34954	Very Low (Q1)	9.5	5.2	High (Q4)	41.2	4.7
Tanore	211001	Moderate (Q3)	19.1	4.0	Moderate (Q3)	40.7	4.1
Sirajganj District	**3289850**	**Low (Q2)**	**10.9**	**1.1**	**Very high**	**52.7**	**3.4**
Belkuchi	390526	High (Q4)	23.9	2.4	Very High (Q5)	51.2	5.4
Chouhali	136727	Low (Q2)	14.5	6.4	Very High (Q5)	61.7	8.9
Kamarkhanda	152314	Very Low (Q1)	8.3	5.0	High (Q4)	48.7	8.4

ANNEX 1: DIVISION, DISTRICT AND UPAZILA LEVEL POVERTY RATES OF 2022 AND 2010 (*Continued*)

Name	Population[20]	2022			2010[21]		
		Quintile	HCR Upper (%)	Standard Error (%)	Quintile	HCR Upper (%)	Standard Error (%)
Kazipur	278279	Moderate (Q3)	18.3	2.3	Very High (Q5)	56.4	4.1
Rayganj	340876	Very Low (Q1)	3.6	2.8	Very High (Q5)	56.5	8.4
Shahjadpur	592610	Moderate (Q3)	15.7	2.0	Very High (Q5)	54.2	5.2
Sirajganj Sadar	608583	Very Low (Q1)	3.8	2.2	High (Q4)	48.1	5.0
Tarash	209096	Very Low (Q1)	3.7	2.1	Very High (Q5)	59.0	6.1
Ullapara	580839	Very Low (Q1)	7.9	2.1	High (Q4)	48.7	6.0
Rangpur Division	**17298631**	**High (Q4)**	**25.0**	**1.3**		**40.6**	**3.1**
Dinajpur District	**3236651**	**High (Q4)**	**25.7**	**2.4**	**Moderate**	**37.3**	**3.8**
Birampur	180549	Very High (Q5)	36.5	3.9	High (Q4)	43.5	5.0
Birganj	350512	High (Q4)	23.2	4.2	High (Q4)	42.5	11.5
Birol	279378	High (Q4)	27.9	10.9	Very High (Q5)	53.1	6.6
Bochaganj	168980	Very High (Q5)	44.6	4.6	High (Q4)	41.8	9.4
Chirirbandar	318152	High (Q4)	21.2	5.2	Very Low (Q1)	18.6	4.0
Fulbari	190033	High (Q4)	27.0	8.1	Moderate (Q3)	36.4	9.7
Ghoraghat	128040	High (Q4)	28.0	9.2	Moderate (Q3)	39.8	10.7
Hakimpur	93438	Moderate (Q3)	19.5	3.8	Moderate (Q3)	35.2	8.1
Kaharole	171854	Very High (Q5)	29.5	10.6	Moderate (Q3)	37.2	6.1
Khansama	195852	High (Q4)	27.4	4.5	High (Q4)	41.5	12.3
Dinajpur Sadar	516003	High (Q4)	24.5	2.9	Low (Q2)	25.2	3.2
Nababganj	250292	High (Q4)	24.4	10.4	High (Q4)	49.4	4.6
Parbatipur	393568	Moderate (Q3)	16.7	5.0	Moderate (Q3)	38.2	13.5
Gaibandha District	**2529359**	**High (Q4)**	**24.6**	**2.0**	**High**	**45.3**	**3.1**
Fulchhari	165143	Moderate (Q3)	19.8	4.9	Very High (Q5)	52.9	13.1
Gaibandha Sadar	486698	Very High (Q5)	31.0	4.1	High (Q4)	42.9	5.1
Gobindaganj	537752	Moderate (Q3)	17.1	3.0	Moderate (Q3)	33.2	4.6
Palashbari	264626	Very High (Q5)	41.7	3.8	High (Q4)	47.1	4.5
Sadullapur	310342	Moderate (Q3)	20.9	3.8	High (Q4)	46.2	14.4
Saghata	286413	High (Q4)	23.0	7.8	Very High (Q5)	54.9	5.6
Sundarganj	478385	High (Q4)	21.9	2.9	Very High (Q5)	51.4	5.7
Kurigram District	**2305840**	**Very High (Q5)**	**31.3**	**2.7**	**Very high**	**60.5**	**4.0**
Bhurungamari	254439	Very High (Q5)	37.6	4.7	Moderate (Q3)	32.8	6.5
Rajibpur	78013	Very High (Q5)	38.5	8.6	Very High (Q5)	68.1	14.2
Chilmari	130830	Very High (Q5)	31.5	10.8	Very High (Q5)	61.6	13.6
Phulbari	184805	High (Q4)	24.5	5.0	Very High (Q5)	65.8	6.8
Kurigram Sadar	351118	Very High (Q5)	39.0	4.6	Very High (Q5)	54.6	10.3
Nageshwari	441325	Very High (Q5)	35.5	4.2	Very High (Q5)	68.2	3.2
Rajarhat	201720	Very High (Q5)	28.6	13.6	Very High (Q5)	53.1	11.6
Roumari	226313	Very High (Q5)	30.2	5.1	Very High (Q5)	69.6	6.0
Ulipur	437277	Moderate (Q3)	20.5	5.2	Very High (Q5)	68.8	5.1

ANNEX 1: DIVISION, DISTRICT AND UPAZILA LEVEL POVERTY RATES OF 2022 AND 2010 (*Continued*)

Name	Population[20]	2022			2010[21]		
		Quintile	HCR Upper (%)	Standard Error (%)	Quintile	HCR Upper (%)	Standard Error (%)
Lalmonirhat District	**1413455**	**Moderate (Q3)**	**20.0**	**2.7**	**Moderate**	**36.4**	**4.3**
Aditmari	248355	Moderate (Q3)	16.5	4.1	Low (Q2)	22.1	4.8
Hatibandha	261862	Very Low (Q1)	9.6	3.3	Moderate (Q3)	35.7	11.4
Kaliganj	274407	High (Q4)	26.5	3.5	High (Q4)	42.9	3.2
Lalmonirhat Sadar	368234	Moderate (Q3)	21.1	7.2	Moderate (Q3)	39.4	5.2
Patgram	260597	High (Q4)	25.2	3.4	Moderate (Q3)	40.2	12.1
Nilphamari District	**2064574**	**High (Q4)**	**22.2**	**2.0**	**Moderate**	**36.0**	**2.8**
Dimla	314675	Moderate (Q3)	20.9	3.8	High (Q4)	43.6	5.2
Domar	279296	Moderate (Q3)	18.4	4.7	Moderate (Q3)	38.8	5.3
Jaldhaka	383369	Very High (Q5)	29.1	4.0	Moderate (Q3)	41.0	5.6
Kishoreganj	265897	High (Q4)	25.9	7.7	Low (Q2)	28.7	5.5
Nilphamari Sadar	515038	Moderate (Q3)	17.7	2.9	Low (Q2)	30.6	4.9
Saidpur	306299	High (Q4)	22.9	5.1	Moderate (Q3)	34.6	8.1
Panchagarh District	**1160775**	**Very High (Q5)**	**33.2**	**4.2**	**Low**	**29.7**	**2.3**
Atowari	139976	Very High (Q5)	29.4	12.5	Low (Q2)	21.1	4.6
Boda	272127	Very High (Q5)	48.2	5.5	Moderate (Q3)	40.3	4.6
Debiganj	263429	Very High (Q5)	30.3	5.3	Moderate (Q3)	39.4	5.1
Panchagarh Sadar	328199	Very High (Q5)	31.6	10.8	Low (Q2)	20.8	5.0
Tentulia	157044	Moderate (Q3)	19.0	4.5	Very Low (Q1)	20.0	4.8
Rangpur District	**3082438**	**High (Q4)**	**21.8**	**2.1**	**High**	**46.7**	**2.9**
Badarganj	310599	High (Q4)	21.5	4.8	Very High (Q5)	59.0	5.4
Gangachara	283675	Moderate (Q3)	15.3	4.7	Very High (Q5)	73.2	5.5
Hajirhat	76167	Very High (Q5)	38.2	7.3	High (Q4)	47.9	14.6
Haragachh	61660	Very High (Q5)	42.0	8.0	High (Q4)	48.4	14.6
Kaunia	236988	High (Q4)	24.7	6.6	High (Q4)	50.3	12.0
Kotwali	310859	High (Q4)	22.4	4.5	Very Low (Q1)	19.8	2.9
Rangpur Sadar	176621	Moderate (Q3)	20.5	3.9	Very High (Q5)	63.1	6.9
Mahiganj	54689	Very High (Q5)	29.9	7.3	Moderate (Q3)	40.7	6.7
Mithapukur	533435	Moderate (Q3)	20.3	4.0	Moderate (Q3)	38.8	6.4
Parshuram	68773	Very High (Q5)	30.6	7.9	Moderate (Q3)	38.6	10.3
Pirgachha	323670	Low (Q2)	14.1	3.6	High (Q4)	45.2	6.4
Pirganj	407669	High (Q4)	22.3	4.4	Moderate (Q3)	37.2	5.4
Tajhat	79421	Very High (Q5)	31.6	7.5	High (Q4)	41.1	8.6
Taraganj	158212	High (Q4)	22.5	7.7	Very High (Q5)	58.9	5.7
Thakurgaon District	**1505539**	**High (Q4)**	**23.3**	**2.6**	**Low**	**25.6**	**3.2**
Baliadangi	205904	Very High (Q5)	30.9	5.2	Low (Q2)	31.0	12.7
Haripur	158103	High (Q4)	23.5	9.9	Low (Q2)	29.0	4.9
Pirganj	260952	High (Q4)	24.0	3.6	Low (Q2)	28.8	4.3

ANNEX 1: DIVISION, DISTRICT AND UPAZILA LEVEL POVERTY RATES OF 2022 AND 2010 (*Continued*)

Name	Population[20]	2022			2010[21]		
		Quintile	HCR Upper (%)	Standard Error (%)	Quintile	HCR Upper (%)	Standard Error (%)
Ranishankail	239193	Moderate (Q3)	17.0	5.1	Low (Q2)	23.0	4.9
Thakurgaon Sadar	641387	High (Q4)	22.8	4.1	Low (Q2)	22.5	4.2
Sylhet Division	**10836513**	**Moderate (Q3)**	**18.5**	**0.9**		**36.2**	**3.3**
Habiganj District	**2321098**	**Low (Q2)**	**10.9**	**0.9**	**Moderate**	**34.6**	**2.4**
Ajmiriganj	125661	Low (Q2)	12.4	6.4	High (Q4)	47.1	5.4
Bahubal	216474	Moderate (Q3)	20.3	1.7	Moderate (Q3)	38.6	8.5
Baniachong	353339	Low (Q2)	11.7	2.7	Low (Q2)	32.0	6.3
Chunarughat	338982	Low (Q2)	11.1	1.6	Moderate (Q3)	39.1	3.7
Habiganj Sadar	296592	Very Low (Q1)	7.4	1.3	Low (Q2)	29.1	5.6
Lakhai	157465	Low (Q2)	10.2	2.3	High (Q4)	41.5	9.1
Madhabpur	376071	Very Low (Q1)	9.1	1.9	Low (Q2)	25.5	3.6
Nabiganj	363472	Low (Q2)	10.0	1.7	Moderate (Q3)	37.2	7.3
Shayestaganj	93042	Very Low (Q1)	6.2	3.3	Low (Q2)	30.5	3.6
Moulvibazar District	**2088869**	**Moderate (Q3)**	**20.4**	**1.4**	**Moderate**	**36.8**	**1.8**
Baralekha	278828	Low (Q2)	12.1	2.7	Low (Q2)	27.1	3.0
Juri	161181	High (Q4)	25.8	6.7	High (Q4)	41.8	7.1
Kamalganj	286682	High (Q4)	22.0	2.1	Moderate (Q3)	39.0	3.6
Kulaura	394156	High (Q4)	26.5	2.5	Moderate (Q3)	40.1	3.4
Moulvibazar Sadar	365077	Low (Q2)	11.0	2.4	Low (Q2)	26.0	4.1
Rajnagar	248235	Low (Q2)	12.8	3.1	Moderate (Q3)	40.3	5.3
Sreemangal	354710	Very High (Q5)	31.3	2.4	High (Q4)	45.4	4.7
Sunamganj District	**2675216**	**High (Q4)**	**27.2**	**1.7**	**High (Q4)**	**42.2**	**2.2**
Bishwambharpur	189574	Very High (Q5)	46.7	5.2	High (Q4)	43.5	5.1
Chhatak	442203	Very High (Q5)	29.3	2.4	High (Q4)	42.2	4.0
Derai	252129	Moderate (Q3)	19.1	4.4	Very High (Q5)	61.5	4.4
Dharmapasha	132247	High (Q4)	25.7	10.7	High (Q4)	44.3	8.5
Dowarabazar	258969	High (Q4)	22.9	3.4	High (Q4)	45.6	7.4
Jagannathpur	261626	Very High (Q5)	28.9	4.0	Moderate (Q3)	37.9	5.9
Jamalganj	185134	Very High (Q5)	30.2	4.4	Moderate (Q3)	39.6	4.3
Madhyanagar	95248	High (Q4)	25.5	9.5	High (Q4)	42.4	6.2
Shalla	116907	Very High (Q5)	34.8	4.9	High (Q4)	41.4	5.8
Shantiganj	203664	High (Q4)	28.2	11.7	High (Q4)	41.2	8.1
Sunamganj Sadar	313964	Moderate (Q3)	20.0	3.9	Low (Q2)	29.3	4.8
Tahirpur	223551	High (Q4)	22.7	4.6	Moderate (Q3)	39.2	5.1
Sylhet District	**3751330**	**Moderate (Q3)**	**16.0**	**1.0**	**Low**	**30.6**	**1.7**
Airport	87535	Very Low (Q1)	9.2	2.7	Very Low (Q1)	15.3	3.8
Balaganj	122741	Moderate (Q3)	17.1	7.8	Low (Q2)	25.9	4.3
Beanibazar	254846	Moderate (Q3)	20.0	2.7	Low (Q2)	23.0	3.4
Bishwanath	234310	Moderate (Q3)	19.8	3.5	Low (Q2)	25.6	5.5

ANNEX 1: DIVISION, DISTRICT AND UPAZILA LEVEL POVERTY RATES OF 2022 AND 2010 (*Continued*)

Name	Population[20]	2022			2010[21]		
		Quintile	HCR Upper (%)	Standard Error (%)	Quintile	HCR Upper (%)	Standard Error (%)
Companiganj	191183	Moderate (Q3)	19.5	3.5	Very Low (Q1)	42.9	7.6
Dakkhin Surma	294637	Very Low (Q1)	9.1	2.4	Low (Q2)	22.0	4.9
Fenchuganj	112362	Moderate (Q3)	16.9	3.2	Low (Q2)	27.0	6.2
Golapganj	327314	High (Q4)	22.2	2.3	Low (Q2)	29.3	4.3
Gowainghat	353502	Moderate (Q3)	19.1	3.6	High (Q4)	45.0	5.5
Jalalabad	30081	Very Low (Q1)	7.9	2.6	Very Low (Q1)	17.2	3.7
Jaintapur	197738	Low (Q2)	12.3	4.0	Low (Q2)	28.8	6.0
Kotwali	238680	Very Low (Q1)	9.3	1.6	Very Low (Q1)	16.2	2.5
Moglabazar	19921	Moderate (Q3)	15.9	6.8	Very Low (Q1)	18.1	4.0
Kanaighat	315777	Low (Q2)	9.9	2.9	High (Q4)	46.4	5.0
Osmaninagar	212394	Moderate (Q3)	20.2	3.1	Low (Q2)	27.2	7.5
Sylhet Sadar	418670	Moderate (Q3)	20.1	2.0	Low (Q2)	25.5	4.1
Shahparan	76022	Very Low (Q1)	8.3	1.9	Very Low (Q1)	11.5	2.5
Zakiganj	263617	Low (Q2)	13.5	3.5	Very High (Q5)	53.0	5.4

ANNEX 2
DIVISION, DISTRICT AND UPAZILA LEVEL EXTREME POVERTY OF 2022

[**Low:** HCR < 2.15%, **Moderate:** 2.16% < HCR < 5.52%, **High:** HCR > 5.53%]

Division, District, and Upazila	Legend[22]
Barishal Division	**High**
Barguna District	**High**
Amtali	Moderate
Bamna	High
Barguna Sadar	Moderate
Betagi	High
Patharghata	High
Taltali	High
Barishal District	**High**
Agailjhara	High
Babuganj	Moderate
Bakerganj	High
Banaripara	High
Barishal Sadar (Kotwali)	Moderate
Gaurnadi	High
Hijla	High
Mehendiganj	High
Muladi	High
Ujirpur	High
Bhola District	**High**
Bhola Sadar	High
Borhanuddin	High
Charfasson	High
Daulatkhan	High
Lalmohan	High
Monpura	High
Tazumuddin	High
Jhalokati District	**High**
Jhalokathi Sadar	High
Kanthalia	High
Nalchhity	High
Rajapur	High
Patuakhali District	**High**
Bauphal	High

Division, District, and Upazila	Legend[22]
Dashmina	High
Dumki	High
Galachipa	High
Kalapara	Low
Mirzaganj	Moderate
Patuakhali Sadar	Moderate
Rangabali	Moderate
Pirojpur District	**High**
Bhandaria	High
Indurkani	High
Kawkhali	High
Mathbaria	High
Nazirpur	High
Nesarabad (Swarupkathi)	High
Pirojpur Sadar	High
Chattogram Division	**Moderate**
Bandarban District	**High**
Alikadam	High
Bandarban Sadar	Moderate
Lama	High
Naikkhongchhari	High
Rowangchhari	High
Ruma	High
Thanchi	High
Brahmanbaria District	**High**
Akhaura	Moderate
Ashuganj	Moderate
Banchharampur	Low
Bijoynagar	Moderate
Brahmanbaria Sadar	Moderate
Kasba	Moderate
Nabinagar	High
Nasirnagar	High
Sarail	High

[22] Low: Extreme Poverty <2.15%, Moderate: 2.16%< Extreme Poverty <5.52%, and High: Extreme Poverty>5.53%

Division, District, and Upazila	Legend[22]
Chandpur District	**High**
Chandpur Sadar	High
Faridganj	Moderate
Haimchar	High
Hajiganj	High
Kachua	Low
Matlab Dakkhin	High
Matlab Uttar	High
Shahrasti	High
Chattogram District	**Moderate**
Akbarshah	Low
Anwara	High
Bakalia	Low
Banshkhali	High
Bayejid Bostami	Low
Boalkhali	Moderate
Chalk Bazar	Low
Chandanaish	Moderate
Chandgaon	Low
Chattogram Port	Low
Double Mooring	Low
EPZ	Low
Fatikchhari	Moderate
Halishahar	Low
Hathazari	Moderate
Karnaphuli	Moderate
Khulshi	Low
Kotwali	Low
Lohagara	Moderate
Mirsarai	High
Pahartali	Low
Panchlaish	Low
Patenga	Low
Patiya	Moderate
Rangunia	Low
Raozan	Moderate
Sadarghat	Low
Sandwip	Moderate
Satkania	Moderate
Sitakunda	Low

Division, District, and Upazila	Legend[22]
Cox's Bazar District	**High**
Chakaria	High
Coxs Bazar Sadar	Low
Eidgaon	Low
Kutubdia	High
Maheshkhali	High
Pekua	Moderate
Ramu	High
Teknaf	Moderate
Ukhia	High
Cumilla District	**Moderate**
Adarsha Sadar	Low
Barura	High
Brahmanpara	Moderate
Burichang	Moderate
Chandina	Moderate
Chauddagram	Moderate
Daudkandi	Moderate
Debidwar	Low
Homna	Moderate
Laksam	Moderate
Lalmai	Low
Manoharganj	Moderate
Meghna	Moderate
Muradnagar	Low
Nangalkot	Low
Sadar Dakkhin	Low
Titas	Moderate
Feni District	**Moderate**
Chhagalnaiya	Low
Daganbhuiyan	Moderate
Feni Sadar	Low
Fulgazi	Low
Parashuram	Moderate
Sonagazi	Moderate
Khagrachhari District	**Moderate**
Dighinala	High
Guimara	Moderate
Khagrachhari Sadar	Moderate
Lakkhichhari	High

ANNEX 2: DIVISION, DISTRICT AND UPAZILA LEVEL EXTREME POVERTY OF 2022 (*Continued*)

Division, District, and Upazila	Legend[22]
Mahalchhari	Moderate
Manikchhari	Moderate
Matiranga	High
Panchhari	Moderate
Ramgarh	Moderate
Lakshmipur District	**Moderate**
Kamalnagar	High
Lakshmipur Sadar	Low
Raipur	Moderate
Ramganj	Moderate
Ramgati	High
Noakhali District	**Low**
Begumganj	Low
Chatkhil	Low
Companiganj	Moderate
Hatiya	Low
Kabirhat	Low
Noakhali Sadar	Low
Senbag	Low
Sonaimuri	Low
Subarnachar	Moderate
Rangamati District	**Moderate**
Baghaichhari	Moderate
Barkal	Moderate
Belaichhari	Moderate
Jurachhari	Moderate
Kaptai	Moderate
Kawkhali	Moderate
Langadu	Moderate
Naniarchar	Moderate
Rajasthali	Low
Rangamati Sadar	Low
Dhaka Division	**Moderate**
Dhaka District	**Low**
Adabar	Low
Badda	Low
Banani	Low
Bangshal	Low
Bhasantek	Moderate

Division, District, and Upazila	Legend[22]
Bhatara	Low
Bimanbandar	Low
Cantonment	Low
Chawkbazar	Low
Dakkhinkhan	Low
Darussalam	Low
Demra	Low
Dhamrai	Low
Dhanmondi	Low
Dohar	Low
Gendaria	Low
Gulshan	Low
Hatirjheel	Low
Hazaribag	Low
Jatrabari	Low
Kadamtali	Low
Kafrul	Low
Kalabagan	Low
Kamrangichar	Low
Keraniganj	Low
Khilgaon	Low
Khilkhet	Low
Kotwali	Low
Lalbag	Low
Mirpur	Low
Mohammadpur	Low
Motijheel	Low
Mugda	Low
Nawabganj	Low
Newmarket	Low
Pallabi	Low
Paltan	Low
Ramna	Low
Rampura	Low
Rupnagar	Low
Sabujbag	Low
Savar	Low
Shah Ali	Low
Shahbag	Low
Shahjahanpur	Low

ANNEX 2: DIVISION, DISTRICT AND UPAZILA LEVEL EXTREME POVERTY OF 2022 (*Continued*)

Division, District, and Upazila	Legend[22]
Shere Bangla Nagar	Low
Shyampur	Low
Sutrapur	Low
Tejgaon	Low
Tejgaon Shilpa Elaka	Low
Turag	Low
Uttara Purba	Low
Uttarkhan	Low
Uttara Pashchim	Low
Wari	Low
Faridpur District	**Low**
Alfadanga	Low
Bhanga	Low
Boalmari	Low
Char Bhadrasan	Moderate
Faridpur Sadar	Moderate
Madhukhali	Low
Nagarkanda	Low
Sadarpur	Low
Saltha	Moderate
Gazipur District	**Moderate**
Basan	Moderate
Gachha	Low
Gazipur Sadar	Low
Joydebpur	Low
Kaliakair	Low
Kaliganj	Low
Kapasia	Low
Kashimpur	Moderate
Konabari	High
Pubail	Moderate
Sreepur	Low
Tongi Pashchim	High
Tongi Purba	Moderate
Gopalganj District	**Low**
Gopalganj Sadar	Low
Kashiani	Low
Kotalipara	Moderate
Muksudpur	Low
Tungipara	Low

Division, District, and Upazila	Legend[22]
Kishoreganj District	**Moderate**
Austagram	Moderate
Bajitpur	Moderate
Bhairab	High
Hossainpur	Moderate
Itna	Moderate
Karimganj	Moderate
Katiadi	Moderate
Kishoreganj Sadar	Moderate
Kuliarchar	Moderate
Mithamain	High
Nikli	High
Pakundia	Low
Tarail	Moderate
Madaripur District	**High**
Dasar	High
Kalkini	High
Madaripur Sadar	High
Rajoir	High
Shibchar	High
Manikganj District	**Low**
Daulatpur	Moderate
Ghior	Low
Harirampur	Low
Manikganj Sadar	Low
Saturia	Low
Shibalay	Low
Singair	Low
Munshiganj District	**Low**
Gazaria	Low
Louhajang	Low
Munshiganj Sadar	Moderate
Sirajdikhan	Low
Sreenagar	Low
Tongibari	Low
Narayanganj District	**Low**
Araihazar	Low
Bandar	Moderate
Narayanganj Sadar	Low
Rupganj	Moderate

ANNEX 2: DIVISION, DISTRICT AND UPAZILA LEVEL EXTREME POVERTY OF 2022 (*Continued*)

Division, District, and Upazila	Legend[22]
Sonargaon	Low
Narsingdi District	**High**
Belabo	High
Manohardi	Moderate
Narsingdi Sadar	High
Palash	Moderate
Raipura	High
Shibpur	Moderate
Rajbari District	**Low**
Baliakandi	Low
Goalanda	Low
Kalukhali	Low
Pangsha	Low
Rajbari Sadar	Low
Shariatpur District	**Moderate**
Bhedarganj	Moderate
Damudya	Low
Gosairhat	Moderate
Naria	Low
Shariatpur Sadar	Moderate
Zajira	Moderate
Tangail District	**Low**
Basail	Low
Bhuanpur	Low
Delduar	Low
Dhanbari	Low
Ghatail	Low
Gopalpur	Low
Kalihati	Low
Madhupur	Low
Mirzapur	Low
Nagarpur	Low
Sakhipur	Low
Tangail Sadar	Low
Khulna Division	**Moderate**
Bagerhat District	**Moderate**
Bagerhat Sadar	Low
Chitalmari	Moderate
Fakirhat	Low

Division, District, and Upazila	Legend[22]
Kachua	Moderate
Mollahat	Moderate
Mongla	Low
Morelganj	Moderate
Rampal	Low
Sharankhola	High
Chuadanga District	**Moderate**
Alamdanga	Moderate
Chuadanga Sadar	Moderate
Damurhuda	Moderate
Jibannagar	Moderate
Jashore District	Moderate
Abhaynagar	Moderate
Bagharpara	Moderate
Chaugachha	Low
Jashore Sadar	Low
Jhikargachha	Moderate
Keshabpur	Moderate
Manirampur	Moderate
Sharsha	Low
Jhenaidah District	**Moderate**
Harinakundu	Moderate
Jhenaidah Sadar	Moderate
Kaliganj	Moderate
Kotchandpur	Moderate
Maheshpur	Moderate
Shailkupa	Moderate
Khulna District	**Low**
Batiaghata	Low
Dacope	Moderate
Daulatpur	Low
Dighalia	Low
Dumuria	Low
Khalishpur	Low
Khan Jahan Ali	Low
Khulna Sadar	Low
Koyra	Moderate
Paikgachha	Moderate
Phultala	Moderate
Rupsa	Low

Division, District, and Upazila	Legend[22]
Sonadanga	Low
Terokhada	Low
Kushtia District	**Moderate**
Bheramara	Moderate
Daulatpur	Moderate
Khoksa	Moderate
Kumarkhali	Moderate
Kushtia Sadar	Moderate
Mirpur	Moderate
Magura District	**Moderate**
Magura Sadar	Moderate
Mohammadpur	Moderate
Shalikha	Moderate
Sreepur	Moderate
Meherpur District	**Moderate**
Gangni	Moderate
Meherpur Sadar	Moderate
Mujibnagar	Moderate
Narail District	**Low**
Kalia	Moderate
Lohagara	Low
Narail Sadar	Low
Satkhira District	**Moderate**
Ashashuni	Moderate
Debhata	Moderate
Kalaroa	Low
Kaliganj	Moderate
Satkhira Sadar	Moderate
Shyamnagar	Moderate
Tala	Moderate
Mymensingh Division	**High**
Jamalpur District	**High**
Bakshiganj	High
Dewanganj	High
Islampur	Moderate
Jamalpur Sadar	Moderate
Madarganj	Moderate
Melandaha	High
Sarishabari	High

Division, District, and Upazila	Legend[22]
Mymensingh District	**High**
Bhaluka	Moderate
Dhobaura	High
Fulbaria	Moderate
Fulpur	High
Gafargaon	Moderate
Gouripur	High
Haluaghat	High
Ishwarganj	High
Muktagachha	Low
Mymensingh Sadar	Low
Nandail	High
Tarakanda	High
Trishal	High
Netrakona District	**High**
Atpara	High
Barhatta	High
Durgapur	High
Kalmakanda	High
Kendua	High
Khaliajuri	High
Madan	High
Mohanganj	High
Netrakona Sadar	High
Purbadhala	Moderate
Sherpur District	**High**
Jhenaigati	Moderate
Nakla	High
Nalitabari	High
Sherpur Sadar	High
Sreebardi	Moderate
Rajshahi Division	**High**
Bogura District	**Moderate**
Adamdighi	Moderate
Bogura Sadar	Low
Dhunat	Moderate
Dupchachia	Low
Gabtali	Moderate
Kahaloo	Moderate

ANNEX 2: DIVISION, DISTRICT AND UPAZILA LEVEL EXTREME POVERTY OF 2022 (*Continued*)

Division, District, and Upazila	Legend[22]
Nandigram	Moderate
Sariakandi	High
Shajahanpur	Low
Sherpur	High
Shibganj	Moderate
Sonatala	Moderate
Chapainawabganj District	**High**
Bholahat	High
Chapainawabganj Sadar	High
Gomastapur	High
Nachole	High
Shibganj	High
Joypurhat District	**Moderate**
Akkelpur	Moderate
Joypurhat Sadar	Moderate
Kalai	High
Khetlal	Moderate
Panchbibi	Moderate
Naogaon District	**High**
Atrai	High
Badalgachhi	High
Dhamoirhat	High
Mahadebpur	High
Manda	Moderate
Naogaon Sadar	Low
Niamatpur	Moderate
Patnitala	High
Porsha	High
Raninagar	High
Sapahar	High
Natore District	**High**
Bagatipara	High
Baraigram	High
Gurudaspur	High
Lalpur	High
Naldanga	Moderate
Natore Sadar	High
Singra	High
Pabna District	**Moderate**
Atgharia	Moderate

Division, District, and Upazila	Legend[22]
Bera	High
Bhangura	Moderate
Chatmohar	Moderate
Faridpur	Moderate
Ishwardi	Moderate
Pabna Sadar	Low
Santhia	Moderate
Sujanagar	Moderate
Rajshahi District	**Moderate**
Bagha	Moderate
Bagmara	Moderate
Boalia	Low
Chandrima	Low
Charghat	Moderate
Durgapur	Moderate
Godagari	High
Kashiadanga	Low
Matihar	Low
Mohanpur	Moderate
Paba	Moderate
Puthia	Moderate
Rajpara	Low
Shah Makhdum	Low
Tanore	High
Sirajganj District	**Moderate**
Belkuchi	High
Chouhali	Moderate
Kamarkhanda	Low
Kazipur	High
Rayganj	Low
Shahjadpur	Moderate
Sirajganj Sadar	Low
Tarash	Low
Ullapara	Moderate
Rangpur Division	**High**
Dinajpur District	**High**
Birampur	High
Birganj	High
Birol	High

ANNEX 2: DIVISION, DISTRICT AND UPAZILA LEVEL EXTREME POVERTY OF 2022 (*Continued*)

Division, District, and Upazila	Legend[22]
Bochaganj	High
Chiribandar	High
Dinajpur Sadar	High
Fulbari	High
Ghoraghat	High
Hakimpur	Moderate
Kaharole	High
Khansama	High
Nababganj	High
Parbatipur	Moderate
Gaibandha District	**High**
Fulchhari	High
Gaibandha Sadar	High
Gobindaganj	High
Palashbari	High
Sadullapur	High
Saghata	High
Sundarganj	High
Kurigram District	**High**
Bhurungamari	High
Chilmari	High
Kurigram Sadar	High
Nageshwari	High
Phulbari	High
Rajarhat	High
Rajibpur	High
Roumari	High
Ulipur	High
Lalmonirhat District	**High**
Aditmari	Moderate
Hatibandha	Moderate
Kaliganj	High
Lalmonirhat Sadar	High
Patgram	High
Nilphamari District	**High**
Dimla	High
Domar	Moderate
Jaldhaka	High
Kishoreganj	High
Nilphamari Sadar	Moderate

Division, District, and Upazila	Legend[22]
Saidpur	High
Panchagarh District	High
Atowari	High
Boda	High
Debiganj	High
Panchagarh Sadar	High
Tentulia	High
Rangpur District	**High**
Badarganj	High
Gangachara	Moderate
Hajirhat	High
Haragachh	High
Kaunia	High
Kotwali	Moderate
Mahiganj	High
Mithapukur	High
Parshuram	High
Pirgachha	Moderate
Pirganj	High
Rangpur Sadar	High
Tajhat	High
Taraganj	High
Thakurgaon District	**High**
Baliadangi	High
Haripur	High
Pirganj	High
Ranishankail	Moderate
Thakurgaon Sadar	High
Sylhet Division	**Moderate**
Habiganj District	**Low**
Ajmiriganj	Moderate
Bahubal	High
Baniachong	Low
Chunarughat	Moderate
Habiganj Sadar	Low
Lakhai	Low
Madhabpur	Low
Nabiganj	Low
Shayestaganj	Low

ANNEX 2: DIVISION, DISTRICT AND UPAZILA LEVEL EXTREME POVERTY OF 2022 (*Continued*)

Division, District, and Upazila	Legend[22]
Moulvibazar District	**High**
Baralekha	Moderate
Juri	High
Kamalganj	High
Kulaura	High
Moulvibazar Sadar	Low
Rajnagar	Moderate
Sreemangal	High
Sunamganj District	**High**
Bishwambharpur	High
Chhatak	High
Derai	Moderate
Dharmapasha	High
Dowarabazar	Moderate
Jagannathpur	High
Jamalganj	High
Madhyanagar	High
Shalla	High
Shantiganj	High
Sunamganj Sadar	Moderate

Division, District, and Upazila	Legend[22]
Tahirpur	Moderate
Sylhet District	Moderate
Airport	Low
Balaganj	Moderate
Beanibazar	Moderate
Bishwanath	Moderate
Companiganj	Moderate
Dakkhin Surma	Low
Fenchuganj	Moderate
Golapganj	Moderate
Gowainghat	Moderate
Jaintapur	Moderate
Jalalabad	Low
Kanaighat	Low
Kotwali	Low
Moglabazar	Low
Osmaninagar	Moderate
Shahparan	Low
Sylhet Sadar	High
Zakiganj	Moderate

ANNEX 3
POTENTIAL VARIABLES

Variables	Description
hh_age_avg	Household mean age
hh_avg_educ	HH average. years of education by members
hh_cook_elc	HH dwelling cooking fuel source: electricity
hh_cook_gas	HH dwelling cooking fuel source: supply gas/LPG gas/Biogas
hh_cook_keds	HH dwelling cooking fuel source: kerosene/paraffin/petrol/diesel
hh_cook_oth	HH dwelling cooking fuel source: other sources
hh_cook_wdc	HH dwelling cooking fuel source: traditional fuel (wood/coal/straw/etc.)
hh_dep_ratio	HH proportion members aged 0-14 and 65+ yrs to members 15-64.
hh_dw_slm	HH dwelling type: slum = 1
hh_ecn_agr	HH premise-based economic activity: agriculture
hh_ecn_bagr	HH premise-based economic activity: both agriculture and non-agriculture
hh_ecn_nagr	HH premise-based economic activity: non-agriculture
hh_ecn_no	HH premise-based economic activity: none
hh_elect	HH dwelling electricity source: grid, solar, or other sources
hh_head_age	Household head age
hh_head_b	HH head religion: Buddhist
hh_head_bnk	HH head 15+ has a bank insurance/microcredit/post office savings account
hh_head_c	HH head religion: Christian
hh_head_d	HH head marital status: divorced
hh_head_dis	HH head with disabilities
hh_head_educ	HH head highest years of education
hh_head_educ_prc	HH head with primary education complete
hh_head_educ_pri	HH head with primary education incomplete
hh_head_educ_sec	HH head with secondary education complete
hh_head_educ_sei	HH head with secondary education incomplete
hh_head_educ_ter	HH head with tertiary education
hh_head_educ0	HH head with no education
hh_head_h	HH head religion: Hindu
hh_head_int	HH head has used the internet in the last 3 months
hh_head_ls_nlf	HH head labor status: not in the labor force
hh_head_ls_u	HH head labor status: unemployed
hh_head_ls_wrk	HH head labor status: employed
hh_head_m	HH head marital status: married
hh_head_male	Household head male
hh_head_mbnk	HH head 15+ has mobile banking account
hh_head_mob	HH head has a mobile phone
hh_head_msl	HH head religion: Muslim

ANNEX 3: POTENTIAL VARIABLES (*Continued*)

Variables	Description
hh_head_nm	HH head marital status: never married
hh_head_nmsl	HH head religion: non-Muslim
hh_head_nrw	HH head literacy: cannot read or write
hh_head_r	HH head literacy: only read
hh_head_rw	HH head literacy: can read and write
hh_head_s	HH head marital status: separated
hh_head_w	HH head marital status: widow/widower
hh_head_wrk_agr	HH head labor field: working for wage/profit in agriculture
hh_head_wrk_ind	HH head labor field: working for wage/profit in industry
hh_head_wrk_s	HH head labor type: working for wage
hh_head_wrk_srv	HH head labor field: working for wage/profit in service
hh_memb_abr	HH members living abroad
hh_memb_rabr	HH members who returned permanently from abroad in the last two 5 years
hh_mx_educ	HH max. years of education by members
hh_own	HH dwelling ownership: owned
hh_rent	HH dwelling ownership: rent
hh_rmt	HH received foreign remittances in the last 2 years
hh_roof_cmt	HH dwelling roof: cement, concrete, brick, terracotta
hh_roof_met	HH dwelling roof: metal tin/CI Sheet/Corrugated
hh_roof_oth	HH dwelling roof: none/tent/other material
hh_sex_ratio	HH sex ratio: male to female
hh_sh_age0	HH proportion of members aged 0 years.
hh_sh_age0_14	HH proportion of members aged 0_14 years.
hh_sh_age0_4	HH proportion members aged 0-4 years.
hh_sh_age1	HH proportion of members aged 1 year.
hh_sh_age15_64	HH proportion of members aged 15_64 years.
hh_sh_age2	HH proportion of members aged 2 years.
hh_sh_age3	HH proportion of members aged 3 years.
hh_sh_age4	HH proportion of members aged 4 years.
hh_sh_age65plus	HH proportion of members aged 65+ years.
hh_sh_bnk	HH proportion of members 15+ that have bank insurance/microcredit/post office
hh_sh_dis	HH proportion of members with disabilities
hh_sh_female	HH proportion of female members
hh_sh_int	HH proportion of members that used the internet in last 3 months
hh_sh_ls_wrk	HH proportion employed
hh_sh_male	HH proportion of male members
hh_sh_mbnk	HH proportion of members 15+ that have a mobile banking account.
hh_sh_mob	HH proportion of members that have a mobile phone
hh_sh_nrw	HH proportion of members 5+ that cannot read or write
hh_sh_r	HH proportion of members 5+ that can only read
hh_sh_rw	HH proportion of members 5+ that can read and write

Variables	Description
hh_sh_wrk_agr	HH proportion working in agriculture
hh_sh_wrk_ind	HH proportion working in industry
hh_sh_wrk_s	HH proportion labor type: salary working
hh_sh_wrk_srv	HH proportion working in service
hh_sh1564_rw	HH proportion of members 15-64 that can read and write
hh_size	Household size
hh_size_age0	HH members aged 0 years
hh_size_age0_14	HH members aged 0_14 years
hh_size_age1	HH members aged 1 years
hh_size_age15_64	HH members aged 15_64 years
hh_size_age2	HH members aged 2 years
hh_size_age3	HH members aged 3 years
hh_size_age4	HH members aged 4 years
hh_size_age65plus	HH members aged 65+ years
hh_size_sq	Household size squared
hh_snt_no	HH dwelling toilet: no latrine available /open defecation
hh_snt_shr	HH dwelling toilet type: shared
hh_snt_sl	HH dwelling toilet: safe latrine
hh_snt_ul	HH dwelling toilet: unsafe latrine
hh_sp_educ	HH spouse's highest years of education
hh_sp_educ_prc	HH spouse with primary education complete
hh_sp_educ_pri	HH spouse with primary education incomplete
hh_sp_educ_sec	HH spouse with secondary education complete
hh_sp_educ_sei	HH spouse with secondary education incomplete
hh_sp_educ_ter	HH spouse with tertiary education
hh_sp_educ0	HH spouse with no education
hh_wall_cmt	HH dwelling walls: cement, concrete, brick, terracotta
hh_wall_met	HH dwelling walls: metal tin/CI Sheet
hh_wall_oth	HH dwelling walls: none or other material
hh_wall_wdst	HH dwelling walls: wood/bamboo/mat/palm tree/betel tree/straw/chan
hh_wo_rent	HH dwelling ownership: without rent
hh_wshr_f	HH dwelling hand washing facility: has facility
hh_wshr_nof	HH dwelling hand washing facility: no facility
hh_wt_opip	HH dwelling water source: other than pipe water
hh_wt_otap	HH dwelling water source: other than tap
hh_wt_otaptube	HH dwelling water source: other than tap and tubewell
hh_wt_otube	HH dwelling water source: other than tubewell
hh_wt_pip	HH dwelling water source: pipe
hh_wt_tap	HH dwelling water source: tap
hh_wt_taptube	HH dwelling water source: tap or tubewell
hh_wt_tube	HH dwelling water source: tubewell

ANNEX 4
SELECTION OF ELIGIBLE VARIABLES BY DOMAIN

Variables	Normalized distance to HIES 95 CI by domain																
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	Avg.
hh_sh_age2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
hh_sh_age3	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
hh_size_age2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
hh_size_age65plus	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
hh_sh_age0_4	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000
hh_elect	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
hh_head_msl	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.018	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001
hh_size_age3	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.020	0.001
hh_age_avg	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.016	0.000	0.000	0.004	0.000	0.000	0.000	0.000	0.001
hh_wt_pip	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.008	0.000	0.000	0.000	0.000	0.010	0.017	0.002
hh_wt_taptube	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.008	0.000	0.000	0.000	0.000	0.010	0.017	0.002
hh_size_age1	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.024	0.000	0.014	0.002
hh_sh_rw	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.007	0.002	0.000	0.008	0.000	0.007	0.000	0.000	0.015	0.002
hh_head_age	0.000	0.000	0.004	0.000	0.000	0.018	0.000	0.012	0.000	0.010	0.002	0.000	0.000	0.000	0.000	0.000	0.003
hh_sh_age15_64	0.000	0.000	0.000	0.000	0.000	0.016	0.000	0.000	0.000	0.000	0.000	0.000	0.020	0.021	0.000	0.000	0.004
hh_sh_nrw	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.030	0.000	0.000	0.000	0.003	0.028	0.004
hh_size_age4	0.000	0.000	0.006	0.000	0.000	0.000	0.004	0.060	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.004
hh_sh_mob	0.000	0.021	0.000	0.000	0.004	0.000	0.000	0.004	0.000	0.000	0.000	0.000	0.010	0.037	0.000	0.000	0.005
hh_dep_ratio	0.000	0.000	0.000	0.000	0.000	0.064	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.026	0.000	0.000	0.006
hh_sh_age1	0.000	0.015	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.039	0.000	0.037	0.006
hh_head_rw	0.000	0.000	0.000	0.044	0.000	0.000	0.039	0.000	0.000	0.000	0.000	0.000	0.000	0.013	0.000	0.000	0.006
hh_sh1564_rw	0.000	0.000	0.001	0.023	0.000	0.008	0.016	0.012	0.000	0.000	0.017	0.000	0.000	0.022	0.000	0.000	0.006
hh_sp_educ_sec	0.000	0.000	0.000	0.000	0.000	0.105	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.007
hh_memb_abr	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.109	0.000	0.000	0.000	0.000	0.000	0.007
hh_head_wrk_srv	0.009	0.000	0.000	0.032	0.000	0.010	0.000	0.000	0.000	0.000	0.000	0.067	0.000	0.000	0.000	0.000	0.007
hh_cook_wdc	0.000	0.000	0.002	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.117	0.000	0.000	0.007
hh_sh_age4	0.000	0.000	0.058	0.000	0.000	0.000	0.000	0.063	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.008

ANNEX 4: SELECTION OF ELIGIBLE VARIABLES BY DOMAIN (*Continued*)

Variables	Normalized distance to HIES 95 CI by domain																
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	Avg.
hh_roof_met	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.034	0.029	0.067	0.008
hh_head_d	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.130	0.000	0.000	0.000	0.000	0.000	0.000	0.008
hh_head_nmsl	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.135	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.008
hh_head_m	0.026	0.006	0.000	0.004	0.030	0.010	0.002	0.000	0.000	0.014	0.009	0.023	0.003	0.011	0.000	0.005	0.009
hh_head_educ_pri	0.000	0.000	0.000	0.132	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.015	0.009
hh_sh_age0_14	0.000	0.000	0.000	0.000	0.000	0.080	0.000	0.000	0.007	0.027	0.000	0.033	0.000	0.000	0.000	0.000	0.009
hh_wall_met	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.161	0.000	0.000	0.010
hh_own	0.005	0.019	0.025	0.016	0.000	0.000	0.000	0.000	0.000	0.000	0.026	0.028	0.033	0.032	0.000	0.000	0.011
hh_sh_female	0.025	0.019	0.000	0.000	0.012	0.000	0.017	0.000	0.032	0.014	0.012	0.020	0.040	0.000	0.000	0.000	0.012
hh_head_educ_ter	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.015	0.193	0.000	0.000	0.013
hh_sh_male	0.028	0.021	0.000	0.000	0.013	0.000	0.018	0.000	0.036	0.015	0.013	0.022	0.044	0.000	0.000	0.000	0.013
hh_head_nrw	0.000	0.000	0.000	0.102	0.000	0.000	0.037	0.000	0.000	0.000	0.000	0.000	0.000	0.089	0.000	0.000	0.014
hh_rmt	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.135	0.046	0.056	0.015
hh_wall_cmt	0.000	0.027	0.000	0.000	0.000	0.000	0.000	0.055	0.000	0.000	0.000	0.000	0.000	0.155	0.000	0.005	0.015
hh_sp_educ_pri	0.000	0.000	0.000	0.000	0.000	0.029	0.000	0.000	0.162	0.000	0.056	0.000	0.000	0.000	0.000	0.000	0.015
hh_cook_gas	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.249	0.000	0.000	0.016
hh_sp_educ_ter	0.000	0.070	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.201	0.000	0.000	0.017
hh_head_h	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.273	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.017
hh_sp_educ0	0.000	0.000	0.000	0.062	0.000	0.000	0.000	0.035	0.000	0.000	0.000	0.000	0.000	0.128	0.017	0.041	0.018
hh_head_educ	0.000	0.000	0.000	0.070	0.000	0.000	0.056	0.000	0.000	0.000	0.000	0.000	0.031	0.126	0.000	0.000	0.018
hh_avg_educ	0.000	0.011	0.000	0.041	0.000	0.000	0.031	0.000	0.047	0.000	0.000	0.000	0.073	0.117	0.000	0.000	0.020
hh_head_educ_sec	0.000	0.000	0.000	0.000	0.000	0.101	0.000	0.000	0.000	0.000	0.222	0.000	0.000	0.000	0.000	0.000	0.020
hh_size_age0_14	0.009	0.007	0.000	0.000	0.000	0.112	0.004	0.000	0.067	0.064	0.000	0.063	0.000	0.000	0.000	0.000	0.020
hh_head_educ_sei	0.000	0.000	0.000	0.179	0.049	0.000	0.000	0.024	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.075	0.020
hh_head_s	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.041	0.300	0.000	0.000	0.000	0.021
hh_wt_tube	0.000	0.000	0.000	0.000	0.033	0.000	0.000	0.003	0.000	0.153	0.037	0.000	0.000	0.091	0.021	0.009	0.022
hh_wt_otap	0.005	0.000	0.017	0.000	0.037	0.009	0.004	0.000	0.002	0.108	0.042	0.000	0.002	0.083	0.010	0.035	0.022
hh_head_mob	0.020	0.048	0.022	0.022	0.052	0.018	0.000	0.000	0.046	0.020	0.012	0.000	0.006	0.029	0.062	0.068	0.027
hh_head_dis	0.000	0.000	0.190	0.000	0.000	0.000	0.103	0.000	0.000	0.000	0.168	0.000	0.000	0.000	0.000	0.000	0.029
hh_roof_cmt	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.148	0.000	0.000	0.000	0.000	0.184	0.113	0.086	0.033
hh_head_educ_prc	0.003	0.000	0.070	0.000	0.098	0.000	0.071	0.000	0.000	0.000	0.000	0.000	0.021	0.000	0.203	0.094	0.035

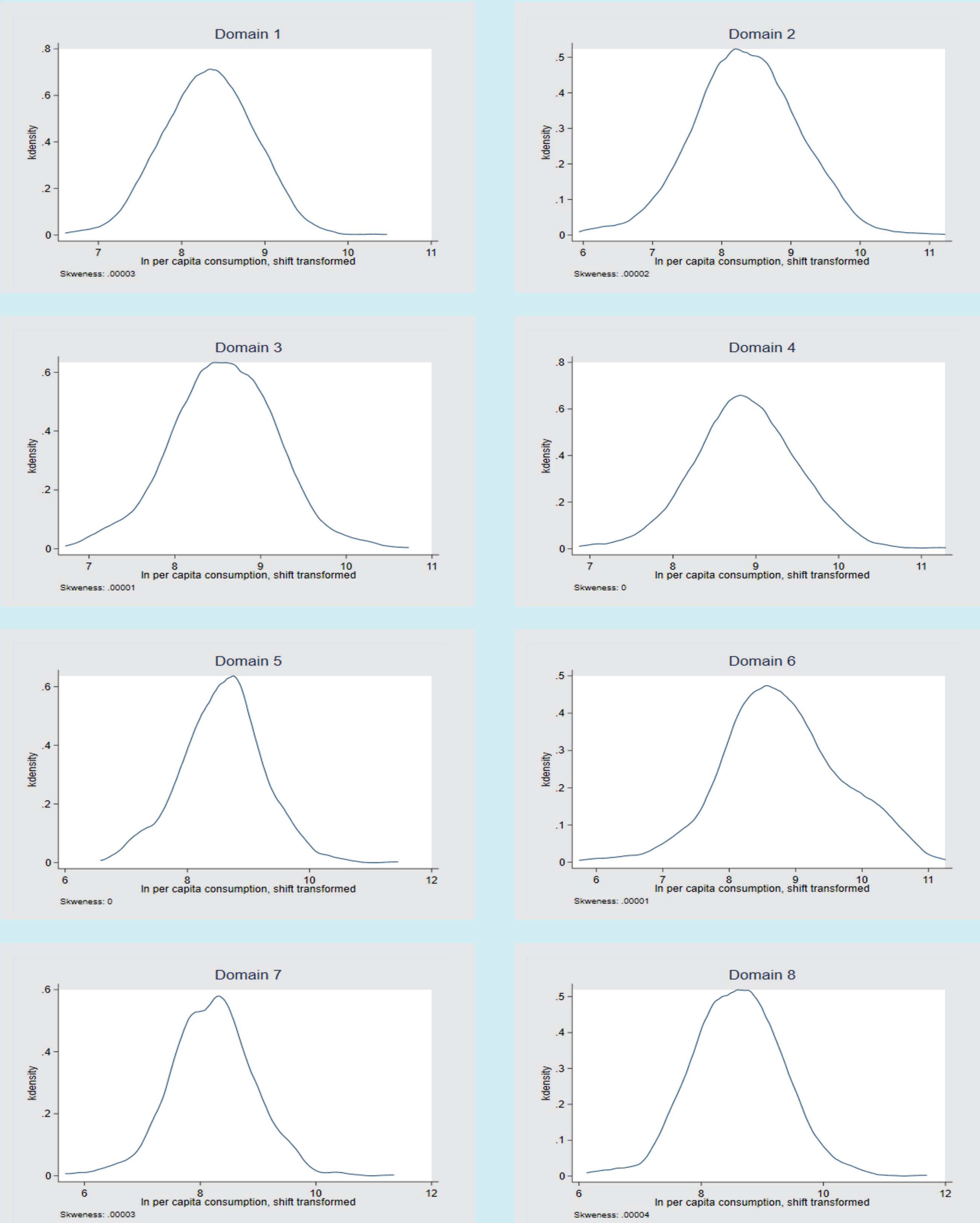
ANNEX 4: SELECTION OF ELIGIBLE VARIABLES BY DOMAIN (*Continued*)

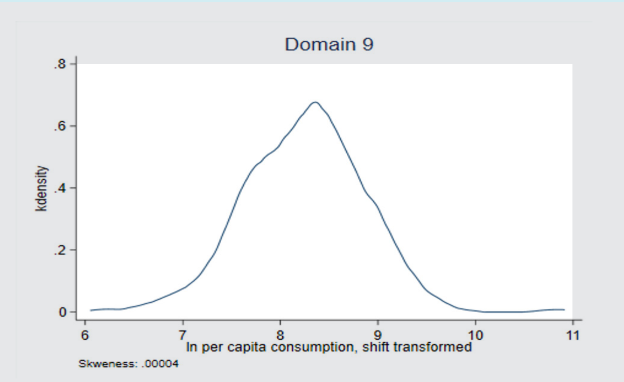
Variables	Normalized distance to HIES 95 CI by domain																
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	Avg.
hh_wshr_f	0.000	0.000	0.000	0.047	0.003	0.000	0.000	0.007	0.150	0.087	0.065	0.027	0.000	0.000	0.140	0.049	0.036
hh_rent	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.591	0.000	0.037
hh_wall_oth	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.176	0.000	0.000	0.000	0.000	0.000	0.092	0.000	0.326	0.037
hh_sex_ratio	0.057	0.080	0.000	0.000	0.060	0.042	0.039	0.047	0.070	0.062	0.022	0.060	0.083	0.003	0.000	0.000	0.039
hh_sh_wrk_srv	0.053	0.000	0.000	0.167	0.091	0.160	0.000	0.065	0.000	0.000	0.000	0.110	0.000	0.000	0.000	0.000	0.040
hh_mx_educ	0.047	0.046	0.014	0.044	0.022	0.000	0.043	0.036	0.108	0.015	0.017	0.023	0.098	0.126	0.032	0.000	0.042
hh_sh_dis	0.000	0.286	0.000	0.078	0.000	0.000	0.000	0.000	0.000	0.000	0.141	0.000	0.000	0.000	0.188	0.000	0.043
hh_head_male	0.089	0.084	0.069	0.039	0.026	0.012	0.028	0.038	0.059	0.055	0.038	0.072	0.045	0.036	0.002	0.013	0.044
hh_snt_shr	0.171	0.000	0.267	0.000	0.075	0.000	0.000	0.006	0.074	0.000	0.000	0.000	0.000	0.000	0.115	0.000	0.044
hh_head_ls_u	0.000	0.000	0.301	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.300	0.085	0.061	0.000	0.047
hh_head_int	0.060	0.361	0.012	0.000	0.112	0.030	0.000	0.000	0.045	0.000	0.087	0.000	0.000	0.048	0.021	0.000	0.048
hh_size	0.057	0.067	0.042	0.026	0.033	0.088	0.044	0.056	0.103	0.075	0.050	0.074	0.045	0.034	0.035	0.000	0.052
hh_head_wrk_s	0.000	0.076	0.093	0.069	0.000	0.000	0.000	0.000	0.068	0.085	0.027	0.090	0.102	0.107	0.000	0.124	0.053
hh_head_educ0	0.000	0.065	0.018	0.174	0.064	0.088	0.105	0.000	0.004	0.014	0.000	0.000	0.040	0.205	0.052	0.065	0.056
hh_sh_wrk_s	0.022	0.061	0.003	0.000	0.000	0.000	0.000	0.000	0.175	0.039	0.156	0.058	0.216	0.145	0.000	0.049	0.058
hh_size_sq	0.063	0.090	0.029	0.000	0.017	0.116	0.066	0.062	0.152	0.093	0.067	0.101	0.038	0.021	0.020	0.000	0.058
hh_size_age15_64	0.076	0.071	0.049	0.042	0.053	0.059	0.045	0.072	0.117	0.076	0.065	0.065	0.079	0.075	0.020	0.000	0.060
hh_wall_wdst	0.000	0.200	0.000	0.000	0.000	0.000	0.000	0.098	0.000	0.570	0.168	0.000	0.000	0.000	0.000	0.000	0.065
hh_sp_educ_prc	0.179	0.000	0.027	0.061	0.108	0.053	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.557	0.104	0.068
hh_sp_educ	0.112	0.157	0.037	0.134	0.098	0.030	0.096	0.061	0.060	0.034	0.000	0.046	0.056	0.173	0.062	0.040	0.075
hh_sh_bnk	0.073	0.244	0.000	0.010	0.089	0.000	0.167	0.095	0.235	0.244	0.000	0.000	0.100	0.000	0.031	0.000	0.081
hh_sp_educ_sei	0.044	0.245	0.016	0.163	0.152	0.055	0.079	0.136	0.014	0.107	0.000	0.067	0.077	0.044	0.000	0.122	0.082
hh_sh_age0	0.140	0.000	0.217	0.000	0.097	0.299	0.000	0.129	0.000	0.101	0.000	0.000	0.148	0.000	0.207	0.000	0.084
hh_sh_age65plus	0.124	0.019	0.000	0.000	0.028	0.000	0.112	0.124	0.228	0.118	0.167	0.034	0.188	0.194	0.000	0.029	0.085
hh_ecn_agr	0.000	0.379	0.000	0.000	0.000	0.000	0.000	0.058	0.090	0.160	0.000	0.000	0.000	0.350	0.038	0.390	0.092
hh_sh_int	0.220	0.421	0.000	0.000	0.213	0.209	0.000	0.031	0.085	0.048	0.000	0.000	0.000	0.099	0.133	0.017	0.092
hh_head_nm	0.000	0.185	0.000	0.000	0.000	0.514	0.000	0.000	0.000	0.176	0.015	0.279	0.241	0.108	0.000	0.000	0.095
hh_head_bnk	0.000	0.186	0.000	0.102	0.132	0.094	0.136	0.123	0.277	0.168	0.051	0.000	0.040	0.000	0.095	0.132	0.096
hh_head_w	0.329	0.048	0.000	0.156	0.322	0.000	0.139	0.000	0.064	0.027	0.057	0.107	0.158	0.037	0.046	0.076	0.098
hh_sh_mbnk	0.178	0.175	0.000	0.037	0.234	0.150	0.011	0.000	0.127	0.077	0.070	0.071	0.044	0.067	0.193	0.138	0.098
hh_sh_ls_wrk	0.104	0.110	0.110	0.000	0.003	0.000	0.114	0.006	0.179	0.034	0.296	0.106	0.307	0.150	0.082	0.067	0.104

ANNEX 4: SELECTION OF ELIGIBLE VARIABLES BY DOMAIN (*Continued*)

Variables	Normalized distance to HIES 95 CI by domain																
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	Avg.
hh_roof_oth	0.000	0.000	0.000	0.514	0.000	0.000	0.000	0.154	0.067	0.000	0.000	0.000	0.000	0.000	0.311	0.719	0.110
hh_sh_r	0.000	0.000	0.377	0.169	0.008	0.202	0.436	0.138	0.000	0.000	0.000	0.000	0.171	0.274	0.000	0.000	0.111
hh_head_ls_wrk	0.125	0.114	0.135	0.014	0.107	0.020	0.088	0.050	0.204	0.073	0.231	0.097	0.211	0.093	0.119	0.142	0.114
hh_size_age0	0.194	0.000	0.305	0.000	0.088	0.403	0.000	0.261	0.036	0.232	0.000	0.000	0.138	0.000	0.343	0.000	0.125
hh_head_mbnk	0.210	0.221	0.077	0.115	0.263	0.207	0.040	0.000	0.233	0.099	0.051	0.043	0.015	0.038	0.287	0.299	0.137
hh_head_r	0.000	0.215	0.000	0.084	0.000	0.826	0.318	0.648	0.000	0.000	0.000	0.000	0.112	0.000	0.000	0.000	0.138
hh_ecn_nagr	0.000	0.482	0.000	0.000	0.079	0.251	0.449	0.308	0.054	0.000	0.270	0.129	0.097	0.075	0.029	0.060	0.143
hh_snt_sl	0.177	0.196	0.113	0.104	0.147	0.034	0.227	0.151	0.179	0.196	0.212	0.114	0.089	0.071	0.374	0.120	0.156
hh_head_wrk_agr	0.487	0.000	0.359	0.069	0.164	0.000	0.010	0.000	0.252	0.000	0.282	0.000	0.310	0.069	0.506	0.000	0.157
hh_dw_slm	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.508	0.000	0.000	1.000	0.694	0.000	0.000	0.000	0.565	0.173
hh_ecn_bagr	0.089	0.106	0.449	0.148	0.000	0.273	0.000	0.209	0.248	0.321	0.207	0.000	0.000	0.121	0.174	0.424	0.173
hh_sh_wrk_agr	0.449	0.000	0.308	0.000	0.117	0.000	0.003	0.000	0.143	0.000	0.805	0.356	0.382	0.000	0.604	0.000	0.198
hh_wshr_nof	0.000	0.000	0.000	0.525	0.033	0.000	0.000	0.078	0.601	0.517	0.432	0.342	0.000	0.000	0.664	0.395	0.224
hh_head_ls_nlf	0.184	0.265	0.144	0.046	0.213	0.107	0.319	0.225	0.336	0.212	0.482	0.296	0.383	0.253	0.148	0.296	0.244
hh_wt_opip	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	3.594	0.000	0.000	0.000	0.000	0.129	0.754	0.280
hh_wt_otaptube	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	3.594	0.000	0.000	0.000	0.000	0.129	0.754	0.280
hh_cook_keds	0.000	1.262	0.000	0.000	0.000	0.000	1.000	1.000	0.000	0.000	1.000	0.000	0.000	1.000	0.000	0.000	0.329
hh_wo_rent	0.000	0.000	1.190	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.389	1.494	2.011	0.231	0.000	0.000	0.395
hh_wt_otube	0.000	0.000	0.000	0.000	0.853	0.000	0.000	0.011	0.000	2.334	0.828	0.000	0.000	2.356	0.240	0.029	0.416
hh_cook_oth	1.000	1.000	1.000	1.000	0.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	1.000	0.000	0.000	0.438
hh_snt_no	0.000	1.000	0.000	1.000	1.000	1.000	0.000	0.000	0.677	0.364	0.515	1.000	0.000	0.328	0.091	0.286	0.454
hh_ecn_no	0.627	0.118	0.526	0.000	0.266	0.000	0.617	0.000	1.790	0.297	0.563	0.005	1.387	0.424	0.752	0.176	0.472
hh_snt_ul	0.681	0.921	0.395	0.502	0.604	0.253	0.824	0.899	0.266	0.552	0.664	0.648	0.237	0.220	0.517	0.321	0.532
hh_memb_rabr	0.491	0.378	0.649	0.647	0.507	0.448	0.461	0.812	0.416	0.481	0.507	0.698	0.000	0.476	0.832	0.861	0.541
hh_head_c	1.000	1.000	0.884	1.000	1.000	0.000	0.000	0.000	1.000	0.000	1.000	0.000	0.000	1.000	0.000	1.000	0.555
hh_cook_elc	0.000	0.771	7.497	0.605	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	0.248	0.000	1.624	0.734
hh_head_b	1.000	1.000	0.000	0.000	1.000	0.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.750
hh_wt_tap	1.000	0.000	1.000	0.000	1.000	0.009	1.000	0.000	1.000	1.709	1.000	0.000	1.000	2.183	1.000	0.124	0.752
hh_sh_wrk_ind	1.105	1.530	0.561	0.070	0.000	0.000	1.049	1.205	0.844	0.581	1.314	1.371	1.322	1.482	0.415	1.298	0.884
hh_head_wrk_ind	1.204	1.624	0.872	0.540	0.231	0.207	0.829	1.364	0.812	0.848	1.045	1.199	1.188	1.484	0.661	1.532	0.977

ANNEX 5
NORMALITY OF TRANSFORMED DEPENDENT VARIABLE FOR MODELING

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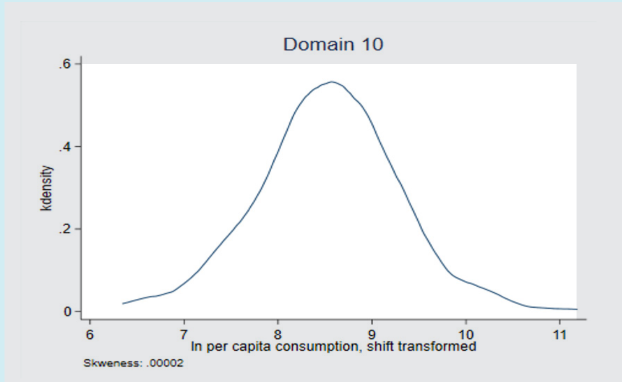
9
10
11
ln per capita consumption, shift transformed
Skweness: .00004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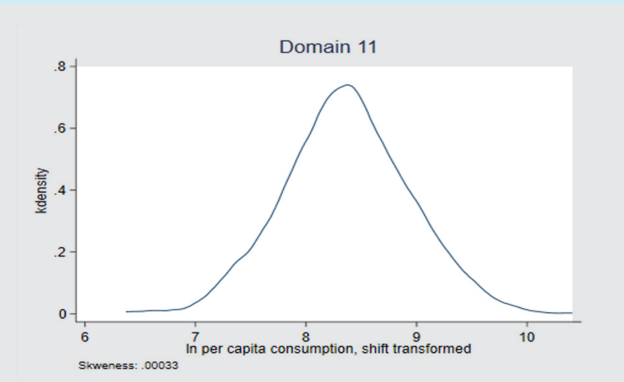
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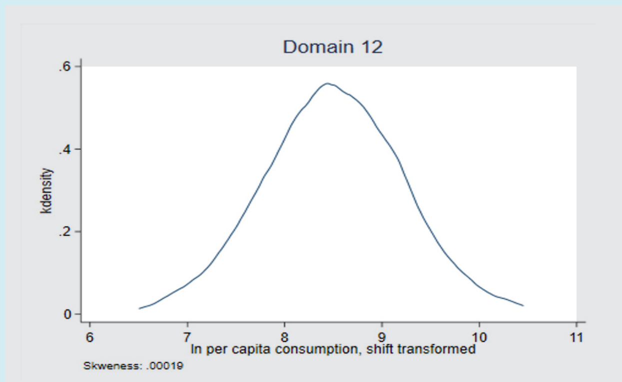
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9
10
11
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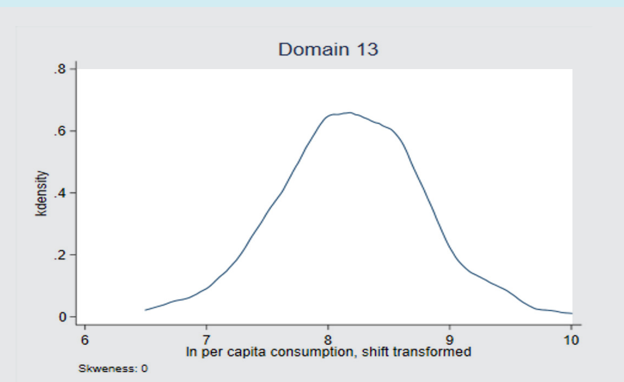
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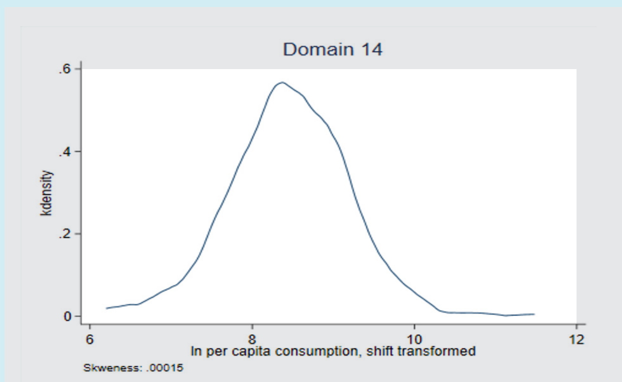
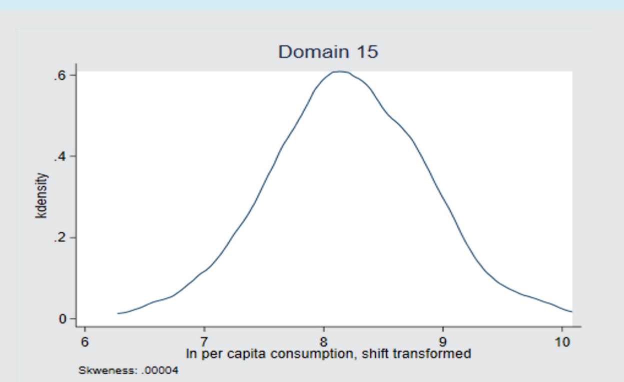
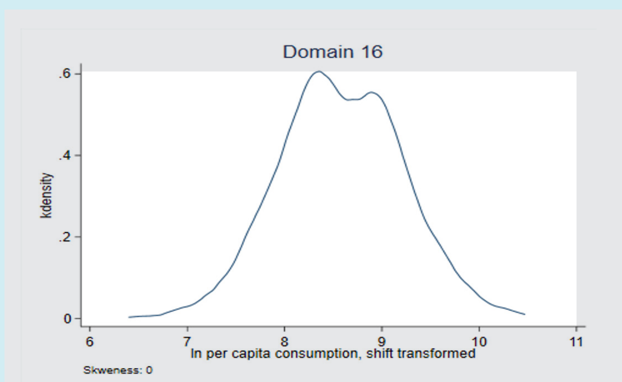
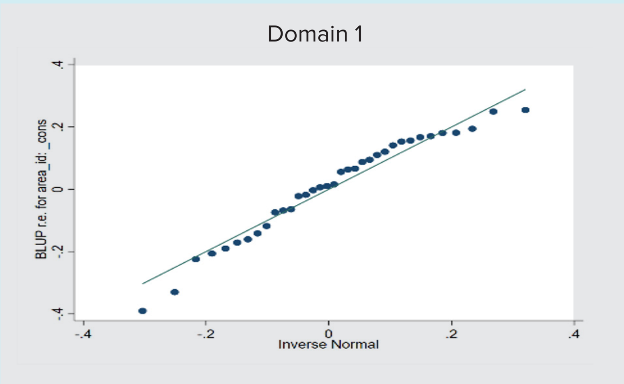
7
8
9
10
ln per capita consumption, shift transformed
Skweness: 0

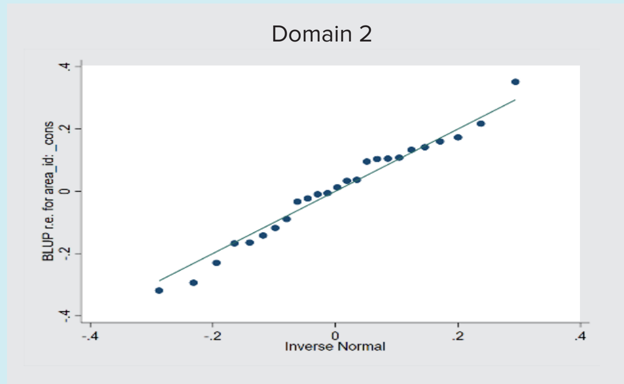

Domain 14
kdensity
0
.2
.4
.6
6
8
10
12
ln per capita consumption, shift transformed
Skweness: .00015

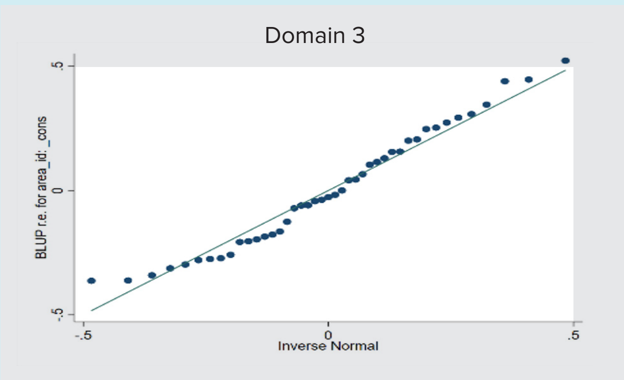

Domain 15
kdensity
0
.2
.4
.6
6
7
8
9
10
ln per capita consumption, shift transformed
Skweness: .00004

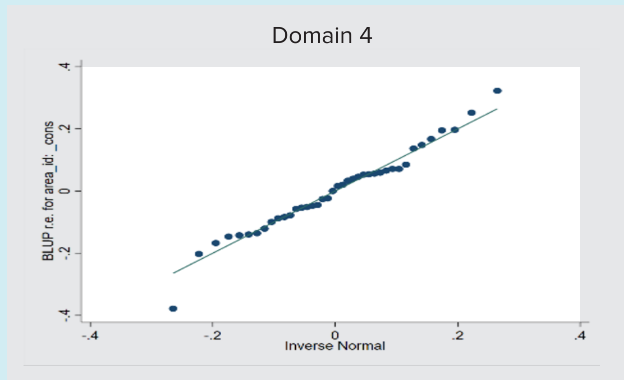

Domain 16
kdensity
0
.2
.4
.6
6
7
8
9
10
11
ln per capita consumption, shift transformed
Skweness: 0

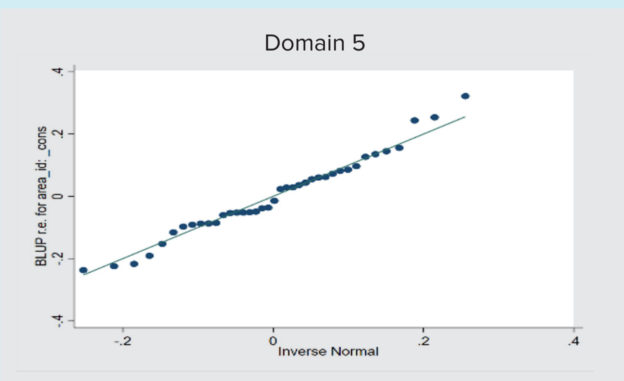
ANNEX 6
SAMPLE QUANTILES OF PREDICTED RANDOM EFFECTS VS. THEORETICAL NORMAL DISTRIBUTION, NORMAL Q-Q

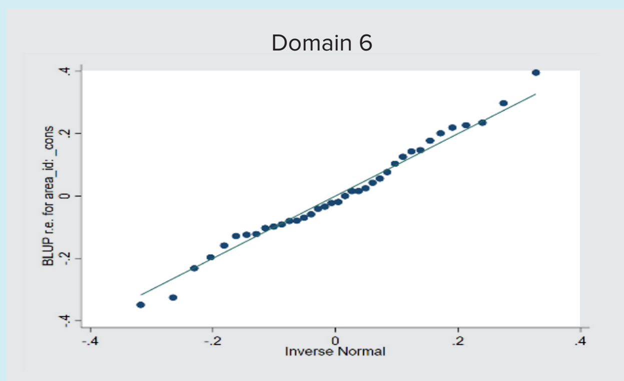


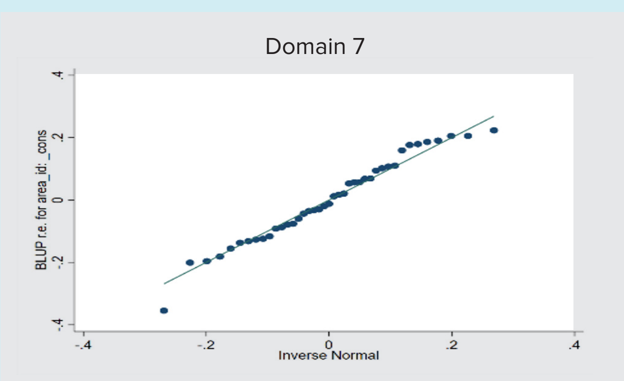


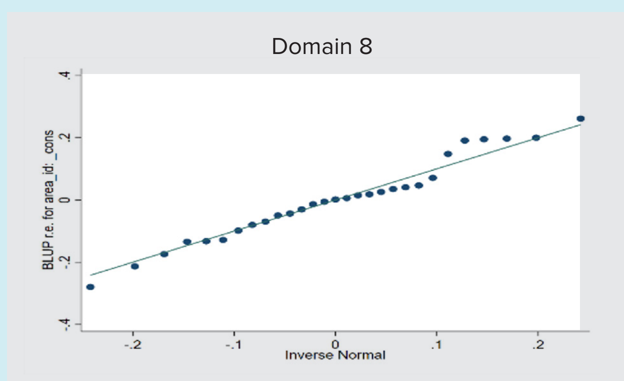


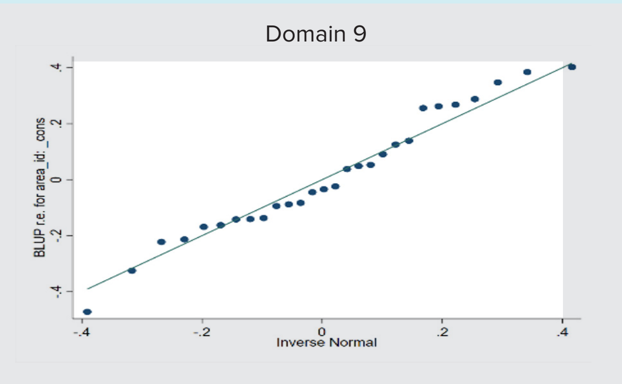


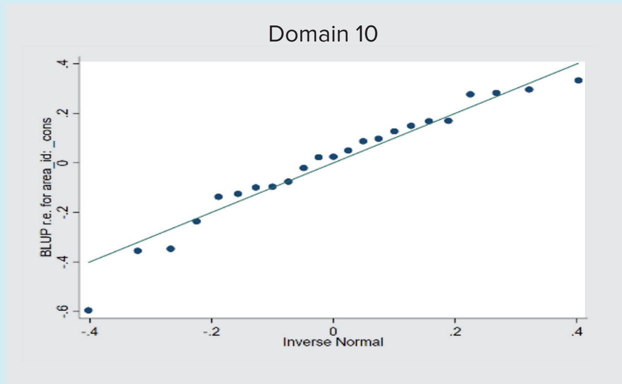


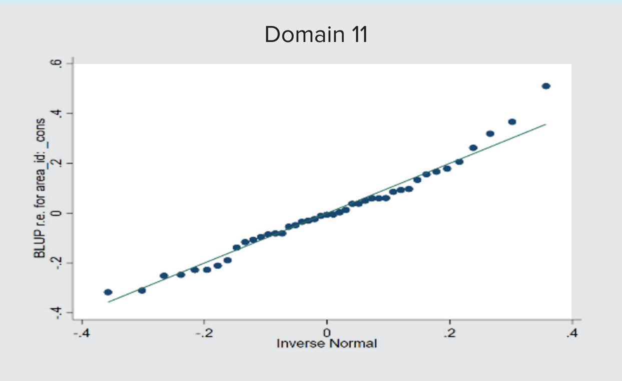


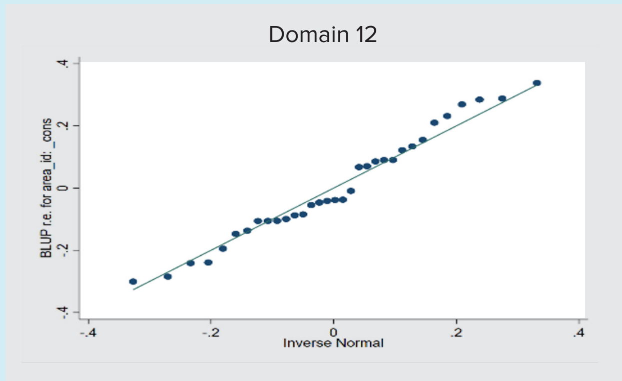


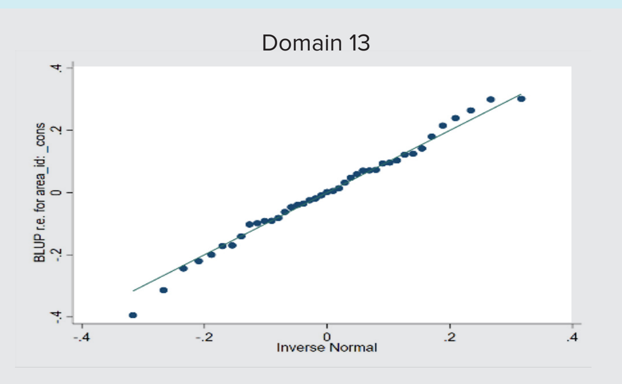


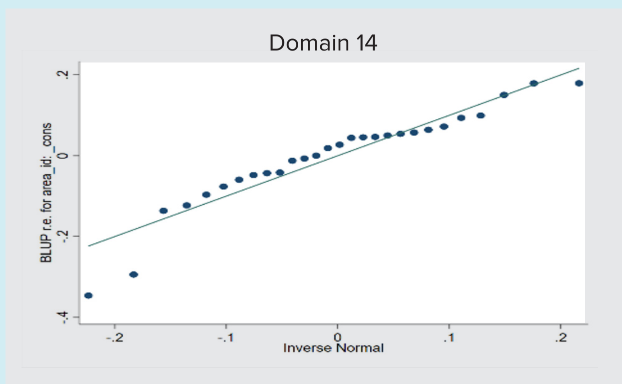

Domain 9
BLUP r.e. for area_id: _cons
-.4 -.2 0 .2 .4
Inverse Normal
-.4 -.2 0 .2 .4

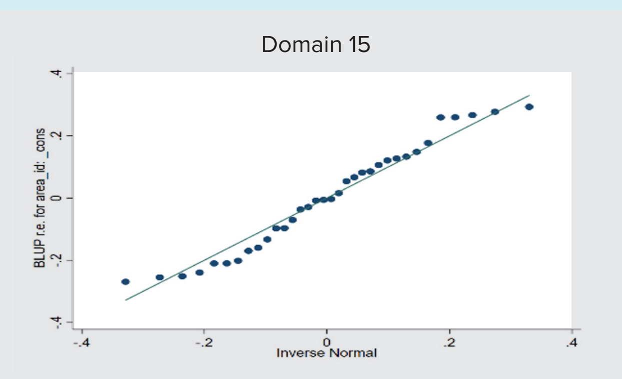

Domain 10
BLUP r.e. for area_id: _cons
-.6 -.4 -.2 0 .2 .4
Inverse Normal
-.4 -.2 0 .2 .4

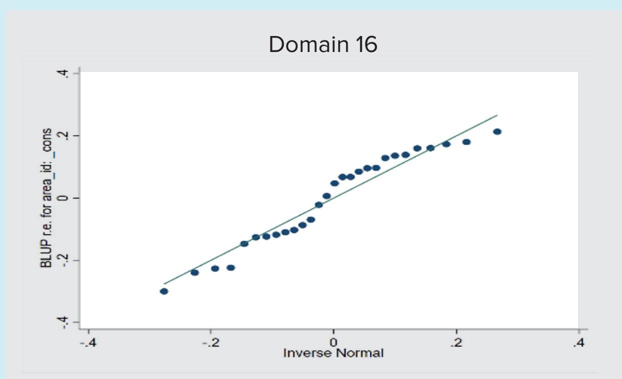

Domain 11
BLUP r.e. for area_id: _cons
-.4 -.2 0 .2 .4 .6
Inverse Normal
-.4 -.2 0 .2 .4


Domain 12
BLUP r.e. for area_id: _cons
-.4 -.2 0 .2 .4
Inverse Normal
-.4 -.2 0 .2 .4


Domain 13
BLUP r.e. for area_id: _cons
-.4 -.2 0 .2 .4
Inverse Normal
-.4 -.2 0 .2 .4

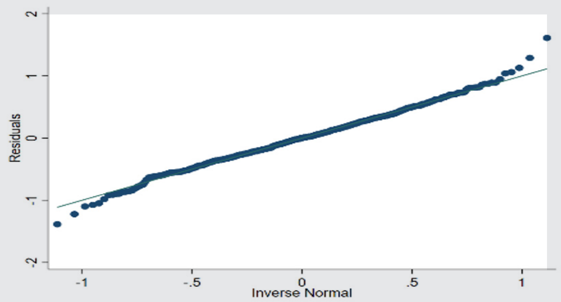

Domain 14
BLUP r.e. for area_id: _cons
-.4 -.2 0 .2
Inverse Normal
-.2 -.1 0 .1 .2


Domain 15
BLUP r.e. for area_id: _cons
-.4 -.2 0 .2 .4
Inverse Normal
-.4 -.2 0 .2 .4

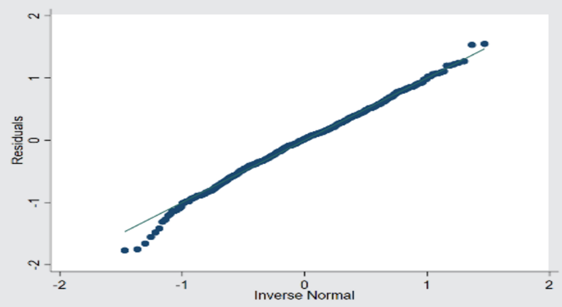

Domain 16
BLUP r.e. for area_id: _cons
-.4 -.2 0 .2 .4
Inverse Normal
-.4 -.2 0 .2 .4

ANNEX 7
SAMPLE QUANTILES OF RESIDUALS AGAINST THEORETICAL QUANTILES OF A NORMAL DISTRIBUTION, NORMAL Q-Q

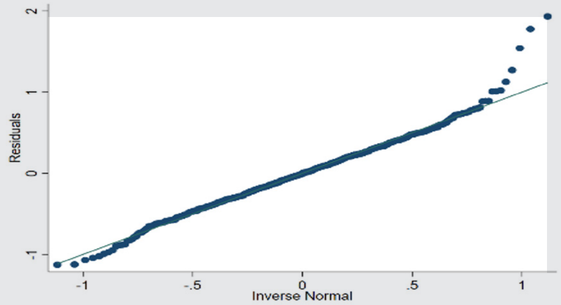
Domain 1



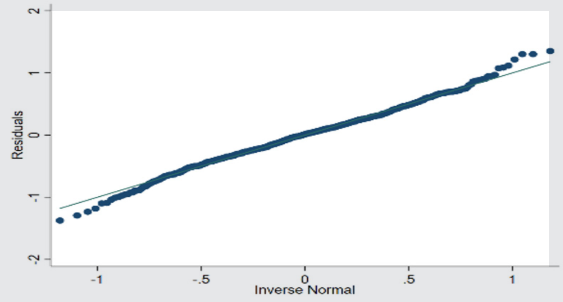
Domain 2



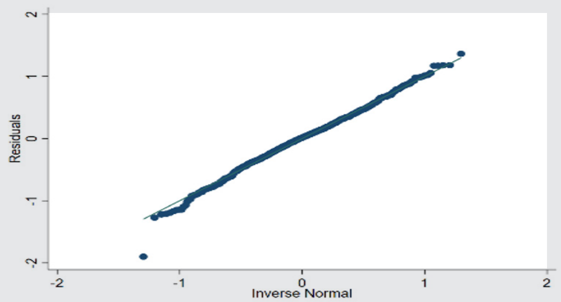
Domain 3



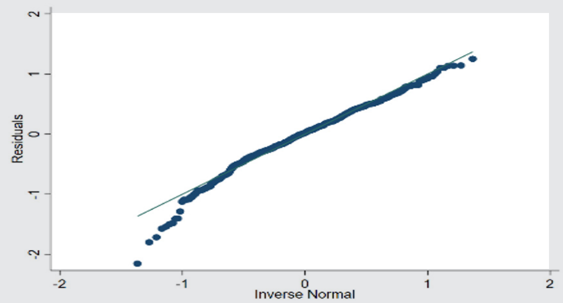
Domain 4



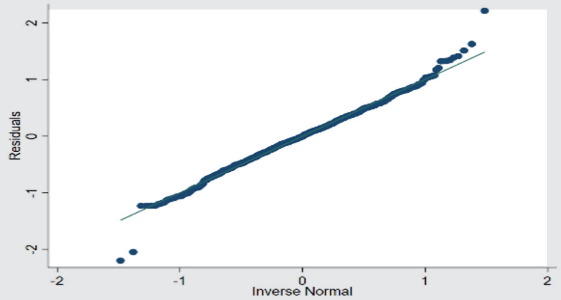
Domain 5



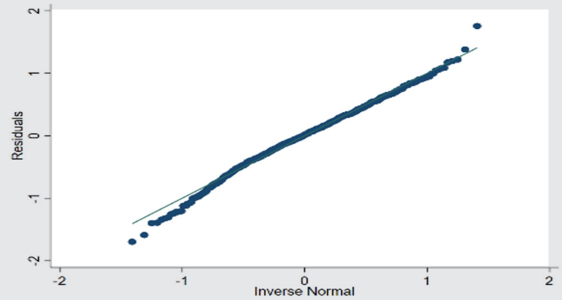
Domain 6



Domain 7

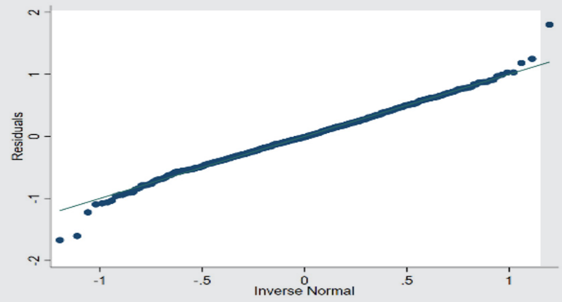


Domain 8

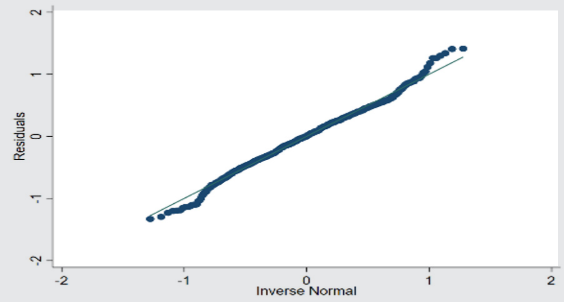


ANNEX 7: SAMPLE QUANTILES OF RESIDUALS AGAINST THEORETICAL QUANTILES OF A NORMAL DISTRIBUTION, NORMAL Q-Q (*Continued*)

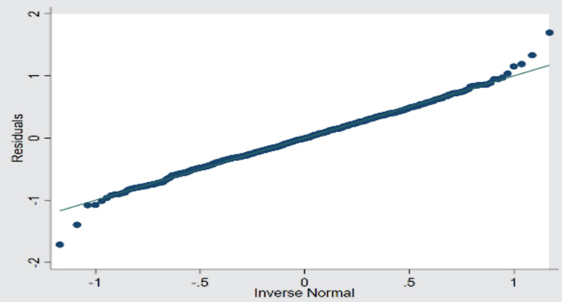
Domain 9



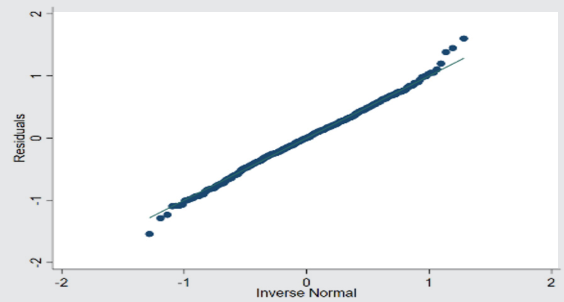
Domain 10



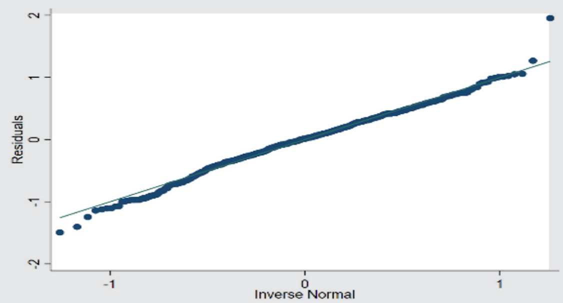
Domain 11



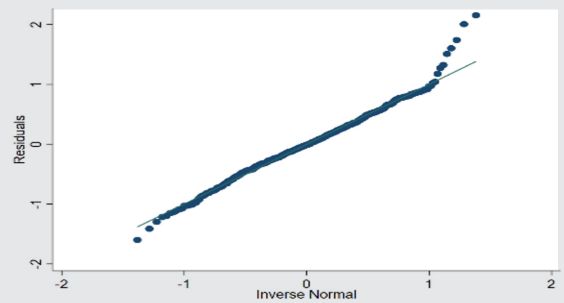
Domain 12



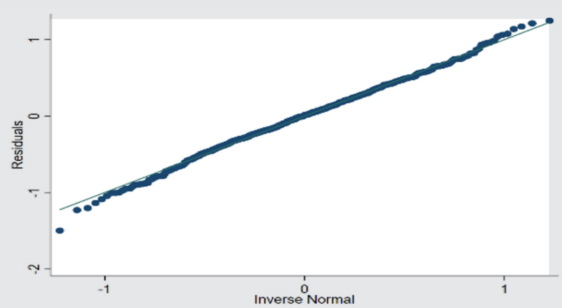
Domain 13



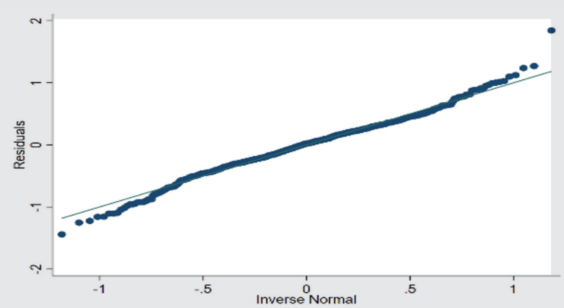
Domain 14



Domain 15



Domain 16



ANNEX 8
OFFICIALS ENGAGED IN POVERTY MAP OF BANGLADESH 2022

1. POVERTY AND LIVELIHOOD STATISTICS (PLS) CELL TEAM, BBS

Core Team Members	
1.	Mr. Mohiuddin Ahmed *MPH*, Deputy Director, BBS and Focal Point Officer, PLS Cell, BBS
2.	Mrs. Farhana Sultana, Deputy Director, BBS
3.	Mr. Ashadur Alam Prodhan, Statistical Officer, BBS
4.	Mr. S M Anwar Husain, Assistant Statistical Officer, BBS

2. THE WORLD BANK (WB) TEAM

(Not According to Seniority)

1.	Ms. Ximena Del Carpio, Practice Manager, Poverty and Equity Global Practice, South Asia Region
2.	Mr. Sergio Olivieri, Senior Economist, Statistician
3.	Mr. Ayago Esmubancha Wambile, Senior Economist
4.	Ms. Nethra Palaniswamy, Senior Economist
5.	Mr. Jaime Estuardo Fernandez Romero, Data Scientist
6.	Mr. FNU Jonaed, Research Analyst
7.	Mr. Virgilio Galdo, Consultant
8.	Mr. Faizuddin Ahmed, Consultant

3. THE WORLD FOOD PROGRAMME (WFP) TEAM

(Not According to Seniority)

1.	Mr. Takahiro Utsumi, Head of Research, Assessment and Monitoring (RAM), WFP
2.	Ms. Din Ara Wahid, VAM Officer, RAM, WFP
3.	Mr. Mohammad Mahabubul Alam, Programme Policy Officer, RAM, WFP
4.	Ms. Arifeen Akter, Programme Policy Officer, RAM, WFP
5.	Ms. Sanjida Showkat, Programme Policy Officer - Geospatial Analysis and Mapping, RAM, WFP
6.	Ms. Kaniz Fatema, Senior Programme Associate, RAM, WFP

ANNEX 9
VARIOUS COMMITTEE/TEAM: POVERTY MAP OF BANGLADESH 2022

1. STEERING COMMITTEE

(Not According to Seniority)

Committee Members		
1.	Senior Secretary/Secretary, Statistics and Informatics Division (SID)	Chairperson
2.	Director General, Bangladesh Bureau of Statistics (BBS)	Member
3.	Additional Secretary (Dev.), Statistics and Informatics Division (SID)	Member
4.	Representative, Finance Division	Member
5.	Representative, IMED, Planning Commission	Member
6.	Representative, SEI Div., Planning Commission	Member
7.	Representative, Programming Div., Planning Commission	Member
8.	Representative, GED, Planning Commission	Member
9.	Representative, NEC-ECNEC, Planning Commission	Member
10.	Joint Secretary (Dev), Statistics and Informatics Division (SID)	Member
11.	Director, National Accounting Wing, BBS	Member
12.	Focal Point Officer, Poverty and Livelihood Statistics (PLS) Cell, BBS	Member
13.	Deputy Secretary (Dev-1), Statistics and Informatics Division (SID)	Member Secretary

2. TECHNICAL COMMITTEE

(Not According to Seniority)

Committee Members		
1.	Director General, Bangladesh Bureau of Statistics (BBS)	Chairperson
2.	Joint Secretary (Dev), Statistics and Informatics Division (SID)	Member`
3.	Deputy Director General, Bangladesh Bureau of Statistics (BBS)	Member
4.	Representative, SEI Div., Planning Commission	Member
5.	Representative, GED, Planning Commission	Member
6.	Representative, Macroeconomic Wing, Finance Division	Member
7.	Representative, Ministry of Social Welfare	Member
8.	Deputy Secretary (Dev-1), Statistics and Informatics Division (SID)	Member
9.	Director, NAW/Demography and Health/Census/Computer Wing, BBS	Member
10.	Dr. Syed Shahadat Hossain, Professor, ISRT, DU	Member
11.	Joint Director, NAW, BBS	Member

Technical Committee (Continued.)

Committee Members		
12.	Representative, BIDS	Member
13.	Project Director, PHC 2021 Project, BBS	Member
14.	Deputy Director/Statistical Officer, PLS Cell, BBS	Member
15.	Representative, The World Bank, Dhaka Office	Member
16.	Representative, WFP, Dhaka Office	Member
17.	Focal Point Officer, Poverty and Livelihood Statistics (PLS) Cell, BBS	Member Secretary

3. REPORT REVIEW TEAM

(Not According to Seniority)

Team Members	
1.	Dr. Dipankar Roy, Joint Secretary, Statistics and Informatics Division (SID)
2.	Dr. Syed Shahadat Hossain, Professor, ISRT, DU
3.	Dr. Mohammad Yunus, Research Director, BIDS

4. EDITORS FORUM, BBS

(Not According to Seniority)

Team Members		
1.	Deputy Director General, Bangladesh Bureau of Statistics (BBS)	Chairperson
2.	Director, Agriculture/Census/Computer/Demography and Health/Industry and Labour/FA&MIS/National Accounting Wing, BBS	Member
3.	Project Director, PHC 2021 Project, BBS	Member
4.	Focal Point Officer, SVRS in digital platform, BBS	Member
5.	Focal Point Officer, Poverty and Livelihood Statistics (PLS) Cell, BBS	Member
6.	Deputy Director/Statistical Officer, PLS Cell, BBS	Member
7.	Director, SSTI Wing, BBS	Member Secretary

5. REPORT SCRUTINY COMMITTEE OF STATISTICS AND INFORMATICS DIVISION (SID)

(Not According to Seniority)

Committee Members		
1.	Additional Secretary (Informatics), Statistics and Informatics Division	Chairperson
2.	Joint Secretary (Budget, Financial Management and Audit and ICT), Statistics and Informatics Division	Member
3.	Joint Secretary (Informatics), Statistics and Informatics Division	Member

Report Scrutiny Committee of Statistics and Informatics Division (Continued.)

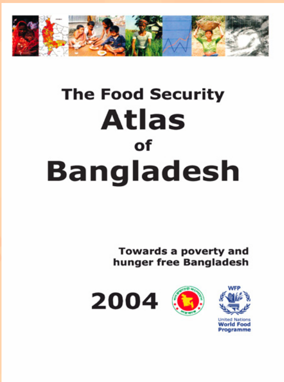
Committee Members		
4.	Deputy Secretary, Developmen-2, Statistics and Informatics Division	Member
5.	Deputy Secretary, Informatics-1, Statistics and Informatics Division	Member
6.	Deputy Secretary (Coordination and Reform Section), Statistics and Informatics Division	Member
7.	Focal Point Officer, Poverty and Livelihood Statistics Cell, BBS	Member
8.	Deputy Director, Publication Section, FA & MIS Wing, BBS	Member
9.	Deputy Secretary, Informatics-2, Statistics and Informatics Division	Member Secretary

6. WORKING COMMITTEE

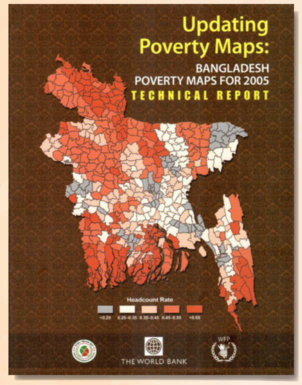
(Not According to Seniority)

A. Team Members		
1.	Mr. Mohiuddin Ahmed, MPH, Focal Point Officer, Poverty and Livelihood Statistics (PLS) Cell, BBS	Chairperson
2.	Mr. Mohammad Saddam Hossain Khan, Deputy Director, National Accounting Wing, BBS	Member
3.	Mr. Mohammad Shafiqul Islam, Deputy Director, National Accounting Wing, BBS	Member
4.	Mr. Md. Alamgir Hossen, Deputy Director, Demography and Health Wing, BBS	Member
5.	Mr. Muhammad Mizanoor Rahman Howlader, Deputy Director, National Accounting Wing, BBS	Member
6.	Ms. Aziza Rahman, Deputy Director, Industry and Labour Wing, BBS	Member
7.	Mr. Abdul Alim Bhuiyan, Deputy Director, Industry and Labour Wing, BBS	Member
8.	Mr. Tufail Ahmed, Deputy Director, National Accounting Wing, BBS	Member
9.	Mr. Md Arif Hossain, Deputy Director, Census Wing, BBS	Member
10.	Mr. Mohammad Ariful Islam, Deputy Director, National Accounting Wing, BBS	Member
11.	Ms. Asma Akhtar, Deputy Director, Demography and Health Wing, BBS	Member
12.	Deputy Director/Statistical Officer/Asst Statistical Officer (All), PLS Cell, BBS	Member
13.	Ms. Ismat Zerin, Statistical Officer, Census Wing, BBS	Member
14.	Representative, The World Bank, Dhaka Office	Member
15.	Representative, WFP, Dhaka Office	Member
16.	Mr. Mohammad Rafiqul Islam, Deputy Director, Agriculture Wing, BBS	Member
17.	Md. Ashadur Alam Prodhan, Statistical Officer, PLS Cell, BBS	Member Secretary

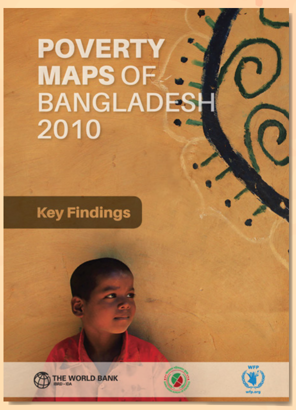
ANNEX 10
POVERTY MAP OF BANGLADESH REPORTS BY BBS, WFP AND WB



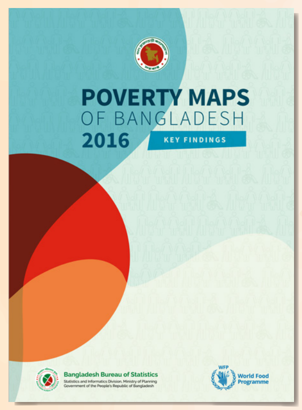
2000



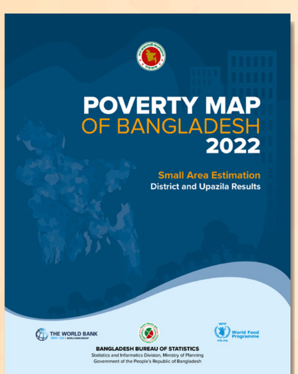
2005



2010



2016



2022

BANGLADESH BUREAU OF STATISTICS
Statistics and Informatics Division, Ministry of Planning
Government of the People's Republic of Bangladesh