Technical Appendix

Economic Development and Nutrition Transition in Ghana: Taking Stock of Food Consumption Patterns and Trends

ReSAKSS Annual Trends and Outlook Report (ATOR) 2015, Chapter 4*

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A1: Limitations of Food Balance Sheets data

The accuracy of Food Balance Sheets (FBS) data has been questioned because of data gaps in the underlying statistics and several methodological limitations (Gabbert and Weikard 2001; Nube 2001; Smith 1998; Svedberg, 1999, 2002). One of the main criticisms is that per capita food supply available in a country for human consumption—referred to as 'food availability' here—is calculated as the residual of total quantity of foodstuffs produced; plus the total quantity imported; minus the total quantity exported; adjusted to any change in stocks; and minus the total quantities used for livestock feed and seed, put to manufacture for food and nonfood uses, and lost during storage and transportation. Hence, the accuracy of this residual value depends on the accuracy and completeness of the statistics of all other variables of the food equation, which are usually collected by different national organizations/ministries, often applying different methods and probably varying rigor. Data for some variables or certain years of a variable are often missing or are unreliable, which requires making assumptions to construct the residual value. Macronutrient (calorie, protein, and fat) availability values are directly derived from the food availability values. The potential accuracy of the macronutrient availability values may be even lower than that of the food availability values, because just a few food items constitute the main macronutrient sources (especially in the case of protein and fat), so small inaccuracies in the quantities of these foods can result in large biases in overall macronutrient availability values.

For Ghana, the FBS data indicate that the per capita calorie availability at the time of the fifth round of the Ghana Living Standard Survey (GLSS) in 2005–2006 was about 2,700 kcal per day. This value appears to somewhat overstate the actual average per capita calorie consumption, considering that the physiological dietary energy requirements for a man of average Ghanaian stature with moderate physical activity level are 2,650 kcal per day (FAO et al. 2001) and that 30 percent of the population were estimated to have consumed less than 1,800 kcal per day in 2005–2006, using the GLSS data (Coulombe and Wodon 2012). Beyond potential data and methodological errors, lower survey-based consumption values may be due to food waste occurring within the household (during storage, in meal preparation, as plate waste, and with quantities fed to domestic animals or thrown away), which is not accounted for in the FBS (FAOSTAT 2016).

However, the accuracy of the available GLSS estimate of the prevalence of calorie deficiency (by Coloumbe and Wodon 2012) can be questioned too, given that the underlying computation requires several strong assumptions. For example, quantities for all consumed food items purchased in the market (as opposed to own-produced) have not been collected in the GLSS. Therefore, the authors have to use reported food expenditures and regional food prices for approximating consumed food quantities in order to derive per capita calorie consumption amounts and deficiency rates. Consumed quantities for own-produced foods are reported in local, non-metric measurement units, which may vary by region and for which standard (regional) conversion factors are unavailable. Hence, the conversion of these food quantities into standard metric measurement units is likely to be imprecise and is potentially biased. Coloumbe and Wodon (2012) provide no information about how they addressed this conversion problem or if they even used the reported value estimates of the produced foods to compute food quantities, which, in turn, involves other—perhaps even stronger—assumptions. The authors do not provide descriptive statistics of per capita calorie consumption, which would help to assess the accuracy of their estimated prevalence rates of calorie deficiency.

A2: Description of Ghana Living Standard Survey data and calculation of food consumption per adult equivalent

The Ghana Living Standard Survey (GLSS) is a nationwide, cross-section household survey and is designed to generate information on people's living conditions. The fifth and sixth round (GLSS5, GLSS6) were designed to provide nationally and regionally representative indicators that are comparable over time. Consequently, both rounds applied the same sampling methodology, used the same questionnaires, and covered the same broad range of topics, including demographic characteristics, household agriculture, and household food and non-food consumption. The targeted sample size of the GLSS5 was 8,700 households, and the targeted sample size of the GLSS6 was 18,000 households (GSS 2014). Food consumption data are available for 8,639 households in the GLSS5 and 16,772 households in the GLSS6.

The GLSS5 and GLSS6 collected food consumption data using two separate questionnaire modules. These two food consumption modules provide detailed information only for foods consumed at home. Food consumption outside the home is therefore excluded from our analysis; it is of minor relevance in the context of Ghana. The first module records food consumption from own-production (for farming households), and the second module records food consumption from food purchases. The first module provides information on quantities of the consumed, own-produced food items and their estimated unit selling prices at the time of the interview, as reported by the interviewee. The second module provides information on the reported amounts spent for purchasing the consumed food items; it did not record quantities or unit prices of the purchased food items. Hence, accurate total food consumption quantities—or calorie and nutrient consumption amounts—cannot be calculated. Therefore, our analysis uses reported monetary values of consumed own-produced foods and reported food expenditures (instead of food quantities) for measuring food consumption. For calculating total consumption in farming households, we assume that the estimated selling prices for own-production are equivalent to the purchasing prices for the same food items (omitting potential marketing margins).

In the GLSS5, food consumption is surveyed by using a repeated three-day recall questionnaire, which asks the interviewees to list all food items consumed over the past three days. In the GLSS6, a repeated five-day recall questionnaire is used. To survey food consumption, the same households were visited ten times at intervals of three days during the GLSS5 field work and five times at intervals of five days during the GLSS6 field work. Thus, both the GLSS5 and the GLSS6 cover a total period of 30 days. For calculating average daily food consumption, we averaged across all recall periods, taking into account when households were unavailable for interview during one of the visits. We assume that the difference in the length of the recall period between the GLSS5 and the GLSS6 does not affect the consumption estimates. We calculated means without considering survey sampling weights, which hence provide an average for the survey sample populations.

To reduce the potential bias from outlier observations, we applied a conservative approach to replace extreme food consumption values but refrained from dropping entire household observations. We replaced the values of 23 food item observations in the GLSS5 and 28 food item observations in the GLSS6 with the value at the 90th percentile of that particular food item. The replaced observations account for 0.01 percent of all food item observations in the GLSS5 and less than 0.01 percent of all food item observations in the GLSS5.

For calculating household total consumption expenditure, we added household total non-food expenditures—available in the released GLSS datasets and computed by the Ghana Statistical Service (GSS)—to household total food consumption. We deflated all GLSS6 consumption values to the price levels at the time of the GLSS5. We used a general consumer price deflator (.4093) provided by GSS (2014). Hence, the observed large differences in average household (food) consumption levels between 2005–2006 and 2012–2013 may be partly due to the applied deflator value and should not be over-interpreted.

We express all household consumption levels on the basis of adult equivalence. For converting household consumption values into consumption values per adult equivalent (AE), we used household-specific information on household size, sex and age of household members (available from the GLSS5 and GLLS6 data), and individual dietary energy requirements provided by FAO et al. (2001). We computed household-specific AE weights as the sum of household members expressed as shares of an adult male aged 30–59 years. We assume moderate physical activity levels for all individuals and an optimum population median body mass index of Ghanaian men and women with average body heights for all adults.

A3: Classification of food items into food groups

Our classification of food items into six main food groups follows the classifications underlying common dietary diversity scores, particularly the Household Dietary Diversity Score (HDDS) of the Food and Nutrition Assistance (FANTA) project of the United States Agency for International Development (USAID) (Swindale and Bilinsky 2006a, 2006b) and the Minimum Dietary Diversity Score for Women (MDDS-W) of the Food and Agriculture Organization of the United Nations and USAID's FANTA project (FAO and FHI 360, 2016; Kennedy et al. 2011). Although common dietary diversity scores have different maximum numbers of food groups, they all differentiate between animal-source foods, pulses and nuts, cereals, roots and tubers, vegetables and fruits, and meal additives. They differ in the level of disaggregation, further breaking down these main food groups. Our classification of food items is limited to the breakdown into the six main food groups, which constitutes the highest nutritionally sound aggregation level. The food items within one group are similar in total protein content, protein source, and protein quality. A mixture of at least cereals and pulses and nuts or animal-source foods is needed for a sufficient and well-balanced protein nutrition (Millward 1999; Pereira and Vincente 2013; Schönfeldt and Hall 2012; Young and Pellett 1994). Table A3.1 gives an overview of all food groups and food items.

Table A3.1. Grouping of food items

Food groups and subgroups	Food items (as listed in GLSS questionnaires)	Number of food items per subgroup
Animal-source foods		
Fish & seafood	Crustaceans, fresh and frozen fish, dried fish, smoked fish, fried fish, canned fish, slated fish, other fish	8
Beef	Corned beef, beef	2
Chicken	Chicken	1
Other meats	Pork, goat meat, mutton, wild game, other meat, other domestic poultry, game birds	7
Milk & dairy products	Fresh milk, milk powder, evaporated tinned milk, milk products	4
Eggs	Chicken eggs, other eggs	2
Pulses & nuts		
Beans	Beans, soybeans, cowpeas	3
Groundnuts	Groundnuts, Bambara beans	2
Other	Coconut, other pulses and nuts	2
Cereals		
Maize	Maize, maize ground, kenkey/banku	3
Rice	Local rice, imported rice	2
Wheat	Sugar bread, other bread, wheat flour	3
Other	Sorghum, millet, millet flour, other cereals, other cereal products	5
Roots & tubers		
Cassava	Cassava, cassava-dough, gari	3
Plantain	Plantain	1
Yams	Yam, cocoyam	2
Other	Sweet potatoes, other starchy staples, other processed starchy staples	3
Vegetables & fruits		
Tomato	Fresh tomatoes, tomato puree	2
Pepper	Pepper	1
Onion	Onions	1
Other vegetables	Cocoyam leaves, garden eggs, carrots, okoro, cabbage, other leafy vegetables, other vegetables	7
Fruits	Banana, orange/tangerine, pineapple, mango, pawpaw, avocado pear, watermelon, canned or processed fruits, other fruits not canned	9
Meal additives		
Palm oil	Palm kernel oil, palm oil, palm nuts	3
Other oils & fats	Coconut oil, groundnut oil, shea butter, margarine butter, other vegetable oils	5
Sugar & sweets	Sugar, honey, biscuits, ice cream, chocolate, condensed milk, other confectioneries	5
Condiments & beverages	Black pepper, salt, ginger, dawa[a], other condiments, baby food, baby milk, cola nuts, coffee, chocolate drinks, tea, other beverage drinks, soft drinks and minerals, malta and malt drinks, fruits juices, bottled mineral water[b], sachet mineral water[b], schnapps, whiskies and gins, akpeteshie, other spirits, palm wine, pito/brukutu, other local wine, other imported wine, local beer, imported beer, other stout	30
Total number of food subgroups / items	*26*	*116*

Source: Authors' representation based on GLSS5 and GLSS6 data.

Note: [a] Food item is not listed in the GLSS5 questionnaire.

[b] Food items are aggregated in the GLSS5 questionnaire.

A4: Engel curve estimations

All Engel curves were estimated using fractional polynomial regressions of degree 2 and robust estimators of variance. Since the precise functional forms of the Engel curve estimation equations that fit the data best are initially unknown, we applied fractional polynomial regressions. Hence, the shapes of the estimated Engel curves were determined endogenously in the model estimations by the underlying survey data. To allow for non-linearity and concavity of the Engel curves, we chose fractional polynomials of degree 2 (that is, STATA's default option). We chose a robust estimator of variance, so the obtained standard errors are robust to some (unknown) kinds of misspecification of the functional forms. To avoid extreme outlier observations influencing the specifications of the functional forms, we dropped observations of the one-percent richest households from the estimation samples. Table A4.1 presents the estimated Engel curve equations of best model fits—which yield the predicted values for the Engel curve graphs presented in the book chapter—and measures of overall model fit.

Table A4.1. Estimated Engel curve equations

Estimation sample	N	Food group	Best-fit functional form	F	R^2
Southern Ghana, urban areas, GLSS5 (2005–06)	3,048	Total food	$y = \alpha + \beta_1 * (x^2 - 0.5024491025) + \beta_2 * (x^2 * \ln(x) + 0.172908044) + \varepsilon$	703.3	0.594
		Animal-source foods	$y = \alpha + \beta_1 * (x - 0.7088364427) + \beta_2 * (x^3 - 0.3561542344) + \varepsilon$	632.9	0.496
		Pulses & nuts	$y = \alpha + \beta_1 * (x - 0.7088364427) + \beta_2 * (x^3 - 0.3561542344) + \varepsilon$	106.0	0.144
		Cereals	$y = \alpha + \beta_1 * (x^2 - 0.5024491025) + \beta_2 * (x^2 * \ln(x) + 0.172908044) + \varepsilon$	233.4	0.333
		Roots & tubers	$y = \alpha + \beta_1 * (x^2 - 0.5024491025) + \beta_2 * (x^2 * \ln(x) + 0.172908044) + \varepsilon$	49.16	0.096
		Vegetables & fruits	$y = \alpha + \beta_1 * (x - 0.7088364427) + \beta_2 * (x^3 - 0.3561542344) + \varepsilon$	236.4	0.235
Southern Ghana, urban areas, GLSS6 (2012–13)	5,912	Total food	$y = \alpha + \beta_1 * (x - 1.277493072) + \beta_2 * (x * \ln(x) - 0.3128575684) + \varepsilon$	2,095	0.538
		Animal-source foods	$y = \alpha + \beta_1 * (x - 1.277493072) + \beta_2 * (x^3 - 2.084854067) + \varepsilon$	845.6	0.397
		Pulses & nuts	$y = \alpha + \beta_1 * (x^2 - 1.63198855) + \beta_2 * (x^2 * \ln(x) - 0.3996733763) + \varepsilon$	209.1	0.145
		Cereals	$y = \alpha + \beta_1 * (x^{0.5} - 1.130262391) + \beta_2 * (x - 1.277493072) + \varepsilon$	668.4	0.218
		Roots & tubers	$y = \alpha + \beta_1 * (x - 1.277493072) + \beta_2 * (x^2 - 1.63198855) + \varepsilon$	110.7	0.070
		Vegetables & fruits	$y = \alpha + \beta_1 * (x - 1.277493072) + \beta_2 * (x^2 - 1.63198855) + \varepsilon$	969.2	0.374
Southern Ghana, rural areas, GLSS5 (2005–06)	2,970	Total food	$y = \alpha + \beta_1 * (x^{0.5} - 0.6437733738) + \beta_2 * (x^2 - 0.1717639592) + \varepsilon$	1,935	0.749
		Animal-source foods	$y = \alpha + \beta_1 * (x^{0.5} - 0.6437733738) + \beta_2 * (x^2 - 0.1717639592) + \varepsilon$	820.6	0.523
		Pulses & nuts	$y = \alpha + \beta_1 * (x^{0.5} - 0.6437733738) + \beta_2 * (x^3 - 0.0711865692) + \varepsilon$	123.1	0.166
		Cereals	$y = \alpha + \beta_1 * (x^{-0.5} - 1.553341658) + \beta_2 * (x^{0.5} - 0.6437733738) + \varepsilon$	727.6	0.379
		Roots & tubers	$y = \alpha + \beta_1 * (x^{0.5} - 0.6437733738) + \beta_2 * (x^3 - 0.0711865692) + \varepsilon$	155.8	0.242
		Vegetables & fruits	$y = \alpha + \beta_1 * (x - 0.4144441569) + \beta_2 * (x^2 - 0.1717639592) + \varepsilon$	434.3	0.397
Southern Ghana, rural areas, GLSS6 (2012–13)	4,967	Total food	$y = \alpha + \beta_1 * (x - 0.7529631823) + \beta_2 * (x* \ln(x) + 0.2136449805) + \varepsilon$	2,731	0.685
		Animal-source foods	$y = \alpha + \beta_1 * (x^{0.5} - 0.8677345114) + \beta_2 * (x^{0.5} * \ln(x) + 0.2462100766) + \varepsilon$	1,706	0.508
		Pulses & nuts	$y = \alpha + \beta_1 * (x - 0.7529631823) + \beta_2 * (x^3 - 0.4268951521) + \varepsilon$	154.2	0.122
		Cereals	$y = \alpha + \beta_1 * (x^{0.5} - 0.8677345114) + \beta_2 * (x - 0.7529631823) + \varepsilon$	789.3	0.328
		Roots & tubers	$y = \alpha + \beta_1 * (x^{0.5} - 0.8677345114) + \beta_2 * (x^3 - 0.4268951521) + \varepsilon$	180.0	0.159
		Vegetables & fruits	$y = \alpha + \beta_1 * (\ln(x) + 0.2837389471) + \beta_2 * (x^{0.5} - 0.8677345114) + \varepsilon$	839.5	0.338

Table A4.1—continued

Estimation sample	N	Food group	Best-fit functional form	F	R^2
Northern Ghana, urban areas, GLSS5 (2005–06)	501	Total food	$y = \alpha + \beta_1 * (x^2 - 0.1919494076) + \beta_2 * (x^3 - 0.0840969343) + \varepsilon$	231.5	0.692
		Animal-source foods	$y = \alpha + \beta_1 * (x^2 - 0.1919494076) + \beta_2 * (x^3 - 0.0840969343) + \varepsilon$	95.62	0.533
		Pulses & nuts	$y = \alpha + \beta_1 * (x^2 - 0.1919494076) + \beta_2 * (x^2 * \ln(x) + 0.1584084986) + \varepsilon$	3.3	0.026
		Cereals	$y = \alpha + \beta_1 * (x^2 - 0.1919494076) + \beta_2 * (x^3 - 0.0840969343) + \varepsilon$	32.0	0.277
		Roots & tubers	$y = \alpha + \beta_1 * (x^{-2} - 5.209706102) + \beta_2 * (x^{0.5} - 0.6619065733) + \varepsilon$	89.51	0.224
		Vegetables & fruits	$y = \alpha + \beta_1 * (x^3 - 0.0840969343) + \beta_2 * (x^3 * \ln(x) + 0.0694019808) + \varepsilon$	14.97	0.180
Northern Ghana, urban areas, GLSS6 (2012–13)	1,450	Total food	$y = \alpha + \beta_1 * (x^{0.5} - 0.920233269) + \beta_2 * (x - 0.8468292693) + \varepsilon$	642.0	0.624
		Animal-source foods	$y = \alpha + \beta_1 * (x - 0.8468292693) + \beta_2 * (x^3 - 0.6072780459) + \varepsilon$	173.1	0.461
		Pulses & nuts	$y = \alpha + \beta_1 * (x^{-1} - 1.180875575) + \beta_2 * (x^{-1} * \ln(x) - 0.196327857) + \varepsilon$	42.7	0.029
		Cereals	$y = \alpha + \beta_1 * (x^{0.5} - 0.920233269) + \beta_2 * (x^{0.5} * \ln(x) + 0.1529944641) + \varepsilon$	155.8	0.252
		Roots & tubers	$y = \alpha + \beta_1 * (x^2 - 0.7171198114) + \beta_2 * (x^2 * \ln(x) + 0.1192255974) + \varepsilon$	13.47	0.074
		Vegetables & fruits	$y = \alpha + \beta_1 * (x^{0.5} - 0.920233269) + \beta_2 * (x^3 - 0.6072780459) + \varepsilon$	209.6	0.394
Northern Ghana, rural areas, GLSS5 (2005–06)	2,026	Total food	$y = \alpha + \beta_1 * (x - 0.2196034194) + \beta_2 * (x^2 - 0.0482256618) + \varepsilon$	1,956	0.866
		Animal-source foods	$y = \alpha + \beta_1 * (x - 0.2196034194) + \beta_2 * (x^3 - 0.01059052022) + \varepsilon$	258.2	0.389
		Pulses & nuts	$y = \alpha + \beta_1 * (x^3 - 0.0105905202) + \beta_2 * (x^3 * \ln(x) + 0.0160545085) + \varepsilon$	10.7	0.093
		Cereals	$y = \alpha + \beta_1 * (x - 0.2196034194) + \beta_2 * (x^3 - 0.01059052022) + \varepsilon$	119.4	0.269
		Roots & tubers	$y = \alpha + \beta_1 * (x^{0.5} - 0.4686186289) + \beta_2 * (x^3 - 0.0105905202) + \varepsilon$	142.2	0.256
		Vegetables & fruits	$y = \alpha + \beta_1 * (x^3 - 0.0105905202) + \beta_2 * (x^3 * \ln(x) + 0.0160545085) + \varepsilon$	45.29	0.321
Northern Ghana, rural areas, GLSS6 (2012–13)	4,257	Total food	$y = \alpha + \beta_1 * (x - 0.4552858374) + \beta_2 * (x^3 - 0.094374013) + \varepsilon$	2,150	0.764
		Animal-source foods	$y = \alpha + \beta_1 * (x^2 - 0.2072851937) + \beta_2 * (x^2 * \ln(x) + 0.1630981765) + \varepsilon$	323.3	0.387
		Pulses & nuts	$y = \alpha + \beta_1 * (x^2 - 0.2072851937) + \beta_2 * (x^2 * \ln(x) + 0.1630981765) + \varepsilon$	59.1	0.089
		Cereals	$y = \alpha + \beta_1 * (x - 0.4552858374) + \beta_2 * (x^3 - 0.094374013) + \varepsilon$	270.7	0.284
		Roots & tubers	$y = \alpha + \beta_1 * (x^{0.5} - 0.6747487217) + \beta_2 * (x^3 - 0.094374013) + \varepsilon$	157.8	0.161
		Vegetables & fruits	$y = \alpha + \beta_1 * (x - 0.4552858374) + \beta_2 * (x * \ln(x) + 0.3582324841) + \varepsilon$	327.0	0.245

Source: Authors' estimation based on GLSS5 and GLSS6 data.

Note: y = household food (group) consumption per adult equivalent per day; x = 0.1 * (household total consumption expenditure per adult equivalent per day).

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