Predicting Within Country Household Food Expenditure Variation Using International Cross-Section Estimates

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ABSTRACT

There is a long and distinguished literature involving demand analysis using international cross-section data. Such models are widely used for predicting national per capita consumption. However, there is nothing in this literature testing the performance of estimated models in predicting demands across the income spectrum within a single country. This paper fills the gap. We estimate an AIDADS model using cross-section international per capita data, and find that it does well in predicting food demand across the income distribution within Bangladesh. This suggests that there may be considerable value in using international cross-section analysis to study poverty and distributional impacts of policies.

Keywords: International cross-section demand system, across income spectrum prediction, household data, AIDADS, food demand, Bangladesh

JEL Classification: B40, D12, Q11

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1 Motivation

International cross-section demand systems have long been used to estimate the national per capita demands and the evolution of spending patterns as countries become wealthier (e.g., Engel, 1857). Houthakker (1957) notes that empirical consumption studies took on an international flavor from a very early date. Theil in the late seventies, extended this work to cross-country estimation of consumption demand as a system; a survey of his studies can be found in Clements and Qiang (2003). Researchers have tested the consistency of such international cross-section data with a single preference structure (Dowrick and Quiggin 1994); alternative models have been compared on the basis of their theoretical consistency (Deaton and Muellbauer 1980) and their ability to predict per capita consumption for countries (Cranfield et al. 2003). Functional forms employed by these studies have ranged from the Rotterdam model to the more recent An Implicitly Directly Additive Demand System (AIDADS). In an interesting application[1] Theil and Finke (1984) use cross-section estimates to do a time-series analysis of the preference changes of Dutch consumers over time; however, no study[2] to date has evaluated the ability of demand systems estimated from international cross-country per capita data to predict demand across the income spectrum within a given country; and a priori there is no reason to expect that a system estimated for a per capita representative agent should hold for the heterogeneous population.

With the increasing interest in poverty impacts of external shocks (Levinsohn, Berry and Friedman 2000; Cranfield et al. 2007; Hertel and Winters 2006), having a valid demand system for eliciting the impacts of such changes on consumption, across the income spectrum can be very useful. This is an important aspect of household response to price

[1] Another interesting work we came across is Clements and Chen (2010). They work the Engel's Law in the opposite direction, using per capita food budget shares to decipher the per capita real income for a country.

[2] A useful though somewhat dated list of cross-country studies appears in Selvanathan and Selvanathan (1993).

changes.[3] Yet it can be difficult to obtain high quality data with sufficient price and income variation to permit estimation of an appropriate household demand system – particularly for most developing countries. Therefore, using an international cross-section demand system is very appealing and such an approached has been used by Cranfield et al. (2007) – which raises the question: How accurately can such a demand system predict consumption patterns across the income spectrum for any given country? If such models are to be used for characterizing the consumption response of the poorest segment of the population, then its ability to at least reproduce observed consumption of poor at original prices should be assessed. With the improving availability of detailed Household Survey data, it is possible now to carry out such an evaluation.

We attempt to evaluate a particular demand system: AIDADS, estimated using per capita data from International Comparison Project (ICP) 1996. We compare the fit of its predicted expenditure shares with the actual observed shares across the income distribution obtained from Household and Income Expenditure Survey (HIES) 2000 for Bangladesh.[4] Sections 2 and 3 below briefly describe the survey data and estimation approach used in the process, before discussing the details of results (section 4) and conclusions (section 5).

2 Estimation Strategy

Estimation is undertaken at the level of four aggregate commodities – which jointly exhaust total consumption expenditure. The four commodities are: food, non-durables, durables and services. ICP 1996 provides us with the cross-sectional data on total nominal and real expenditure in 1996 USD for 26 commodities and population, for 114 countries; of which 40 are high income, 53 middle income and 21 are low income according to the World Bank Country Classification Tables (2007). A list of the countries

[3] Friedman and Levinsohn (2002) find that incorporating household behavioral responses to the commodity price rises following the Indonesian Financial Crisis, cut the households' welfare losses in half.

[4] Choice of Bangladesh is determined by availability of reliable household data.

is provided in Appendix Table 1. The 26 ICP commodities are aggregated to arrive at corresponding data for the four aggregates. Appendix Table 2 outlines the mapping from the 26 ICP commodities to the four aggregate commodity groups. Validation of budget shares is focused on aggregate food expenditures for which a clear correspondence between the household survey data and the aggregated ICP data exists.

The model used here is the one employed by Cranfield et al. (2007); only we use a different commodity aggregation. The estimated system is used to predict budget shares across the income spectrum in Bangladesh, for the four commodity groups. The model employed here also addresses the macro-micro synthesis due to its ability to model aggregate per capita expenditure as a weighted average of the individual expenditures across the income distribution; Cranfield et al. use an entropy-based procedure to that end, estimating per capita demand as an explicit aggregation of households' demands at different points of the distribution. To describe the approach more clearly, if x_{it}^{h} is the demand for commodity i by household h in country t then the aggregate national per capita demand for the same commodity (x_{it}) is assumed to be a weighted sum of x_{it}^{h} for all the h where s_{it}^{h} are the associated weights; this relationship can also be written in terms of budget shares instead of quantity demands using information on P_{it} and Y_t – price of commodity i and per capita income in the country

$$x_{it} = \sum_h \left(s_{it}^{h} \cdot x_{it}^{h}\right) \leftrightarrow w_{it} = \frac{P_{it}}{Y_t} \sum_h \left(s_{it}^{h} \cdot x_{it}^{h}\right) \qquad (1)$$

The corresponding model demand equation is

$$\widehat{w}_{it} - v_{it} = \frac{P_{it}}{Y_t} \sum_c \sum_l \{\rho_{tcl} \cdot [x_{itcl}]\} \qquad \forall\, i, t$$

where $\widehat{w}_{it}$ is the estimated budget share, v_{it} is the corresponding error, x_{itcl} are the demands at household levels and ρ_{tcl} the associated weights used in arriving at national per capita demands. c and l can be interpreted as indices associated with households (see Cranfield 1999 for more details). However the national level data, which is used to estimate the demand system, does not provide data on disaggregated consumption: x_{it}^{h}, but only on the aggregate x_{it}. We also know that the disaggregated individual households demand just like those for the per capita representative, are determined by its income and the prices it faces (which are assumed to be the same for all households and spatial differences in prices are not taken into account). We can construct the income levels for households y_t^h across income distribution by using the Deininger and Squire (1996) income distribution data (see Cranfield 1999 for details); and the national level price vector P_t are observable from the cross-country international data. One can put all this information together to rewrite equation (1) as follows, where $f(.)$ is the functional specification (AIDADS) of the demand system.

$$w_{it} = \frac{P_{it}}{Y_t}\sum_h \left(s_{it}^h \cdot f(y_t^h, P_t)\right), \qquad (2)$$

the corresponding model demand equation is

$$\widehat{w}_{it} - v_{it} = \frac{P_{it}}{Y_t}\sum_c \sum_l \left\{\rho_{tcl}\left[\gamma_i + \frac{\alpha_i + \beta_i e^{u_{tcl}}}{1+e^{u_{tcl}}}\left(\frac{Y_{tcl} - \sum_i P_{it}\gamma_i}{P_{it}}\right)\right]\right\} \qquad \forall\, i, t,$$

and we have all the information to estimate the parameters in equation (2). The parameters thus estimated are then used to predict the values for the expenditure differentiated households' budget shares.

We follow the same approach. For a detailed formal treatment of the model used here please see Cranfield (1999); for convenience a short summary is provided in Appendix A. Table 1 gives the estimated parameters for the cross-country model. The first column reports the subsistence level of expenditure that a household in Bangladesh needs to undertake for each member in order to survive. This column shows the expenditure to be concentrated on basic needs. Column two gives the marginal expenditure shares at the subsistence level of income, whereas the third column gives the marginal expenditure shares for consumption at the richest end of income distribution. From the table we can see that a household with a low level of income spends almost 59 percent of its incremental income on food as against none of the increment in income spent on food by a rich household. As these are shares, they add up to one. For a policy analysis exercise, these parameters suggest that the food consumption impact of a negative shock will be disproportionately borne by the households at the lower end of income distribution, owing to the higher budget shares they allocate to food.

Table 1: Parameter Estimates Of The AIDADS Demand System

Commodity Groups	γ_i	α_i	β_i
Food	0.40	0.59	0
Non-Durables	0.01	0.32	0.27
Durables	0	0.01	0.11
Services	0	0.08	0.62

Source: Model estimation results

As noted above, the idea of using an international demand system to predict expenditures across the income distribution within a country is quite new and this is the first attempt to test the validity of this approach.

3 Survey Data and Methodology

For validation purposes, household data is used from the HIES for the year 2000, conducted by Bangladesh Bureau of Statistics. It provides household level data for income, expenditure and consumption. HIES 2000 has a total of 7,440 households surveyed, each identified in the survey by a unique household code. Of the 7,440; 5,040 were rural and 2,400 were urban, reflecting the dominant rural population in the country. HIES reports the actual number of days and number of people in the household for households for which daily food consumption data are collected. For more details the reader is referred to the survey report (BBS 2003).

The information used from the survey is the households' consumption expenditure split into two aggregate categories – food and non-food expenditure which is used to calculate observed food expenditure shares, to validate the model results with respect to food consumption.[5] Using the survey information, we construct two data series–

- Percentile per capita total expenditure
- Percentile per capita food expenditure

A ratio of the two above is the observed food budget share for the percentile group. These are used to evaluate model predictions of the same. In constructing these two series it is important to note that each of the 7,440 households represents a fraction of total households in the country or in similar vein one could say that the per capita individual associated with each of the 7,440 households represents a different fraction of total population. To be able to divide the country population into percentiles we need to know how much of the population fraction is represented by each of the 7,440 representative individuals. This information is provided in the survey in the form of individual weights. We use these weights to divide the survey sample into groups which represent exact one percent population fractions. Note that owing to different weights being associated with each of the 7,440 individuals, the number of such individuals in each percentile group can be different. This was part of the problem; even after dividing the 7,440 individuals into percentile groups, one cannot take a simple average of their associated per capita annual expenditures to arrive at the average for the concerned percentiles, as it would ignore the differing importance associated with each individual. Therefore we need to first weight the per capita expenditure for each household by the individual weights.

The steps involved in calculating the percentile per capita total expenditure and percentile per capita food expenditure are as follows; the subscript $(\mathrm{h} = 1 \ldots 7{,}440)$ denotes survey household –

i. Derive the annual per capita expenditure for each household $(\mathrm{pcaexp_h})$ using the number of days over which the data for the household were collected $(\mathrm{d_h})$ and the

[5] Validation is undertaken only for food consumption. The reason being that observed food expenditure for Bangladesh is available from the HIES 2000 whereas the expenditure on all the other commodities appears in the survey as an aggregate non-food expenditure. It would be very difficult to map the consumption of households to the other three non-food commodity groups and has not been attempted here.

associated per capita total expenditure for the household ($\mathrm{pcexp_h}$) reported in the survey. This is done because our model is estimated using ICP data which are in annual per capita units:

$$\mathrm{pcaexp_h} = \frac{\mathrm{pcexp_h}}{\mathrm{d_h}} \cdot 365. \tag{3}$$

ii. Sort the annual per capita expenditure derived from equation (3) in ascending order to be able to calculate percentile groups with increasing income for each subsequent group.

iii. Before[6] dividing the population into percentile groups however, get the annual weighted per capita expenditure ($\mathrm{wpcaexp_h}$) using the individual weight ($\mathrm{weight_h}$) provided in the survey. This is done because each individual in the survey represents not an individual but a fraction of the total population of the country. So it is appealing to weight the representative individual's per capita expenditure by some measure of the fraction that the individual represents.

$$\mathrm{wpcaexp_h} = \mathrm{pcaexp_h} \cdot \mathrm{weight_h} \tag{4}$$

iv. To divide these into percentiles calculate the individual's weight share

$$\mathrm{wp_h} = \frac{\mathrm{weight_h}}{\sum_i \mathrm{weight_i}} \cdot 100 \tag{5}$$

v. Calculate the cumulative individual weights

$$\mathrm{cwp_h} = \textstyle\sum_0^h \mathrm{wp_h} \qquad \text{where } \mathrm{h} = 1 \ldots 7{,}440 \tag{6}$$

[6] This step is undertaken before dividing the population into percentile groups because the division as is mentioned later, involves splitting the marginal individuals and their associated expenditures.

If the calculations are correct, $cwp_{7440} = 100$. On basis of the cumulative individual weights, we construct j groups, each consisting of exact one percent of the sample households. This means that the cumulative weight for each of the 100 groups should be exactly '1' or that individual weight shares within each percentile should add up to '1'.

$$\sum_h wp_h^j = 1 \qquad \forall\, j = 1 \dots 100 \text{ and where } h \in j \tag{7}$$

This requires breaking the unit (and its associated wp_h and $wpcaexp_h$) on the margin of a percentile, with some portion of it falling into the n^{th} percentile while the rest into $n + 1^{th}$ percentile group. The division is determined on the basis of how much of its share is required to make the of n^{th} percentile's individual weights sum to 1.

vi. For each percentile group, calculate the weighted expenditure average, a simply average of $wpcaexp_h$ calculated as per equation (4), and find the minimum and maximum weighted expenditure in the group to compare it across the groups as a consistency check. The minimum for the $n + 1^{th}$ percentile group should be equal or less than the maximum for the n^{th} percentile group. This gives us the annual per capita expenditure in local currency for each percentile.

vii. To construct the food expenditure for the 100 percentiles, steps i, iii and vi above are repeated but now using food expenditure instead of the total expenditure. It is important to note that the data remains sorted as it was in step ii.

viii. The ratio of the food expenditure to the total expenditure then gives the survey-based observed food budget shares for each of the percentiles.

ix. We also need the total expenditure for these percentiles to be used in the demand model (as a proxy for income) in order to get the predicted food budget shares. To convert these into comparable 1996 USD units, a convenient trick is used. First calculate the ratio of weighted per capita total expenditure (average of $wpcaexp_h$)

for each percentile to the weighted total expenditure for the whole sample. These ratios are then applied to the per capita expenditure calculated using the ICP 1996 data. This translates the survey income distribution to comparable 1996 dollar units.

The percentile per capita total expenditure series, modified as per step ix above is then used along with the demand system parameters listed in Table 1 to predict the food budget shares for the percentiles, to be compared with the survey observed budget shares for the same.

4 Results

The HIES observed budget shares are calculated as per step viii above and plotted along with the country's budget shares predicted using the international cross-section model; where the predictions are made by letting the income vary according to the series constructed in step ix above. Results are shown visually in a set of figures below. In all the figures, the vertical axis reports the percent share of a commodity in total consumption expenditure while the horizontal axis represents the natural log of per capita total annual expenditure. Movement along the horizontal axis represents increasing expenditure, i.e. richer households.

Figure 1 shows the survey-based food budget shares. The scatter points in the figure represent population percentiles ascending in expenditure. Its co-ordinates are the pair of the food budget share and natural log of per capita annual total expenditure. Conforming to Engel's law the food budget shares are decreasing in total expenditure.

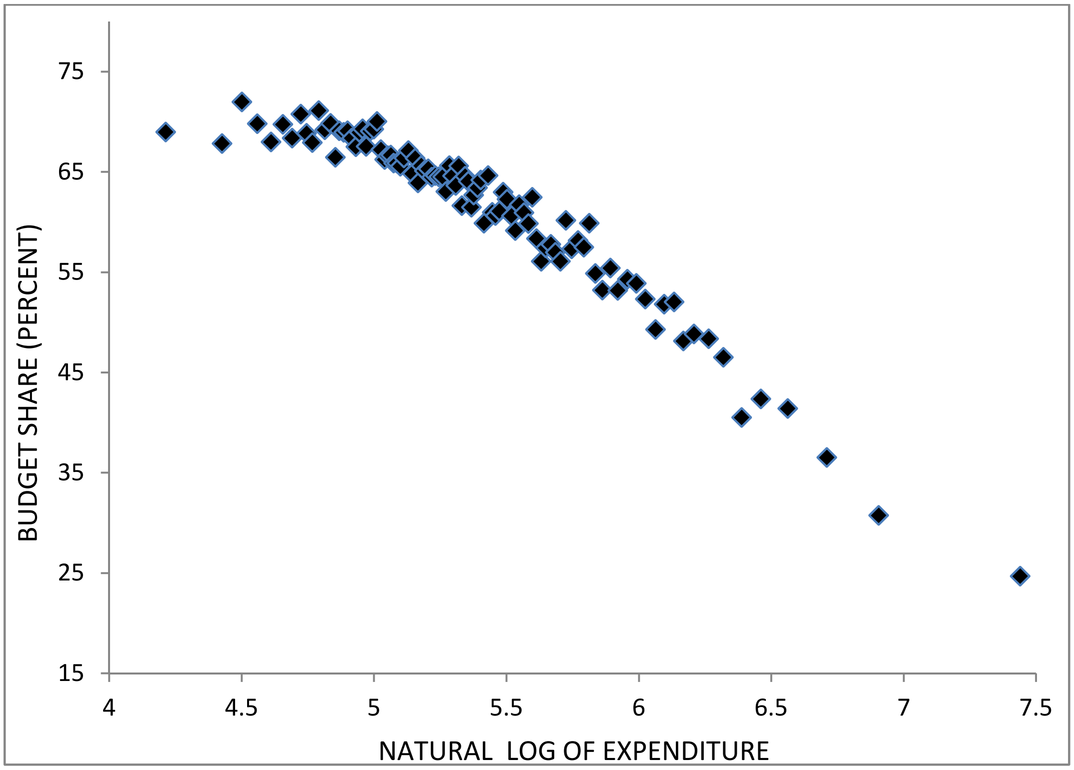

Figure 1: Survey Observed Food Budget Shares For Bangladesh

Figure 2 superimposes model-predicted food budget shares onto Figure 1. It shows that the AIDADS model, estimated using mean per capita consumption and income distribution, predicts the food budget shares quite accurately for nearly the entire expenditure spectrum, including the percentiles around the nutritional poverty line.[7] As can be seen the AIDADS Engel curve allows for non-linearity in comparison to two other very popular demand specifications; a homothetic Cobb-Douglas (constant budget shares and therefore linear Engel curves) or Constant Elasticity function.[8] Also as against for some other rank 2 and rank 3 systems like AIDS (Deaton and Muellbauer 1980) and QAIDS (Banks *et al* 1997) the predicted budget shares always remain within the [0,1] interval even in the face of large changes in income.

[7] The nutritional poverty line is defined in terms of per day per capita calorie intake. BBS 2003 identifies the population fraction consuming less than 2122Kcal is identified as nutritionally poor and claims to have approximately 44% of the population in Bangladesh to be nutritionally poor.

[8] For a CES the budget shares vary with prices but are independent of income. With prices fixed this is equivalent to constant budget shares and linear Engel curves. So even though the shares differ across the countries, they do not differ across income distribution with in a country.

As might be anticipated, at the very extreme ends, the estimated model either over or under predicts food consumption. We suspect that this is due to the fact that the subsistence parameter here is determined not by the lowest consumption levels observed in Bangladesh but in a country which is poorer and thus has subsistence budget shares that are higher than those observed in Bangladesh. By imposing the subsistence levels observed in Bangladesh one could hope to perform better towards the extreme ends of the expenditure distribution as well.

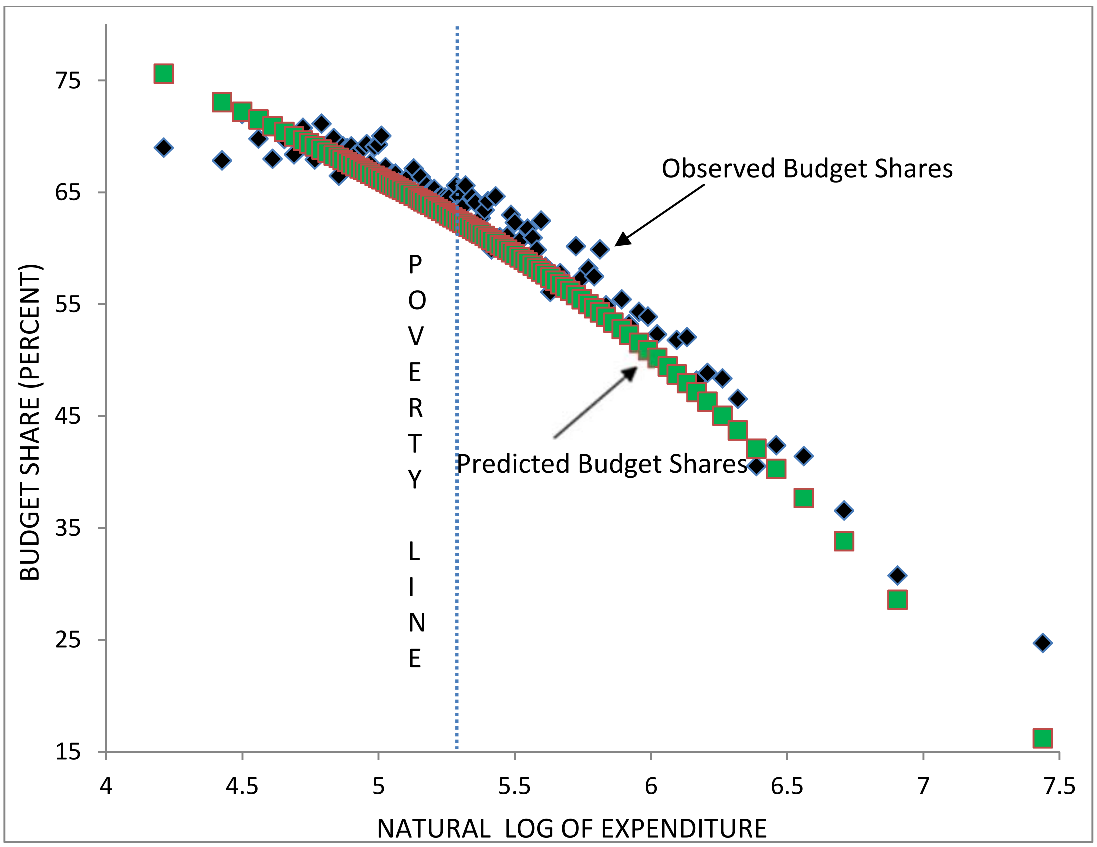

Figure 2: Comparing Observed And Predicted Food Budget Shares In Bangladesh

Although we do not attempt a similar validation for the other three aggregate commodities for reasons mentioned before, it is interesting to observe how their predicted budget shares vary across the expenditure distribution for Bangladesh (Figure 3). The patterns of the budget shares for non-food commodities, especially for services that are rising with increasing income, conform to expectations.

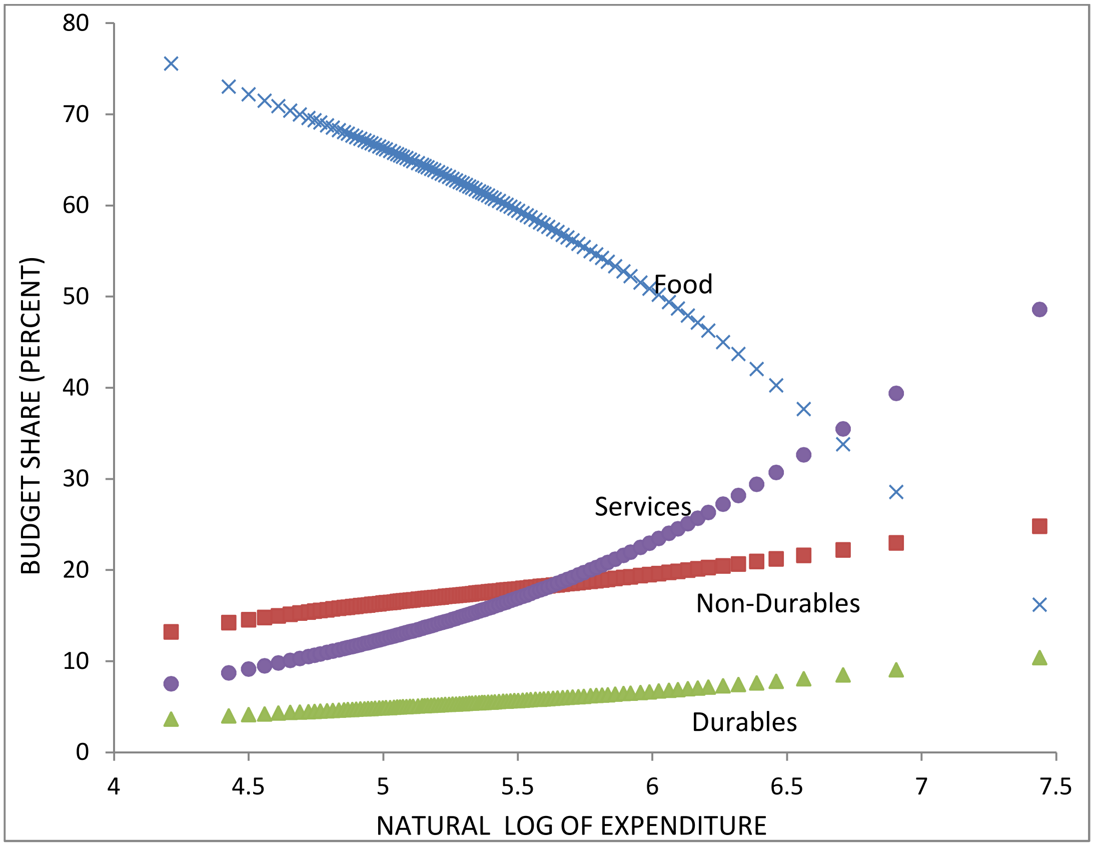

Figure 3: AIDADS Predicted Budget Shares For All Commodities in Bangladesh

5 Implications

The results here support the use of AIDADS international cross-section demand system,[9] estimated using maximum entropy or some macro-micro synthesis technique, as a tool to predict within country expenditure patterns across the income spectrum. The estimated model as we have shown closely follows the observed consumption shares for food and non-food[10] commodities in Bangladesh.

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[9] However like AIDADS, the demand system used for the purpose should have rank three and be estimated using some information about income distribution in the sample countries. E.g. an LES (a rank 2 demand system) estimated using the same data and method of aggregation across consumers, does not do as well (Verma 2007).

[10] As the shares for food and non-food consumption groups add up to exhaust total consumption expenditure, success in replicating budget shares for one implies the same for the other.

This study provides evidence that even though they are based on national per capita observations, international cross-section studies of demand can be used to shed light on the differential across the income spectrum impacts on household level demand. This is important when it comes to, for example, predicting the effects of recent commodity price surges or similar shocks (policy intended or otherwise), on consumption patterns across the countries' income distribution.[11] By estimating an explicit demand system, such models also offer added value for international poverty studies. To mention some advantages:

First, although the estimation approach used here does not completely replace the need for using household data when it is available, it is less demanding in terms of data requirements as compared to models estimated using household data especially when reliable household data is difficult to obtain for most developing countries. Where reliable household consumption data do exist, they are often difficult to map to international consumption categories, which can make comparisons across countries difficult.

Second, using an explicit demand system accounts for household adjustments of expenditure patterns (unlike using expenditure functions as in Ivanic and Martin 2008) in response to price[12] shocks and thereby is better able to capture the associated welfare impacts. Ignoring such behavioral responses has been shown by Friedman and Levinsohn (2002) to yield biased welfare results.

Third, as claimed by Cranfield et al. (2007) linking poverty to household utility (as a measure of welfare) provides a more precise analysis of impact of such shocks on poverty than a monetary measure like a dollar per day, which can be adjusted for differences in purchasing power before the shocks but does not allow for differences such shocks can

[11] Note that we don't make any claims about validating the price responses across the country's population, in absence of price variations in survey data. However the income effect of any price change, as we evaluate is quite accurate.
[12] Note however that the ability of this system to accurately predict the impact of price changes has not yet been evaluated; the present study is an attempt only at evaluating its ability to predict the impact of income changes on demand.

make to purchasing power parities itself. Focusing on a measure like utility, that accounts for both is superior.

And fourth, a cross-section approach offers a vehicle for conducting comparable analyses across different countries. One could see it as a choice of either assuming a single monetary measure of a dollar per day or assuming common preferences across countries (represented by the same demand function).

Building on these advantages, variants of this international cross-section demand system have been successfully embedded in economy-wide simulation models in order to assess the poverty impacts of global trade reforms across a diverse set of developing countries (Verma et al. 2011; Hertel et al. 2009).

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APPENDIX A: AIDADS, Maximum Likelihood and Maximum Entropy Estimation

Max $\quad -0.5\, ln \prod_i^{n-1} r_{ii}^2 - \sum_t \sum_c \sum_l \rho_{tcl}\, ln\, \rho_{tcl}$

with respect to α, β, γ, κ, u_t, u_{tcl}, ρ_{tcl}, v_{it}, r_{is}

Subject to –

1) $\sum_i \frac{\alpha_i+\beta_i e^{u_{tcl}}}{1+e^{u_{tcl}}}\, ln\left(\frac{1}{P_{it}} \frac{\alpha_i+\beta_i e^{u_{tcl}}}{1+e^{u_{tcl}}}\, (Y_{tcl} - \sum_i P_{it}\gamma_i)\right) - u_{tcl} = \kappa \qquad \forall\, t, c, l$

2) $\widehat{w}_{it} = \frac{P_{it}}{Y_t} \sum_c \sum_l \left\{\rho_{tcl}\left[\gamma_i + \frac{\alpha_i+\beta_i e^{u_{tcl}}}{1+e^{u_{tcl}}}\left(\frac{Y_{tcl}-\sum_i P_{it}\gamma_i}{P_{it}}\right)\right]\right\} + v_{it} \qquad \forall\, i, t$

3) $\sum_l \rho_{tcl} = \frac{1}{number\ of\ classes(c)} \qquad \forall\, t, c$

4) $\sum_l \rho_{tcl}\, Y_{tcl} = Quintile_{tc} Y_t \qquad \forall\, t, c$

5) $Y_{tcl} - \sum_i P_{it}\, \gamma_i \geq \varepsilon \qquad \forall\, t, c, l$

6) $\sum_i \alpha_i = 1$

7) $\sum_i \beta_i = 1$

8) $\sum_{s=1}^{n-1} r_{si} r_{sj} = \sum_{t=1}^{T} v_{it} v_{jt} \qquad \forall\, i\ \&\ j = 1, 2, \ldots, n-1$

(without distribution equations (3) and (4) drop out and (1), (2) and (4) modify by dropping subscripts l and c)

n: number of aggregate goods

α_i: marginal budget shares for good i at the lower levels of income spectrum

β_i: marginal budget shares for good i at the upper levels of income spectrum

γ_i: subsistence level of consumption of good i

κ: kappa in the utility equation

u_t & u_{tcl}: utility in country t or at level l of class c in country t (whichever is applicable as per data availability for the country

ρ_{tcl}: weights used in the distribution for level l of class c in country t

v_{it}: error term in the demand equation for good i in country t

r_{is}: cholesky factors of the variance covariance matrix of the error terms

P_{it}: price for good i in country t

Y_t and Y_{tcl}: per capita income in country t at level l of class c

W_hat_{it}: estimated budget share of good i in per capita expenditure in country t

Appendix Table 1: Country List And Classification

No.	COUNTRY	WORLD BANK CLASSIFICATION	No.	COUNTRY	WORLD BANK CLASSIFICATION
1	Albania	Lower middle income	58	Lithuania	Upper middle income
2	Antigua and Barbuda	High income: nonOECD	59	Luxembourg	High income: OECD
3	Argentina	Upper middle income	60	Macedonia	Lower middle income
4	Armenia	Lower middle income	61	Madagascar	Low income
5	Australia	High income: OECD	62	Malawi	Low income
6	Austria	High income: OECD	63	Mali	Low income
7	Azerbaijan	Lower middle income	64	Mauritius	Upper middle income
8	Bahamas	High income: nonOECD	65	Mexico	Upper middle income
9	Bahrain	High income: nonOECD	66	Moldova	Lower middle income
10	Bangladesh	Low income	67	Mongolia	Lower middle income
11	Barbados	High income: nonOECD	68	Morocco	Lower middle income
12	Belarus	Upper middle income	69	Nepal	Low income
13	Belgium	High income: OECD	70	Netherland	High income: OECD
14	Belize	Upper middle income	71	NewZealand	High income: OECD
15	Benin	Low income	72	Nigeria	Low income
16	Bermuda	High income: nonOECD	73	Norway	High income: OECD
17	Bolivia	Lower middle income	74	Oman	High income: nonOECD
18	Botswana	Upper middle income	75	Pakistan	Low income
19	Brazil	Upper middle income	76	Panama	Upper middle income
20	Bulgaria	Upper middle income	77	Peru	Lower middle income
21	Cameroon	Lower middle income	78	Philippines	Lower middle income
22	Canada	High income: OECD	79	Poland	Upper middle income
23	Chile	Upper middle income	80	Portugal	High income: OECD
24	Congo	Lower middle income	81	Qatar	High income: nonOECD
25	CotedIvoir	Low income	82	Romania	Upper middle income
26	CzechRep	High income: OECD	83	Russian Federation	Upper middle income

Appendix Table 1: Country List And Classification (Contd.)

No.	COUNTRY	WORLD BANK CLASSIFICATION	No.	COUNTRY	WORLD BANK CLASSIFICATION
27	Denmark	High income: OECD	84	Senegal	Low income
28	Dominica	Upper middle income	85	Sierra Leon	Low income
29	Ecuador	Lower middle income	86	Singapore	High income: nonOECD
30	Egypt	Lower middle income	87	Slovakia	High income: OECD
31	Estonia	High income: nonOECD	88	Slovenia	High income: nonOECD
32	Fiji	Upper middle income	89	Spain	High income: OECD
33	Finland	High income: OECD	90	SriLanka	Lower middle income
34	France	High income: OECD	91	StKitNevis	Upper middle income
35	Gabon	Upper middle income	92	StLucia	Upper middle income
36	Georgia	Lower middle income	93	StVinGren	Upper middle income
37	Germany	High income: OECD	94	Swaziland	Lower middle income
38	Greece	High income: OECD	95	Sweden	High income: OECD
39	Grenada	Upper middle income	96	Switzerlnd	High income: OECD
40	Guinea	Low income	97	Syria	Lower middle income
41	HongKong	High income: nonOECD	98	Tajikistan	Low income
42	Hungary	High income: OECD	99	Tanzania	Low income
43	Iceland	High income: OECD	100	Thailand	Lower middle income
44	Indonesia	Lower middle income	101	Trinidad Tobago	High income: nonOECD
45	Iran	Lower middle income	102	Tunisia	Lower middle income
46	Ireland	High income: OECD	103	Turkey	Upper middle income
47	Israel	High income: nonOECD	104	Turkmenistan	Lower middle income
48	Italy	High income: OECD	105	Ukraine	Lower middle income
49	Jamaica	Upper middle income	106	United Kingdom	High income: OECD
50	Japan	High income: OECD	107	Uruguay	Upper middle income
51	Jordan	Lower middle income	108	USA	High income: OECD
52	Kazakhstan	Upper middle income	109	Uzbekistan	Low income
53	Kenya	Low income	110	Venezuela	Upper middle income
54	Korea	High income: OECD	111	Vietnam	Low income
55	Kyrgyz	Low income	112	Yemen	Low income
56	Latvia	Upper middle income	113	Zambia	Low income
57	Lebanon	Upper middle income	114	Zimbabwe	Low income

Appendix Table 2: Commodity Classification

ICP no.	26 categories available in 1996 ICP data	Aggregate Commodity Group
1	Bread and cereals	food
2	Meat	food
3	Fish	food
4	Milk, cheese and eggs	food
5	Oils and fats	food
6	Fruit, vegetables and potatoes	food
7	Other food	food
8	Non-alcoholic beverages	food
9	Alcoholic beverages	food
10	Tobacco	NonDurable
11	Clothing including repairs	NonDurable
12	Footwear including repairs	NonDurable
13	Gross rent and water charges	NonDurable
14	Fuel and power	NonDurable
15	Furniture, floor coverings and repairs	Durable
16	Other household goods and services	Durable
17	Household appliances and repairs	Durable
18	Medical services and products	Services
19	Personal transportation equipment	Durable
20	Operation of transportation equipment	Services
21	Purchased transport services	Services
22	Communication	Services
23	Recreation and culture	Services
24	Education	Services
25	Restaurants, cafes and hotels	Services
26	Other goods and services	Services