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Commodity Price Volatility and Nutrition Vulnerability

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Contents

List of Tables

List of Figures

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ABSTRACT

In this paper we examine the impact of commodity price volatility on calorie attainment and its variability for households at the nutritional poverty line in Bangladesh. We focus on the first two moments of the distribution of calorie consumption and consider the differential impacts across socioeconomic groups within the country. The framework developed is then used to examine the direction and magnitude of the shift in those moments as a result of implementation of a special safeguard mechanism aimed at preventing import surges.

Keywords: price volatility, nutritional vulnerability, calorie intake, household consumption, Computable General Equilibrium, Model validation, Bangladesh

1. MOTIVATION AND INTRODUCTION

Global economic forces over the past decade have buffeted commodity markets – including those for farm and food products. To the extent that the poor are involved in the production of such commodities, they may benefit through higher incomes – either as farm owners or as agricultural wage earners. On the other hand, the burden of higher food prices falls disproportionately on the poor, especially in the least developed countries, where households may spend as much as 70 percent of their income on food. With these two effects working in opposite directions, the impact of higher prices on the poor is ambiguous.

A related cause of concern is food price volatility. Volatility in food prices and income translates into uncertainty in food consumption and caloric intake. Since the poor are often malnourished to begin with, volatility combined with high food prices makes them nutritionally vulnerable.[1] A lot has been said about the effects of the recent surge in prices on the poor, but less has been written about the impact of sustained price volatility on poverty and calorie attainment. Interestingly, however, the related topics of trade liberalization, poverty, and food security have enjoyed relatively more attention. In this paper, we attempt to build an analytical bridge between these different areas of work.

Research examining the links between trade and poverty using both econometric (Winters, McCulloch, and McKay 2004) and simulation methods (Hertel and Reimer 2005) has seen a recent surge. In their analysis of the poverty impacts of the Doha Development Agenda, Hertel and Winters (2006) emphasize the important role of labor markets in transmitting the impact of changing trade policies to poor households. Capturing these labor market effects requires a general equilibrium approach. This paper draws on one such framework for linking global trade impacts to the income of poor households in developing countries (Hertel et al. 2004). Their approach combines a global general equilibrium model with a set of micro-simulation models aimed at assessing the income effects of changes in trade policies on poor households.

Poverty by itself however, is a very broad indicator of well-being. If we think more specifically in terms of basic needs, food security and nutrition come to the fore. There are many dimensions to nutrition: social, physical, economic, environmental, and so on (von Braun, Swaminathan, and Rosegrant 2003). Nutrition can be assessed from an input or output perspective; the first approach concentrates on measuring the intake of calories, protein, zinc, vitamins, and other such micronutrients depending on the age, health, gender, and occupational characteristics of an individual, whereas the second evaluates nutritional status by looking at outcomes of the intake that get manifested in anthropometric measures. This paper focuses on one single dimension of the input measurement approach to nutrition,[2] namely, the calorie intake per capita per day. Although adequate calorie intake by itself does not ensure proper nutrition, it is very important as without adequate calories the body has difficulty absorbing micronutrients. We model the household demand for food and nonfood items as a function of prices and income and then translate it into calorie intake. The goal of this study is to estimate the calorie intake distribution for individuals around the nutritional poverty line in Bangladesh[3] as a function of commodity price volatility where the latter is driven by volatility in production. With this framework, we can then evaluate the impact of policies aimed at reducing price volatility on calorie consumption distribution.

The methodology applied here is a combination of global general equilibrium analysis, econometric analysis of consumption behavior with a particular focus on households at low levels of income, analysis of the caloric content of consumption, and micro-simulation analysis of household behavior. The aim is to link global economic changes to calorie changes for poor people in developing countries. To understand the impact of such changes on nutrition, we need to take a closer look at: (a)

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[1] Bhutta et al. (2008) show how the effects of similar strategies to improve nutrition differ across poor and comparatively better off populations.

[2] Although we are considering the calorie consumption (food security) aspect only, adequate care in early years and health status also play an important role as determinants of nutritional status (see Black et al. 2008).

[3] We choose Bangladesh as a focus country because it is classified as one of the least developed countries and it is a major net importer of rice—one of the most volatile commodities in terms of price and the staple food for its population.

consumption patterns of the poor; (b) how consumption is likely to respond to changes in market conditions, particularly, changes in income and relative prices; and finally, (c) how these changes in consumption translate into changes in nutritional status.

We work with a relatively new concept, the nutritional poverty line (NPL), and focus on the well-being of the population in the vicinity of the NPL. We borrow the concept of the NPL from the Household Income and Expenditure Survey (HIES 2000). That survey's criterion for determining the NPL is daily per capita calorie intake;[4] the survey classifies a person consuming 2,122 kilocalories (Kcal) or less per day as nutritionally poor. By the population in the vicinity of the NPL we mean the one percent population around it. As we were primarily interested in the person on the very margin (NPL), taking the whole population would not accurately represent that person. At the same time we did not want our results to be susceptible to some idiosyncratic behavior of one representative individual just at the NPL as identified by the survey. By taking a one percent section we rule out that possibility while as closely representing as possible a person at the NPL.

The focus country for this study is Bangladesh, one of the least developed countries of particular concern to international development organizations, and a major net importer of rice – the staple food for its population. However, the methodology proposed could be applied to assess the caloric impacts of multilateral trade policies affecting price volatility in a wide range of developing countries.[5] Also, while this paper focuses on calorie intake, the general approach is amenable to extensions covering micronutrients associated with food consumption, provided the data are available.

The next section outlines the general framework for study. Section 3 offers a detailed description of the data and the main building blocks of the model – the household consumption demand system, and modified general equilibrium model along with the new nutrition module. It reports our work aimed at computable general equilibrium (CGE) model validation based on its ability to capture historic price volatility and calorie consumption distribution and elaborates our comparative statics approach to modeling the impact of a special safeguard mechanism on nutrition. Results are discussed in Section 4. Section 5 offers conclusions and an agenda for further research.

[4] In classifying a section of population as lying below the NPL, the survey does not explicitly consider information on variables such as people's physical activity, which according to nutrition literature is an important variable (see FAO 2001).

[5] See Hertel et al. (2008) for an illustration of a similar approach to assessing the poverty impacts of the Doha Development Agenda.

2. OVERVIEW OF THE ANALYTICAL FRAMEWORK

There are two primary channels through which one may expect commodity price volatility to affect an individual's consumption: one is the change in the price of goods consumed and the second is the change in disposable income for commodity sellers. The first channel has long been emphasized in empirical work and theory alike. The latter however, has only relatively recently started to receive its due share of attention. Faced with these two changes, economic theory postulates that households maximize utility, subject to a new budget constraint determined by current income,[6] and in the process, reach a new optimal consumption bundle. This consumption change is likely to imply a change in calorie intake.[7] We seek to assess the size and direction of such changes and how the policy environment affects them.

Having made the case as to why volatile commodity prices should affect calorie intake, and also keeping in mind the policy dimension of our study, we proceed to outline the quantitative framework designed to link price volatility and calorie consumption distribution. The method employed in this analysis has three main elements: econometric estimation of a demand system, incorporation of that demand system into a CGE model in which stochastic simulations may be conducted, and finally, analysis of the caloric impacts of simulated changes. In the first stage we seek a demand characterization that can span the entire spectrum of population in the country. The cause of concern is that people differ widely in terms of per capita income; therefore, we want to refrain from making the simplistic assumption of homothetic preferences. Accordingly, we choose An Implicit Directly Additive Demand System (AIDADS), as it nicely replicates the observed food expenditure shares for Bangladesh across the entire income distribution, as shown in Figure 1. We model the demand for various commodities as shares in total expenditure, and the observed and estimated values of this dependent variable – "budget shares" – are plotted against the population percentiles ascending in per capita total expenditure. The AIDADS consumption demand for a commodity as modeled depends on income of the agent and prices of the commodities consumed, including both food and nonfood goods. So if for a given policy there are differential changes in factor incomes across households, this is accounted for by the income term, while changes in food and nonfood prices have a direct effect on consumption and hence calorie intake for a given household.[8]

Following Cranfield et al. (2002), the demand system is estimated using three pieces of international cross-section data: (a) information on the distribution of expenditure across households within each country; (b) data on per capita income and consumption variation across countries; and (c) data on price variation across countries within the sample. This estimation is undertaken employing the maintained hypothesis that all countries may be characterized by a common set of preferences. This has its limitations, and so, in a second stage, the estimated parameters of the international demand system are adjusted to replicate observed aggregate per capita consumption in the CGE model (Golub 2006). This calibration step is necessary before we can incorporate this demand system into any equilibrium model, which is the second building block of our analysis.

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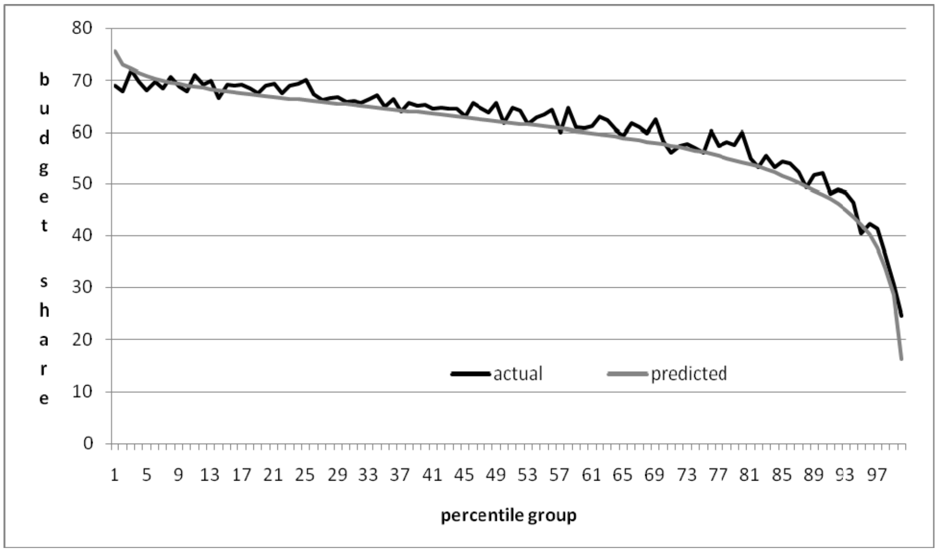
[6] The household's response to an adverse shock to current income may be to draw down its assets (dis-saving). However, a proper treatment of asset accumulation and de-accumulation would require a dynamic framework that is beyond the scope of this study. In addition, the focus households in this study are extremely poor, suggesting that they have few assets to deplete.

[7] A change in foods consumed does not necessarily translate into changes in calorie intake if energy content is similar for substitution foods. However, the system models consumption at a very high aggregate level (e.g., cereals) and does not provide the possibility of substitution among disaggregated foods with similar energy content (e.g., wheat and rice).

[8] As mentioned previously, socio cultural and physiological factors exist that play an important role in consumption decisions, but our model does not capture those.

Figure 1. Observed and predicted budget shares for food in Bangladesh



Source: Verma, Preckel, and Hertel (2007).

The CGE model here makes a distinction between household groups, or strata, on the basis of their sources of income. The effect of a change in policy on consumption of low-income households in different population strata is evaluated by applying the post-simulation level of income and prices, to the customized demand system. So the composition of household consumption changes according to stratum-specific income changes and stratum-generic commodity price changes.[9]

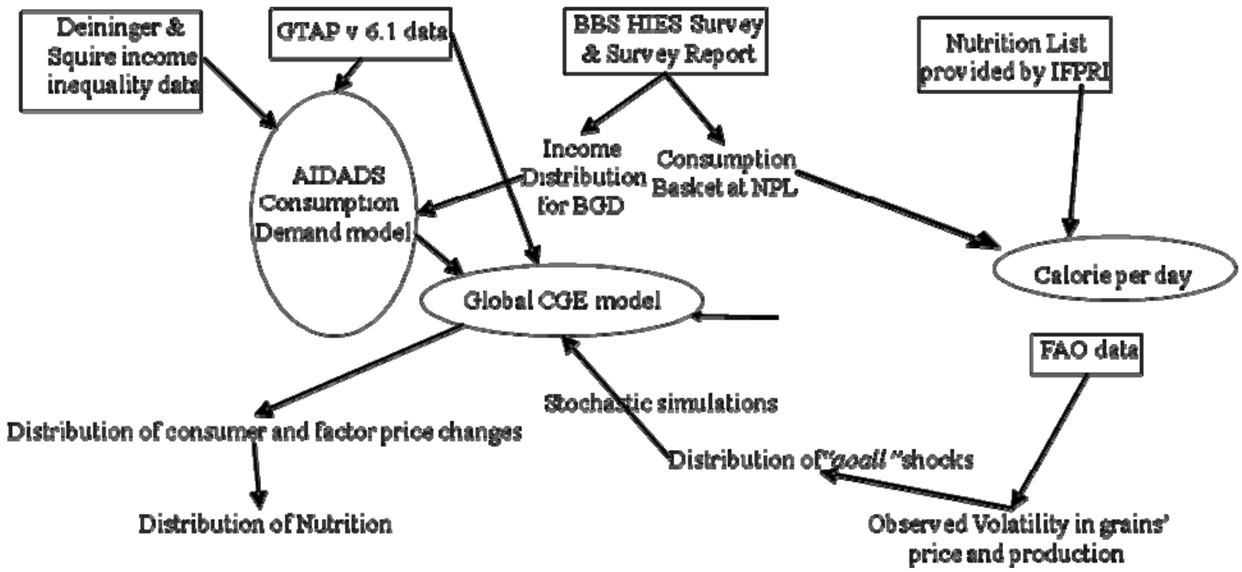
This brings us to the third part of the story: caloric impacts. To evaluate such impacts we must know the caloric content of the consumption goods purchased by low-income households. Once we know that, we are in a position to make the link from a global or domestic economic shock to changes in domestic prices and changes in wages by stratum, to household consumption changes, and finally to changes in calorie attainment.

The analytical framework just outlined is used to evaluate the impact of volatility in staple grain prices seen historically on calorie intake of poor people in Bangladesh. Figure 2 offers an overview of the analytical framework. The data sources are inscribed in the rectangular boxes and the arrows point to the part of the model where they are used. The figure contents are described further in the following section.

Having made the case that a policy too can affect price volatility, we compare these impacts with those that would have been seen if a different policy regime had been in place. One such important policy aimed at commodity market volatility that has received particular attention in the past year is the proposal by developing countries to allow for a Special Safeguard Mechanism (SSM) under the Doha Development Agenda of the World Trade Organization (WTO 2008). The basic idea is to permit countries to shield themselves from world price volatility by levying temporary additional tariffs, intended to offset import quantity surges (quantity trigger) and/or import price drops (price trigger). Clearly it is a policy that aims to affect either import quantity volatility or price volatility, and it is worth analyzing using the framework developed in this study. SSM is also known to be one of the stumbling blocks on which Doha failed to reach consensus. It is of particular interest to the poor, insofar as they spend a large share of their income on food. Whether SSM is or is not beneficial to the poor is an empirical question we aim to address here by means of a policy experiment.

[9] It is generally the case that the change in prices a household faces as a result of a trade policy depends on its geographic area of residence in the country (Nicita 2006). In this study differential price transmission within a country is overlooked and commodity markets are modeled at the national level to limit the complexity of our study.

Figure 2. Data and its utilization



Source: Adapted from Ivanic (2006).

3. DATA AND METHODOLOGY

With the objective of deriving the calorie consumption distribution owing to price volatility, the next question that demands attention is which model to use. Household models are known to richly capture agent response, which is very important for this study, but we have also highlighted the importance of general equilibrium models for determining income changes. Therefore, we use a CGE model with an embedded household model. Lofgren, Robinson, and El-Said (2003) discuss different poverty analysis approaches in a CGE framework using household data. We adopt the micro-simulation approach here, and this section details all the components involved – the consumption demand model, the global CGE model, and the micro-simulation analysis of household behavior involving stochastic shocks. As we expect volatility in the world markets to creep into individual country markets with trade linkages, we prefer a multi-country to a single-country CGE model. It also makes possible analysis of policy changes in trading-partner economies.

The subsections that follow consider all components of the model and data required to estimate it.

Data

The data come from various sources, and the use of data in this analysis can be better understood by simultaneously consulting Figure 2 and this section. The Global Trade Analysis Project (GTAP) Data Base, version 6.1 (Dimaranan 2006), is used to characterize global consumption (as well as production and trade) for 57 commodities in 75 regions of the world. Income distribution information from the Deininger and Squire (1996) data set (for all countries other than Bangladesh in our sample) as well as the HIES 2000, provided by IFPRI are used in estimating the per capita international cross-section demand system. The latter also provides information used in the validation of our demand system.

We use the HIES 2000 data for obtaining a detailed consumption profile for population at the NPL. The consumption profile is then combined with data on calorie content for Bangladesh-specific food items provided by IFPRI, to get the caloric content for all consumption commodities. The results are provided in Table 1, which reports the average daily calorie intake from consumption of survey commodities for the group of households in the neighborhood of the NPL. Note that the way the survey data are collected leaves open the question of seasonal variation in food consumption and calorie intake; months of malnutrition are observed every year in northern Bangladesh (Zug 2006), but unfortunately our data are collected for a period of 15 days in one season, so we do not observe the seasonal difference. Being derived for a much disaggregated level of commodities, this list could be utilized by other studies, general equilibrium or otherwise in nature, interested in a different aggregation or more disaggregated analysis. Note that the total caloric intake per capita per day derived using this approach is 2,126 Kcal, which is very close to that reported in HIES 2000 (2,122 Kcal).

The commodities in Table 1 are mapped to the 19 farm and food GTAP commodities and to nine AIDADS consumption commodities in the global economic model, so that as GTAP consumption levels change, we can deduce the associated impacts on calorie attainment.

Finally, FAOSTAT data on production and price time series for Bangladesh over the years 1985–2000 are used to obtain measures of historic volatility in prices and production of staple grains and oilseeds. These are, in turn, inputs into the specification validation of the stochastic model simulations.

Table 1. Calorie intake of the poor from daily consumption

Survey Food Commodities	Derived Calories per Capita per Day
Apple	0.0978
Arum/ Ol-kachu/ Kachur-mukhi	7.1127
Baila/ Tapashi	0.1009
Balsam apple	1.1802
Bean/ Lobey	2.6920
Beaten rice	1.5837
Beef	4.0052
Biri	0.0000
Biscuits	0.0508
Black berry	0.1145
Bread/ Bonruti	2.2703
Brinjal	6.1559
Buffalo	0.5880
Cake	4.0527
Cauliflower/ Cabbage	1.5137
Chickling-Vetch (mug)	0.2809
Chocolate	0.0153
Cigarette	0.0000
Curd	0.2324
Dried fish	2.8566
Duck	0.5848
Duck egg	1.1975
Emblic/ Amra/ Kamranga	0.0747
Flour	1.3398
Food grains:...as yet undefined...	44.5495
Grape	0.0128
Green banana/ Green papaya	3.1765
Green coconut	0.0000
Green gram (boot)	17.1883
Guava	0.5396
Halua/ Batasha/ Kadma	0.0000
Hen	1.9203
Hen egg	2.7654
Hilsa	7.0727
Ice-cream	0.0042
Jack fruit	11.5139
Jilapi/ Bundia/ Amriti	1.7168
Kai/ Magur/ Shinghi/ Koi	0.3543
Kalisha	0.0000

Table 1. Continued

Survey Food Commodities	Derived Calories per Capita per Day
Khaja/ Logenze/ Toffee	0.0000
Ladies' finger	0.9913
Leeches	0.0719
Lentil (musur)	13.7727
Liquid milk	11.4546
Liquid of Sugarcane/ Date/ Palm	0.0311
Mala-kachi/ Chala-chapila	2.8500
Mango	23.7271
Mashkalai	6.2977
Meals	0.0000
Melon/ Bangi	0.0000
Molasses (Sugarcane/ Date/ Palm)	12.9062
Mustard oil	39.0128
Mutton	0.4238
Orange	0.0492
Other fish	2.7834
Other fruits	0.2930
Other meat	0.1395
Other miscellaneous food	0.0000
Other oil & fats	1.6965
Other pulses	2.1392
Other sweetmeat	0.2824
Other tobacco & tobacco products	0.0000
Other vegetables	12.7225
Pangash/ Boal/ Air	0.6148
Pea gram (kheshari)	10.2126
Perbol	0.0000
Pickles	0.0000
Pineapple	1.0410
Pop rice	0.5014
Potato	55.1245
Prepared Betel-leaf	0.0142
Puffed rice	12.6766
Puti/ Big Puti/ Telapia/ Nilotica	6.2072
Rasogolla/ Chamcham/ Shandash	0.4211
Rhui/ Katla/ Mrigel/ Kal baush	2.8359
Rice – Coarse	1508.7986
Rice – Medium	169.3767
Ripe banana	4.7707

Table 1. Continued

Survey Food Commodities	Derived Calories per Capita per Day
Ripe papaya	0.0549
Sea fish	0.0000
Shoal/ Gajar/ Taki	1.0046
Shrimp	10.7520
Silver carp/ Grass carp/ Miror carp	3.7453
Snacks	0.0000
Snake gourd/ Ribbed gourd	0.8954
Soybean oil	51.1924
Spinach/ Amaranta/ Basil	4.9606
Sugar/ Misri	5.8117
Sweetmeat	0.0000
Tangra/ Eelfish	3.9875
Tea/ Coffee	0.0000
Tea/ Coffee leaf	0.1238
Tobacco leaf	0.0000
Tomato	0.5881
Vermicelli/ Suji	0.0000
Water gourd	7.5984
Wheat	1.0636
White gourd/ Pumpkin	1.0970
Sum	**2,126.03**

Source: Authors' calculations using HIES 2000.

Consumer Demand System: AIDADS

AIDADS Estimation

The AIDADS specification of consumer demand, as mentioned previously, is estimated using the GTAP Data Base, version 6.1, consisting of 57 commodity sectors and 75 individual countries (there are also 12 composite regions in that database, for a total of 87 countries/regions). For estimation purposes, the 57 GTAP sectors are aggregated into nine broader AIDADS commodity groups. Table 2 details the mapping scheme we follow. The focus on consumption and nutrition calls for keeping food categories relatively more disaggregated; accordingly, there are seven food and only two nonfood AIDADS commodity groups.[10]

The method employed for estimation is maximum likelihood with maximum entropy. We use GAMS (General Algebraic Modeling System) to estimate this highly nonlinear system. A formal treatment of the model is specified in Cranfield (1999); for convenience a short summary is provided in Appendix 1.

Estimation of this international demand system gives parameters of the demand function that differ across commodity groups but are the same for all countries due to the assumption of common

[10] The major food commodity groups are defined as dairy, grains, meat, oil, sugar, fruits and vegetables, and other processed. Manufacturing and services are the two nonfood commodity groups.

preferences. These estimates are given in the first three columns of Table 3. The first column reports the expenditure share of a commodity in total subsistence expenditure that a household in Bangladesh needs to undertake for each member in order to survive. The column shows the expenditure to be concentrated to basic needs. Column two gives the estimated *marginal expenditure shares* at subsistence level of income, whereas the third column gives the same for consumption at the right tail of income distribution. From the table we can see that a household with a low level of income spends almost 60 percent[11] of its incremental income on food as against only 15 percent spent by a rich household. As these are shares, they add to one. For policy analysis exercise, these parameters suggest that the impact of high volatility in food prices will be disproportionately borne by the households at the lower end of income distribution, owing to the higher budget shares they allocate to food.

These country-generic share parameters, however, do not exactly reproduce the observed per capita level of consumption for Bangladesh, when evaluated at Bangladeshi prices and per capita income. To impose this necessary condition for use in the CGE model, we calibrate the commodity-specific parameter estimates to make them country/region specific as well. This deserves further discussion.

Table 2. Sectoral mapping scheme linking GTAP sector and AIDADS commodities

No.	GTAP Sector	TRAD_COMM	AIDADS Commodity
1	Paddy rice	Rice	Grain
2	Wheat	Wheat	Grain
3	Cereal grains nec*	Crsgrns	Grain
4	Vegetables, fruit, nuts	OthCrps	Fruits
5	Oilseeds	Oilseeds	Grain
6	Sugar cane, sugar beet	Sugar	Sugar
7	Plant-based fibers	Cotton	Mfg
8	Crops nec*	OthCrps	Fruits
9	Bovine cattle, sheep and goats, horses	Cattle	Meat
10	Animal products nec*	NRumin	Meat
11	Raw milk	Milk	Dairy
12	Wool, silk-worm cocoons	TextAppl	Mfg
13	Forestry	Forest	Mfg
14	Fishing	Fish	Meat
15	Coal	Utility	Svcs
16	Oil	Petrol	Mfg
17	Gas	Utility	Svcs
18	Minerals nec*	HvyMnfcs	Mfg
19	Bovine meat products	PrBeef	Meat
20	Meat products nec*	PrNRumn	Meat
21	Vegetable oils and fats	PrOilsd	Oil
22	Dairy products	PrDairy	Dairy
23	Processed rice	PrRice	Grain
24	Sugar	PrSugar	Sugar

[11] The numbers are arrived at by adding the shares for dairy, grains, meat, oil, sugar, fruits and vegetables, and other processed.

Table 2. Continued

No.	GTAP Sector	TRAD_COMM	AIDADS Commodity
25	Food products nec*	OthFdBev	Othrproc
26	Beverages and tobacco products	OthFdBev	Othrproc
27	Textiles	TextAppl	Mfg
28	Wearing apparel	TextAppl	Mfg
29	Leather products	TextAppl	Mfg
30	Wood products	HvyMnfcs	Mfg
31	Paper products, publishing	HvyMnfcs	Mfg
32	Petroleum, coal products	Petrol	Mfg
33	Chemical, rubber, plastic products	HvyMnfcs	Mfg
34	Mineral products nec*	HvyMnfcs	Mfg
35	Ferrous metals	HvyMnfcs	Mfg
36	Metals nec*	HvyMnfcs	Mfg
37	Metal products	HvyMnfcs	Mfg
38	Motor vehicles and parts	Autos	Mfg
39	Transport equipment nec*	TransCom	Svcs
40	Electronic equipment	Electron	Mfg
41	Machinery and equipment nec*	OthMnfcs	Mfg
42	Manufactures nec*	OthMnfcs	Mfg
43	Electricity	Utility	Svcs
44	Gas manufacture, distribution	Utility	Svcs
45	Water	Utility	Svcs
46	Construction	Constrct	Svcs
47	Trade	WRtrade	Svcs
48	Transport nec*	TransCom	Svcs
49	Water transport	TransCom	Svcs
50	Air transport	TransCom	Svcs
51	Communication	TransCom	Svcs
52	Financial services nec*	FinSvce	Svcs
53	Insurance	Utility	Svcs
54	Business services nec*	FinSvce	Svcs
55	Recreational and other services	HsEdHe	Svcs
56	Public Administration, Defense, Education, Health	HsEdHe	Svcs
57	Dwellings	HsEdHe	Svcs

* nec: not elsewhere specified.

Table 3. Estimated and calibrated demand system parameters

Commodities	Estimated			Calibrated	
	(1)	(2)	(3)	(4)	(5)
	Expenditure Share at Subsistence Level of Income in Bangladesh	Marginal Expenditure Share at Subsistence Level of Income	Marginal Expenditure Share at High Levels of Income	Marginal Expenditure Share at Subsistence Level of Income	Marginal Expenditure Share at High Levels of Income
Dairy	0	0.039	0.017	0.008	0.003
Grains	0.189	0.124	0	0.265	0
Meat	0	0.116	0.045	0.119	0.042
Oil	0.025	0.017	0.004	0.029	0.006
Sugar	0	0.030	0.003	0.034	0.003
Fruits and vegetables	0.785	0.104	0.008	0.041	0.003
Other processed	0	0.167	0.073	0.044	0.017
Manufacturing	0	0.164	0.227	0.154	0.194
Services	0	0.238	0.624	0.307	0.731

Source: Authors' calculation and estimation of AIDADS parameters.

Calibration

For calibration purposes we work with 34 CGE model regions instead of the 75 countries used in the estimation stage. The focus country (Bangladesh) and some countries of interest (India and China) remain disaggregated, whereas others are aggregated into geographic regions to reduce the dimensions of the CGE model.

Details of the calibration procedure adapted from Golub (2006) are given in Appendix 2. To outline it briefly; for each of the 34 regions we scale up two of the demand equation parameters by a fraction less than (greater than) one if the system was initially over- (under-) predicting the budget shares for the region. The fraction in question here is the error ratio in prediction. This gives new demand equation parameter estimates. The scaled parameters, however, fail to satisfy the utility equation, which is an important part of the system; therefore, as a second step we let the utility equation parameters adjust to bring the system to balance.[12] The end result is new estimates of the utility and demand equation that differ across countries (unlike initial estimates), and we are able to reproduce the observed expenditure shares for each country at its respective per capita income. Note that only the share parameters change post-calibration; subsistence parameters remain unchanged. The reason is our assumption that any difference in observed and estimated per capita budget shares originates in the discretionary[13] and not necessary (subsistence) expenditure. The post-calibration demand parameter estimates from GAMS are fed into the general equilibrium model. These calibrated estimates for Bangladesh can be seen in columns 4 and 5 of Table 3. The new estimates can be interpreted in a similar fashion as the old ones.

Validation of the Demand System

Calibration ensures that we replicate national, per capita demands for each commodity. However, we also want to assess our ability to predict consumption patterns at very low levels of income. As

[12] This second step is undertaken for the simultaneous equation system and not just for the utility equation in isolation.
[13] See Appendix 2 for the distinction between discretionary and subsistence budget shares.

mentioned, the system is estimated using cross-country per capita national consumption data along with income distribution information, as opposed to household-level consumption data of which only income distribution information is used; therefore, its capability of correctly predicting expenditures for individual households – and particularly for the poor households – can be questioned. This issue was examined in a related study (Verma, Hertel and Preckel 2007). They use the HIES 2000 data to observe the food budget shares across the income spectrum in Bangladesh and the AIDADS system to predict the food[14] budget shares for these different income levels. The comparison of the observed and predicted shares yields close-fitting curves, as can be seen from Figure 1. Therefore, we can be more confident in our assertions when it comes to predicting the effects of policy changes on consumption patterns across the income distribution within the country.[15] It is an important implication as such models are frequently employed in poverty studies.

Computable General Equilibrium Model

We employ a general equilibrium model to estimate the impacts of any simulated changes on factor earnings and commodity prices in 34 countries and regions. The model used here is a slightly modified version of the standard GTAP model. As mentioned earlier, consumer demand is now represented via AIDADS instead of the usual constant difference of elasticity specification of the standard model.

Following Hertel et al. (2004) we categorize households into five groups that rely almost exclusively (95 percent or more) on one of the following sources of income: agricultural self-employment, nonagricultural self-employment, rural wage labor, urban wage labor, and transfer payments. The remaining households are grouped as rural or urban diversified, giving us a total of seven strata. Further, the CGE model introduces segmentation between agricultural and nonagricultural factors markets, following Keeney and Hertel (2005). This segmentation allows for differential impacts originating from a shock on factor earnings across strata; faced with such changes, households maximize utility subject to their respective budget constraint and in the process reach a new consumption bundle. This latter exercise involves micro-simulation techniques.

Nutrition Module

Simulation results from the modified CGE model fed into the AIDADS model yield associated consumption changes. To be able to say something about the accompanying change in nutritional status, we need to sum up the changes in calorie intake that a person experiences due to a change in the consumption of the seven food commodities. This requires adding a nutrition module to the CGE model that essentially computes the total change in per capita calorie intake at the NPL, and also its decomposition across the consumption commodities.

Recall that in the GTAP model, consumption corresponds to aggregate goods, the quantity of which is expenditure evaluated at base period prices. Therefore, to estimate calorie changes we need to know calorie content per base period dollar for each of the seven food commodities. We start with a measure for "*calorie intake per day per capita from consumption of a GTAP commodity's physical quantity at the NPL*" ($CalC_g$), and proceed from there to obtain a measure of calories per dollar spent on the AIDADS commodity. The specifics of obtaining $CalC_g$ are outlined in Appendix 3.

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[14] We merely quote their finding and do not try to improve upon their attempt by trying to validate the demand system for disaggregated food commodities. Doing so for disaggregated commodities will involve mapping issues that can be very tricky. Also, the focus is on making the point that the demand system does well in capturing responses at lower levels of income, which is easily made using the aggregate food category.

[15] The model with the estimation scheme employed here can also be used in the macro-micro synthesis context as it handles aggregation issues—the aggregate mean per capita expenditure being modeled as a weighted average of the individual expenditures.

Further, let g, a, r *and* s denote the indices for GTAP commodities, AIDADS commodities, region, and stratum respectively. The approach to generating the change in per capita calories at the NPL may then be described as follows:

Using the mapping from 57 GTAP commodities to nine AIDADS commodities we obtain the "*per day per capita calorie intake from consumption of the AIDADS commodity in physical units*." This is simply the sum of calorie intake from the GTAP goods that are components of the specific AIDADS commodity.

$$Cal_{ar} = \sum_{g} CalC_{g} \quad \forall g \in a$$

Note that this is not stratum specific, as we do not expect the calorie content of the commodities consumed by poor people belonging to different strata to differ.[16] This is reflected in our formulation that follows, which states that per day per capita calorie intake at the NPL is the same, irrespective of which stratum the individual belongs to:

$$Cal_{asr} = Cal_{ar}$$

Once we have this, we can calculate the "calorie content per dollar spent on consumption for the AIDADS commodity at base period prices." Let us denote it by N_{asr}:

$$N_{asr} = \frac{Cal_{asr}}{C_{asr}\frac{1000000}{365}}$$

where C_{asr} is the per capita annual consumption expenditure in millions of dollars on commodity a, in stratum s of region r. Note that in the expression above the unit of the numerator is calories per day per capita and that of the denominator is dollars per day per capita. Accordingly, the units for N_{asr} are *calories per dollar,* which is what we had set out to achieve.

As alluded to earlier, we are interested in obtaining the change in "*calories from each commodity*" NUT_{asr} and change in "*total calories*" $TNUT_{sr}$. The first would simply be the change in consumption of each commodity multiplied by the coefficient N_{asr}:

$$\Delta NUT_{asr} = N_{asr}\left[(C_{asr})\left(\frac{dC_{asr}}{C_{asr}}100\right)\left(\frac{1}{100}\right)\left(\frac{1000000}{365}\right)\right]$$

The term $\left(\frac{dC_{asr}}{C_{asr}}100\right)$ in the preceding expression appears in the general equilibrium model as a linear (percent change) variable associated with the per capita consumption at the NPL. For deriving the change in total per capita calories at the NPL, we just need to sum over commodities the changes in commodity-specific calories:

[16] The assumption involved is that people at the NPL all have similar per capita income to begin with and owing to it consume commodities of similar quality. That is a simplification as it does not account for differences in consumption owing to other factors such as gender, age, health status, and so on.

$$\Delta TNUT_{sr} = \sum_{a} \Delta NUT_{asr}$$

Simulation: Stochastic Shocks Approach

Given our interest in understanding the interplay between trade policies and calorie consumption in the presence of commodity price volatility, we need to develop a stochastic simulation approach for our CGE model. We first seek to model the process by which stochastic prices arise and then compare the results of that process with the FAO observed price volatility to check whether the model is a valid representation of the reality. Ensuring that our model can replicate the observed historic volatility in prices is very important for the credibility of our policy experiments. To that end we employ Stochastic Simulation Analysis (SSA), outlined in Arndt (1996), which for a specified distribution recovers the means and standard deviation for endogenous variables. We then overlay alternative policy regimes on top of this baseline to examine the changed moments of distribution for calorie consumption owing to the policy change.

If we were interested only in the consumption-side impact of commodity price volatility, we could randomly sample from grain price distribution and shock the prices in the consumer demand system to see the impact on calorie intake. However, we are also interested in the income-side impacts, and furthermore, we wish to overlay alternative trade policy regimes. This makes prices in our model endogenous. Therefore, we approach the issue in an indirect fashion. We postulate that volatile prices arise from volatility in output,[17] which we can also observe from the FAO production data. Since output is endogenous to our model, we seek to replicate the observed volatility in prices and outputs by means of output productivity shocks. More is said below about the distribution of the productivity shocks from which we sample.

Using the stochastic shocks serves three purposes. First, with this method we can use it to validate the CGE model. Second, we can generate the calorie intake distribution for the poor at the NPL. Finally, we can analyze the impacts of Special Safeguard Mechanism.

CGE Model Validation

The previously described mechanism works well to generate caloric changes in the wake of price and income changes, provided that the model offers a good approximation to the real world, but we have not yet tested this. This issue is the topic of the present section. We do so by examining whether the model can reproduce the crop price volatility seen historically. This is also the strategy for a CGE model validation recently espoused by Valenzuela et al. (2007).

The main objective of the modeling exercise is to be able to infer the distribution of endogenous variables (particularly nutrition) owing to volatility (not just changes) in prices of certain agricultural commodities. We focus on grains – rice, wheat, coarse grains, and oilseeds – with the reason being that grains make up the major share of agricultural production and they consist of a large proportion of poor households' consumption. In terms of calorie intake at the NPL, it turns out that about three-quarters of the total 2,126 Kcal is obtained through the consumption of staple grains alone.

To set target (observed) volatility we make use of data from FAOSTAT. The used measure of volatility is the standard deviation.[18] Details about the process of setting target volatility and SSA can be found in Appendix 4.

Estimated volatility obtained as a result of technology shock sensitivity analysis along with observed volatility is reported in Table 4. As can be seen, the estimated standard deviation in prices is

[17] This is a valid assumption to make for agricultural commodities as output is often sluggish in adjustment and the burden of market clearing is disproportionately borne by prices.

[18] Although modeling volatility in a more systematic manner, as in Valenzuela (2006), would be desirable, to begin with we decide on a simpler approximation to set up the machinery and keep the model simple on the volatility estimation front.

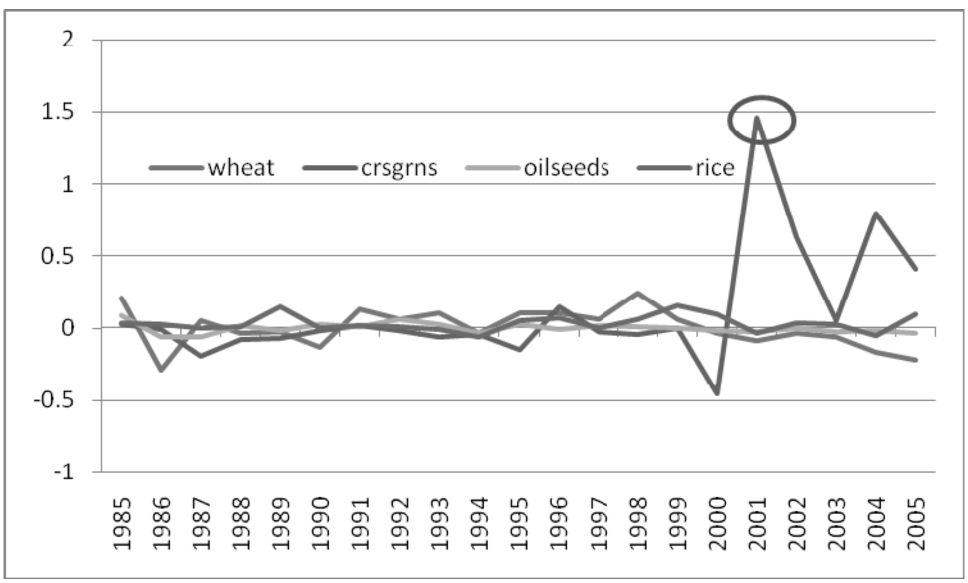
quite close for rice, coarse grains, and oilseeds. Wheat fits less well, but the historical series is dominated by a few outliers as shown in Figure 4. The outliers have undue influence on the historically observed standard deviation.

Table 4. Observed and estimated volatility in output and prices in Bangladesh

	Output		Price	
Commodity	Observed Standard Deviation	Estimated Standard Deviation	Observed Standard Deviation	Estimated Standard Deviation
Rice	5.88	5.86	13.58	14.03
Wheat	13.36	16.15	19.62*	7.69
Coarse Grains	41.02**	9.15	7.69	9.62
Oilseeds	3.77	11.15	8.47	8.73

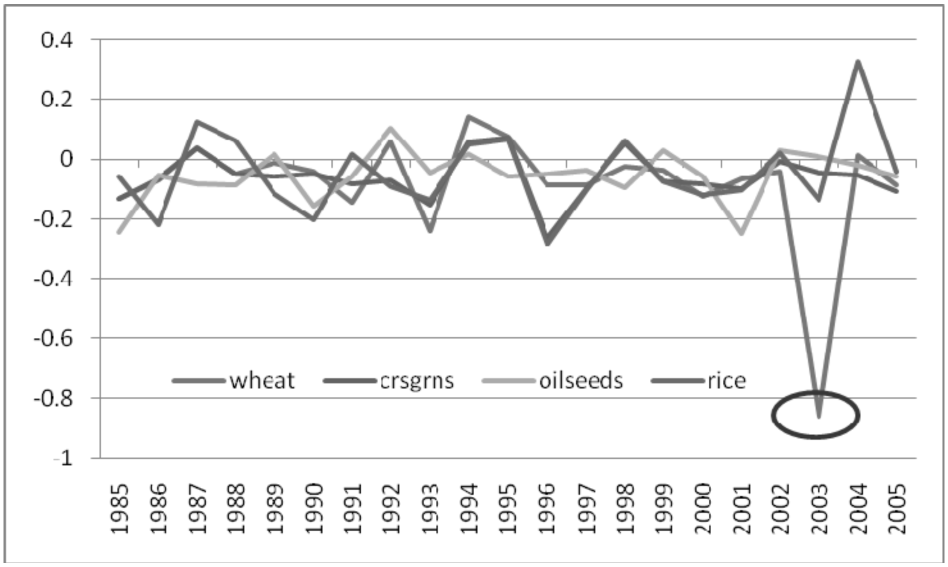
Source: Authors' calculation using FAO data and SSA results.
* This high number results from a jump in the price series, which appears to be a result of some change in the wheat policy regime. This gives rise to an outlier problem in the series as is pointed out in Figure 4. Once this point is dropped from the series, the standard deviation result turns out to be 8.57, which is quite close to the model results.
** The number appears again as a result of an outlier in the coarse grain production series (see Figure 3).

Figure 3. The year-on-year proportionate change in production



Source: Authors' calculation using FAO production data.

Figure 4. The year-on-year proportionate change in prices



Source: Authors' calculation using FAO price data.

Policy Experiment: Special Safeguard Mechanism

One point of interest in this analysis is how the implementation of Special Safeguard Mechanism affects the caloric distribution. Arguments in favor of SSM expect it to either raise mean caloric attainment or reduce the associated standard deviation, or both. Whether the data support this intended result of SSM is what we try to infer from our simulations. But first we briefly outline the type of SSM considered.

According to the most recent WTO modality proposal on SSM, a country can resort to either a price- or volume-based SSM. We concentrate on import volume triggering the SSM into action. Hertel and Martin (2008) provide a simplified interpretation of the technical modalities. The model here follows those authors in modeling the SSM.

To briefly outline, if a product's imports in a year surpass their base year value by a given percentage, the country has a right to raise tariffs on that particular product, subject to an upper bound. We model this as a complementary slackness condition between the supplementary tariff and an expression involving the ratio of imports to maximum permissible growth in imports – indicating import surge. Any time imports exceed the permissible hike in quantity, the supplementary import tariff is introduced, raising prices of imported products and thereby restricting imports to the permissible level. By restricting supply, the import restriction affects the price of domestic products as well. This change in domestic and imported prices gets translated into calorie change through the demand system link.

To derive a distribution of calories with the SSM implemented, we do the same SSA experiment as before. The objective is to see what the price volatility would have been and how in turn it would affect the distribution of calorie intake around the NPL.

4. RESULTS

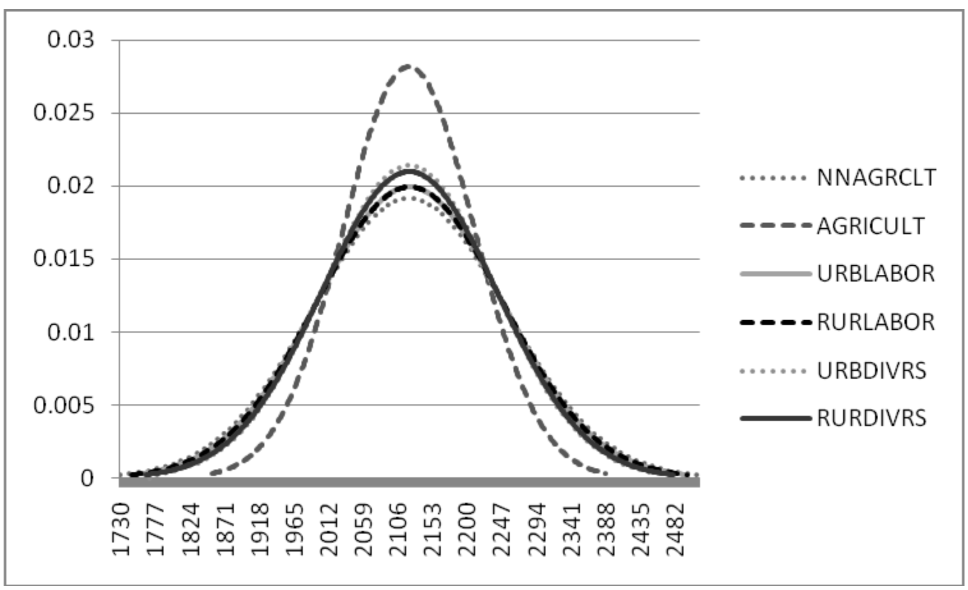
The stochastic simulations are conducted under two different policy scenarios, as outlined in the previous section. The first is without the special safeguard mechanism and the second is with the SSM operational. Each gives a different set of calorie consumption distributions.

We assume that the distribution of calories is normal[19] for the people around the NPL. With the normality assumption, we need only mean and variance for the calorie change variable (which we have from SSA) to fully characterize its distribution. We are therefore now in a position to say something about the distribution of calories[20] for a person belonging to households in the neighborhood of the NPL, drawn from any of the seven strata.

The distributions for each stratum in the absence of the SSM are plotted in Figure 5a. The plotted probability distributions cover three standard deviations around the mean. The horizontal axis represents daily per capita calorie intake, and the vertical axis has the associated probability density.

Note that the standard deviation for the agricultural stratum is relatively tighter compared with all others. This is an expected result because their access to food (even if they are net buyers of food) is much less dependent on the market,[21] and hence the effect of food price volatility on their consumption and calorie intake is relatively modest. This result—the agriculturally self-employed are less vulnerable to the impact of high price volatility on calories—by itself is interesting and is worth further exploration. We have not found any studies contradicting or supporting our finding here.

Figure 5a. Nutritional distribution (no SSM) for individuals at the nutritional poverty line in the baseline (by earnings stratum)



Source: Authors' calculation using model simulation results.

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[19] We are not claiming that the true distribution is normal; it could be skewed or it could be truncated. Unfortunately, the only information we have about the distribution is its mean and standard deviation. We use the normal distribution for illustrative purposes only.

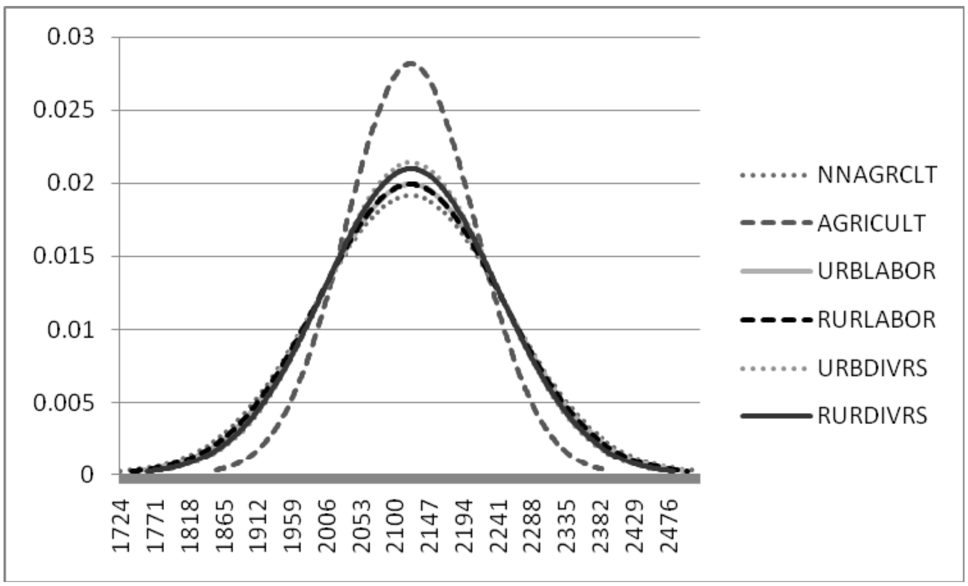
[20] We can derive the mean for calories from the mean for the *change in calories* variable (2,126 – calories) and the standard deviation for the two is the same owing to the standard relation: if $A = B + constant$ then $\sigma_A = \sigma_B$.

[21] In keeping with our maintained hypothesis of the separation of farm firm and household activities in the micro-simulation model, all the households in each stratum (including agriculturally self-employed) buy all their food while the agriculturally self-employed households also sell food. So for agricultural households, the consumer and producer price effects tend to offset one another. Therefore, their terms of trade, real incomes, and nutritional attainment are less volatile.

The mean and standard deviation for some variables of interest under the different policy scenarios are reported for comparison in Table 6. It can be seen that crop and oilseed prices become more volatile in the presence of SSM. Those for imported products are higher owing to the hike in import tariffs; domestic production is sold at a higher price given the drop in aggregate supply. Domestic production increases but not by enough to cover the supply shortage. Also, intuitively it seems reasonable that the prices should fluctuate more to clear the market if attempts are made to restrict quantities.[22]

Figure 5b shows that the mean nutrition distribution across strata still retains the same ordering under the SSM as under the previous (non-SSM) regime; agricultural strata still witness the least standard deviation for calorie intake. Visually no difference is apparent barring the changed numbers on the horizontal axis.

Figure 5b: Nutritional distribution (SSM) for individuals at the nutritional poverty line in the baseline (by earnings stratum)



Source: Authors' calculation using model simulation results.

Note: In both figures we exclude the transfer stratum, as it earns its income by government transfers and not by means of any factors of production it owns.

[22] Following the same logic, any attempts at quantity trigger implementation should stabilize prices. The quantity trigger, however, is more difficult to model and needs to be studied separately. For likely impacts of quantity trigger on poverty one can refer to Hertel and Martin (2008).

Table 6. Mean and standard deviation outcomes for key variables in Bangladesh (percentage change from 2001 base)

Mean										
Crop	**Power of Tariff**		**Import Price**		**Domestic Price**		**Import Quantity**		**Output**	
	No SSM	**SSM**	**No SSM**	**SSM**	**No SSM**	**SSM**	**No SSM**	**SSM**	**No SSM**	**SSM**
Rice	0	6.40	-1.52	4.70	1.54	1.65	37.05	-11.65	-0.17	-0.15
Wheat	0	3.25	-0.88	2.19	-0.02	1.67	2.34	-1.77	-1.20	1.44
Coarse grains	0	0.08	0.17	0.25	0.82	1.04	0.05	0.28	-0.01	0.09
Oilseeds	0	1.77	0.69	2.28	0.73	1.03	0.92	-2.72	0.00	0.32

Standard Deviation										
Crop	**Power of Tariff**		**Import Price**		**Domestic Price**		**Import Quantity**		**Output**	
	No SSM	**SSM**	**No SSM**	**SSM**	**No SSM**	**SSM**	**No SSM**	**SSM**	**No SSM**	**SSM**
Rice	0	8.13	4.34	8.22	14.03	14.16	86.49	26.79	5.86	5.84
Wheat	0	5.50	6.38	6.42	7.69	9.30	17.04	12.07	16.15	13.00
Coarse grains	0	0.42	5.03	4.89	9.62	9.85	3.83	3.99	9.15	9.03
Oilseeds	0	3.67	8.31	7.12	8.73	9.00	17.56	12.53	11.15	10.78

Source: Systematic sensitivity analysis of stochastic shocks in the CGE model.

For individual stratum, the differences in caloric distribution across policy regimes are compared by plotting alongside it's distributions under the two regimes. The shift in the distribution for all strata can be seen in Figure 6. The moments of the distribution are reported separately in Table 7.

Figure 6. Nutritional distribution with and without an SSM

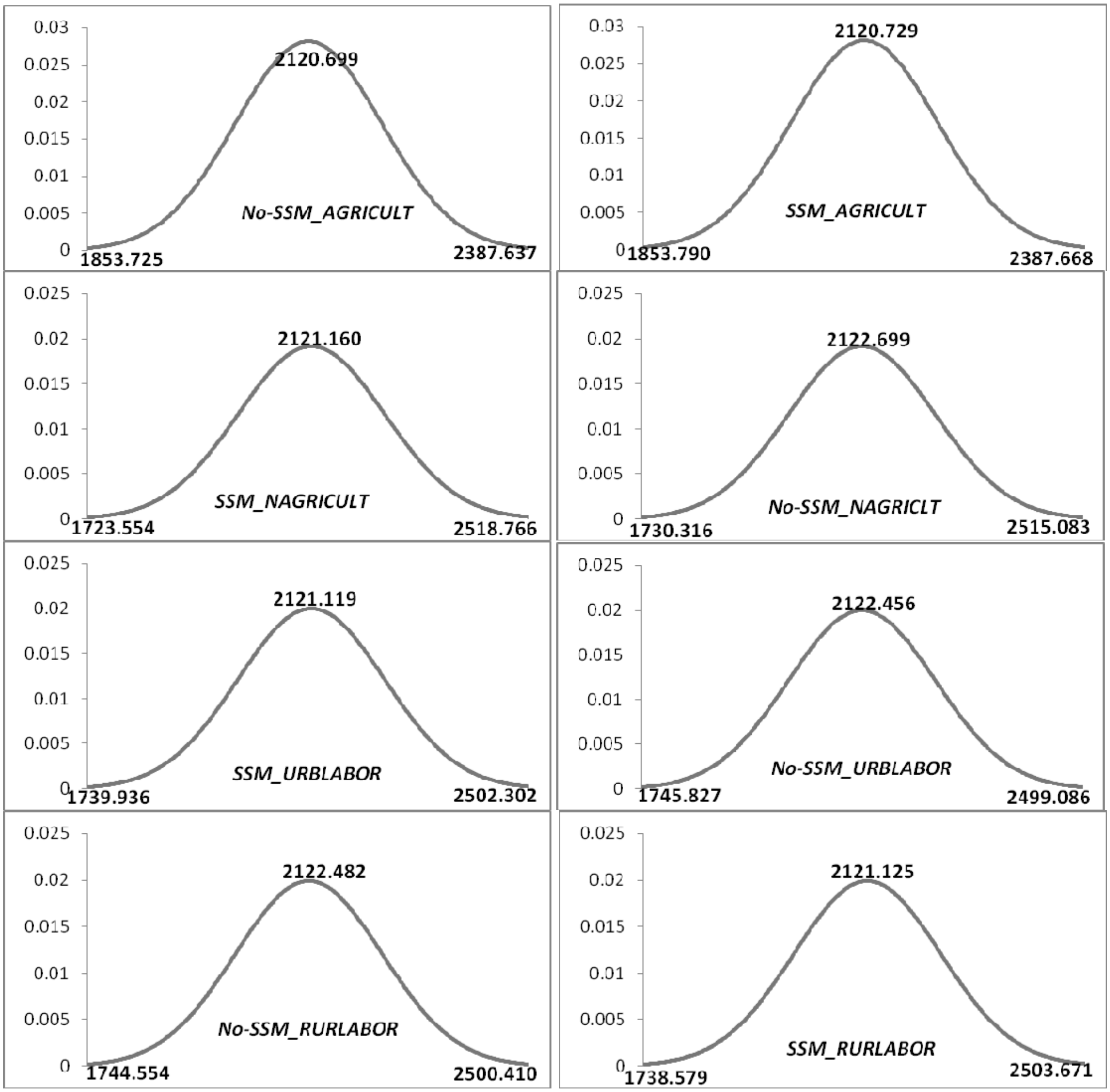
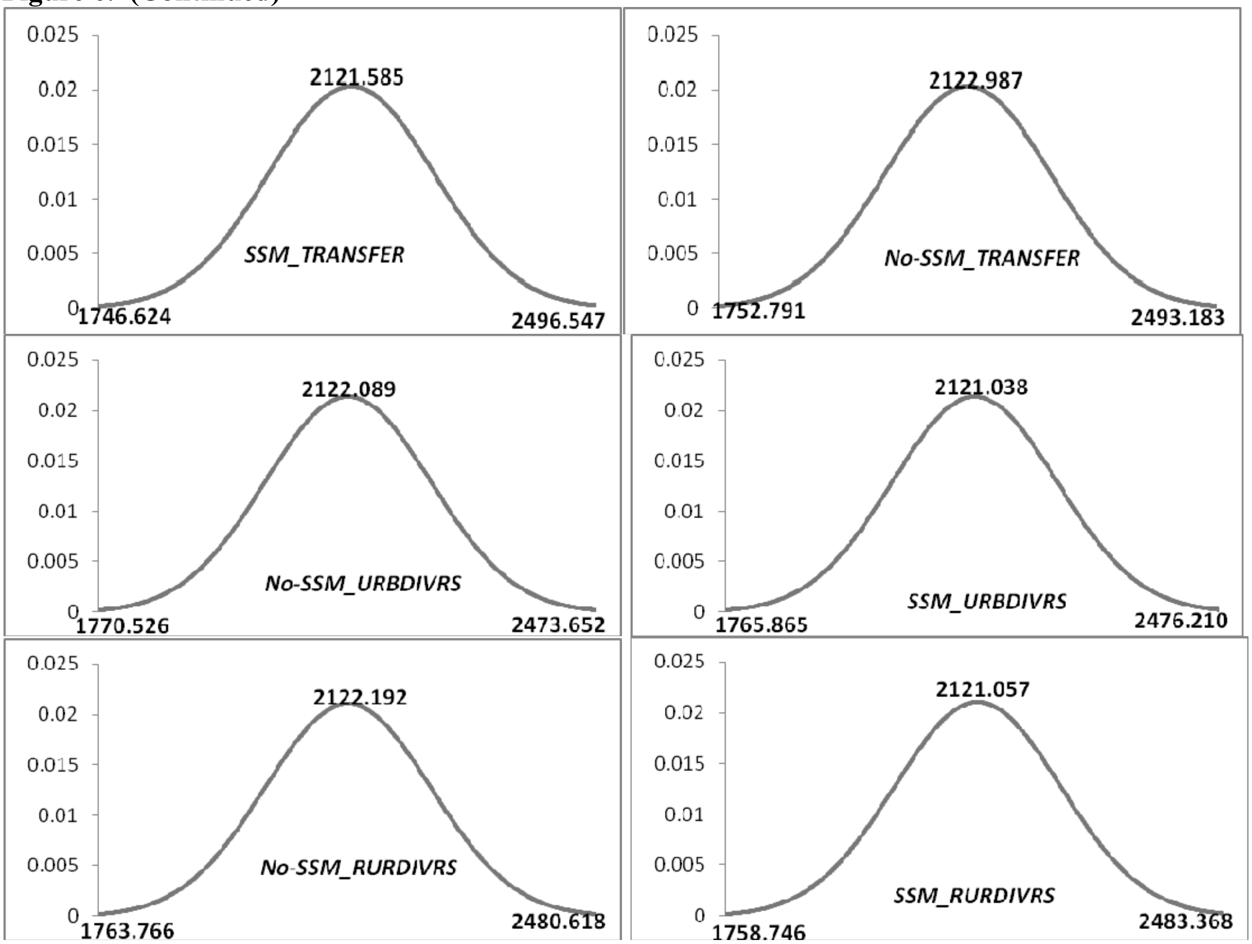


Figure 6. (Continued)



Source: Authors' calculation using model simulation results.

Table 7. Moments of nutrition distribution with and without a quantity-triggered special safeguard mechanism (SSM)

	Non-SSM		SSM	
Stratum	**Mean**	**Standard Deviation**	**Mean**	**Standard Deviation**
AGRICULT	**2120.69**	88.99	**2120.72**	88.97
NNAGRCLT	**2122.69**	130.79	**2121.16**	132.53
URBLABOR	**2122.45**	125.54	**2121.11**	127.06
RURLABOR	**2122.48**	125.97	**2121.12**	127.51
TRANSFER	**2122.98**	123.39	**2121.58**	124.98
URBDIVRS	**2122.08**	117.18	**2121.03**	118.39
RURDIVRS	**2122.19**	119.47	**2121.05**	120.77

Source: Authors' calculation using model results.

Two main points emerge from comparing the distributions across regimes. First, the mean and standard deviation/volatility get worse for all but the agricultural stratum. Second, there do not appear to be large differences between the distributions under the different policy regimes. Both of these points deserve further discussion.

The agricultural stratum, as we defined, draws more than 95 percent of its income from agricultural self-employment. These are the people that we should expect to be least affected as buyers of food and actually even benefit from higher mean domestic prices translating into higher incomes. This is what the distribution for the agriculturally self-employed group seems to be capturing. So this stratum is adversely affected by the higher consumer prices, but it also benefits from higher income. We expected to see similar higher-income effects for the rural labor stratum.

The small difference in the mean and standard deviation for all strata can be due to the fact that despite being a major food importer, Bangladesh imports a very small percentage of its rice consumption. It can be deduced from Food and Agricultural Statistics data in Table 8 that between the years 2000 and 2008 imports of rice in Bangladesh at their maximum varied from about 1 to 5 percent of the domestic production. Though there has been emphasis in the country on building stocks of grain commodities, the rate of depletion has been higher than accumulation (Shahabuddin 2008) and so it is safe to assume that imports make for a similar share in consumption as in production. A policy affecting rice import quantity or prices, therefore, should not be expected to have a major impact, given the small initial share of imports in consumption and relatively limited domestic production volatility.

Table 8. Rice production and consumption data

Year	Milled Production (in ’000 metric tons)	Total Consumption* (in ’000 metric tons)	Production as Percentage of Consumption
1999/2000	23,066	23,766	97
2000/01	25,086	24,958	101
2001/02	24,310	25,553	95
2002/03	25,187	26,100	97
2003/04	26,152	26,700	98
2004/05	25,600	26,900	95
2005/06	28,758	29,000	99
2006/07	29,000	29,764	97
2007/08	28,800	30,400	95

Source: Authors’ calculation using Foreign Agricultural Service data.
* Total consumption includes food, seed, feed, industrial, and waste.

The analysis here shows that given that the imports in Bangladesh do not constitute a large share of consumption and that the majority of its poor population is not concentrated in the agriculturally self-employed stratum (Hertel et al. 2007), the SSM—which was one of the triggers for the collapse of the ministerial meeting under the Doha Development Agenda in July 2008 (ICTSD 2008)—does not lead to any significant changes for the impoverished population in Bangladesh. It cannot be a policy tool that can help the poor be less vulnerable, as we have seen from the calorie consumption distributions.

Our analysis also suggests that SSM policies will adversely affect the countries that rely heavily on imports to meet their consumption needs for staple grains. Particularly the poor, whom we argued to be mostly net buyers of food, seem to lose in terms of caloric attainment, the magnitude of which depends on what share of consumption is met through imports. Any gains from the SSM appear to be concentrated in a particular stratum that represents the producers in the economy. These gains in this stratum might differ across households depending on the magnitude of their net sales. However, whether producers can realize the potential benefits of higher commodity prices depends on price transmission (price controls and export bans are often used), transaction costs (which are quite high in developing countries in the absence of infrastructure), and cash/credit constraints (Oxfam 2008). These are some realities that our model overlooks.

Another important issue that the model here does not address is that of consumption smoothing. It is often argued that the effects of any temporary negative shocks to consumption will often be countered by the sale of assets. Kazianga and Udry (2006), studying households in rural Burkina Faso, however, found little evidence for consumption smoothing against income risk. We decided to overlook the consumption smoothing argument for the following reasons. First, the population that we are concerned about has very limited assets to begin with; that is why they are so poor. Second, they can counter a temporary negative shock by drawing down their assets in one period; however, the findings of Kazianga and Udry (2006) seem to suggest that the risk attitudes of the poor place higher weights on adverse income draws and they therefore try to conserve their assets to face the expected future negative shocks. Third, the dis-savings option can be rightly captured only in a dynamic framework, and dealing with stochastic shocks in a dynamic framework becomes far too complicated and the framework loses much of its analytical tractability.

5. CONCLUSIONS

The household consumption side of this study capitalizes on recent advances in demand system analysis that emphasize consumption behavior at extremely low levels of income (Cranfield et al. 2004). In particular, we use AIDADS, which devotes two-thirds of its parameters to consumption behavior at the subsistence level of income. By estimating this demand system with a combination of macro- (i.e., international cross-section) and micro- (i.e., household survey) data, we establish a firm empirical link between aggregate outcomes and disaggregate consumption choices[23] in the face of price and income changes. We use calorie conversion factors to translate these changes in consumption at low levels of income into changes in calorie outcomes.

For policy analysis purposes, it is important to investigate and understand the potential nutrition implications of a macroeconomic food trade policy. As briefly mentioned earlier, the two priors to think about when arguing for any policy are: how important are imports in the consumption basket in terms of share of consumption, and from where do the poor derive the majority of their income? The higher the share of imports in consumption, the more will be the adverse effect of an import price increase resulting from policy implementation. Such potential vulnerabilities are greater for certain subsections (children younger than two in poor households) of the population dependent on imported foods. The adverse price effect *ceteris paribus* affects poor people in all strata equally. The positive income effect of higher domestic agricultural prices is, however, reaped by the poor (self-employed or labor) only in the agricultural stratum. Also, as the impact differs across strata, the impact of a policy on the poor as a whole will also depend on the share of each stratum in the poverty population. The thin trade market and the low domestic production volatility for the important staple grains also contribute to mute the effects of policy on caloric distribution.

We apply our methodology to Bangladesh, but it could be applied to other developing countries for which comparable calorie conversion and survey data are available. In addition, whereas the present paper is by nature more of a country case study, as more data becomes available one could expand the number of focus countries in the hope of learning what happens to calories at the NPL in general. The aim would be to incorporate countries that import higher shares of their grain consumption.[24] It would be interesting to see what happens to the poor in those countries; we already know from some studies that their food consumption has drastically fallen (von Braun 2008).

In addition, the approach could be extended to intake of other micronutrients if one could acquire a country-specific commodity list necessary for the purpose. With the possibility of including other micronutrients in the model, we can possibly link intake of these to anthropometric characteristics of the population, and be able to say something nutrition defined more precisely. With anthropometric measures it also becomes important to differentiate between households on the basis of their demographic composition, as households with young children especially below two years of age will be more prone to adverse effects of increased price volatility; so it would require stratifying the households not only by income source but also by demographic composition.

Finally, we have not said anything about what happens to the distribution over time. There are, we know, econometric studies that explore that issue, but if we were to incorporate a high-frequency (say yearly or so) version of the household data we could learn something about how this distribution changes, and that would be an alternative approach to generating the change in the distribution overtime.

The framework herein does not claim to incorporate all the fine details that arise with a topic as complicated as nutrition, and neither do we claim to be able to address all questions with this model. An analysis of changes in calorie intake as a measure of nutrition vulnerability has its limitations, and further investigation is needed into changes in dietary quality and micronutrient nutrition. The highlight of the

[23] Apart from price and income changes, other important factors such as age, education level of mothers, physiological status, and cultural practices determine people's consumption choices (FAO 2001); those, however, are not accounted for in the present analysis.

[24] For example, Lebanon is known to import about 40 percent of its food requirements.

paper, however, remains that we now have in place a framework by which to analyze the impacts of crop price volatility on caloric distribution.

APPENDIX 1

Maximum Entropy Estimation of the AIDADS Consumer Demand System

The idea behind maximum entropy is to get parameter estimates for the demand system that are consistent with some known facts about the population's income distribution. Thus, estimation takes place at the level of individual (or, rather, percentile-representative) households, with national per capita demand being obtained *as an aggregation across the income distribution*. The system estimated can be written as follows:

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—

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

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

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

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

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

$$\sum_i \alpha_i = 1 \qquad (6)$$

$$\sum_i \beta_i = 1 \qquad (7)$$

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

where:

n: number of aggregate goods
α_i: marginal budget shares for good i at the lower levels of the income spectrum
β_i: marginal budget shares for good i at the upper levels of the income spectrum
γ_i: subsistence level of consumption of good i
κ: kappa in the utility equation
u_t and u_{tcl}: utility in country t or at level l of class c in country t (whichever is applicable according to the 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
$\hat{w}_{it}$: estimated budget share of good i in per capita expenditure in country t

In terms of data requirements, we use countries' private consumption expenditure for a commodity, which in GTAP terminology is the sum of private consumption expenditure on imports (VIPA) and private consumption expenditure on domestic production (VDPA). As for prices, we approximate those by the ratio of the value of imports at market prices to that at world prices. It can be argued that this measure is more representative of tariffs than commodity prices; however, this is the best measure of prices available from the GTAP database. Population numbers are used to derive per capita consumption and income since the demand system is estimated in per capita terms.

APPENDIX 2

Calibration of the AIDADS Consumer Demand System

For calibration purposes, the squared difference of equation 1 of the AIDADS model given in Appendix 1 is minimized for each region individually.

$$\left\{\sum_i \frac{\alpha_i + \beta_i e^{u_t}}{1 + e^{u_t}} \ln\left(\frac{1}{P_{it}} \frac{\alpha_i + \beta_i e^{u_t}}{1 + e^{u_t}} \left(Y_t - \sum_i P_{it}\gamma_i\right)\right) - u_t - \kappa\right\}^2 \qquad \forall\, t$$

Being done at the country level, this gives an optimal value of country-level utility u_t for each of the 34 regions. The parameters $\alpha_i, \beta_i, \gamma_i, \kappa$ remain at their estimated levels, and P_{it}, Y_t are the observed/calculated data.

Once we have all the above parameters along with the utility at country level, it is easy to calculate the predicted discretionary budget shares $\hat{d}_{it}$ and predicted consumption $\hat{x}_{it}$ for each commodity i in region t as follows:

$$\hat{d}_{it} = \frac{\alpha_i + \beta_i e^{u_t}}{1 + e^{u_t}} \left(1 - \frac{\sum_i P_{it}\gamma_i}{Y_t}\right)$$

$$\hat{x}_{it} = \frac{\alpha_i + \beta_i e^{u_t}}{1 + e^{u_t}} \left(\frac{Y_t - \sum_i P_{it}\gamma_i}{P_{it}}\right) + \gamma_{it}$$

The actual discretionary budget shares can be calculated as

$$d_{it} = \hat{d}_{it} + (x_{it} - \hat{x}_{it}) \frac{P_{it}}{Y_t}$$

Next, the ratio of actual to fitted discretionary budget shares is used to scale α_i, β_i. As the ratio involves a country index, the scaled parameters now vary by country as well as commodity: α_{it}, β_{it}. Furthermore, as mentioned in Appendix 1, these being shares, we need to ensure that for each region they add up to one. So, finally, our new scaled estimates are $\alpha_{it}^c = \alpha_{it} / \sum_i \alpha_{it}$ and $\beta_{it}^c = \beta_{it} / \sum_i \beta_{it}$

Given that we now have the starting values for utility along with the customized parameters, the next step is to minimize the sum of squared errors of the demand equation. Once again, given that the objective is to replicate per capita consumption at the country level, use is made of the demand equation at the country level. The errors are minimized by letting the variables u_t and κ adjust.

$$Min_{u_t,\kappa} \sum_t \sum_i v_{it}^2$$

$$subject\ to -$$

$$\sum_{i} \frac{\alpha_{it}^{c} + \beta_{it}^{c} e^{u_t}}{1 + e^{u_t}} \, ln\left(\frac{1}{P_{it}} \frac{\alpha_{it}^{c} + \beta_{it}^{c} e^{u_t}}{1 + e^{u_t}} \left(Y_t - \sum_{i} P_{it}\gamma_i\right)\right) - u_t = \kappa \qquad \forall\, t$$

$$x_{it} - \gamma_i - \frac{\alpha_{it}^{c} + \beta_{it}^{c} e^{u_t}}{1 + e^{u_t}} \left(\frac{Y_t - \sum_i P_{it}\gamma_i}{P_{it}}\right) = v_{it} \qquad \forall\, i, t$$

This step ensures that the observed per capita consumption and the predicted match to the order of about eight decimal points.

Note that the preceding calibration procedure attributes all the difference between observed and predicted per capita budget shares to the discretionary part of the budget shares; the subsistence part given by $\frac{P_{it}\gamma_i}{Y_t}$ is assumed to be calculated correctly and so is not tampered with in the calibration stage.

APPENDIX 3

Estimating Calorie Consumption per Unit of Expenditure in Initial Equilibrium

The HIES 2000 database, along with the other aggregate expenditures, provides detailed data on consumption. It reports data on consumption of 7,440 representative households, each identified in the survey by a unique household code. We in particular use the following data series:

- Per capita total expenditure of household for the survey period: $pcexp_h$
- Number of days over which the data for each household were collected: d_h
- Number of individuals in the population that a given household represents. Let's call this last one individual weight: $weight_h$

Given the per capita total expenditure of the household and the number of days to which the data corresponds, we can calculate the per capita annual expenditure for the household. We use this series to sort the entire survey in order to divide the households into income percentiles[25].

$$pcaexp_h = \frac{pcexp_h}{d_h} \cdot 365$$

To divide the population into income percentiles, we construct another variable that we call *weight percent:* wp_h. If we assume that the total population consists of 100 individuals, then wp_h represents how many of those 100 are represented by the household h.

$$wp_h = \frac{weight_h}{\sum_i weight_i} 100$$

Next we use this variable to divide the sample of 7,440 households into j groups (j = 1 … 100) such that

$$\sum_h wp_h^j = 1 \qquad \forall\, j \;\&\; where\ h \in j$$

So the percent share of population belonging to each group j equals 1. Note that in order to meet this requirement we had to split some of the households into two with each part belonging to an adjacent different percent group. This completes our objective of splitting the household sample into one hundred "1 percent" groups.

The objective of the whole exercise is to derive the *calorie intake per day per capita from consumption of a GTAP commodity's quantity at the NPL.* To do that, we need to know the consumption of the nutritionally poor. But first we need to identify the nutritionally poor population. Here a piece of information from the Bangladesh Bureau of Statistics 2003 survey report putting the percentage of the population below the NPL at 44.3 percent comes to our rescue. For our purposes we identify the one single household whose cumulative weight closely corresponds to that percentage figure and then take about a 0.5 cumulative weight percentage on each side of that one household, so that the total for the

[25] This per capita annual expenditure $pcaexp_h$ when multiplied by the individual weight should give us the total annual expenditure of the population represented by that household.

$$Y_h = pcaexp_h \cdot weight_h$$

We use the variable Y_h as a proxy for household income.

group equals 1. This gives us 74 such households whose collective percentage weight in the population equals ~1.02. We expect this group to represent the population around the NPL.[26]

Once we have identified the nutritionally poor, the next step involves getting a detailed consumption profile of this group. Given that we have a household-specific identifier code, we can extract the consumption data for the nutritionally poor households. The consumption data reports the household identifier code, an identifier for the day of the survey period to which it corresponds, and the list of commodities consumed on each of the days along with the quantity consumed. We aggregate those data over the days to get a list of all the commodities (i) and associated quantities consumed by any given household (qc_h^i) over the entire survey period. Once we have an exhaustive list of the consumption commodities for this 1 percent population group (there are 98 such commodities), we next want to know the calorie content of these commodities. As many of the consumption commodities turn out to be region (country) specific, we prefer a local rather than a standard calorie content list. We use such a list provided by IFPRI and try to map the 98 commodities to that list, which we are able to do for all but 15 goods. The calorie content ($CalCon_i$) is given in Table 1.

This calorie content information can be combined with the data on qc_h^i to get the total calorie intake ($totcal_h^i$) of the household for the survey period from consumption of commodity i:

$$totcal_h^i = qc_h^i \cdot \frac{CalCon_i}{100}$$

Given the survey information on household size n_h in each household, we derive from this the per capita calorie intake for a representative household individual ($pccal_h^i$):

$$pccal_h^i = \frac{totcal_h^i}{n_h}$$

So now we have the per capita calorie intake for 74 representative individuals having a one-to-one mapping with the representative 74 nutritionally poor households. But note that the weights of these representative individuals in the entire country population are not the same, and therefore we cannot take the simple average over these individuals to get the per capita calorie intake of a representative nutritionally poor person. Here we again use the individual weights we derived before and get weighted per capita calorie intake of an individual belonging to household h from consumption of commodity i denoted ($wpccal_h^i$):

$$wpccal_h^i = pccal_h^i \cdot wp_h$$

Now taking the simple average over individuals to get the per capita calorie intake of a representative nutritionally poor person is feasible. Note that this still gives us the per capita calorie intake for the entire survey period and not per day, so we divide these by 14 (the survey period) to get the per day per capita calorie intake of a nutritionally poor person from consumption of commodity i $CalC_i$; and when summed over the commodities, it should give us a number close to 2,122Kcal (per day per capita calorie intake of a person at the NPL):

[26] Along with the percentage of the population below the NPL, the report also puts the per capita calorie intake of the nutritionally poor at 2,122Kcal. Note that the dollar/day income poverty line and the nutritional poverty line for Bangladesh lie pretty close together, which makes it easier to use the income-sorted household sample to identify the nutritionally poor population section. As mentioned in the data section of the paper, the close correspondence of per capita per day calorie consumption of the thus identified group (2,126Kcal) with the figure given in the survey report confirms that we are not completely off track.

$$CalC_i = \sum_h wpccal_h^i \qquad \text{and} \qquad \sum_i CalC_i = 2126Kcal \,!$$

We are close but not yet done! To be able to use this information, we need to map these 98 survey commodities i into the 17 GTAP food commodities g. Once we have the mapping scheme in place, we use it to get $CalC_g$ such that:

$$CalC_g = \sum_j CalC_j \qquad \forall j \in g$$

And, as mentioned in the paper, $CalC_g$ (calorie intake per day per capita from consumption of a GTAP commodity's physical quantity at the NPL) is what is finally read into the GTAP model as an outside parameter.

APPENDIX 4

Setting Target Volatility Using FAOSTAT Data

The FAOSTAT annual time series data on production (in tons) and prices (U.S. dollars [USD]/ton) spans the years 1984 to 2005. The assumption can be made that this time period adequately captures historic volatility. Given that GTAP reports the variables in terms of the percentage change and not levels, we accordingly transformed our production and price series into year-on-year proportionate changes. The resulting production series are plotted in Figure 3. With the exception of recent swings in the price of wheat, most year-on-year changes are well within the +/− 50 percent interval. As a measure of production volatility for the four commodities, we take the standard deviation of the transformed (i.e., year-on-year percentage changes) production series.

For prices, a few things needed to be addressed before we could obtain a similar proportionate change series. First, the FAO prices are reported for individual coarse grains and oilseed crops, and not at the GTAP aggregate level. To get a meaningful price series for the group, we take a production-weighted average of prices for barley, millet, and sorghum to get prices for coarse grains; and of castor oilseed, coconuts, groundnuts, linseed, rapeseed, seed cotton, and sesame seed to get the same for oilseeds.

Second, FAO reports price series in USD/ton units starting from 1991. To derive a series starting in 1984, we had to take the prices in Local Currency Unit (LCU)/ton from FAO's price archive data and undertake a similar exercise as outlined previously to obtain a price series in LCU/ton for coarse grains and oilseeds. The latter was then converted to USD/ton prices using the International Monetary Fund's (IMF) exchange rate series (period average). These series are then spliced together to get the price series for rice, wheat, coarse grains, and oilseeds for the period 1984–2005.

Third, there is the issue of nominal versus real prices. GTAP uses real variables, so we must deflate FAO nominal prices by the GDP deflator index. The deflator index is taken from the IMF. We decided to first rebase the index to the year 1984. This gives us the real price series corresponding to the four nominal series we obtained earlier.

Finally, we take the year-on-year proportionate changes in the real price series. The price series thus obtained are shown in Figure 4. Just as for production, the standard deviation of the transformed price series gives us the target price volatility for the four grain commodities. The resulting standard deviations for prices and output in Bangladesh are given in Table 4.

We conduct a systematic sensitivity analysis and employ output technology shocks (*aoall*) to generate the historically observed volatility in output. To begin with, the extreme points of the assumed triangular distribution for the sensitivity analysis are taken to be $\sqrt{6}$ times the normalized standard regression error for staple grains. The estimates for the latter are taken from Valenzuela (2006). Table 5 reports these extreme endpoint values. We assume these shocks are independent across regions but are perfectly correlated across the four crops in a given region.

However, this does not reproduce (falls short of) the observed output volatility because output is endogenous and not perfectly correlated with technology; therefore the latter shocks must be adjusted. We scale up the shocks for Bangladesh with a particular interest in replicating price volatility—especially so for rice, as it is the crop from which households at the NPL derive more than 70 percent of their calorie intake.

With the model generating endogenous output and price volatility, we can compare the standard deviation of these changes to those observed historically. In doing so, we find that the standard deviation of estimated prices is too low, requiring some adjustment in the CGE model. Accordingly, we raise the subsistence parameter associated with staple grains consumption in our model. This makes demand less price responsive and raises the associated standard deviation of prices. The resulting model gives us a better match with price volatility in Bangladesh. Table 4 reports the observed and generated numbers for comparison.

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