High Food Prices and their Implications for Poverty in Uganda

From Demand System Estimation to Simulation

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PRELIMINARY RESULTS – NOT SUITABLE FOR CITATION

Abstract

This paper represents an initial attempt at assessing the importance of estimated demand systems for the simulation of large price shocks with respect to poverty analysis. Using a Ugandan household survey data set and an estimated flexible demand system, three different approaches to simulating the compensated expenditure budget due to large food price shocks are compared: a non-behavioral microaccounting, and three behavioral demand systems (LES, CDE, and QUAIDS). The aim of this study is twofold. First, to provide an indication whether it is worthwhile to invest in the estimation of a demand system for similar consumption side poverty impact analyses. Second, to provide a sense of the magnitude in the loss of fidelity from using a less flexible instead of a more flexible demand system within computable general equilibrium analyses of poverty impacts. The results show that using no demand system overestimates poverty impacts to quite some extent. The differences between using either of the three demand systems are rather small but may be more substantial in the extremes.

Keywords: Demand system, simulation, Uganda, food price inflation, poverty.

1 Introduction

The repeated occurrence of high food price spells has started intensive research on the impacts of these events on income distribution and poverty, in particular. Initial empirical work attempting to assess the poverty impacts used first-order analysis using household data that differentiates between net buyers and net sellers of food (e.g., Ivanic and Martin, 2008; Wodon et al., 2008; Zezza et al., 2008; Aksoy and Isik-Dikmelik, 2008; Benson et al., 2008; Simler, 2010).

One common feature as well as a major critique of such analyses is that they disregard the second-order impacts of the price changes on both the supply and consumption sides

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(see, e.g., Aksoy and Hoekman, 2010). The objective of the present study is the quantification of the effect of this neglect on the consumption side. More specifically, the aim of this study is twofold. First, to provide an indication whether it is worthwhile to invest in the estimation of a demand system for similar consumption side poverty impact analyses. Second, to provide a sense of the magnitude in the loss of fidelity from using a less flexible instead of a more flexible demand system within computable general equilibrium (CGE) analyses of poverty impacts.

As the basis of this study, a 13-item censored Quadratic Almost Ideal Demand System (QUAIDS) is estimated over data of the Uganda 2005/2006 National Household Survey (UNHS) which covers a representative set of 7426 households. The estimated parameters are used to simulate the impact of the recent food price spikes on poverty. The shocks are calculated from price time series data for several food commodities and Ugandan market locations which are matched to the households of UNHS. As the Linear Expenditure System (LES) and the Constant Difference in Elasticity (CDE) of Substitution are two of the most popular demand systems used in CGE models, LES and CDE are calibrated, for each household separately, to approximate the QUAIDS elasticities in the point of the base data. Then, the non-behavioral first-order poverty impacts as well as the behavioral poverty impacts employing the three demand systems are simulated. The demand system simulations are conducted fixing the base-period utility and calculating the compensating variation utilizing an algorithm devised by Vartia (1983).

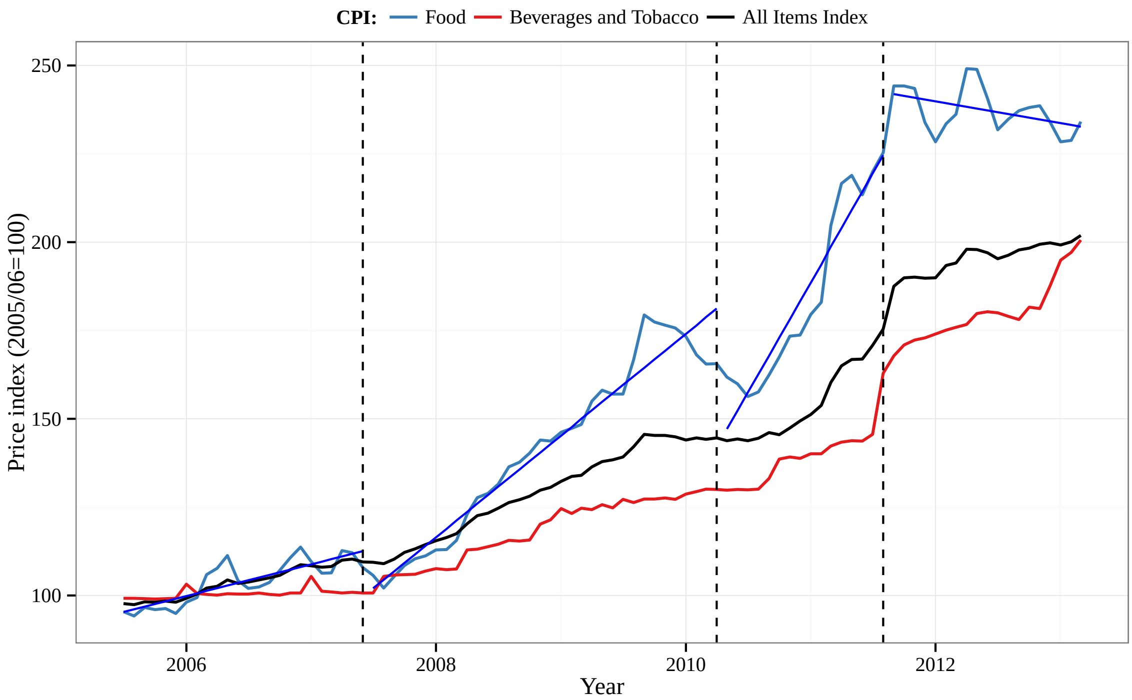
Uganda has a high poverty rate of 31% according to official figures (in 2006, Table 6.9, UBoS, 2006) and even 52% based on the 1.25$/day poverty line (in 2005, World Bank, 2010). It is highly agriculture-centered with 73.3% of the working population working in the agriculture, forestry, and fishing sectors in 2005/06 (UBoS, 2006, Table 4.5) which account for 25% of total value added in 2009.[1] 49.2% of Ugandan households name subsistence farming as their major source of earnings while only 20.8% name wage employment (UBoS, 2006, Table 7.3). This indicates a low dependence of household incomes on markets. Then, apart from rice and wheat, Uganda is largely self-sufficient in terms of the staple foods it consumes. In fact, Uganda is an important source of food for neighboring countries. Additionally, Ugandans base their diets on a variety of staple foods of which many are not actively traded on international markets, see Benson et al. (2008). Finally, Uganda is a landlocked country with poor transport connections to seaports and thus has high transport and transactions. In summary, Uganda appears to be quite well insulated from price shocks on the world market.

Nevertheless, Uganda experienced dramatic consumer price inflation over the period from 2005/06 to 2013 with food prices increasing significantly more than prices for non-food as presented in Figure 1 using undeflated official Ugandan CPI data.

[1] World Bank (2010), series "Agriculture, value added (% of GDP)".

The topmost line represents the consumer food price index. The regression lines clearly indicate the occurrence of two periods where food prices rose much faster than the overall CPI (food has a weight of 27% in the overall CPI).

Figure 1: Ugandan food and non-food price indices



Source: Own computation from Bank of Uganda CPI data (base=2005/06), `http://www.bou.or.ug/bou/rates_statistics/statistics.html`, retrieved April 24, 2013.

2 Data and approach

The aim of this study is first, to provide an indication whether it is worthwhile to invest in the estimation of a demand system for similar consumption side poverty impact analyses. Second, to provide a sense of the magnitude in loss of fidelity in consumption-side reactions from using LES or CDE instead of a more flexible demand system like the QUAIDS within CGE model analyses of equivalent price shocks.

2.1 Data

The simulations are based on the UNHS 2005/06 which includes a sample of 7,426 households, corresponding to 40,449 individuals, and is nationally representative, see UBoS (2006). Inflated by sample weights, the sample represents a population of 28,428,169 individuals.[2]

[2]Five households had to be deleted due to missing data, leaving 7421 households.

To derive actual price shocks of food price peaks, we utilize a price time series collected by Farmgain Uganda which contains weekly data for many Ugandan locations and food items. As not all items disaggregated in estimated demand system are present in that data, in particular, non-food, the series is complemented with regional monthly CPI data taken from the Uganda Bureau of Statistics (UBoS)(UBoS, 2008, 2009, 2011, 2013).

2.2 Approach

The foundation is built on the estimation of a censored Quadratic Almost Ideal Demand System (QUAIDS, Banks et al. (1997)) as described in Boysen (2012). It is a 13 item two-stage demand system model, estimated for rural and urban households separately where the first stage budgeting between food and non-food is represented by a Working-Leser-type function and the main, second-stage is represented by a QUAIDS accounting for socio-demographic household characteristics and censoring and focuses on food items.

Two less flexible demand systems examined, the Linear Expenditure System (LES, Stone (1954)) and the Constant Difference of Elasticities of substitution (CDE, Hanoch (1975)) which are the most common demand systems used in CGE models. Consistent sets of LES and CDE parameters are derived for each individual household using the UNHS and estimates of Ugandan rural and urban demand systems, respectively. To generate consistent parameter sets, a LES or CDE, respectively, is calibrated to fit those given income and own price elasticities as good as possible in terms of a generalized maximum entropy (GME) objective function (see Golan et al. (1996)) and the theoretical constraints of the LES or CDE, similar to the approach applied in Yu et al. (2003). The LES and CDE are fitted individually for each household. The GME procedure is implemented in GAMS.

A last approach included is a simple microaccounting which assumes that households are not adapting their consumption to the new price pattern and thus quantities consumed remain fixed for each household while prices change according to the shocks. This is the standard approach for first-order studies. It has the advantage of being relatively quick to implement and transparent. Nevertheless, neglecting behavioral adaptation of household consumption to price shocks represents a worst case assumption for the simulation of income impacts.

By using a demand system, quantities change together with prices so that a pure price index-based approach for evaluating the after price shock real income, as is used for microaccounting, is not applicable. Hence, compensating variation (CV) is employed as an alternative money-metric measure. The compensated expenditure is calculated by finding the expenditure budget which allows the household to keep its utility at pre-shock level while adjusting its consumption to the new price levels. The CV of the LES, CDE and

QUAIDS models is simulated using the algorithmic approach introduced by Vartia (1983). It basically exploits Shephard's Lemma to calculate a movement along a compensated demand curve to approximate the CV. The approach has been shown to approximate the real CV with very high accuracy. The Vartia procedure as well as the demand system simulations are implemented in the statistical programming language R (R Core Team, 2013).

2.3 Poverty lines and measures

For measuring poverty, we employ an absolute poverty line and the measures P_α introduced by Foster et al. (1984).[3] The poverty headcount index P_0 measures the percentage of people falling below the poverty line. The poverty gap P_1 measures the extent by which poor people fall under the poverty line as a percentage of the poverty line on average. The poverty severity index P_2 squares that shortfall percentage of each person before averaging and thus gives more weight to more severely affected people.

Rural and urban poverty lines are derived such that they reproduce the poverty headcounts of 34.2% in rural and 13.7% in urban areas, as reported in the UNHS Report on the Socio-Economic Survey (UBoS, 2006, Table 6.3.2 (a)), when applied to the adjusted household survey data. The UBoS poverty lines are based on the *cost of basic needs approach*, which accounts for the cost of meeting physical calorie needs and allows for vital non-food expenditure, such as clothing and cooking fuels, valued using the average consumption basket of the poorest 50% of the population (UBoS, 2006, Section 6.3). The rural and urban poverty lines account for the differences in prices and consumption baskets of the respective subpopulations. Per capita consumption expenditure is used the income measure. Household income is measured as the sum of the values of market and non-market consumption, both valued at market prices. It should be noted that our poverty classification is not directly comparable with the classification in the official report of the UBoS (2006) due to differences in data adjustments.

3 Simulations

3.1 Scenarios

Two sets of price shocks are simulated, representing months of high food price indices in Uganda. These are the changes from 2005/06 to September 2009 and to April 2012.

[3]The formula is given as $P_\alpha = \frac{1}{N} \cdot \sum_{i=1}^{N} \left(\frac{z-y_i}{z}\right)^\alpha \cdot I_i$ with N: population size, z: poverty line, y_i: income of individual i, and $I_i = \begin{cases} 1 & \text{if } y_i < z \text{ and} \\ 0 & \text{otherwise.} \end{cases}$ Setting the parameter α to 0, 1, or 2 computes the poverty headcount, gap, or severity index, respectively.

Each of these shocks is simulated using the microaccounting approach (MAC), the LES, the CDE, and the QUAIDS. The items shocked are alcohol and tobacco, beans, cassava, fats and oils, fish, fruits and vegetables, livestock products, maize, matooke, other foods, sugar, sweet potatoes, and non-food. The markets distinguished are Arua, Gulu, Jinja, Kabale, Kampala, Lira, Masaka, Masindi, Mbale, Mbarara, Soroti, and Tororo. Each household is shocked with the price inflation of its geographically closest market (according to GPS coordinate distances) for which a price shock is available.

The after-shock consumption budget is calculated by first dividing the initial budget by the after-shock compensated expenditure to get budget deflator and then this is multiplied by the initial budget times the overall CPI index to account for an increase in income. Thus, for all households it is assumed that their income rises in line with the overall CPI. This very crude approach is adopted to avoid absurd negative income effects as the overall price level increased strongly not only due to the food prices but also to non-food prices.

The shocks are presented in Table 1. Price indices for several market and item combinations in September 2009 reach almost 300% of increase from the 2005/06 level and many register more than 300% of increase in April 2012. By contrast, the increase in the overall CPIs for the regions is about 150% in September 2009 and 200% in April 2012. Thus, depending on the needs and preferences of the consumers, these large price variations across markets and items might affect individual households rather differently.

3.2 Results

Table 2 presents first results from the simulations. Overall, the strong food price inflation appears to push the consumption budget of many people under the poverty line. Depending on the demand system approach, the poverty headcount increases by 3.8 to 4.9 percentage points given September 2009 prices and an overall CPI index-increased income. Rural poor people are more strongly affected with a headcount increase by 4.4 to 5.6 percentage points while the headcount increases by 0.6 to 1.4 percentage points in urban areas.

By April 2012, prices have increased even more. The poverty headcount increases again by up to 0.5 percentage points compared to September 2009.

Considering the differences in the FGT results between the MAC, LES, and QUAIDS-based simulations, the MAC approach represents the worst case outcome where households are not able to substitute between consumption items in reaction to adverse shifts in relative prices. On the national level, the September 2009 poverty headcount increase of the MAC approach is 0.9 percentage points or 21% higher than that of the QUAIDS. The three behavioral demand system approaches show quite significant differences in the results compared to the microaccounting approach. In urban areas, the poverty headcount

Table 1: Regional price shock index values with base=2005/06

Item	Arua	Gulu	Jinja	Kabale	Kampala	Kiboga	Lira	Masaka	Masindi	Mbale	Mbarara	Soroti	Tororo
September 2009													
Overall CPI index	159	160	155	–	143	–	–	146	–	148	152	–	–
Livestock products	239	–	–	220	178	230	184	162	153	–	214	129	176
Fats and oils	197	200	192	–	176	–	–	170	–	178	186	–	–
Other foods	197	200	192	–	176	–	–	170	–	178	186	–	–
Sweet potatoes	160	–	–	136	–	100	262	195	251	–	285	222	156
Matooke	221	–	–	78	113	110	295	122	206	–	149	167	192
Beans	268	–	–	229	241	218	267	215	226	–	248	233	240
Maize	253	–	–	240	201	201	167	207	197	–	214	205	250
Sugar	197	200	192	–	176	–	–	170	–	178	186	–	–
Fruits and vegetables	191	–	–	166	156	192	182	124	193	–	275	92	118
Non-food	130	135	138	–	131	–	–	137	–	136	140	–	–
Cassava	192	–	–	173	200	175	278	212	195	–	207	191	247
Alcohol and tobacco	141	138	123	–	124	–	–	124	–	120	126	–	–
Fish	154	–	–	211	147	140	144	122	200	–	214	291	112
April 2012													
Overall CPI index	220	227	206	–	193	–	–	202	–	205	204	–	–
Livestock products	294	–	–	305	217	291	225	216	184	–	222	196	223
Fats and oils	279	285	260	–	247	–	–	234	–	264	246	–	–
Other foods	279	285	260	–	247	–	–	234	–	264	246	–	–
Sweet potatoes	142	–	–	176	–	102	242	124	344	–	253	297	265
Matooke	239	–	–	119	178	186	390	231	293	–	290	207	290
Beans	366	–	–	316	310	273	300	329	312	–	353	336	332
Maize	292	–	–	288	239	231	217	263	288	–	266	336	350
Sugar	279	285	260	–	247	–	–	234	–	264	246	–	–
Fruits and vegetables	251	–	–	328	296	281	306	205	314	–	361	239	289
Non-food	176	191	180	–	172	–	–	191	–	179	188	–	–
Cassava	263	–	–	202	241	232	234	242	219	–	184	272	270
Alcohol and tobacco	191	202	178	–	176	–	–	170	–	175	176	–	–
Fish	346	–	–	430	296	256	311	270	342	–	503	450	283

Source: Own computation from UBoS CPI and Farmgain Uganda price data.

effect is even more than halved.

The LES and CDE results differ to a rather small extent from the QUAIDS results in aggregate with differences in headcount percentage point increase of 0 to 0.3 on the national level and similar in rural and urban areas separately. This hints that the calibrated LES and CDE functions approximate the original QUAIDS functions to a good extent. But the much lower flexibility of the LES as apparent in the theoretical restrictions of the LES, which limit, for example, own price elasticities to the interval -1 and 0, income elasticities to positive values or all goods to be gross complements, suggest that there are strong limitations to the approximation. By contrast, the CDE is theoretically somewhat more flexible than the LES, see Jensen et al. (2011).

Looking at the ratio between the LES- and QUAIDS-simulated compensated expenditures for the September 2009 shock, there are differences from about -30% up to +5% but the 5% to 95%-quantile range lies between 0.99 and 1.01. Thus, there are cases of strong divergence of individual household effects and LES results deviate in positive and negative directions from the QUAIDS results but for the large majority of households, the differences are in the order of less than absolute 1%. These figures are astoundingly

Table 2: Simulation results: FGT poverty indices

		September 2009				April 2012			
	2005/06	MAC	LES	CDE	QUAIDS	MAC	LES	CDE	QUAIDS
National									
Headcount	31.06	4.92	4.03	3.80	4.06	5.53	4.58	4.41	4.59
Gap	9.62	2.52	1.99	1.90	2.02	2.68	2.19	2.10	2.24
Severity	4.20	1.36	1.07	1.02	1.09	1.41	1.14	1.10	1.18
Rural									
Headcount	34.21	5.56	4.65	4.39	4.69	6.26	5.23	5.05	5.30
Gap	10.64	2.84	2.25	2.15	2.30	3.03	2.48	2.38	2.56
Severity	4.65	1.54	1.21	1.15	1.24	1.59	1.29	1.24	1.35
Urban									
Headcount	13.70	1.40	0.64	0.58	0.58	1.50	1.02	0.91	0.68
Gap	3.99	0.77	0.58	0.54	0.49	0.81	0.61	0.57	0.49
Severity	1.70	0.41	0.31	0.29	0.26	0.42	0.32	0.30	0.25

The columns show point changes in the indices from the Base column. The poverty figures use rural and urban poverty lines, respectively. Source: Own computation.

similar for the CDE to QUAIDS ratio of compensated expenditures.

4 Summary and Conclusions

This paper represents an initial attempt at assessing the importance of estimated demand systems for the simulation of large price shocks with respect to poverty analysis. Using a Ugandan household survey data set and an estimated flexible demand system, four different approaches to simulate the compensated expenditure budget due to large food price shocks are compared: microaccounting, LES, CDE, and QUAIDS. While the first is a mere mapping of a vector of new prices to given quantities, the latter three are behavioral demand systems allowing for substitution between consumption items. The LES and CDE are frequently used in CGE models but also recognized to be quite limited in their flexibility to depict real world consumption behavior. The QUAIDS, on the other hand, is a rather recent, flexible demand system.

Based on the estimated parameters of a two-stage QUAIDS, LES and CDE demand systems are calibrated to fit the given income and own price elasticities as good as possible by use of a generalized maximum entropy procedure. The LES and CDE are fitted individually for each household to the individual household-specific elasticities as derived from the QUAIDS.

The results indicate that all demand systems yield results rather different from those of the microaccounting approach. For example, the urban poverty headcount effect simulated using the QUAIDS is less than 50% of that simulated using the microaccounting approach.

The results between the LES, CDE, and QUAIDS demand systems seem quite close for the large majority of cases but show substantially deviations in the extremes. The urban poverty figures point out that noteworthy differences do exist in the details.

With regard to the use of demand systems in CGE models, and in particular to those which integrate large sets of households into the model, it seems that calibrating LES or CDE parameters individually for each household might be valuable to mimic the behavior of more flexible demand systems.

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