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USING HOUSEHOLD AND DISTRICT LEVEL DATA FOR GEOGRAPHIC TARGETING:

A METHODOLOGICAL EXERCISE WITH BANGLADESH DATA

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INTRODUCTION AND OBJECTIVES OF THE STUDY

Previous studies on Bangladesh indicated persistent geographic effects on poverty (Ravallion and Wodon 1999; Sen 2000) and pointed to the need for geographic targeting for reducing the severity of poverty (Task Force Report 1991; Sen 1997). The policy problem then turns out to be a problem of identifying the poor and the poorest areas. Once validated, such mapping can serve as the guide for allocating resources to the poor areas. Within the poor areas, conventional household based targeting can be used for reaching out to the poorest and the most vulnerable.

The accurate poverty-mapping exercise based on geographic information, however, requires a range of socio-economic information at suitable levels of regional disaggregation, which is typically absent in the census and district level data. District level data, for instance, contain some broad information on land availability and cropping patterns, physical infrastructure such as road, irrigation and electricity, social infrastructure such as schools and health centers, rainfall and flooding. Household level data—as typified by the HES data—contains detailed information on household and community level resource endowments as well as information on income, consumption, and employment. To generate the same range of information at the district level would have been prohibitively costly. The question is whether the two sets of data can be combined in a way to generate regional poverty maps on a more defensible basis. The present paper attempts to address this question from a methodological point of view. In fact, while in this report we generated a ranking of the districts in Bangladesh in terms of poverty, the main purpose of this report is not to determine a clear allocation plan for Bangladesh, instead it is to determine a methodological strategy that can be used to generate such a ranking. In other words, we conducted a methodological exercise that shows how it is possible to predict local outcomes based on household models and locally available data in Bangladesh.

METHODOLOGY AND RESULTS

In this paper we suggested to use a parametric approach, such as the one used by Nick Minot (2000) for Vietnam. John Hoddinott and Saul Morris (1999) used a similar method for Cote d'Ivoire. For other attempts, see the paper by Hentschel, et. al. (2000) on Ecuador.

Specifically the following steps were adopted:

1. We estimated a typical household income determination model with household and community level variables;
2. We re-ran the same model but with only limited household level variables for which exact mapping at district level is possible;
3. We predicted the district level per capita consumption expenditure (used for poverty ranking) by using the coefficients obtained in model 1, but by replacing the household level variables (as far as possible) by district level variables;
4. We produced the output in the form of regional poverty maps;
5. We also produced maps indicating the regional distribution of VGD cards and FFE food allocation for checking their poor area sensitivity based on our model.

The data set used for this exercise is a combination of household level primary data, census data and district level aggregate published data. The household level data set used in the report is the 1995/96 Household Expenditure Survey (HES) that has been collected by the BBS and that has been the main source of information for the analysis of poverty levels and trends in Bangladesh for the past few years. The district level data was collected from published and secondary data sources.

The results of the models are encouraging and suggestive of the importance of the approach combining household surveys and district level data.

CONCLUSIONS AND ISSUES FOR FURTHER RESEARCH

In this report we presented the results of a methodological exercise aimed at the determination of regional poverty maps for Bangladesh. The main purpose of the exercise was to show that it is possible and worthwhile to use local level data, like the

district level data, and coefficients derived from a structural model to predict levels of poverty indicators at local levels. There are of course a few limitations to the model and the results presented here, and there are several issues that deserve further research. Additionally, we believe that it would be important to do the following:

1. Expand the list of matched indicators between household and district data sets;
2. Given the importance of vulnerability of poor areas to natural disaster, include flood related variables in the estimation of the above models;
3. Test the model at administrative disaggregations at the sub-district level and below;
4. Use the census data tape for finer disaggregations at sub-district levels;
5. Test the same methodology to predict and map other relevant poverty outcomes (like malnutrition, food security, caloric deficiency and so on).

1. INTRODUCTION

Previous studies on Bangladesh have indicated persistent geographic effects on poverty (Ravallion and Wodon 1999; Sen 2000) and have pointed out the need for geographic targeting for reducing the severity of poverty (Task Force Report 1991; Sen 1997). The policy problem then turns out to be how to identify the poor and the poorest areas. Once validated, such a mapping can serve as the guide for allocating resources to the poor areas. Within the poor areas, conventional household based targeting can then be used for reaching out to the poorest and the most vulnerable.

An accurate poverty-mapping exercise based on geographic information, however, requires a range of socio-economic information at suitable levels of regional disaggregation, which are typically absent in the census and district level data. District level data, for instance, contain some broad information on land availability and cropping patterns, physical infrastructure such as roads, irrigation and electricity, social infrastructure such as schools and health centers, rainfall and flooding. Household level data—as typified by the Household Expenditure Survey (HES) data—contains detailed information on household and community level resource endowments as well as information on income, consumption, and employment. To generate the same range of information at the district level is prohibitively costly. The question is whether the two sets of data can be combined in a way to generate regional poverty maps in a rigorous way. The present paper presents a methodology to do exactly this.

MAIN OBJECTIVE OF THE STUDY

One of the most important goals of any poverty analysis exercise is to be able to identify and rank poor areas and to generate maps that can simply illustrate and guide the allocation of resources to different regions in the country.

While in this report we generated some ranking of the districts in Bangladesh in terms of poverty, the main purpose of this report is not to determine a clear allocation

plan for Bangladesh. Instead, it is to determine a methodological strategy that can be used to generate such a ranking. In other words, we have conducted a methodological exercise that shows how it is possible to predict local outcomes based on household models and locally available data in Bangladesh.

Among the most relevant poverty level measures considered for this exercise include level of poverty, poverty incidence and level of food security. Here we have estimated alternative levels of poverty, represented by the average level of per capita expenditure.

2. METHODOLOGY AND DATA

THE METHODOLOGY

In this paper we suggest the use of a parametric approach to develop regional poverty rankings, similar to the ones used by Nick Minot (2000) for Vietnam, John Hoddinott and Saul Morris (1999) for Cote d'Ivoire and Hentschel et. al. (2000) for Ecuador.[1]

In particular, we have decided to adopt the following steps in the estimation of the model. First, we used household level data to estimate a typical household income determination model using household and community level variables. In this case household income is expressed in terms of per capita expenditure, given the better properties of the expenditure data compared to the income data (the estimates of the expanded model, are presented in Table 2). It is important to stress that the purpose of the model is not to find the better explanatory variables for the level of income, but to find a set of variables that are strongly correlated with it that can improve the quality of the prediction.

Next, we ran the same basic model, but we limited the set of the variables used in the model to the household level variables that are available also at the district level. While the estimates of the full model give better results, the model with limited number of variables can be used for prediction using aggregate local available data, (which in our case is district-level data). This regression model based on a smaller set of variables is presented in Table 3. Of course, if the number of variables that are available both at the household and the district level is larger, then the quality of the estimates and the prediction will improve as well.

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[1] For a review of the literature that describes other similar efforts to use household level data and census data to develop poverty mapping, see Hentschel et. al. (2000).

Then we used the coefficients from the results of the model with a limited number of variables available at the household and district levels and the district level means of the same variables (as far as possible) to predict the level of per capita expenditure for each of the districts. In a few cases, when the variables at the household level were not available, we replaced them with the district level means of household level variables.

Finally, we used the results of the estimations of the predictions of the models to produce regional poverty maps at the district level. This step was very important to demonstrate the ultimate application of the methodology presented here and to visually compare the results obtained using alternative models. In addition, we produced maps indicating the regional distribution of Vulnerable Group Development (VGD) cards and Food for Education (FFE) food allocation (Map 5 and 6 respectively) for a preliminary comparison between those allocation plans and the results of our model.

THE DATA

The data set used for this exercise is a combination of household level primary data, census data and district level aggregate published data. The household level data set used in the report is from the 1995/96 Household Expenditure Survey (HES). This data, collected by the Bangladesh Bureau of Statistics (BBS), has been the main source of information for the analysis of poverty levels and trends in Bangladesh in recent years.

The district level data used in the report is data available from secondary sources at local level. These data are collected at the local level by various ministries and departments. In contrast, the bulk of the household level data used for the estimation of the model, comes from a single data set that contains a large amount of information for each of the households.

Another key difference between the two data sets is that while the household data set needs to be very consistent for each of the households included in the estimation model, such a consistency is not required between the sources of data at the district level. Nevertheless, it is expected that the means of the variables from the household and the

district level data will be similar to each other. Table 1 presents a comparison of the means at the district level of four variables from the household data set and the district level data - land per household, availability of sanitation, literacy and availability of electricity – for each of the 63 districts. These calculated means confirm that the two data sources are highly comparable and that the district level data can be used for the calculation of the prediction of poverty variable outcomes.

Table 1 — Comparisons between Household Level Survey and District Level Data for Four Predictors

District Code	Ave. Land Owned per Household		Proportion of HHs with Sanitation		Adult Literacy		Proportion of HHs with Electricity	
	HH Survey	District	HH Survey	District	HH Survey	District	HH Survey	District
1	1.52	1.32	0.54	0.35	0.53	0.54	0.14	0.20
4	1.67	1.60	0.39	0.33	0.47	0.48	0.11	0.16
6	1.09	1.05	0.53	0.45	0.50	0.54	0.36	0.14
9	1.42	1.01	0.36	0.25	0.50	0.41	0.23	0.10
10	1.57	0.98	0.36	0.33	0.36	0.41	0.24	0.26
12	0.71	0.99	0.19	0.18	0.29	0.35	0.16	0.13
13	0.62	0.71	0.32	0.39	0.42	0.43	0.20	0.24
15	0.51	0.76	0.46	0.34	0.50	0.46	0.52	0.42
18	1.02	1.34	0.24	0.21	0.41	0.42	0.11	0.27
19	0.87	0.87	0.30	0.37	0.43	0.52	0.25	0.35
22	0.93	0.73	0.19	0.25	0.31	0.35	0.11	0.16
26	0.39	0.92	0.75	0.63	0.67	0.57	0.89	0.69
27	1.18	1.37	0.14	0.17	0.49	0.40	0.07	0.22
29	1.27	1.31	0.26	0.20	0.41	0.44	0.15	0.13
30	0.93	0.85	0.47	0.47	0.55	0.51	0.36	0.31
32	0.66	0.92	0.16	0.16	0.36	0.37	0.06	0.14
33	0.98	1.16	0.45	0.28	0.56	0.44	0.42	0.11
35	1.19	1.52	0.22	0.27	0.38	0.54	0.00	0.12
36	1.08	1.35	0.20	0.27	0.40	0.40	0.25	0.32
38	1.53	1.15	0.17	0.13	0.30	0.37	0.00	0.21
39	0.83	0.97	0.19	0.30	0.20	0.29	0.16	0.12
41	1.77	1.24	0.25	0.34	0.44	0.48	0.17	0.31
42	0.85	1.24	0.23	0.24	0.60	0.63	0.01	0.08
44	1.33	1.49	0.40	0.14	0.38	0.42	0.30	0.14
46	3.09	1.94	0.15	0.14	0.40	0.35	0.00	0.12
47	0.86	1.40	0.64	0.45	0.62	0.55	0.60	0.31
48	0.66	1.09	0.24	0.17	0.26	0.41	0.21	0.15
49	0.92	1.10	0.01	0.14	0.30	0.30	0.00	0.04
50	0.96	0.98	0.18	0.18	0.28	0.35	0.11	0.21
51	0.78	0.89	0.29	0.18	0.45	0.47	0.15	0.20
52	1.24	1.13	0.10	0.25	0.20	0.41	0.00	0.07
54	0.92	1.20	0.05	0.22	0.15	0.38	0.00	0.20
55	1.46	1.52	0.43	0.21	0.38	0.39	0.08	0.14
56	0.84	1.07	0.07	0.17	0.17	0.39	0.00	0.14
57	2.20	1.22	0.05	0.21	0.15	0.35	0.10	0.25
58	1.59	1.11	0.34	0.23	0.45	0.43	0.24	0.22
59	0.81	0.76	0.05	0.24	0.38	0.51	0.38	0.39
61	0.95	1.10	0.25	0.15	0.39	0.42	0.18	0.17
64	1.20	1.36	0.17	0.23	0.38	0.42	0.15	0.21
65	1.66	1.62	0.40	0.24	0.55	0.48	0.35	0.11
67	0.41	0.66	0.42	0.41	0.53	0.50	0.67	0.62
68	0.76	0.78	0.32	0.30	0.40	0.40	0.33	0.24
69	1.62	1.22	0.03	0.21	0.40	0.40	0.02	0.26
70	0.94	1.33	0.35	0.11	0.28	0.28	0.13	0.11
72	1.66	1.44	0.18	0.13	0.31	0.40	0.14	0.16
73	0.89	1.15	0.19	0.19	0.25	0.31	0.18	0.13
75	0.45	0.97	0.25	0.25	0.27	0.47	0.25	0.24
76	0.97	1.18	0.27	0.30	0.38	0.35	0.25	0.19
77	1.93	1.66	0.00	0.24	0.22	0.39	0.00	0.07
78	2.37	1.53	0.35	0.34	0.60	0.50	0.18	0.14
79	1.08	1.21	0.50	0.46	0.60	0.65	0.21	0.13

Table 1 — Comparisons between Household Level Survey and District Level Data for Four Predictors (Continued)

District Code	Ave. Land Owned per Household		Proportion of HHs with Sanitation		Adult Literacy		Proportion of HHs with Electricity	
	HH Survey	District	HH Survey	District	HH Survey	District	HH Survey	District
81	0.80	1.08	0.26	0.20	0.38	0.42	0.23	0.21
82	1.26	1.23	0.45	0.21	0.43	0.35	0.27	0.12
84	1.35	2.39	0.40	0.20	0.62	0.42	0.68	0.20
85	0.72	1.00	0.16	0.11	0.29	0.33	0.16	0.17
86	1.25	1.12	0.08	0.17	0.17	0.37	0.00	0.07
87	1.30	1.25	0.23	0.25	0.50	0.47	0.32	0.16
88	1.99	1.07	0.18	0.20	0.48	0.31	0.20	0.12
89	1.42	1.03	0.02	0.13	0.23	0.32	0.00	0.10
90	1.63	1.76	0.16	0.22	0.26	0.32	0.09	0.16
91	1.45	1.40	0.16	0.27	0.24	0.38	0.11	0.22
93	1.04	1.07	0.21	0.25	0.33	0.40	0.19	0.22
94	1.32	1.62	0.02	0.15	0.43	0.36	0.03	0.12
Total	**1.02**	**1.11**	**0.33**	**0.29**	**0.43**	**0.44**	**0.29**	**0.25**

Source: HES 95/96 and District level

Table 2 — Determinants of Per Capita Consumption Expenditure: Results for Expanded Model

Dependent Variable: Log of per capita annual consumption

Independent Variables	Coefficient	t
Log of land owned	0.107	26.600
Share of land rented-in	0.034	3.611
No. of family members	-0.073	-23.544
Log of total workers	0.130	8.368
Share of non-agricultural workers	0.070	5.077
Share of female workers	-0.098	-3.454
Electricity access (0, 1)	0.141	6.506
Remittance (0, 1)	0.149	7.735
Level of Education of the Household head	0.022	10.070
Level of Education of wife	0.011	3.687
Religion (0, 1)	0.030	1.577
Sanitation (0, 1)	0.201	12.015
Percent of tribal households in district	0.001	0.552
Electricity access district	0.003	4.031
Literacy both sex 7+ in district	0.004	3.124
Barisal Division	0.051	1.717
Chittagong Division	0.226	11.219
Dhaka Division	0.144	8.871
Khulna Division	0.068	3.169
Sylhet Division	0.292	11.381
Constant	8.792	211.581

No of Observations: ---------- 4378
R-squared: ----------0.4042

3. THE RESULTS

Table 2 presents the results of the estimation of level of the per capita expenditure using all the variables available in the household data set. The results of this model are not very different from other similar models that attempt to explain the level of household per capita expenditure. Level of land available, owned or rented-in, has a significant and positive impact on the determination of per capita expenditure, as does the number of total workers and non-agricultural workers in the household. The general level of human capital, represented by the level of education of the household head and his spouse, also has a positive impact on the level of per capita expenditure. Other proxies for the level of living, such as the level of sanitation and access to electricity, also are clearly positively correlated with the level of expenditure. On the other hand, the number of household members and the share of female workers (who are usually paid lower wages), have a negative impact on the level of per capita expenditure. Finally, we also added dummy variables for five of the six divisions in Bangladesh to control for structural differences that exist between these broad geographical regions.

The results of the small model that contains only variables that are available both in the household data set and the district level data set are presented in Table 3. As expected, the explanatory power of this reduced model, as expressed by the R squared, is much lower than the larger model (a drop from .4 to .3). In this model as well, land availability is a strong determinant of the level of per capita expenditure. The results with respect to literacy sanitation and access to electricity remain similar in both models.

The coefficients derived from the models presented above have been used to generate predicted average level of per capita expenditure at district level. The comparisons between the alternative predictions are presented in Table 4. In the first set of predictions, we used the coefficients from the expanded model and the means from the household level data set. In the second set, the household data set has been used in

combination with the coefficients from the small model. In the third and final set of predictions, the district level data has been used in combination with the coefficients from the small model.

Table 3 — Determinants of Per Capita Consumption Expenditure: Results for Small Model

Dependent Variable: Log of per capita annual consumption

Dependent Variables	Coefficient	t
Log of land owned	0.086	22.590
Sanitation (0, 1)	0.247	14.190
Percent of tribal households in district	0.001	0.361
Literacy	0.136	9.774
Electricity access(0, 1)	0.209	9.563
Barisal Division	0.085	3.753
Chittagong Division	0.260	13.700
Dhaka Division	0.166	9.808
Khulna Division	0.110	5.134
Sylhet Division	0.265	9.960
Constant	8.699	618.068

No of Observations: ----------4693
R-squared: ----------0.2945

Table 4 — Actual and Predicted Values of Per Capita Consumption Expenditure Based on Different Models

Code	District Name	Actual PC exp	Expanded model HH data	Small model HH data	Small model Dist. data
1	Bagerhat	9,534	9,377	8,663	8,380
4	Barguna	10,620	8,201	7,734	8,160
6	Barisal	10,140	8,896	8,699	8,128
9	Bhola	9,972	7,497	7,734	7,510
10	Bogra	9,085	7,208	6,886	7,254
12	Brahmanb	8,644	7,200	7,778	8,746
13	Chandpur	8,491	8,197	8,230	9,289
15	Chittago	12,934	9,453	9,161	9,612
18	Chuadang	6,910	7,117	7,179	8,103
19	Comilla	8,601	8,699	8,601	9,703
22	Cox's Ba	10,526	7,149	8,316	8,752
26	Dhaka	21,555	11,389	9,529	10,248
27	Dinajpur	7,793	6,356	6,255	7,104
29	Faridpur	8,193	7,700	7,976	8,305
30	Feni	11,811	10,079	9,633	9,860
32	Gaibandh	8,001	6,195	5,935	6,715
33	Gazipur	14,297	9,060	8,716	8,344
35	Gopalgan	7,493	7,283	7,488	8,646
36	Habiganj	9,261	9,105	8,799	9,682
38	Joypurha	8,699	6,424	6,385	6,900
39	Jamalpur	7,942	6,915	7,357	8,112
41	Jessore	9,662	7,834	7,584	8,454
42	Jhalokat	7,863	7,418	7,115	7,818
44	Jhenaida	10,571	8,120	8,123	7,826
46	Khagrach	8,468	9,223	9,201	9,396
47	Khulna	10,526	8,825	8,500	8,854
48	Kishoreg	7,604	6,739	7,099	8,104
49	Kurigram	4,681	5,295	5,755	6,582
50	Kushtia	8,356	6,492	6,696	7,643
51	Laksmipu	9,440	8,675	8,648	8,937
52	Lalmonir	7,670	6,076	5,868	6,902
54	Madaripu	7,036	6,968	6,871	8,337
55	Magura	6,978	7,017	7,646	7,943
56	Manikganj	7,681	6,827	6,910	8,057
57	Meherpur	6,052	6,406	6,835	7,924
58	Maulviba	12,245	9,751	9,498	9,285
59	Munshiga	10,505	7,963	7,712	8,526
61	Mymensin	8,435	7,583	7,517	8,125
64	Naogao	9,000	6,562	6,169	7,213
65	Narail	12,456	8,415	8,377	8,091

Table 4 — Actual and Predicted Values of Per Capita Consumption Expenditure Based on Different Models (Continued)

Code	District Name	Actual PC exp	Expanded model HH data	Small model HH data	Small model Dist. data
67	Narayang	13,667	.	.	.
68	Narsingd	10,148	7,682	7,804	8,267
69	Natore	7,183	6,495	6,267	7,157
70	Nawabgan	7,636	5,307	6,064	6,716
72	Netrokon	8,371	7,274	7,521	8,233
73	Nilphamr	7,388	5,839	6,268	6,813
75	Noakhali	9,162	7,643	7,954	9,242
76	Pabna	6,396	6,334	6,644	7,151
77	Panchaga	5,954	5,912	6,081	7,103
78	Patuakha	8,453	8,598	8,259	8,114
79	Pirojpur	9,923	8,597	7,985	8,341
81	Rajbari	9,808	6,230	6,202	7,023
82	Rajshahi	8,458	8,010	8,614	8,154
84	Rangamat	16,692	11,886	10,891	10,000
85	Rangpur	7,011	5,862	5,997	6,683
86	Satkhira	6,690	5,997	6,881	7,960
87	Shariatp	9,446	7,665	7,778	8,013
88	Sirajgan	7,404	6,804	6,996	6,770
89	Sherpur	7,058	6,645	7,033	7,817
90	Sunamgan	7,344	7,434	7,982	9,350
91	Sylhet	9,959	8,106	8,320	9,487
93	Tangail	8,774	8,185	7,845	8,358
94	Thakurga	7,739	6,092	6,173	6,983

THE MAPS

The predictions presented in Table 4 have been used to generate district level poverty maps for Bangladesh. The maps present the distribution of average per capita expenditure grouped in four categories, from the poorest to the richest. The interval between the maps has been selected using the method of Natural Breaks in ArcView (the software package used to prepare the maps).[2]

The first map in Figure 1 presents the distribution of the actual per capita expenditure level. It is not surprising that the districts of Dhaka and Chittagong are among those with the highest per capita expenditure. The results of the first set of predictions, obtained using the full model and the household data set (Figure 2), are able to replicate quite well, with the exception of a few districts, the actual data.

The following two figures, Figure 3 and 4, present the projections calculated using the small model. The first impression is that these last two maps do not yield the same level of difference in poverty level between districts that are close to each other. This is understandable, because the map in Figure 4 uses a smaller number of variables and thus are not able to differentiate as much across districts. At the same time, though, the difference between the estimates obtained with the household data set, reported in Figure 3 and those with district level data, reported in Figure 4, are not very large. Nonetheless, if more data were available and a greater number of variables were common to both data sets, it would be possible to improve the quality of the estimates.

In the last two figures, we present for illustrative purposes the distribution of the allocation of the VGD and the FFE programs. It is interesting to note the differences in the allocations of the two programs. The distribution of the VGD program reflects the thana level poverty distribution maps elaborated by WFP that give a lot of weight to the areas in the northwest in general, and along the Jamuna river in particular. On the other

[2] This method identifies breakpoints between classes using a statistical formula (Jenk's optimization). This method is rather complex, but basically the Jenk's method minimizes the sum of the variance within each of the classes. Natural Breaks finds groupings and patterns inherent in the data.

hand, the distribution of the FFE, which is not targeted at all, follows very closely the distribution of the population, as it appears in the 1991 census.

4. CONCLUSIONS

In this report we presented the results of a methodological exercise aimed at the determination of regional poverty maps for Bangladesh. The main purpose of the exercise is to show that it is possible and worthwhile to use local level data, like the district level data, and coefficients derived from a structural model to predict levels of poverty indicators at local levels. We found that the results are encouraging and suggestive of the importance of the approach combining household survey and district level data.

There are several reasons why this is desirable. Most importantly, data on individual households is not available every year and usually, with the exception of census data, does not have a great level of disaggregation. The use of local level data, instead, allows for the preparation of regional predictions as soon as new aggregate data is available, and the method can be applied at any level of disaggregation, as long data is available. For example, it would be feasible to collect necessary secondary level data in one district for a given number of subregions (for example thanas), and use the model to compare and map the level of poverty only for that district.

There are of course a few limitations to the model and the results presented here and there are several issues that deserve further research. First of all, it is important to improve the quality of the data set used for the estimation. The level of per capita expenditure used for the estimation and the predictions, needs to be adjusted to reflect differences in the cost of leaving. Similarly, the list of explanatory variables available in the household and district data sets should be expanded. Second, in order to give due importance to the issues of the vulnerability of poor areas to natural disasters, flood related indicator variables should be added to the estimation procedure of the above models.

It would also be good to test the model for its use at a level of disaggregation lower than the district. This could be done by making a comparison between estimates obtained with aggregate data at the sub-district level and below and census level data, when this data are available in the year 2002.

Finally, it would be interesting to test the same methodology to predict and map other relevant poverty outcomes (like malnutrition, food security, caloric deficiency and so on), besides the level of per capita expenditure.

REFERENCES

Hentschel, Jesko, Jean Lanjouw, Peter Lanjouw and Javier Poggi, 200. "Combining census and survey data to study special dimensions of Poverty: A case study of Ecuador" *The World Bank Economic Review* Vol 14. No. 1 pp 147-66.

Hoddinott, John and Morris, Saul, 1999 "Pipeline study: Cote d'Ivoire, Research Paper # 3"; Mimeo. International Food Policy Research Institute, Washington D. C.

Minot, Nicholas, 1998. "Generating Disaggregate Poverty Maps: An Application to Vietnam" MSSD Discussion paper No. 25. International Food Policy Research Institute, Washington D. C.

Ravallion, Martin and Wodon, Quentin 1999; "Poor Areas or only Poor People?" *Journal of Regional Science* Vol 39, No. 4 pp 689-711.

Task Force Report (1991): "Task Force Report on Poverty Alleviation". In: *Report of the Task Forces on Bangladesh Development Strategies for the 1990s*, Vol. 1, University Press Ltd, Dhaka, 1991 (with Mahabub Hossain, S.R. Osmani and others);

Sen (1997): "Poverty and Policy" in Rehman Sobhan (Ed.), *Growth or Stagnation? A Review of Bangladesh's Development 1996*, Centre for Policy Dialogue and University Press Ltd, Dhaka, February 1997, pp. 115-160;

Sen (2000): Bangladesh Poverty Analysis: Trends, Policies and Institutions, Background Paper Prepared for the *Poverty Partnership Agreement* between ADB and GoB, April 2000 (forthcoming in the September 2001 issue of the *South Asia Economic Journal*).

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