Research Report No. 70

INCOME POVERTY AT DISTRICT LEVEL: AN APPLICATION OF SMALL AREA ESTIMATION TECHNIQUE

SOCIAL POLICY AND DEVELOPMENT CENTRE

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By

Haroon Jamal

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SUMMARY

The objective of this research is to provide estimates of income poverty at the district level with the help of information available in household surveys; PSLM and HIES 2004-05. Both surveys are combined to produce poverty measures at district level using small area estimation technique. The technique uses the welfare (consumption or income) function to estimate and predict poverty with the help of non-monetary poverty correlates. This study estimates consumption functions separately for urban and rural areas and the coefficients of the estimated functions are applied to predict poverty incidence for provinces and for districts.

1. INTRODUCTION

The Federal Bureau of Statistics (FBS), Government of Pakistan (GoP) conducted the nationwide Pakistan Social and Living-Standards Measurement Survey (PSLM) during 2004-05. The design of the PSLM was based on the Core Welfare Indicator Questionnaire (CWIQ) survey instrument, which essentially collects simple welfare indicators and indicators of access and use of public services and the level of satisfaction with theses services. The survey provides district level welfare indicators with a sample size of about 76,500 households.

On the other hand, Household Integrated Economic Survey (HIES) usually collects very detailed information on household characteristics, including its consumption level and income, but the coverage is generally limited and only representative of a relatively large geographical unit. In the case of Pakistan, HIES covers about 16000 households, which according to FBS, is an appropriate sample size for providing reliable estimates of key characteristics at national and regional (urban/rural) level.

To fully analyze the district level data generated through PSLM, it is necessary to devise a means for distinguishing poor from non-poor households or arranging household responses and welfare status according to consumption or income groups/quintiles. Thus, there is a need to identify a set of poverty correlates or predictors and estimate their respective weights to predict household consumption and to rank households for poverty analysis at the district level.

Fortunately, both surveys (PSLM and HIES) have been conducted during 2004-5. By combining the respective strengths of these surveys, the simulated-welfare mapping method is applied, which aims at estimating welfare indicators for small administrative areas. The approach uses HIES data to estimate a model of per capita consumption expenditure (or any other household or individual-level indicator of wellbeing) as a function of variables that are available in both surveys (small survey, representative at national/regional level and the large survey, representative at district level). The resulting parameter estimates from this estimation procedure are then used in a simulation to predict per capita consumption for each household in the large survey. Using the predicted per capita consumption, household level measures of poverty is then calculated and aggregated for small areas, such as districts.

This research note provides estimates of poverty at the district level. Predicted consumption functions, separately for urban and rural Pakistan were estimated with the help of non-monetary correlates of consumption and applied to predict poverty at sub-national and sub-provincial levels. The paper uses unit record data of both surveys. HIES section of the PSLM is mainly used for the estimation of monetary poverty. It includes standard and detailed consumption modules and is traditionally used to estimate poverty in Pakistan.

The paper is divided as follows: Section 2 discusses the methodology for modeling predicted welfare function. The estimated poverty correlates are provided in section 3. Application of the welfare functions to predict poverty at sub-national level is presented in section 4, while the last section gives the concluding remarks.

2. MODELING PREDICTED WELFARE

The small area estimation technique is straightforward[1]. Let W be an indicator of welfare, based on the distribution of a household-level variable of interest, yh. Using the smaller and richer data sample, we estimate the joint distribution of yh and a vector of covariates, xh: By restricting the set of explanatory variables to those that can also be linked to households in the larger sample, this estimated distribution can be used to generate the distribution of yh for any sub-population in the larger sample, conditional on the sub-population's observed characteristics. This, in turn, allows us to generate the conditional distribution of W, in particular, its point estimate and prediction error.

It is assumed that the approximating mean function $h(x,\theta)$ is linear in its parameters. That is the conditional expectation E(y|x) of the response given the covariates is related to the linear predictors by the response link function $h(x,\theta)$. Some continuous variables with strong predictive capabilities were dichotomized to discriminate between poor and non-poor households. These regressors were constructed and included in the model to capture the effects of qualitative independent variables. The resulting variables were then fitted into a

1 For detailed methodology, see Elbers at el (2002 and 2003),

model which contains both continuous and discrete variables. The structural form of the model is specified by the equation (1) below:

$$Y_j = X_j \beta + \lambda_{j1}\gamma_1 + \lambda_{j2}\gamma_2 + \lambda_{jk}\gamma_k + \mu_j \qquad (1)$$

where, Y_j is the response variable; X_j is a matrix of continuous explanatory variables; λs are the respective explanatory discrete variables; βs are the estimated coefficients relative to the continuous variables; γs are the estimated coefficients associated with the selected discrete variables; and μ_j is the standard error term. The best poverty predictors were the ones that contributed to a significant marginal increase in the explanatory power of the model.

The response variable may be represented by the total household expenditure[2]. It is a standard multivariate regression analysis and estimates the partial correlation coefficient between expenditure and the explanatory variables. Typically, a logarithmic transformation is applied to the response surface to make the relationship between the *y* and the *xs* linear. The transformation stabilizes the error variance, reduces asymmetry in the distribution of error terms and improves the prediction. The estimated weighted function is continuous and allows the construction of predicted household expenditure, which is used as a basis for poverty analysis for small administrative areas.

Alternatively, a dichotomous variable explaining poor/non-poor status may be represented as a response variable. In this case, a logit or probit regression of the binary variable is estimated using the maximum likelihood estimation procedure. Based on the assumptions about the error term of the model, probability is computed to predict the household poor/non-poor status.

The selection of appropriate poverty predictors is the next step in the modeling welfare function. Initially the set of regressors includes a host of explanatory variables that are both

[2] The household expenditure is often divided by the poverty line to ensure comparability across regions. Since, in this paper urban and rural welfare predicted functions are estimated separately, it was not felt necessary to divide household expenditure by the poverty line.

discrete and continuous. These initial regressors are essentially household level variables[3]that focus on: household assets, education level and literacy, employment, household amenities, housing quality, household structure, demographic characteristics and geographical location. These variables[4] were constructed from the HIES, 2004-05 survey and only those that strongly correlated with household total expenditure were retained for further testing. A stepwise procedure allows one to calibrate the models by dropping explanatory variables with less predictive power[5]. Optimal poverty predictors are selected using a combination of multiple regression analysis and tests for correlation and prediction. Once the poverty predictors are identified, their corresponding weights may be used to predict response (household expenditure) variable.

3. POVERTY CORRELATES

As mentioned earlier, two alternative methods of specifying the response (dependent) variable are available. A continuous variable (log of household expenditure) or a binary variable may be used to statistically correlate household characteristics with poverty status or consumption behavior. However, it is argued that poverty status binary variable (poor/non-poor) is computed from household expenditure and by using this variable, one may lose much of the information available about the actual relationship between expenditure and its explanatory factors. It is, therefore, recommended that the analysis is best carried out with the expenditure variable rather than the poor/non-poor status of households.

Nonetheless, to check the sensitivity of results and the relative power of prediction, both methods are applied to estimate the welfare function. To a large extent both alternatives yielded similar prediction power, statistical significance of poverty predictors and goodness

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[3] The member level variables such as literacy and enrollment are aggregated at the household level for consistency in the estimation. This aggregation of individual characteristics at the household level produces variables such as proportion of children enrolled in each household, proportion of household members who are literate.

[4] The choice of variables is, however, restricted and depends on the availability of data in both surveys. For instance, overseas and domestic remittances are important poverty/non-poverty predictors, but were not included in the initial list of predictors due to non-availability of relevant information in PSLM.

[5] Various statistical selection criteria are available in selecting the best model. These statistics include Akaike Information Criterion, Amemiya Prediction Criterion, Mallows' Prediction Criterion and Schwarz prediction Criterion. In this paper, Akaike Information Criteria is used to select the best model.

of fit. Table 1, portrays a comparative picture of both methods in terms of percentage of correct prediction[6].

TABLE 1
PREDICTED POWER OF ESTIMATED WELFARE FUNCTIONS

	Percentage of Correctly Predicted Households		
	Non-Poor	**Poor**	**Overall Correct Prediction**
Urban Areas:			
OLSQ Regression	91.1	59.6	82.7
Logistic Regression	91.2	60.0	82.9
Rural Areas:			
OLSQ Regression	91.2	39.8	76.6
Logistic Regression	90.9	41.0	76.7

Source: Author's Estimates

It is evident from Table 1 that welfare functions work relatively well in urban areas. Both specifications estimated 83 percent cases appropriately in the actual category of households. In rural areas, however, the prediction power is somewhat reduced and about 77 percent cases were put in the right category of households. Having reached a conclusion that both specifications are the same in terms of prediction power, further description of results and application are based on a multivariate regression analysis that specifies logarithm of expenditure as the dependent variable[7].

Table 2 and 3, present regression results of estimated welfare function for urban and rural areas, respectively. The adjusted R-Square, which is a measure of goodness of fit, is 0.65 for urban and 0.42 for rural areas. In a cross-section analysis, these magnitudes are considered well enough for acceptability of the model. The magnitudes of the Durbin-Watson statistic indicate that the relationship between consumption and poverty predictors is not spurious. Multicollinearity among independent variables, which makes the coefficients statistically less efficient and insignificant, is tested through the condition index. The index value greater than

[6] Similar results were obtained using HIES 2000-01, see Jamal (2005).

[7] The detailed results of logit estimates are provided in the Appendix, Table– A1 and Table– A2.

30 indicates severity of multicolinearity and points to the less reliability of magnitude of coefficients. The estimated results however, indicate that the value of the condition index is 15 for urban as well as rural areas. Having illustrated the summary statistics of estimated welfare functions, some observations regarding poverty correlates are in order.

TABLE 2
PREDICTED WELFARE FUNCTION – URBAN AREAS
[*Dependent Variable – Logarithm of Total Household Expenditure*]

		Coefficients	t-Statistics
Household Demography:			
Family Size		-0.0857	-39.74
Dependency Ratio		-0.1563	-12.00
Number of Earners in Household		0.0309	5.47
Household Education:			
Highest Education Level in Family – Male		0.0077	4.83
Head of Household:			
Education Level – Primary		-0.0325	-2.09
Education Level – Higher Secondary		0.1284	5.49
Education Level – Tertiary		0.2762	14.94
Occupation – Wage Employment		-0.1098	-9.62
Household Assets:			
Asset Score		0.0762	27.43
Ownership of Non-Residential Property		0.0548	2.57
Housing Quality and Services:			
More Than Three Persons Per Room		-0.0984	-7.76
Telephone Connection		0.2464	17.82
RCC Roofing		0.1104	8.74
Flush System Connected to Sewerage Line		0.0693	5.16
Household Use Gas for Cooking purposes		0.0295	2.22
Locational Variables:			
Large Cities		0.0920	6.82
NWFP Province		0.0399	2.69
Sindh Province		0.0931	6.90
Intercept (Constant)		7.2022	328.48
Summary Statistics:			
Adjusted R-Square	0.65	Condition Index	15.0068
F-Value	596.84	Durbin-Watson	1.507

Source: Author's Estimates based on HIES, 2004-05

TABLE 3
PREDICTED WELFARE FUNCTION – RURAL AREAS
[Dependent Variable – Logarithm of Total Household Expenditure]

	Coefficients	t-Statistics
Demography:		
Family Size	-0.0661	-46.58
Dependency Ratio	-0.1303	-11.87
Education:		
Out of School Children – Primary	-0.0601	-5.71
Out of School Children – Secondary	-0.0199	-1.91
Highest Education Level in Family – Female	0.0063	4.49
Head of Household:		
Education Level	0.0086	7.95
Age of Head (Squared)	0.00003	8.49
Occupation – Non-farm Household	-0.1192	-12.98
Occupation – Sharecropper (HARI)	-0.0607	-3.83
Household Assets:		
Livestock Ownership	0.0596	6.25
Asset Score	0.0461	22.81
Ownership of Non-Agricultural Land	0.1279	6.20
Ownership of Non-Residential Buildings/House	0.0647	2.95
Housing Quality and Services:		
More Than Three Persons Per Room	-0.0665	-7.50
Telephone Connection	0.1730	12.90
No Toilet in House	-0.0350	-3.77
Pucca House (Cemented Structure)	0.0785	6.14
Locational Variables:		
Sindh Province	0.0801	6.97
Balochistan Province	-0.0619	-5.07
Southern Punjab	-0.0488	-3.76
Intercept (Constant)	7.2606	382.01

Summary Statistics:

Adjusted R-Square	0.42	Condition Index	15.0568
F-Value	316.38	Durbin-Watson	1.46

Source: Author's Estimates based on HIES, 2004-05

Family size and dependency are important poverty predictors. The dependency is represented by the proportion of children and members greater than 65. Both determinants are highly correlated with expenditure.

In rural areas, ownership of livestock, non-residential and non-agriculture land are all positively correlated with household expenditure. Further, non-farm households and sharecropping households (Haris) play a dominant role in distinguishing poor from non-poor. In fact, the magnitude of coefficient associated with the variable representing tenurial status is quite large.

The quality of housing structure in terms of material used and housing services/utilities are important determinants of poverty status in both urban and rural areas. The estimated functions indicate that telephone connection (Landline), RCC roofing and cemented structure are important and positive determinants of household consumption expenditure. Moreover housing congestion, represented by households with more than 3 persons per room, appears as a negative significant correlate.

One variable that appears to be highly correlated with aggregated household total expenditure with strong predictive capability is the "asset score". This variable is constructed by assigning equal weight[8] to each of the sixteen assets[9] listed in both PSLM and HIES questionnaires. A constant 1 is assigned to each of the assets detained by the household, and the assets score is obtained by summing up across all assets at the household level. The uniform allocation of score, irrespective of the asset characteristics, tends to smooth out the distribution of assets across households. To the extent that these assets have different values and all exhibit different rates of depreciation, uniform allocation might even increase the distortion in the distribution of household assets. But, what actually matters in this construction is the ownership of assets by a household and not so much the values of the asset

[8] One popular method for obtaining weighted score is the Principal Components Analysis (PCA). The weighted Factor Score, which is derived from PCA is also attempted and used as a regressor instead of score computed by assigning equal weight to each asset. However, no improvement and no significant changes in the results are observed. Therefore, simple scoring of assets is preferred.

[9] These assets are; iron, fans, sewing machine, video/cassette player, tables/chairs, clocks, TV, VCR/VCP,VCD, refrigerator, air-conditioner, air cooler, computer, bicycle, motor cycle, car and tractor.

which are difficult to estimate accurately from surveys which are carried out on a single visit to the household. The maximum asset score is 16 and the minimum is 0, for the poorest households which possess none of the assets listed.

The significant role of education, especially higher education in urban areas, is evident from Table 2. The magnitude of coefficients associated with higher secondary (intermediate) or tertiary education of the head of a household plays a decisive role in determining the household's consumption/poverty status. The role of education of head of household in rural areas is not as important as his experience (age of head). Interestingly, highest education level in the family is appeared as a positive significant correlate of household consumption. However, in urban areas, male education counts, while female education is important in rural areas in distinguishing poor from non-poor households.

5. PREDICTED POVERTY INCIDENCE AT SUB-NATIONAL LEVEL

The estimated non-monetary poverty correlates with the respective weights[10] (coefficients) that are applied to determine the provincial[11] and district level poverty incidence in Pakistan. The estimated response on log scale was transformed back and converted into per capita expenditure to remove the effects of the size of the household. The transformed predicted response was then used to categorize households into poor/non-poor using the poverty lines in Jamal (2007). Table 4, depicts provincial poverty incidences, separately for provincial capitals, large cities, small cities, towns and rural areas. Overall and regional (urban/rural) poverty incidences at district level are presented in the Appendix (Table A3 through Table A6).

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[10] Small adjustments were made in the magnitude of regression constant (average poverty) to make the population weighted poverty figures consistent with national and regional estimates.

[11] The direct estimate of poverty incidence at provincial level from household surveys is not recommended due to large standard errors, non-normality and heteroscedasticity in income or consumption variables, especially for small provinces (NWFP and Baluchistan). The sample design of HIES allows only the computation of the poverty statistics at the national or regional (urban/rural) level with an acceptable measure of reliability. Therefore, household consumption, which is predicted with the help of non-monetary indictors, is used to estimate poverty statistics for provinces also. It is argued that non-monetary variables (demography, education, housing etc.) are less heterogeneous and normally distributed across the sampling stratum. The size of standard error in two-stage estimates depends largely on the degree of disaggregation sought and the explanatory power of the exogenous variables in the first-stage model.

TABLE 4
PREDICTED POVERTY INCIDENCE – 2004-05
[*Percentage of Population Below the Poverty Line*]

Province	Overall	Urban Areas			Rural Areas
		Large Cities	Small Cities and Towns	Overall Urban Areas	
Overall	29.76	14.77	41.12	27.68	30.74
Punjab	27.69	16.47	37.56	27.24	27.89
Sindh	27.18	10.05	44.51	24.32	29.93
NWFP	35.41	34.72	44.29	41.04	34.31
Balochistan	53.11	26.69	56.77	47.62	54.38

Note: Large cities, in Punjab are Lahore, Rawalpindi, Faisalabad, Multan, Gujranwala, Sargodha, Sialkot and Bhawalpur. In Sindh, Karachi, Hyderabad and Sukkur are included in this category. Peshawar and Quetta are from NWFP and Balochistan, respectively.

According to the ranking in terms of low poverty incidence, Sindh ranks second after Punjab, however, the difference in the magnitude in both provinces is very small. This may be explained by the fact that almost 50 percent of Sindh's population resides in large cities (Karachi, Hyderabad and Sukkur), where the lowest poverty incidence is predicted (see Table 4). The plight of residents of small cities and towns are also evident from the table.[12] On the average, 41 percent residents of towns are categorized as poor. As expected, the highest poverty incidences in urban as well as rural areas are predicted for Balochistan.

5. CONCLUDING REMARKS

It is expensive to collect detailed household consumption and income data frequently and from a large segment of the population. After devolution of power to the district levels, it is also argued that district-wise poverty estimates should be available to monitor the impact of policies adopted by the district administration. To act in response, the FBS conducted a nationwide large survey (PSLM) which was designed to give estimates of social and living standard measures of people at district level. This survey instrument essentially collected simple welfare indicators and indicators of access, use of and satisfaction with public services. It was not designed to measure income, consumption or expenditure. FBS also

[12] These findings are consistent with the earlier study by Ercelawn, (1992), for poverty incidence during the 1980's. The finding is also consistent with the poverty incidence predicted (see Jamal 2005), from HIES, 2000-01.

conducted a small survey (HIES) regarding household income and expenditure. However, it is designed to give estimates only at national or regional level. By combining these two surveys and applying small area estimation technique, this study provides estimates of district poverty incidence.

Total household expenditures are statistically analyzed in terms of various household non-monetary (demographic, social, housing) indicators to determine consumption correlates. With the help of these estimated welfare functions, poverty incidences are predicted for provinces and also for districts.

According to predicted provincial poverty incidence, Punjab ranks first, while Balochistan comes fourth. One important finding, which emerged from this exercise, is that residents of small towns and cities are in a vulnerable position. The poverty incidence in small cities and towns, barring Balochistan's rural areas, is the highest in all provinces.

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APPENDIX

TABLE A1
PREDICTED WELFARE FUNCTION – URBAN AREAS
[*Estimates of Logistic Function, Poor = 1*]

	Coefficients	Significant Level
Household Demography:		
Family Size	0.3903	0.0000
Dependency Ratio	0.4884	0.0000
Number of Earners in Household	-0.2138	0.0000
Household Education:		
Highest Education Level in Family – Male	-0.0677	0.0000
Head of Household:		
Education Level – Primary	0.1406	0.1584
Education Level – Higher Secondary	0.0560	0.7916
Education Level – Tertiary	-0.6137	0.0016
Occupation – Wage Employment	0.2757	0.0006
Household Assets:		
Asset Score	-0.3265	0.0000
Ownership of Non-Residential Property	-0.4687	0.0104
Housing Quality and Services:		
More Than Three Persons Per Room	0.5047	0.0000
Telephone Connection	-1.1213	0.0000
RCC Roofing	-0.5434	0.0000
Flush System Connected to Sewerage Line	-0.1175	0.2303
Household Use Gas for Cooking	-0.0842	0.3482
Locational Variables:		
Large Cities	-0.3101	0.0011
NWFP Province	-0.2284	0.0261
Sindh Province	-0.7818	0.0000
Intercept (Constant)	-0.8876	0.0000

Source: Estimates are based on HIES, 2004-05.

TABLE A2
PREDICTED WELFARE FUNCTION – RURAL AREAS
[*Estimates of Logistic Function, Poor = 1*]

	Coefficients	Significant Level
Demography:		
Family Size	0.3020	0.0000
Dependency Ratio	0.4282	0.0000
Education:		
Out of School Children – Primary	0.1971	0.0028
Out of School Children – Secondary	0.0788	0.2302
Highest Education Level in Family – Female	-0.0369	0.0007
Head of Household:		
Education Level	-0.0374	0.0000
Age of Head (Squared)	-.00007	0.0004
Occupation – Non-farm Household	0.6024	0.0000
Occupation – Sharecropper (Hari)	0.3429	0.0007
Household Assets:		
Livestock Ownership	-0.3836	0.0000
Asset Score	-0.2420	0.0000
Ownership of Non-Agricultural Land	-0.4796	0.0047
Ownership of Non-Residential Buildings/House	-0.4137	0.0241
Housing Quality and Services:		
More Than Three Persons Per Room	0.1897	0.0009
Telephone Connection	-0.7053	0.0000
No Toilet in House	0.1799	0.0032
Pucca House (Cemented Structure)	-0.2584	0.0118
Locational Variables:		
Sindh Province	-0.5567	0.0000
Balochistan Province	0.3709	0.0000
Southern Punjab	0.2531	0.0037
Intercept (Constant)	-2.4232	0.0000

Source: Estimates are based on HIES, 2004-05.

TABLE A3
PREDICTED POVERTY INCIDENCE, 2004-05
[*Percentage of Population Below the Poverty Line*]
[Districts of Punjab Province]

Districts	Rank [1 = Highest Incidence] [34= Lowest Incidence]	Region		
		Overall	Urban Areas	Rural Areas
Attock	29	14.11	19.17	12.89
Bahawalnagar	12	32.45	43.00	29.93
Bahawalpur	7	39.46	40.35	39.13
Bhakkar	26	18.21	35.54	14.42
Chakwal	27	18.09	25.75	16.98
D.G.Khan	3	51.01	42.44	52.25
Faisalabad	22	19.84	22.02	18.20
Gujranwala	24	19.04	24.46	13.56
Gujrat	31	12.72	22.56	8.90
Hafiza Abad	20	24.04	39.69	17.37
Jhang	13	32.25	48.27	27.19
Jhelum	32	12.32	21.79	8.84
Kasur	16	28.18	39.97	24.59
Khanewal	8	38.84	49.19	36.63
Khushab	19	24.37	43.74	17.73
Lahore	33	11.60	10.70	14.95
Leiah	6	40.86	50.74	39.09
Lodhran	4	48.37	56.90	47.04
Mandi Bhauddin	28	17.33	31.66	14.79
Mianwali	11	35.38	24.15	38.75
Multan	9	38.40	30.73	42.69
Muzaffargarh	1	56.29	57.09	56.15
Narowal	23	19.30	32.93	17.31
Okara	15	29.98	36.17	28.30
Pakpattan	10	36.70	40.53	35.98
R. Y. Khan	5	45.87	35.71	48.30
Rajanpur	2	54.16	59.77	53.29
Rawalpindi	34	11.32	16.21	6.71
Sahiwal	21	21.66	32.42	19.28
Sargodha	18	25.66	28.47	24.75
Sheikhupura	17	26.20	30.94	24.25
Sialkot	30	13.96	19.41	12.24
T.T.Singh	25	18.95	36.44	15.01
Vehari	14	30.03	41.93	27.58

Source: Estimates are based on HIES, 2004-05.

TABLE A4
PREDICTED POVERTY INCIDENCE, 2004-05
[*Percentage of Population Below the Poverty Line*]
[Districts of Sindh Province]

Districts	Rank [1 = Highest Incidence] [16= Lowest Incidence]	Region		
		Overall	Urban Areas	Rural Areas
Badin	6	34.83	40.94	32.42
Dadu	5	36.44	57.77	32.20
Ghotki	4	40.80	54.14	33.88
Hyderabad	15	23.13	26.31	20.22
Jacobabad	7	34.16	44.29	29.73
Karachi	16	9.15	8.34	26.15
Khairpur	12	27.41	43.54	25.16
Larkana	3	43.33	53.84	40.87
Mirpur Khas	11	28.53	24.10	30.82
Nawab Shah	9	32.68	48.68	22.26
Noshero Feroz	8	33.11	46.79	27.40
Sanghar	14	24.67	39.06	20.63
Shikarpur	1	51.03	57.79	40.28
Sukkur	13	24.96	26.18	22.76
Tharparkar	10	28.92	43.57	24.31
Thatta	2	46.87	50.93	45.73

Source: Estimates are based on HIES, 2004-05.

TABLE A5
PREDICTED POVERTY INCIDENCE, 2004-05
[*Percentage of Population Below the Poverty Line*]
[Districts of NWFP Province]

Districts	Rank [1 = Highest Incidence] [24 = Lowest Incidence]	Region		
		Overall	Urban Areas	Rural Areas
Abotabad	23	21.17	24.89	20.43
Bannu	17	33.20	36.24	33.01
Batagram	18	29.22	.	29.22
Bonair	4	45.38	.	45.38
Charsada	8	40.83	54.43	37.77
Chitral	7	40.96	33.10	41.91
D.I.Khan	15	34.63	32.24	34.97
Hangu	5	43.20	47.06	42.35
Haripur	22	27.25	24.79	27.57
Kark	11	36.93	70.54	34.66
Kohat	19	28.53	41.83	23.62
Kohistan	13	35.56	.	35.56
Lakki Marwat	3	46.49	34.05	47.81
Lower Dir	16	34.62	61.06	32.97
Malakand	10	39.19	58.51	36.99
Mansehra	24	20.74	26.49	20.38
Mardan	6	42.46	53.60	39.63
Nowshera	20	27.98	39.93	24.09
Peshawar	12	36.51	34.72	38.31
Shangla	2	50.79	.	50.79
Swabi	21	27.30	51.37	22.67
Swat	9	39.64	46.45	38.68
Tank	14	34.87	60.95	30.65
Upper Dir	1	54.53	59.57	54.32

Source: Estimates are based on HIES, 2004-05.

TABLE A6
PREDICTED POVERTY INCIDENCE, 2004-05
[*Percentage of Population Below the Poverty Line*]
[Districts of Balochistan Province]

Districts	Rank [1 = Highest Incidence] [24 = Lowest Incidence]	Region		
		Overall	Urban Areas	Rural Areas
Awaran	5	61.54	.	61.54
Barkhan	14	52.84	84.26	49.46
Bolan/Kachhi	19	45.56	67.80	42.41
Chaghi	1	76.91	83.68	75.78
Gwadar	18	47.55	50.14	44.67
Jafarabad	20	44.14	50.51	42.71
Jhal Magsi	13	53.42	70.07	52.71
Kalat	22	41.89	62.94	38.55
Ketch/Turbat	11	54.40	61.06	53.35
Kharan	10	55.52	59.03	55.28
Khuzdar	16	50.96	58.38	48.33
Lasbela	2	66.40	65.75	66.65
Loralai	15	52.10	45.91	52.81
Mastung	21	42.34	36.07	43.57
Musa Khel	12	54.26	.	54.26
Nasirabad	8	57.27	60.66	56.90
Panjgur	17	49.68	25.19	50.87
Pashin	4	62.36	73.17	61.87
Qilla Abdullah	7	58.82	33.56	61.34
Qillah Saifullah	6	60.66	37.52	61.98
Quetta	24	34.15	26.69	46.24
Sibbi	9	55.81	49.04	58.16
Zhob	3	65.99	49.37	67.82
Ziarat	23	41.29	56.31	40.19

Note: Two districts (Dera Bugti and Kohlu) were not enumerated (partly or fully) due to law and order situation in the province.