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Predicting Sub-National Poverty Incidence for Pakistan

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ABSTRACT

This research note provides sub-national estimates of monetary poverty with the help of information available in two household surveys conducted during 2010-11. Data of Pakistan Social and Living Standards Measurement Survey (PSLM) and Household Integrated Economic Survey (HIES) are combined to produce aggregate poverty measures using small area estimation technique. The technique uses the welfare 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 from the HIES dataset and the coefficients of the estimated functions are applied to the PSLM dataset in order to predict poverty for provinces, regions and districts.

JEL Classification: I32, I31

Keywords: Sub-National Poverty, Small Area Estimation Technique, District Poverty Measures, Pakistan

1. PREAMBLE

In Pakistan, the only source to estimate poverty statistics is the Household Integrated Economic Survey (HIES) which is conducted by the Pakistan Bureau of Statistics (PBS). HIES includes standard and detailed consumption modules besides information on household characteristics. However, the coverage is comparatively limited with a sample of 16,000 households across Pakistan. This sample size, according to the PBS, is appropriate for providing reliable estimates of key characteristics at national and regional levels.

PBS also conducts the district representative nationwide Pakistan Social and Living Standards Measurement Survey (PSLM) with a large sample size of about 77,000 households. The design of the PSLM is based on the Core Welfare Indicator Questionnaire (CWIQ) survey instrument, which essentially collects simple welfare indicators ignoring household income and expenditure details. Thus, the PSLM provides the opportunity to estimate social, demographic, education and health-related indicators at district levels.

However, to fully analyse the district level data generated through PSLM, it is necessary to devise a means for determining household welfare status in terms of monetary poverty. Social and other welfare indicators at the district level can thus be analysed by arranging household responses according to poverty status or income/consumption groups (quintiles or deciles).

To predict income or consumption poverty at the sub-national level, there is a need to identify a set of non-monetary poverty correlates and to estimate their respective weights in predicting household consumption. These estimated coefficients or weights are then applied to large datasets using small area estimation (simulated-consumption) technique in order to predict household consumption and poverty status.

In the context of Pakistan, the first attempt to estimate or to predict poverty by applying the small area estimation technique was made by Jamal (2007). HIES and PSLM datasets for the year 2004-05 was used to predict sub-national poverty. Now, with the availability of most recent HIES and PSLM datasets, this research replicates that exercise and provides the latest estimates of monetary poverty at the sub-national level.

Specifically in the context of this research, the most recent HIES data of 2010-11 is used to estimate a model of per capita consumption expenditure as a function of non-monetary variables that are available in both surveys (small survey, HIES, representative at national/regional levels, and the large survey, PSLM, representative at the district level). Consumption functions are estimated separately for urban and rural Pakistan. The resulting parameter estimates from this estimation procedure are then simulated to predict per capita consumption for each household in the PSLM survey of 2010-11. Using the predicted per capita consumption and poverty cut-off point, poverty measures are then calculated and aggregated for provinces, regions and districts.

The paper is organised as follows: Section 2 presents a brief methodology for modelling predicted consumption function. The estimated consumption correlates are discussed in Section 3 while the predicted poverty numbers at the sub-national level are presented in Section 4. The last section is reserved for some concluding remarks.

2. MODELLING PREDICTED WELFARE

The small area estimation technique[1] is straightforward[2]. 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, the joint distribution of yh and a vector of covariates, xh is estimated. 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, generates 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 $h(x,\theta)$. The structural form of the model is specified by the following equation:

[1] In the literature of small area estimation technique three main methods are described: the synthetic, spatial smoothing and regression. However, in the majority of empirical work on income and poverty, regression method is preferred which produces the most valid and precise estimates. This study also employs the regression methods for predicting poverty at the sub-national level.

[2] For detailed methodology, see Elbers at el (2002 and 2003).

$$Y_j = X_{j1}\beta_1 + X_{j2}\beta_2 + X_{j3}\beta_3 + \ldots\ldots + \lambda_{j1}\delta_1 + \lambda_{j2}\delta_2 + \lambda_{j3}\delta_3 + \ldots. + \mu_j$$

where Y_j is the dependent variable; X_s is a vector of continuous explanatory variables; λs are the respective explanatory discrete variables[3]; βs are the estimated coefficients relative to the continuous variables; δs 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 dependent or response variable may be represented by the total household expenditure[4]. 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 which stabilises 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 or dependent 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. Nonetheless, this alternative is not preferred in this research due to the information loss by using censored[5] dependent variable.

[3] Some continuous variables with strong predictive capabilities were dichotomised 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.

[4] 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.

[5] 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. However, according to a similar exercise for the year 2005, it was concluded that to a large extent both alternatives yield similar prediction power, statistical significance of poverty predictors and goodness of fit. See Jamal (2007).

The selection of appropriate poverty predictors is the next step in the modelling welfare function. Initially the set of regressors includes a host of explanatory variables that are both discrete and continuous. These initial regressors are essentially household level variables[6] that focus on: household assets, education level and literacy, employment, household amenities, housing quality, household structure, demographic characteristics and geographical locations. These variables[7] were constructed from the HIES, 2010-11 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. Model with optimal poverty predictors is selected[8] using a combination of statistics of multiple regression analysis and tests for correlation and prediction. Once the poverty predictors are finalised, their corresponding weights are used to predict household expenditure.

3. CORRELATES OF HOUSEHOLD CONSUMPTION

Table A.1 and A.2 in the appendix present regression results of estimated consumption function for urban and rural areas respectively. The adjusted R-Square, which is a measure of goodness of fit, is 0.66 for urban and 0.53 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 30 indicates severity of multicolinearity and points to the magnitude of coefficients being less reliable. The estimated results, however, indicate that the value of the condition index is around 18 and 16 for urban and rural areas respectively. Having illustrated the summary statistics of estimated welfare functions, some observations regarding poverty correlates are in order.

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[6] The member level variables such as literacy and enrolment 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.

[7] 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.

[8] 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, Adjusted R^2 and Akaike Information Criteria are used to select the best model.

As expected, family size and dependency ratio are important predictors. Both determinants are highly correlated with household expenditure in urban as well as in rural areas. Similarly, as expected number of earners also turned out significant positive determinants of household expenditure. In contrast, unemployment of head of household is negatively associated with expenditure.

In the rural context, amount of agriculture land, ownership of livestock and non-residential property are all correlated positively with household expenditure. Further, non-farm households and wage employment play a dominant role in determining the level of consumption. These two variables have negative and significant coefficients. The coefficient associated with households with large farm size is also statistically significant, and as expected, with positive sign.

The quality of housing structure in terms of material used and housing services/utilities are important indicators of standard of living. The estimated functions indicate that telephone connection (landline) in rural area and RCC roofing in both urban and rural areas are significant and positive determinants of household consumption expenditure. Moreover, low housing congestion, represented by rooms per person, appears as a positive and 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[9] to each of the twenty assets[10] listed in both PSLM and HIES questionnaires. The coefficients associated with asset score are positive and highly significant in both urban and rural areas.

[9] A constant 1 is assigned to each of the assets owned by the household, and the assets score is obtained by summing up across all assets at the household level. Of course 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 which are difficult to estimate accurately from surveys. The maximum asset score is 20 and the minimum is 0, for poorest households who possess none of the assets listed.

[10] 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, tractor, mobile, cooking range, stove/burner and washing machine.

The significant role of education in determining level of consumption is evident from regression results (Tables A.1 and A.2 in the appendix). Education levels of both head and spouse of household turned out significant and positive correlates of household consumption in urban as well as in the rural context. Moreover, highest education level in the family is positive significant correlate of household consumption in the urban areas.

To capture the inter-provincial heterogeneity in terms of socio-economic characteristics and standard of living, provincial and other locational dummy variables were introduced in consumption functions. The rural consumption function clearly indicates that the provincial differences exist and play a significant role in determining the level of household consumption. In the urban context, however, only the coefficient associated with the province of Sindh turned out to be significant.

The estimated urban consumption function also indicates that variables representing high and low income areas in large cities[11] are an important determinant of the level of consumption. The coefficients associated with these two variables turned out to be significant with appropriate expected signs.

5. PREDICTED SUB-NATIONAL POVERTY INCIDENCE

The estimated non-monetary poverty correlates with the respective weights[12] (coefficients) are applied to determine the provincial[13] 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

[11] Name of large cities included in the PBS surveys are described in Table-1.

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

[13] 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 Khyber Pakhtunkhwa and Baluchistan provinces which although have small population but are not fully covered geographically in the sample of PBS . 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. That is why Government of Pakistan does not report poverty incidence for provinces in the Economic Surveys. 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.

response was then used to categorise households into poor/non-poor using the poverty lines[14] in Jamal (2012).

Table-1 depicts provincial poverty incidences, separately for large cities, small cities, towns and rural areas for the year 2010-11. Overall and regional (urban/rural) poverty incidences at district level are presented in the Appendix (Table A.3 through Table A.6). For the purpose of inter-temporal comparison, predicted poverty incidence for the year 2004-05 are reproduced from Jamal (2007) and presented in Table-2.

Barring Balochistan province, trends in poverty incidences across province and regions are in line with national estimates. In general, an increase of 7 to 10 percentage points in predicted poverty incidence is observed during 2005 and 2011. In contrast, a drop of 11 percentage points is observed in the case of Balochistan rural poverty incidence. This phenomenon, however, does not seem credible given unstable macroeconomic conditions, hyper inflation and the country's law and order situation as well as that of Balochistan's. One possible explanation of this unexpected outcome is, perhaps, the compromise in the sampling randomness due to logistical problems[15] and the worsening law and order situation in Balochistan after 2007. Further investigation in this regard, however, is imperative to investigate the possible causes.

Table - 1
Predicted Poverty Incidence [2010-11]
[*Percentage of Population Below the Poverty Line*]

		Regions			
		Urban Areas			
	Overall	**Overall**	**Large Cities**	**Small Cities and Towns**	**Rural Areas**
Pakistan	37.33	33.11	24.03	44.90	39.42
Punjab	35.30	31.35	23.63	39.52	37.12
Sindh	38.30	30.75	21.52	53.20	45.34
Khyber Pakhtunkhwa	41.06	48.31	45.03	50.15	39.58
Balochistan	45.24	51.09	36.00	60.51	43.40

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

[14] Rupees 2,248 and 1,854 per capita per month are used as poverty cut-off point for urban and rural areas respectively. Detail methodology is provided in Jamal (2012).

[15] Remote areas may be substituted with easy-to-access areas.

Table - 2 Predicted Poverty Incidence [2004-05] [*Percentage of Population Below the Poverty Line*]					
		Regions			
		Urban Areas			
	Overall	**Overall**	**Large Cities**	**Small Cities and Towns**	**Rural Areas**
Pakistan	**29.76**	**27.68**	**14.77**	**41.12**	**30.74**
Punjab	27.69	27.24	16.47	37.56	27.89
Sindh	27.18	24.32	10.05	44.51	29.93
Khyber Pakhtunkhwa	35.41	41.04	34.72	44.29	34.31
Balochistan	53.11	47.62	26.69	56.77	54.38

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

Source: Jamal (2007)

According to the ranking in terms of poverty incidence, the lowest (35 percent) incidence is observed in Punjab. Sindh ranks second after Punjab with a poverty incidence of about 38 percent; however urban poverty incidence is the lowest in Sindh. This may be explained by the fact that almost 55 percent of Sindh's population resides in large cities (Karachi, Hyderabad and Sukkur) where the lowest (21 percent) poverty incidence is predicted (see Table-1). Nonetheless, significant rise in the incidence of Poverty is also observed in large cities.

The plight of residents of small cities and towns is also evident in the table.[16] On an average, 45 percent residents of towns are categorised as poor, while the comparative percentage for the year 2004-05 is 41.

Highest rural and urban incidence was predicted for Balochistan province for both periods. However, a drop in overall poverty incidence is observed due to the declining trend in rural predicted poverty[17] for Balochistan.

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[16] These findings are consistent with the earlier study by Ercelawn, (1992), for poverty incidence during the 1980s. The finding is also consistent with the poverty incidence estimated from HIES for the year 2000-01 and predicted for the year 2004-05. See Jamal (2005) and Jamal (2007).

[17] Very low rural poverty incidences are predicted for districts Awaran, Mastung, Kohlu, Kalat, Pashine, Sibbi Ziarat, Hernai and Sherani of Balochistan province which seem not plausible. Therefore poverty estimates of these districts are not reported in Table A.6 in the appendix.

5. CONCLUDING REMARKS

Consumption or income poverty measure advocates the case for transfer policies and social safety nets that alleviate poverty in the short run. Thus, it is argued that district-wise poverty estimates should be available to monitor the impact of policies adopted by the provincial and district administration.

To act in response, the PBS conducts nationwide large surveys (PSLM) which were designed to give estimates of social and living standard measures of people at the district level. This survey instrument essentially collects simple welfare indicators and indicators of access, use of and satisfaction with public services, etc. However, it is not designed to measure income, consumption or expenditure. PBS also conducts small surveys (HIES) regarding household income and expenditure. But it is designed to give estimates only at the national or regional level. By combining the strength of these two surveys and applying small area estimation technique, this study provides the estimates of district poverty incidence.

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

According to predicted provincial poverty incidence, the lowest (35 percent) poverty incidence is estimated for Punjab, while about 41 and 45 percent population is predicted poor in Khyber Pakhtunkhwa and Balochistan provinces respectively. One important finding from this exercise is that residents of small towns and cities are in a vulnerable position. The poverty incidence in small cities and towns is the highest in all provinces. The phenomenon, however, is consistent with earlier findings.

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APPENDIX

Table A.1
Predicted Consumption Function – Urban Areas
[Dependent Variable – Logarithm of Total Household Expenditure]

	Coefficients	t-Statistics	Significance
Family Size	-.066	-32.807	.000
Dependency Ratio	.002	7.110	.000
Number of Earners	.031	6.936	.000
Education of Head of Household	.012	10.167	.000
Education level of Spouse	.004	3.896	.000
Highest education in family	.010	6.281	.000
Head of Household – Less than 40 Years	.013	1.339	.181
Unemployment of Head	-.071	-1.776	.076
Wage Employment (Head)	-.051	-5.750	.000
Employer (Head)	.340	11.483	.000
Asset Score	.065	36.674	.000
RCC Roofing (*Pacca* Structure)	.072	7.709	.000
Room per person	.317	29.554	.000
SINDH Province	.009	1.028	.034
High Income areas of large cities	.368	16.214	.000
Low Income areas of large cities	-.045	-3.555	.000
Intercept (Constant)	7.501	365.378	.000
Summary Statistics:			
Adjusted R-Square		0.655	
F-Value		782.810	
Durbin Watson Statistics		1.563	
Condition Index		17.716	

Source: Estimated from Household Level Data of HIES, 2010-11

Table A.2
Predicted Consumption Function – Rural Areas
[Dependent Variable – Logarithm of Total Household Expenditure]

	Coefficients	t-Statistics	Significance
Family Size	-.060	-40.834	.000
Dependency Ratio	.002	9.460	.000
Number of Earners	.027	8.988	.000
Education of Head of Household	.008	9.461	.000
Education level of Spouse	.006	4.352	.000
Head of Household – Less than 40 Years	.016	2.222	.026
Unemployment of Head	-.092	-2.554	.011
Wage Employment (Head)	-.042	-5.795	.000
Nonfarm Employment (Head)	-.098	-12.778	.000
Household with Large Farm Size	.088	4.001	.000
Agricultural Land	.003	7.434	.000
Asset Score	.056	42.816	.000
Ownership of Non-Residential Building	.067	4.312	.000
Livestock	.114	15.605	.000
Pacca House Structure	.044	4.187	.000
Room per Person	.320	27.800	.000
Telephone (PTCL)	.026	3.115	.002
Sindh Province	.111	12.161	.000
Khyber Pakhtunkhwa Province	.101	10.819	.000
Balochistan Province	.190	13.099	.000
Intercept (Constant)	7.670	488.295	.000
Summary Statistics:			
Adjusted R-Square		0.529	
F-Value		547.001	
Durbin Watson Statistics		1.758	
Condition Index		16.209	

Source: Estimated from Household Level Data of HIES, 2010-11

Table A.3
Predicted Poverty Incidence, 2010-11
[Percentage of Population Below the Poverty Line]
[Districts of Punjab Province]

Districts	Rank Order [1 = Highest Incidence] [36= Lowest Incidence]	Overall	Urban	Rural
Attock	27	27.12	28.73	26.67
Bahawalnagar	13	39.02	49.34	36.36
Bahawalpur	5	48.45	44.05	50.39
Bhakhar	20	35.24	51.27	32.26
Chakwal	36	13.86	15.05	13.66
Chiniot	22	32.81	35.50	31.72
D.G.Khan	1	63.96	39.74	67.37
Faisalabad	26	27.41	26.95	27.79
Gujranwala	30	25.92	26.16	25.67
Gujrat	31	24.06	25.17	23.65
Hafizabad	25	29.01	32.79	27.32
Jehlum	33	18.61	25.24	16.30
Jhang	8	44.99	50.28	43.39
Kasur	11	43.20	48.54	41.35
Khanewal	16	37.91	41.13	37.17
Khushab	24	29.24	39.23	25.46
Lahore	28	26.98	24.90	37.42
Layyah	9	44.61	48.10	43.95
Lodhran	12	42.38	56.46	40.18
Mandi Bahuddin	35	14.12	19.66	13.12
Mianwali	17	37.85	50.26	34.56
Multan	10	44.02	34.14	50.14
Muzaffar Garh	2	58.18	47.51	59.95
Nankana Sahib	18	36.70	53.72	32.32
Narowal	19	36.17	43.41	34.96
Okara	15	38.13	36.09	38.48
Pakpattan	7	45.32	36.44	46.93
RahimYar Khan	4	50.21	48.73	50.62
Rajanpur	3	57.79	52.88	58.49
Rawalpindi	34	16.18	16.91	15.47
Sahiwal	21	33.68	38.64	32.74
Sargodha	23	30.95	27.66	32.10
Sheikupura	14	38.80	36.64	40.06
Sialkot	32	23.10	21.71	23.55
T.T.Singh	29	26.91	34.01	25.03
Vehari	6	45.78	36.56	47.83

Table A.4
Predicted Poverty Incidence, 2010-11
[Percentage of Population Below the Poverty Line]
[Districts of Sindh Province]

Districts	Rank Order [1 = Highest Incidence] [23= Lowest Incidence]	Overall	Urban	Rural
Badin	6	53.75	42.76	55.80
Dadu	21	33.06	46.69	29.35
Ghotki	14	45.81	53.66	44.42
Hyderabad	22	27.50	23.92	42.34
Jaccobabad	2	59.42	63.98	58.18
Jamshoro	9	50.24	44.74	52.05
Karachi	23	21.09	20.22	43.55
Kashmore	1	59.81	51.22	61.83
Khairpur	16	41.54	58.64	34.98
Larkana	4	56.34	60.82	53.40
Maitari	15	42.55	47.03	41.26
Mir Pur Khas	20	36.65	33.34	38.27
Nawabshah	18	38.35	52.79	31.73
Nowshero Feroze	13	46.43	58.37	43.48
Sanghar	19	37.27	61.34	28.65
Shahdadkot	8	51.72	72.50	46.77
Shikarpur	5	55.33	52.17	56.21
Sukkur	10	49.05	53.54	45.21
Tando Allah Yar	17	41.33	40.75	41.58
Tando Muda khan	3	57.36	55.98	57.64
Tharparkar	11	46.98	35.32	47.44
Thatta	7	53.66	40.42	55.88
Umer kot	12	46.90	60.17	43.95

Table A.5
Predicted Poverty Incidence, 2010-11
[Percentage of Population Below the Poverty Line]
[Districts of Khyber Pakhtunkhwa Province]

Districts	Rank Order [1 = Highest Incidence] [24= Lowest Incidence]	Overall	Urban	Rural
Abbottabad	23	21.80	17.14	22.60
Bannu	19	32.19	33.44	32.14
Batagram	21	28.42	.	28.42
Bonair	2	56.22	.	56.22
Charsada	9	44.92	55.18	42.79
Chitral	20	31.53	50.45	29.28
D.I.Khan	16	41.02	48.43	39.90
Hangu	3	55.28	67.94	51.75
Haripur	24	20.28	25.31	19.51
Karak	1	61.77	76.15	60.86
Kohat	17	39.60	39.36	39.70
Kohistan	5	49.34	.	49.34
Lakki Marwat	4	51.80	75.30	48.93
Lower Dir	13	42.24	56.95	41.30
Malakand	15	41.20	59.57	39.27
Manshera	22	25.52	15.71	26.22
Mardan	6	48.59	54.78	46.95
Nowshera	7	48.55	63.61	43.68
Peshawar	11	44.24	45.03	43.36
Shangla	14	41.95	.	41.95
Swabi	10	44.43	64.13	40.02
Swat	8	46.09	49.49	45.55
Tank	12	43.77	59.24	41.92
Upper Dir	18	34.48	70.21	33.11

Table A.6
Predicted Poverty Incidence, 2010-11
[Percentage of Population Below the Poverty Line]
[Districts of Balochistan Province]

Districts	Rank Order [1 = Highest Incidence] [20= Lowest Incidence]	Overall	Urban	Rural
Barkhan	3	68.08	79.26	66.67
Bolan/Kacchi	13	53.84	43.74	55.72
Chagi	2	73.26	50.49	75.65
Dera Bugti	11	55.48	53.84	55.54
Gwadar	10	55.59	61.25	50.67
Jafarabad	6	63.05	71.58	60.77
Jhal Magsi	17	42.22	64.98	41.21
Kalat	20	28.21	64.37	22.53
Ketch/Turbat	12	53.88	58.21	52.99
Kharan	14	51.79	58.81	50.58
Khuzdar	16	43.22	68.33	33.87
Lasbilla	7	62.22	68.44	59.47
Lorali	4	67.25	58.37	68.81
Musakhel	1	80.11	.	80.11
Nasirabad	5	65.16	81.34	62.90
Nushki	9	56.12	35.91	61.37
Qillah Saifuallh	18	36.36	60.82	33.47
Quetta	19	31.94	36.00	16.92
Sibbi	21	21.38	28.96	14.05
Washuk	15	48.12	.	48.12
Zhob	8	56.93	68.74	54.48

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