Commodity Price Volatility and Nutrition Vulnerability

Monika Verma and Thomas W. Hertel
Center for Global Trade Analysis, Purdue University*

Abstract

In this paper we examine the impact of commodity price volatility on nutritional attainment of households at the nutritional poverty line in Bangladesh. We focus on the first two moments of the distribution of nutrition and consider the differential impacts across socio-economic groups within the country. We also examine the direction and magnitude of the shift in these moments as a result of implementation of special safeguards measures aimed at preventing import surges.

Selected Paper prepared for presentation at the Agricultural & Applied Economics Association 2009
AAEA & ACCI Joint Annual Meeting, Milwaukee, Wisconsin, July 26-29, 2009

Contact: verma3@purdue.edu, hertel@purdue.edu
*The authors acknowledge financial support from IFPRI for Verma's dissertation research. Special thanks for Joachim von Braun and Antoine Bouet for their encouragement and support for this work and to John Hoddinott and Nicholas Minot for their expert comments and guidance.

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. There has been a lot said about effects of the recent surge in prices on the poor but less has been written on the impact of sustained price volatility on poverty and nutritional 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 *et al.* 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 etc.

(von Braun *et al.* 2003). This paper uses the simplest biological dimension of nutrition, namely the caloric intake per capita per day. We model the household demand for food and non-food items as a function of prices and income and then translate that into nutritional outcomes. The goal of this study is to estimate the caloric intake distribution for individuals at the nutritional poverty line in Bangladesh[1], as a function of commodity price volatility where the latter is driven by volatility in production. With this framework then we can evaluate the impact of policies aimed at reducing price volatility.

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 nutritional content of consumption, and micro-simulation analysis of household behavior. The aim is to link global economic changes to nutritional outcomes in developing countries. In order to understand the impact of these changes on nutrition, we need to take a closer look at: (a) consumption patterns of the poor, (b) how consumption is likely to respond to changes in market conditions – in particular 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 of nutritional poverty line (NPL) and focus on the well-being of the population in the neighborhood of 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 foodstuff for its population. However, the methodology proposed could be applied to assess the nutritional impacts of multilateral trade policies affecting price volatility in a wide range of developing countries.[2] Also, while this paper focuses on caloric intake, the general approach is amenable to extensions covering micro-nutrients 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 data and the main building blocks of the model – household

[1] Choice of Bangladesh as a focus country is driven by the fact that Bangladesh is classified as one of the Least Developed Countries, it is a major net importer of rice and rice is the staple for its population.
[2] See Hertel et al. (2008) for an illustration of a similar approach to assessing the poverty impacts of the Doha Development Agenda.

consumption demand system, modified GE model along with the new nutrition module. It reports our work aimed at CGE model validation based on its ability to capture historic price volatility and nutrition distribution and elaborates our comparative static approach to modeling the impact of Special Safeguards Mechanism on nutrition. Results are discussed in Section 4. Section 5 offers conclusions and agenda for further research.

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[3], and in the process, reach a new optimal consumption bundle. This consumption change is likely to imply a change in caloric intake. We seek to assess the size and direction of these nutritional changes and how they are affected by the policy environment.

Having made the case as to why volatile commodity prices should affect caloric 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 nutritional distribution. The method employed in this analysis has three main elements: econometric estimation of a demand system, incorporation of this demand system into a Computable General Equilibrium (CGE) model in which stochastic simulations may be conducted, and finally, analysis of the nutritional impacts of simulated changes. In the first stage we seek a demand characterization that can span the entire spectrum of population in the country.

[3] The household's response to an adverse shock to current income may be to draw down their assets (dis-saving). However, a proper treatment of asset accumulation and de-accumulation would require a dynamic framework which 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.

The cause of concern is that individuals 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 2. 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 non-food 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 caloric intake for a given household.

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.

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[4].

[4] It is generally the case that the change in prices faced by a household as a result of a trade policy depends on their 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 national level to limit the complexity of our study.

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

The analytical framework outlined above is used to evaluate the impact of volatility in staple grain prices seen historically on caloric intake of poor in Bangladesh. An overview of the analytical framework is offered in Figure 1. The data sources are inscribed in the rectangular boxes and the arrows point to part of the model where these 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 a 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 WTO (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 is worth analyzing using the framework we develop 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 or not SSM is beneficial to the poor is an empirical question which we aim to address here by means of a policy experiment.

3 DATA AND METHODOLOGY

With the objective of deriving the nutritional 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 utilize a CGE model with an embedded household model. Lofgren *et al.* (2003) discuss different poverty analysis approaches in CGE framework using household data. We adopt the micro-simulation approach here and this section details all the components involved – the Consumption Demand Model, Global CGE Model and 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. Also it makes possible analysis of policy changes in trading partner economies.

The subsections below consider all components of model and data required to estimate it.

3.1 Data

The data comes from various sources and its use in this analysis could be better understood by simultaneously consulting Figure 1 and this section. The GTAP database version 6.1 (Dimaranan, 2007) 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 Deninger and Squire 1996 Dataset (for all countries other than Bangladesh in our sample), as well as the Bangladesh Household Income and Expenditure Survey (HIES 2000) provided by IFPRI, are also 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 HIES2000 data for obtaining a detailed consumption profile for population at the NPL[5]. The criterion for determining NPL is daily per capita calorie intake; the HIES Survey classifies an individual with 2122 Kcal or less caloric intake per day as nutritionally poor. 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 caloric intake by survey commodity groups, for the group of households in the neighborhood of the NPL. Being derived for a much disaggregated level of commodities, this list could be utilized by others studies, GE 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 (2126 Kcal), which is very close to that reported in the HIES survey (2122 Kcal).

The commodities in Table 1 are mapped to the 19 farm and food GTAP commodities and to 9 AIDADS consumption commodities in the global economic model, so that as GTAP consumption levels change, we will be able to deduce the associated impacts on nutrition 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.

3.2 Consumer Demand System: AIDADS

3.2.1 AIDADS Estimation

The AIDADS specification of consumer demand, as mentioned above, is estimated using the GTAP database version 6.1, consisting of 57 commodity sectors and 75 individual countries (there are also 12 composite regions in that data base, for a total of 87 countries/regions). For estimation purposes these 57 GTAP sectors are aggregated

[5] We decided to go with one percent number as we were primarily interested in the individual on the very margin (NPL) and taking the whole population would not accurately represent this individual. At the same time we didn't want our results to be susceptible to some idiosyncratic behavior of one representative individual just at the NPL as identified by the survey. Taking one percent sections' average rules this possibility out while as closely representing as possible an individual at NPL.

into 9 broader AIDADS commodity groups. Table 2 details the mapping scheme that we follow. The focus on consumption and nutrition calls for keeping food categories relatively more disaggregated; accordingly there are 7 food and only 2 non-food AIDADS commodity groups[6].

The method employed for estimation is maximum likelihood with maximum entropy. We use GAMS (General Algebraic Modeling Software) to estimate this highly non-linear 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 which differ across commodity groups but are the same for all countries due to the assumption of common preferences. These estimates are given in 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 while 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[7] 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 impact of high volatility in food prices will be disproportionately borne by the households at 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.

[6] The major food commodity groups are defined as Dairy, Grains, Meat, Oil, Sugar, Fruits & Vegetables and Other processed. Manufacturing and Services are the two non-food commodity groups.

[7] The numbers are arrived at by adding the shares for Diary, Grains, Meat, Oil, Sugar, Fruits & Vegetables and Other Processed.

3.2.2 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 other countries of interest (India & China) remain disaggregated, while other countries 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[8]. 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[9] 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.

3.2.3 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 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

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

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 *et al.* 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[10] 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 2. 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.[11] It is an important implication as such models are frequently employed in poverty studies.

3.3 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 before, consumer demand is now represented via AIDADS instead of the usual CDE specification of the standard model.

Following Hertel *et al.* (2004) we categorize household into five groups that rely almost exclusively (95 percent or more) on one of the following sources of income: agricultural self employment, non-agricultural 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 non-agricultural factors markets, following Keeney and Hertel (2005). This segmentation allows for differential impacts originating from a shock, on factor earnings across strata; faced with these changes households maximize utility subjected to their respective budget constraint and in the process

[10] 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 commodity will involve mapping issues which 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.

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

reaching a new consumption bundle. This latter exercise involves micro simulation techniques.

3.3.1 Nutrition Module

Simulation results from the modified CGE model fed into 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 caloric intake that a person experiences due to a change in the consumption of the 7 food commodities. This requires adding a nutrition module to the CGE model which essentially computes the total change in per capita calorie intake at 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 7 food commodities. We start with a measure for "*calorie intake per day per capita from consumption of a GTAP commodity's physical quantity at NPL*" ($CalC_g$), and proceed from there to obtain a measure of calorie per dollar spent on AIDADS commodity. The specifics of obtaining $CalC_g$ are outlined in Appendix 3.

Let $g, a, r \text{ and } s$ denote the indices for GTAP commodities, AIDADS commodities, region and stratum respectively. The approach to generating the change in per capita nutrition at the NPL may then be described as follows:

Using the mapping from 57 GTAP commodities to 9 AIDADS commodities we obtain the "*per day per capita calorie intake from consumption of 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 belonging to different strata, to differ[12]. This is reflected in our formulation below 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 commodities 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 numerator is, calories per day per capita and that of the denominator is dollar per day per capita. Accordingly the units for N_{asr} are to *calorie per dollar*, which is what we had set out to achieve.

As alluded to earlier we are interested in obtaining the change in "*nutrition from each commodity*" NUT_{asr} and change in "*total nutrition*" $TNUT_{sr}$. 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 expression above appears in the GE model as a linear (percent change) variable associated with the per capita consumption at NPL. For deriving the change in total per capita nutrition at the NPL, we just need to sum over commodities the changes in commodity specific nutrition –

12 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.

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

3.4 Simulation: Stochastic Shocks Approach

Given our interest in understanding the interplay between trade policies and nutrition 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 this process with the FAO observed price volatility, to check if the model is valid representation of the reality. It is very important for the credibility of our policy experiments to ensure that our model is able to replicate the observed historic volatility in prices. To this 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 in order to examine the changed moments of distribution for nutrition owing to the policy change.

If we were only interested in the consumption side impact of commodity price volatility, we could randomly sample from grains price distribution and shock the prices in the consumer demand system to see the impact on caloric 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[13] 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 these stochastic shocks serves three purposes. Firstly, it can be used to validate the CGE model. Secondly, it is used to generate the nutrition distribution for

[13] It 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.

poor at the NPL. Finally, it can be used to analyze the impacts of Special Safeguard Measures (SSM).

3.4.1 CGE Model Validation

The above mechanism works well to generate nutritional changes in the wake of price and income changes, provided that the model offers a good approximation to the real world. However, we have not yet tested this. This issue is the topic of the present section. We do so by examining whether or not 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. The reason being – grains comprise the major share of agricultural production and they consist of a large chunk of the poor household consumption. In terms of nutritional intake at NPL, it turns out that about three quarters of the total 2126 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[14]. 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 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. These outliers have undue influence on the historically observed standard deviation.

3.4.2 Policy Experiment: Special Safeguard Measures

One point of interest in this analysis is how the implementation of Special Safeguard Measures affects the nutrition distribution. Arguments in favor of SSM expect

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

it to either raise mean nutritional attainment, or reduce the associated standard deviation, or both. Whether or not the data supports this intended result of SSM, is what we try to infer from our simulations. But first we briefly outline the type of SSM considered.

As per the most recent WTO modality proposal on SSM, a country can resort to either price or volume based SSM. We concentrate on import volume triggering SSM into action. Hertel and Martin (2008), provide a simplified interpretation of the technical modalities. The model here follows those authors in modeling 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 ratio – of imports to maximum permissible growth in imports – indicating import surge. Anytime 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. The import restriction by restricting supply affects the price of domestic products as well. This change in domestic and imported prices gets translated into nutrition change through the demand system link.

To get a distribution of nutrition with SSM implemented, we do the same SSA experiment that we did 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 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 measures and the second is with SSM operational. Each gives a different set of nutrition distributions.

We assume that nutrition is distributed normally for the people in the vicinity of the NPL. With normality assumption, we only need mean and variance for nutrition variable which we got from SSA, to fully characterize its distribution. We are therefore now in a position to say something about the distribution of nutrition[15] 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 SSM are plotted in Figure 5a. The plotted probability distributions cover three standard deviations around the mean. The horizontal axes represents daily per capita calorie intake and the vertical axes has the associated probability density.

Note that the standard deviation for the agricultural stratum is relatively tighter compared to 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[16] and hence the effect of food price volatility on their consumption and calorie intake is relatively modest. This result – agricultural self employed are less vulnerable to impact of high price volatility on nutrition – by itself is interesting and is worth further exploration. We have not found any studies contradicting or supporting our finding here.

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 oilseeds 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 imported quantities.

Figure 5b shows that the mean nutrition distribution across strata still retains the same ordering under SSM as under previous (non-SSM) regime; agricultural strata still

[15] We can derive the mean for nutrition from the mean for the *change in nutrition* variable (2126 – nutrition) and the standard deviation for the two is the same owing to the standard relation: if $A = B + constant$ then $\sigma_A = \sigma_B$

[16] 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 agricultural 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.

witness the least standard deviation for calorie intake. Visually no difference is apparent baring the changed numbers on horizontal axes.

For individual stratum, the differences in nutrition distribution across policy regimes are compared by plotting alongside, their 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.

There are two main points that emerge comparing the distributions across regimes. Firstly, the mean and standard deviation/volatility improve for none but the agricultural stratum. Secondly, there don't 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 over 95% 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 nutrition distribution for 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 rural labor stratum.

The small difference in the mean and standard deviation for all strata is 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 FAS data in Table 8 that between the years 2000 and 2008 imports of rice in Bangladesh at their maximum varied from about 1-5 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 imports quantity or prices therefore, should not be expected to have a major impact on nutrition, given the small initial share in consumption and relatively limited domestic production volatility.

The analysis here shows that given the imports in Bangladesh do not comprise a large share of consumption and the majority of its poor population is not concentrated in agriculturally self employed stratum (Hertel *et al* 2007), SSM which was one of the triggers for the collapse of the Ministerial meeting under the Doha Development Agenda in July 2008 (ICTSD 2008), doesn't lead to any significant changes for the impoverished population in Bangladesh. It cannot be a policy tool that can help poor be less vulnerable as we have seen from the nutritional 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 nutritional attainment, the magnitude of which depends upon what share of consumption is met through imports. Any gains from 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 are able to realize the potential benefits of higher commodity prices depend on price transmission (price controls and export bans are often used), transaction costs (which are quite high in developing countries in 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 effects of any temporary negative shocks to consumption will often be countered by 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. Firstly, the population that we are concerned about has very limited assets to begin with; this 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 poor place higher weights on adverse income draws and 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 way 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 utilize 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 in the face of price and income changes. We use nutritional conversion factors to translate these changes in consumption at low levels of income into changes in nutritional outcomes.

For policy analysis purposes, as briefly mentioned above 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 where from do the poor derive majority of their income. The higher the share of imports in consumption the more will be the adverse effect of import price increase resulting from policy implementation. This adverse effect *cetris paribus* affects poor 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 differ across strata, impact of a policy on nutrition distribution of poor as one group will also depend on share of each stratum in poverty population. Thin trade market and the low domestic production volatility for the important staple grains also contribute to mute the effects policy on nutrition distribution.

The methodology that we develop is applied to Bangladesh, but could also be applied to other developing countries for which comparable nutrition and survey data are available. Also though the present paper is more in nature of country case study, with increasing data availability one can aim towards expanding the number of focus countries and be able to say something about what happens to nutrition at NPL in general. The aim would be to incorporate countries which import higher shares of their grain consumption[17] . It should be interesting to what happens to poor in those countries, we already know from some studies that their food consumption has drastically fallen (von Braun 2008).

The approach could also be extended to other micronutrients intake given that one can get country specific commodity list required for the purpose. With the possibility of including other micro nutrients in the model and we can possibly then link intake of these to anthropometric characteristics of population, and be able to say something about change in these coming out of trade policies.

Also so far we didn't say anything about what happens to the nutrition distribution overtime. There are we know econometric studies that explore that issue, if we can get some high frequency (say yearly or so) version of the household data then we can say something about how this distribution changes and this would be an alternative approach to generating it.

The framework developed here does not claim to incorporate all fine details that arise with a topic as complicated as nutrition neither do we claim to be able to address all the questions with this model. The highlight of the paper however remains that we have now a framework in place to analyze the impacts of crop price volatility, on nutrition distribution.

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

REFERENCES

Arndt, C. 1996. "An Introduction to Systematic Sensitivity Analysis Via Gaussian Quadrature", *GTAP Technical Paper No. 2*.

BBS, 2003. "Report of the Household Income and Expenditure Survey 2000", Bangladesh Bureau of Statistics.

Cranfield, J., 1999. Aggregating Non-Linear Consumer Demands – A Maximum Entropy Approach. Ph.D. Dissertation, Department of Agricultural Economics, Purdue University

Cranfield, J. A. L. & Preckel, Paul V. & Eales, James S. & Hertel, Thomas W., 2004. "Simultaneous estimation of an implicit directly additive demand system and the distribution of expenditure--an application of maximum entropy," *Economic Modelling*, Elsevier, vol. 21(2), pages 361-385, March.

Cranfield, J., Preckel, P., Eales, J. Hertel, T., 2002. Estimating Consumer Demands across the Development Spectrum: Maximum Likelihood Estimates of an Implicit Direct Additivity Model. *Journal of Development Economics*, (68): 289-307.

Deininger, K. and L. Squire, 1996. "A New Data Set Measuring Income Inequality," *The World Bank Economic Review*, *10:565-591.*

Dimaranan, B. (2007). "Global Trade Assistance and Production: The GTAP 6 Data Base", *Center for Global Trade Analysis*, Purdue University.

FAOSTAT. *Food and Agriculture Organization Statistics Databases*.

FAS. "Grain: World Markets and Trade", *Foreign Agricultural Service Circular Series*, various issues.

Golub A., July 2006. "Projecting the Global Economy in the Long Run: A Dynamic General Equilibrium Approach" Ph.D. Dissertation, Department of Agricultural Economics, Purdue University

Hertel, T. W., M. Ivanic, P.V. Preckel, and J.A.L. Cranfield, 2004, "The earnings effects of multilateral trade liberalization: Implications for poverty," *World Bank Economic Review*, Vol. 18, No.2.

Hertel T. W. and Jeffrey J. Reimer. 2005. "Predicting the Poverty Impacts of Trade Reform" *Journal of International Trade and Economic Development* 14(4):377-405.

Hertel, T.W., and L.A. Winters (eds.), 2006. "Putting Development Back Into the Doha Agenda: Poverty Impacts of a WTO Agreement", New York: Palgrave Macmillan, co-published with the World Bank.

Hertel T. W., Roman Keeney, Maros Ivanic, L. Alan Winters, 2007. "Distributional effects of WTO agricultural reforms in rich and poor countries," *Economic Policy*, CEPR, CES, MSH, vol. 22, pages 289-337.

Hertel T. W., R. Keeney, M. Ivanic, L. A. Winters, 2008. "Why Isn't the Doha Development Agenda More Poverty Friendly?", *Review of Development Economics*, forthcoming.

Hertel T.W. and W. Martin, 2008. "Potential Implications of the Special Safeguard Mechanism (SSM) in Agriculture", *draft.*

HIES 2000. "Household Income & Expenditure Survey", *Bangladesh Bureau of Statistics*.

ICTSD 2008. "After the Collapse: Rethinking the Special Safeguard Mechanism for Developing Country Agriculture", *Bridges, Volume 12, No. 4*, International Center for Trade and Sustainable Development, Geneva.

Ivanic, M., 2006. "The Effects of a Prospective Multilateral Trade Reform on Poverty in Developing Countries." in Hertel, T.W. and Winters, L. A., (eds.), *Putting Development Back Into the Doha Agenda: Poverty Impacts of a WTO Agreement*. New York: Palgrave Macmillan, co-published with the World Bank.

Kazianga H. and C. Udry, 2006. "Consumption Smoothing? Livestock, Insurance and Drought in Rural Burkina Faso", *Journal of Development Economics*, Elsevier, vol. 79(2), pages 413-446, April.

Keeney R. and T.W. Hertel, 2005. "GTAP-AGR: A Framework for Assessing the Implications of Multilateral Changes in Agricultural Policies" *GTAP Technical Paper Series* No.24. Purdue University, West Lafayette, Indiana, U.S.A.

Lofgren H., S. Robinson and M. El-Said, 2003. "Poverty and Inequality Analysis in a General Equilibrium Framework: The Representative Household Approach", in *The Impact of Economic Policies on Poverty and Income Distribution: Evaluation techniques and Tools*, edited by Francois Bourguignon and Luiz A. Pereira da Silva; World Bank and Oxford University Press.

Nicita, A. 2006. "Multilateral Trade Liberalization and Mexican Households: The effect of the Doha Development Agenda", in *Poverty and the WTO*, edited by Thomas W. Hertel and L. Alan Winters; Palgrave Macmillan and the World Bank.

Oxfam International, 2008. "Double-Edged Prices Lessons from the food price crisis: 10 actions developing countries should take", *Oxfam Briefing Paper* 121.

Shahabuddin Q. 2008. "Rising food prices in Bangladesh: Causes, poverty impacts and policy actions", *The Financial Express*, Dhaka, August 9, 2008.

Valenzuela, E., May 2006. "Poverty, Vulnerability and Trade Policy in General Equilibrium." Ph.D. Dissertation, Department of Agricultural Economics, Purdue University

Valenzuela, E., T.W. Hertel, R. Keeney and J.J. Reimer. 2007. "Assessing Global CGE Model Validity using Agricultural Price Volatility." *American Journal of Agricultural Economics*, Volume 89, Issue 2, May 2007, Pages: 383-397.

Verma, M., P.V. Preckel, T.W. Hertel, 2007. "Prediction versus Reality: How close is AIDADS?" *mimeo*

von Braun, J., M.S. Swaminathan and M.W. Rosegrant, 2003. "Agriculture, Food Security, Nutrition and the Millennium Development Goals", *2003-2004 IFPRI Annual Report Essay*.

von Braun, J, 2008. "High Food Prices and the Impacts on the Poor in Latin America", July 21, 2008. Presentation at Inter-American Dialogue.

Winters L. A., Neil McCulloch and Andrew McKay, 2004. "Trade Liberalization and Poverty: The Evidence so Far" *Journal of Economic Literature*, Vol. 42, No. 1 (Mar., 2004), pp. 72-115

WTO 2008. "Revised Draft Modalities for Agriculture" Committee on Agriculture, Special Session, World Trade Organization, Geneva, TN/AG/W/4/Rev.3

Table 1: Calorie Intake of Poor from Daily Consumption

Survey Food Commodities	Derived Calorie 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
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
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	**2126.03**

Source: Authors' calculations

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	Oil seeds	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
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

Table 3: Estimated and Calibrated Demand System Parameters

	Estimated			Calibrated	
	(1)	(2)	(3)	(4)	(5)
Commodities	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 & 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

Table 4: Observed & 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 due to a jump in price series which appears to be a result of some change in 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 outlier in the coarse grain production series, see Figure 3.

Table 5: The Extreme End-points for the Triangular Distribution used in SSA

Region	Extreme End-Point
Bangladesh	20.0
India	13.9
Rest of South Asia	13.9
South East Asia	13.9
High Income East Asia	23.6
China	11.7
Oceania	59.6
US & Canada	34.5
Latin America	14.1
Western Europe	16.6
Eastern Europe	23.1
Former USSR	34.3
Middle East & North Africa	36.7
Sub-Saharan Africa	18.7

Source: Adapted from Valenzuela (2007)

Table 6: Mean & 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 CGE model

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

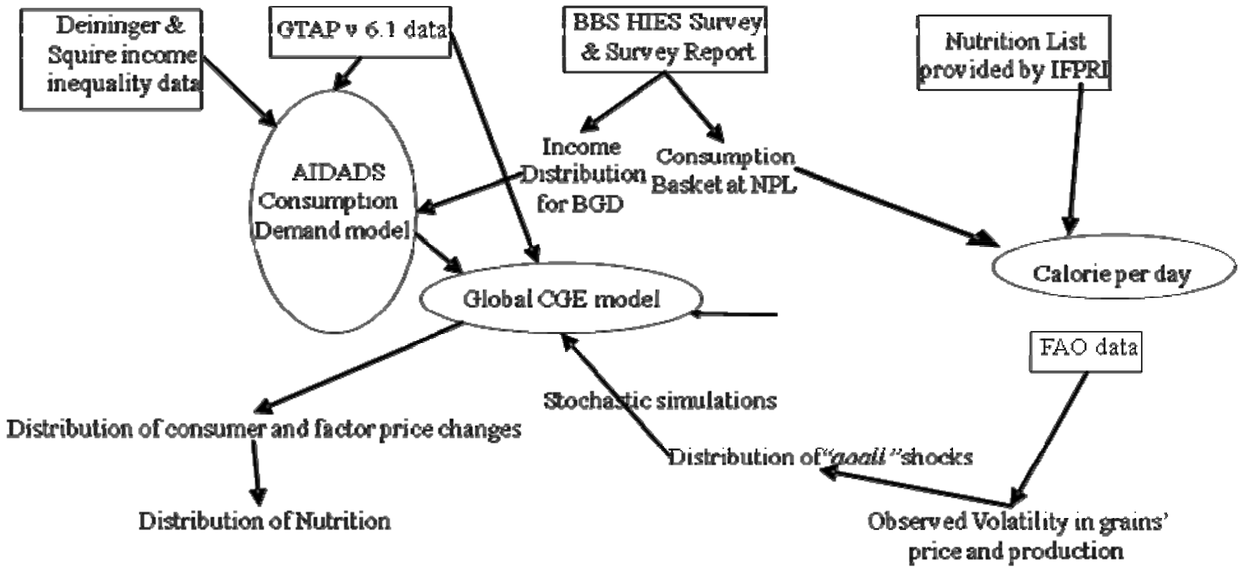
Table 8: Rice Production and Consumption Data

Year	Milled Production (in '000 metric tons)	Total* Consumption (in '000 metric tons)	Production as percent of Consumption
1999/2000	23066	23766	97
2000/01	25086	24958	101
2001/02	24310	25553	95
2002/03	25187	26100	97
2003/04	26152	26700	98
2004/05	25600	26900	95
2005/06	28758	29000	99
2006/07	29000	29764	97
2007/08	28800	30400	95

Source: Authors' calculation using FAS data

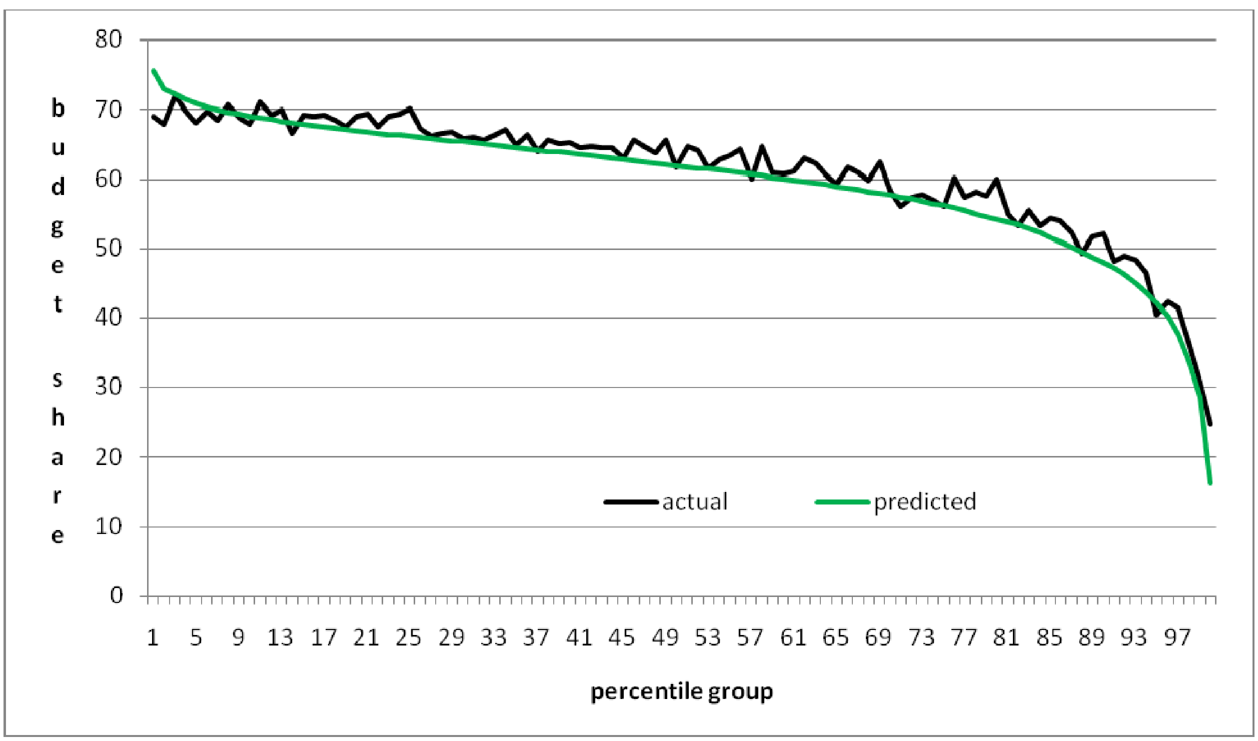
*: total consumption includes food, seed, feed, industrial and waste.

Figure 1: Data and Its Utilization



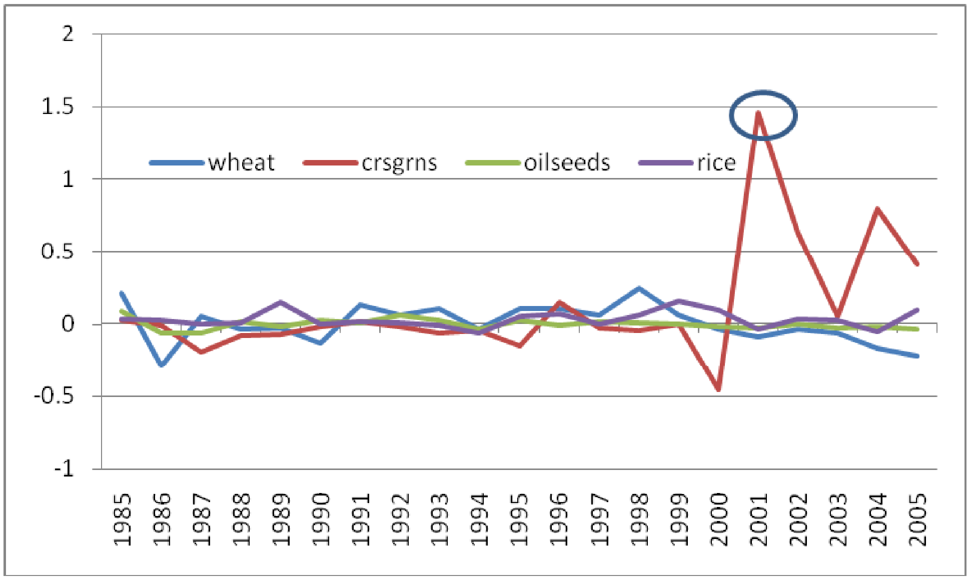
Source: Adapted from Ivanic (2006)

Figure 2: Observed and Predicted Budget Shares for Food in Bangladesh



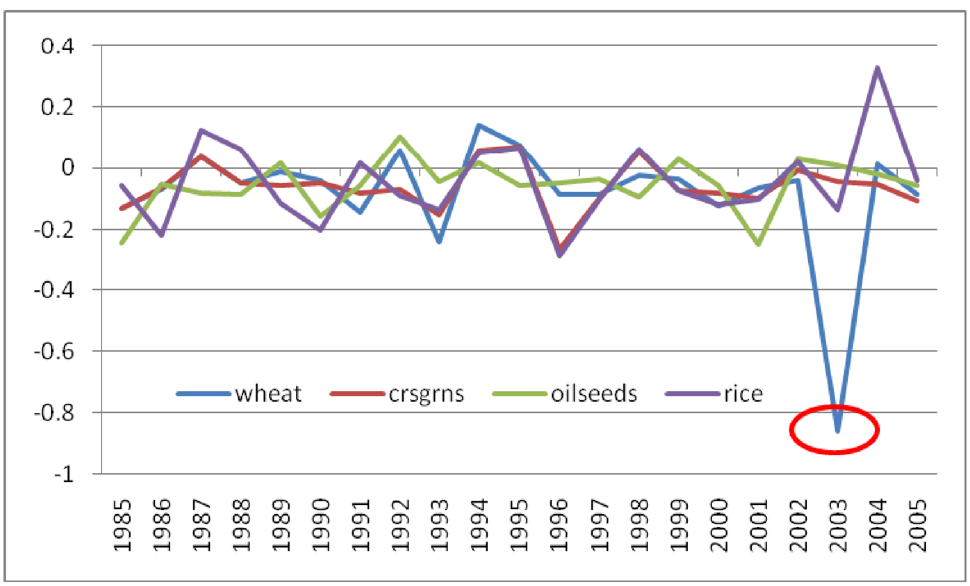
Source: Verma *et al.* (2007)

Figure 3: The Year-on-Year Proportionate Change in Production



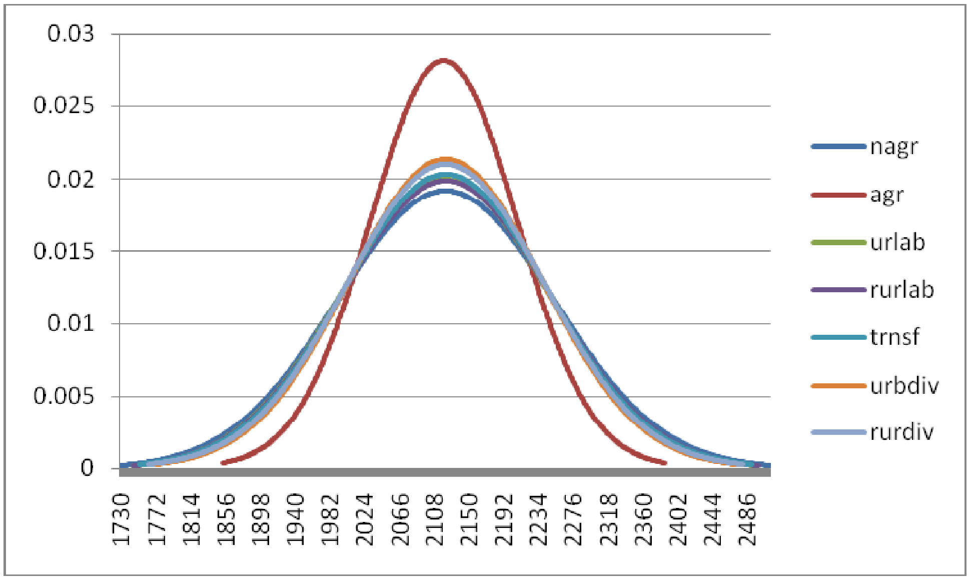
Source: Authors' calculation using FAO production data

Figure 4: The Year-on-Year Proportionate Change in Prices



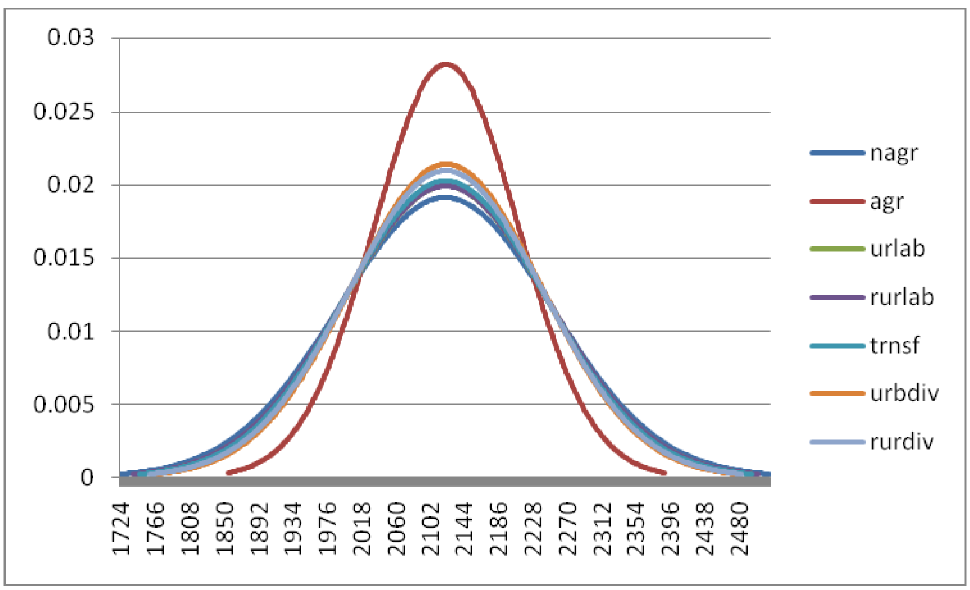
Source: Authors' calculation using FAO price data

Figure 5a: Nutritional Distribution (No SSM) for Individuals at the Nutrition Poverty Line in the baseline (by earnings stratum)



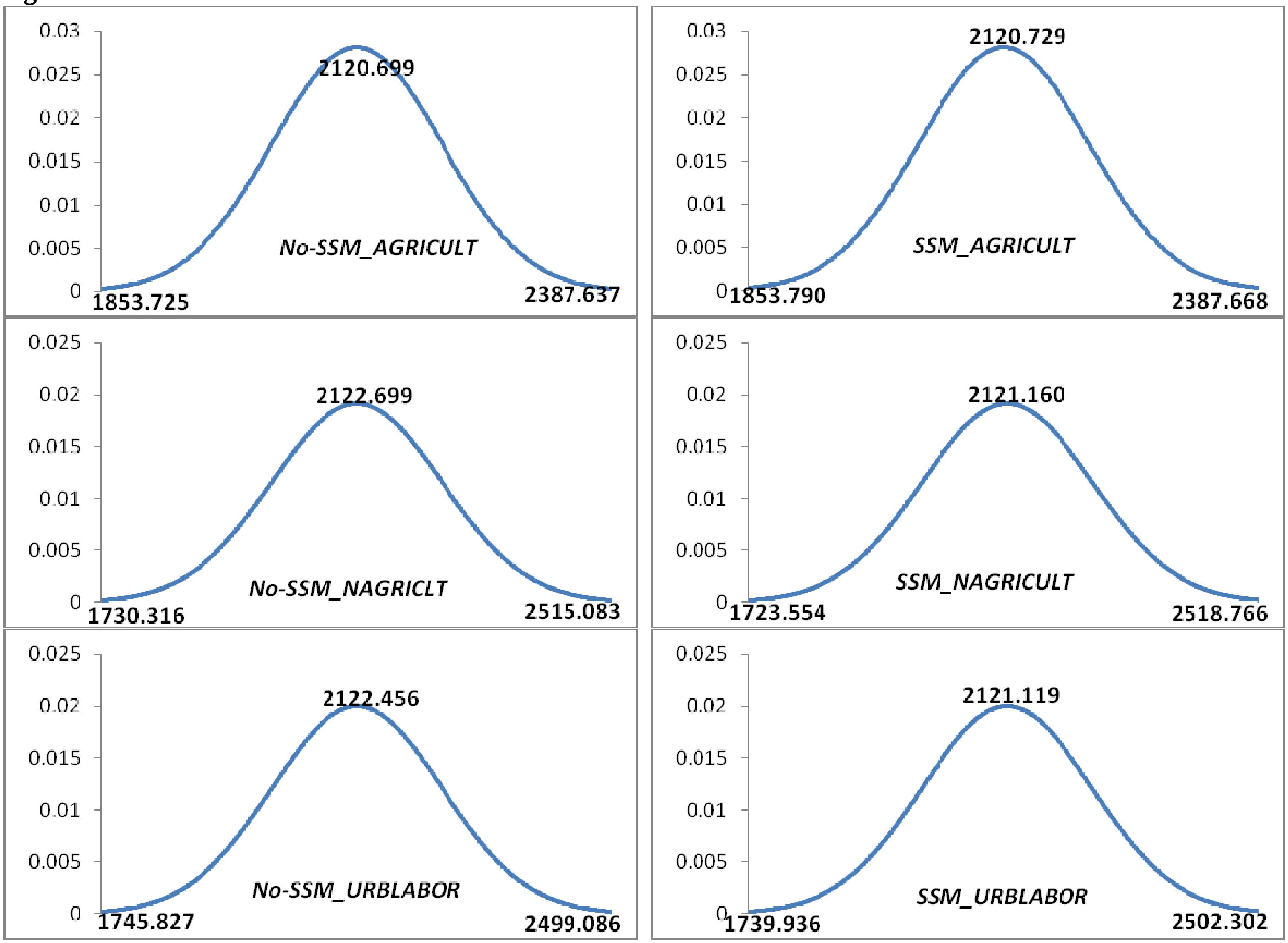
Source: Authors' calculation using model simulation results

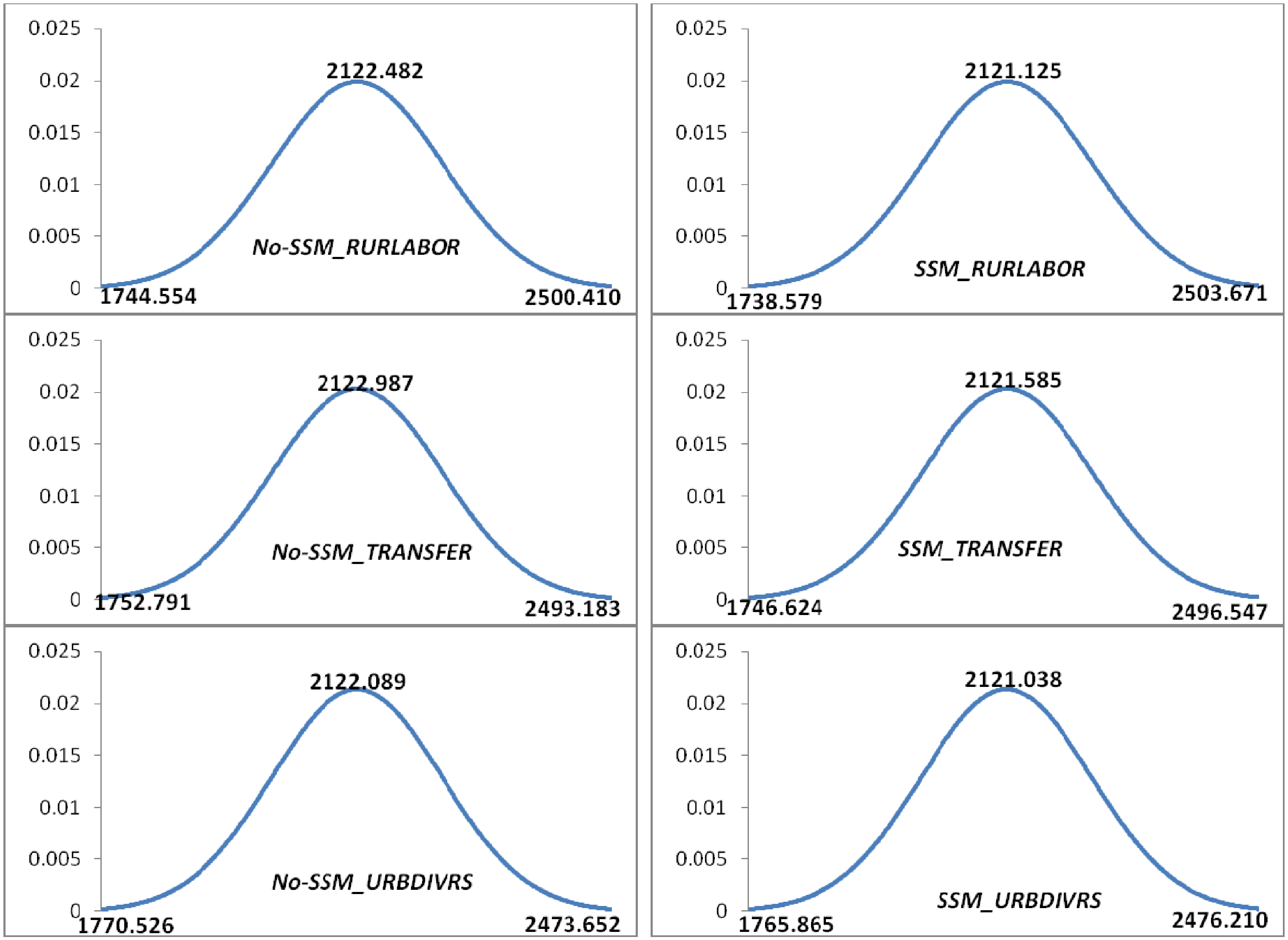
Figure 5b: Nutritional Distribution (SSM) for Individuals at the Nutrition Poverty Line in the baseline (by earnings stratum)

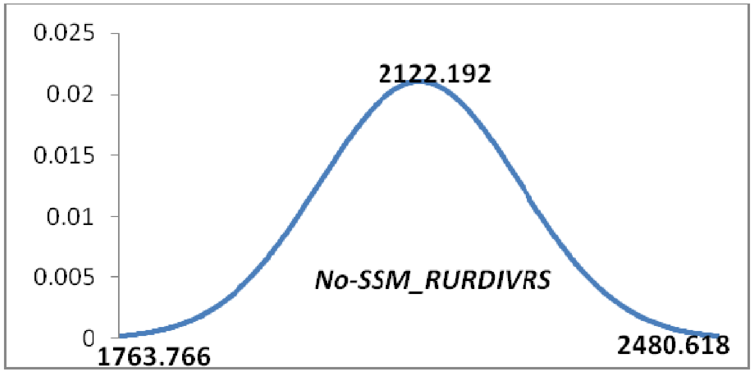


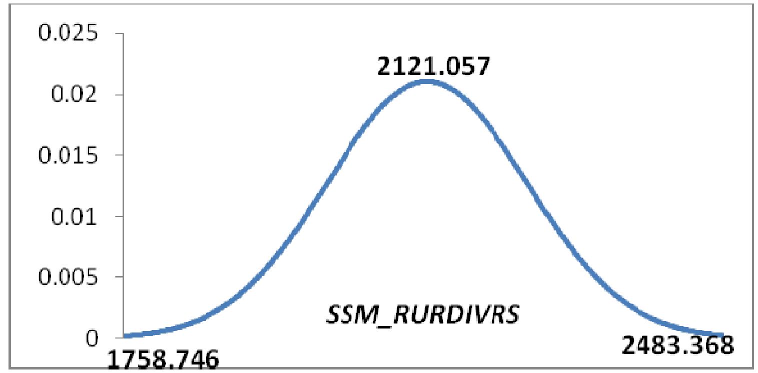
Source: Authors' calculation using model simulation results

Figure 6: Nutritional Distribution with and without SSM




0.025
0.02
0.015
0.01
0.005
0
2122.482
No-SSM_RURLABOR
1744.554
2500.410
2121.125
SSM_RURLABOR
1738.579
2503.671
2122.987
No-SSM_TRANSFER
1752.791
2493.183
2121.585
SSM_TRANSFER
1746.624
2496.547
2122.089
No-SSM_URBDIVRS
1770.526
2473.652
2121.038
SSM_URBDIVRS
1765.865
2476.210





Source: Authors' calculation using model simulation results

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; which 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 below –

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

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

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

Where:

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 & 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 data base. 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 $\alpha^c_{it} = \alpha_{it}/\sum_i \alpha_{it}$ and $\beta^c_{it} = \beta_{it}/\sum_i \beta_{it}$

Given that we now have the starting values for utility along with the customized parameters, 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 country level, use is made of demand equation at country level. The errors are minimized by letting the variables u_t and κ adjust.

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

$$subject\ to -$$

$$\sum_i \frac{\alpha^c_{it}+\beta^c_{it}e^{u_t}}{1+e^{u_t}}\, ln\left(\frac{1}{P_{it}}\frac{\alpha^c_{it}+\beta^c_{it}e^{u_t}}{1+e^{u_t}}\left(Y_t-\sum_i P_{it}\gamma_i\right)\right)-u_t = \kappa \qquad \forall t$$

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

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

Note that the above calibration procedure attributes all the difference between observed and predicted per capita budget shares to discretionary part of the budget shares; subsistence part given by —— is assumed to be calculated correctly and so isn't tempered with in the calibration stage.

APPENDIX 3

Estimating Caloric 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 7440 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 was 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[18].

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

In order to divide the population into income percentiles, we construct another variable which 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 7440 households into j groups (j = 1… 100) such that

[18] 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 this variable Y_h as a proxy for household income.

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

So the percent share of population belonging to each group j equals one. 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 100 'one 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 NPL". To do this 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 BBS 2003 survey report which puts the percentage of population below NPL at 44.3% comes to our rescue. For our purposes we identify the one single household whose cumulative weight closely corresponds to this percentage figure and then take about 0.5 cumulative weight percent on each side of this one household, so the total for the group equals one. This gives us 74 such households whose collective percent weight in the population equals ~1.02. We expect this group to represent the population around the NPL[19].

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, the list of commodities consumed on each of the day along with its quantity consumed. . We aggregate this 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 one percent population group (there are 98 such commodities), we want to know next, the calorie content of these commodities. As many of the consumption commodities turn out to be region (country) specific we prefer a local

[19] Along with the percentage of population below NPL, the report also puts the per capita calorie intake of the nutritionally poor at 2122Kcal. Note that the income (dollar/day) 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 be used for identifying the nutritionally poor population section. As mentioned in data section of the paper, the close correspondence of per capita per day calorie consumption of thus identified group (2126Kcal) with the figure given in the survey report confirms that we are not completely off track.

rather than a standard calorie content list. We use such a list provided by IFPRI and try to map the 98 commodities to this 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 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 per day per cap calorie intake of a nutritionally poor person from consumption of commodity i $CalC_i$; and when summed over commodities it should give us a number close to 2122Kcal (per day per capita calorie intake of a person at NPL)

$CalC_i = \sum_h wpccal_h^i$ and $\sum_i CalC_i = 2126Kcal$!

We are close but not yet done! In order to be able to use this information, we need to map these 98 survey commodities i into 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 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 tones) and Prices (USD/ton) spans the years from 1984 to 2005. The assumption can be made that this time period adequately captures historic volatility. Given that GTAP reports the variables in the percentage change and not levels terms, 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% 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 there were a few things that needed to be addressed before one could obtain a similar proportionate change series. Firstly, the FAO prices are reported for individual coarse grains and oilseed crops, and not at the GTAP aggregate level. To be able 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. In order to be able to get a series starting from 1984, we had to take the prices in LCU/ton from the price archive data of FAO; and undertake a similar exercise as outlined above to obtain a price series in LCU/ton for coarse grains and oilseeds. This 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 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 end points values. We assume these shocks are independent across regions but are perfectly correlated across the four crops in a given region.

However, this doesn't 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 and especially so for rice, as this is the crop from which households at NPL derive over 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 5 reports the observed and generated numbers for comparison.