A Consistent Food Demand Framework for International Food Security Assessment

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Abstract: We present a parsimonious demand modeling approach developed for the annual USDA-ERS *International Food Security Assessment*. The assessment focuses on chronic food insecurity. The approach incorporates price effects, food quality variation across income deciles, and consistent aggregation over income deciles and food qualities. The approach is based on a simple demand approach for four food categories. It relies on the existing sparse data available for the *Assessment*, complemented by own-price and income elasticities and available price data. Beyond consistent aggregation, the framework exhibits desirable characteristics: food quality is increasing with income; price and income responses become less sensitive with increasing income; and increasing income inequality decreases average per capita food consumption. The proposed approach is illustrated for Tanzania. We then use the calibrated model to decompose the impact of income, prices, and exchange rates on food consumption. Next, we assess future food insecurity in Tanzania using the calibrated model and two alternative characterizations of the income distribution (decile based and continuous). Food-insecure population is estimated as well as the implied distributional gap in calorie per day per food insecure person and in total annual food volume in grain equivalent. The latter gauges the depth of the chronic food insecurity.

Keywords: international food security, PIGLOG demand, aggregation, income inequality, food prices, shocks, food gap, Tanzania

JEL codes: F17, Q17, D31

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1. Introduction

Food security assessments are challenging (Barrett, 2002). This paper makes a methodology contribution to the literature on country-wide food security assessments (USDA-ERS, 2012, and 2013; and FAO-IFAD, 2014). These types of assessments are typically made under limited and partial information and data because they cover a large set of countries. More specifically, the paper proposes a systematic approach to introduce prices, food quality heterogeneity, and consistent aggregation over income-decile consumption into the economic model currently used by USDA's Economic Research Service in its annual *International Food Security Assessment* (USDA-ERS, 2013). The *Assessment* projects food consumption per decile for 76 low- and middle-income countries for the forthcoming decade and estimates chronic food insecurity and food gaps to reach food security. The proposed approach is designed to be feasible under the scarce information constraining these large food security assessments.

This paper derives a food demand system for four categories of foods covered by the *Assessment* and by income decile. The approach relies on the PIGLOG[1] demand approach in a basic formulation. This paper explains how to consistently aggregate decile food demands into average consumption per capita as a function of average income and a correction factor exhausting all the information on income distribution across population deciles. Many demand systems do not allow for an explicit link between average demand per capita and a distribution of food across deciles. For each food category, the proposed approach explicitly incorporates a measure of the decile income distribution and provides an aggregation of decile demands into a market average demand for that category which is function of average income corrected for income inequality across deciles, as explained below.

[1]PIGLOG stands for price independent generalized log-linearity. It is a class of demand systems that provide flexible structure with nonlinear income response and exact aggregation of individual demand into a representative consumer demand function of per capita income and, as shown later, the Theil index of income inequality.

Further, the approach allows for variable quality of food items, with quality increasing with increasing income. Various qualities of a given food category are aggregated into an average-quality equivalent that leaves country-level data unchanged, reflecting what happens in the real world. Wealthier consumers upgrade the quality of good they buy relative to poorer consumers. Prices faced by different deciles vary accordingly with quality. Lower-income deciles consume cheaper calories than higher-income deciles do. Within each good category, consumption of heterogeneous qualities can be aggregated over decile in "average-quality" equivalent units. Our characterization of the quality spectrum across deciles uses information from FAO-IFAD's *State of Food Insecurity* (*SoFI*) (see FAO-IFAD, 2014) to estimate the calorie availability of the poorest decile. The integration of these two flagship estimates of food security (USDA's *Assessment* and FAO-IFAD's *SoFI*) is desirable. It combines the predictive power of the food demand framework and *SoFI*'s rich information of the distribution of food availability.

Domestic and world markets are connected in the proposed approach but with significant transaction costs and trade impediments. Domestic and world prices are linked through synthetic transmission equations including tariffs, real exchange rates, transportation and other trade costs.

This paper further explains how to calibrate the demands using the limited information typically available for the annual *Assessment*. Namely, we use average per capita consumption, data on income and income projections, recent income distribution data, to which we add incomplete data on domestic prices, data on and projections of international prices by USDA to 2023, and sparse estimates of income and own-price elasticities available from USDA-ERS (Muhammad et al., 2011). Cross-price effects are ignored because of the scarcity of cross-price estimates. This paper focuses on Tanzania and the country's staple grain, corn. Detailed Excel files are available from the contact author. They present the detailed data and calibration of the

price transmission equations and the demand system and for the four food categories (corn, other grain aggregate, roots and tubers (R&T), and aggregate all other foods) and with projections for 2013–2023. The model presented here also makes use of information on estimated food consumption from the Tanzania USDA model used in the 2013 *Assessment* (see USDA-ERS, 2013).

Once the calibration completed, we derive estimates of food insecurity first using USDA's decile-based approach to income distribution and then using *SoFI*'s information on the distribution of food availability. The juxtaposition of these two approaches allows for validating the respective estimates of population at risk falling below some nutritional targets. In addition, we look at two food availability targets to provide a richer range of estimates (targets x income distribution approaches). We also derive estimates of food gaps, per person and national, to gauge the depth of food insecurity.

The remainder of the paper presents the consumer demand specification, followed by the aggregation to market demand, calibration, price transmission equations, quality scaling, and demand decomposition. Then the food security projections are presented with the estimates of population at risk and the associated food security gaps.

2. Specification of consumer demand

The motivation for using the PIGLOG specification (Muellbauer 1975; Lewbel 1989) is that it is a general specification well-grounded in micro-economic foundations that allows for nonlinear income response. It allows for an explicit aggregation of demand by the 10 deciles for each good category to an aggregate market demand function of the average per capita income corrected for income inequality, namely the Theil index of income inequality (Theil 1967) summarizing the

income distribution over deciles (Muellbauer 1975). Finally with proper calibration, the PIGLOG specification easily exhibits shares of food expenditure that are decreasing with real income. This feature is a stylized fact of food consumption levels determined by income levels. The expenditure shares per good category can be summed-up and demands per category can be aggregated into calories or grain calorie equivalent over categories. In a first step for presentation purposes, we assume quality constant, and then later in the paper, the variable quality and prices using a scaling approach are introduced.

The specification of the PIGLOG expenditure share on good category i, w_i, is

$$w_i = A_i(p_i / P) + B_i(p_i / P)\ln(x / P), \qquad (1)$$

with variable x being the nominal income of the consumer, and with nominal price p_i and price index P for all other goods, which can be approximated by a CPI. Functions A and B are homogenous degree zero in nominal prices p_i and P. We normalize P to 1 without any loss of generality and rewrite the share as $w_i = A_i(p_i) + B_i(p_i)\ln(x)$, with price and income variables being in real terms from now on.

Marshallian demand q_i is

$$q_i = (x / p_i)\left(A_i(p_i) + B_i(p_i)\ln(x)\right). \qquad (2)$$

We further specify $A_i(p_i)=a_{io} + a_{i1}\, p_i$, and $B_i(p_i)=b_{io}+b_{i1}\, p_i$. Other specifications are possible. This one is parsimonious and focuses on the own-price response. All other cross-price effects are subsumed in parameters a_{io} and b_{io}. When data and cross-price estimates are available, more elaborate responses can include cross-price effects in future refinements and elaborations.

The income elasticity of demand i is

$$\varepsilon_{q_i x} = 1 + (B_i(p_i) / w_i) = 1 + [(b_{io} + b_{i1} p_i) / w_i], \qquad (3)$$

which is decreasing in income if B_i is negative. Equation (3) accommodates normal or inferior goods and a range of elasticities over deciles as the share of expenditure w_i varies by decile.

The own-price elasticity is

$$\varepsilon_{q_i p_i} = -1 + (p_i / w_i)((b_{i1} \ln(x) + a_{i1}). \qquad (4)$$

Equation (4) also accommodates a range of elasticities by decile as income and share of expenditure vary by income decile. When calibrated appropriately, income elasticity (3) is decreasing with income. Similarly, the absolute value of price elasticity (4) can be calibrated to be decreasing with income. A free parameter in the calibration allows imposing such patterns as explained below in the calibration section (see Section 4).

3. Aggregating decile demands to the average aggregate demand for good *i*

The PIGLOG formulation allows for aggregation of decile-level demands for any good into the total market demand which can be expressed as an average per capita market demand which is as function of average income corrected by the Theil's entropy measure of income inequality among income classes (Muellbauer 1975) and which uses the same preference parameters as the demand of any individual decile. Here, we assume a distribution of income by population decile, which is the way USDA and many other agencies assess at-risk groups with respect to food insecurity (i.e., the lowest-income deciles being assessed).

Using superscript h to denote decile-specific variables with h=1,…,10, we have decile-level food demand as

$$q_i^h = (x^h / p_i)\left(A_i(p_i) + B_i(p_i)\ln(x^h)\right). \qquad (5)$$

Equation (5) leads to average per capita demand $\overline{q}_i$ by simple aggregation over deciles. The latter is a function of average per capita income $\overline{x}$ and Theil's entropy measure of income inequality z

measured on the decile income distribution:

$$\bar{q}_i = (\bar{x} / p_i)\Big(A_i(p_i) + B_i(p_i)(\ln(\bar{x}) + \ln(10/z))\Big), \qquad (6)$$

with

$$\ln(10/z) = \ln(10) + \sum_{h=1}^{10}(x^h / X)\ln(x^h / X), \text{ and with } X = \sum_{h=1}^{10} x^h = 10\bar{x}. \qquad (7)$$

Entropy measure *z* reaches its maximum at 10 when all deciles have similar income. In this case ln(10/*z*) equals zero. Any income inequality leads to (10/*z*) > 1. Given some inequality and a negative value for $B_i(p_i)$, it can be seen that income inequality decreases the level of average consumption per capita for the corresponding good category. As shown in (6), abstracting from income inequality will overstate average demand relative to the average demand implied by the individual decile demands.

With our chosen specifications of $A_i(p)$ and $B_i(p)$ as defined previously, we can further express average demand for good *i* as

$$\bar{q}_i = (\bar{x} / p_i)\Big((a_{io} + a_{i1}p_i) + (b_{io} + b_{i1}p_i)(\ln(\bar{x}) + \ln(10/z))\Big). \qquad (8)$$

We also define average expenditure share for good category *i* as

$$\bar{w}_i = \Big((a_{io} + a_{i1}p_i) + [(b_{io} + b_{i1}p_i)(\ln(\bar{x}) + \ln(10/z))]\Big). \qquad (9)$$

The elasticity of average demand for good *i* with respect to average income (or total expenditure) is $\varepsilon_{\bar{q}_i\bar{x}} = 1 + (B_i(p_i) / \bar{w}_i) = 1 + [(b_{io} + b_{i1}p_i) / \bar{w}_i]$. (10)

The own-price elasticity of the average demand is

$$\varepsilon_{\bar{q}_i p_i} = -1 + (p_i / \bar{w}_i)(b_{i1}(\ln(\bar{x}) + \ln(10/z)) + a_{i1}). \qquad (11)$$

All consumers in different deciles have similar underlying preferences over good *i* as embodied in parameters a_{io}, a_{i1}, b_{io}, b_{i1}, and their respective consumptions vary because their respective

incomes vary.

4. Calibration for good *i*

Data on average consumption, average income, price, and decile income distribution are available from the Food Security database maintained by USDA-ERS and which relies substantially on FAO data for the food availability. From the decile income distribution data, one can compute the Theil index (equation (7)). Using equations (9) through (11) for the average expenditure share and the two elasticities of average demand for good *i*, demand $\overline{q}_i$ can be calibrated. Then, individual decile demands q_i^h can be calibrated using the parameters recovered in the calibration of the average demand. The calibration uses the observed average expenditure shares of good *i*, an estimate of the two elasticities for the average demand, and a specified value of a free parameter as explained below.

With a system of three linear equations (equations (9)–(11)) with four unknown variables, one parameter remains free. The free parameter (chosen to be b_{io}) is used to insure that decile demands behave consistently with stylized facts of food security as follows. Price sensitivity and income responsiveness decline with income levels; own-price elasticities must be negative; and food expenditure shares tend to fall with increasing income. A range of values of the free parameters allows insuring these stylized facts are satisfied by the calibrated demand system. Here we illustrate by pinning down b_o such that the ratio of price elasticities for the bottom and top deciles is equal to the ratio of the natural logarithm of their income shares of GDP in the base year (see point 1 below).

For any given free parameter value, the system of equations is solved for parameters b_{i1}, a_{i1}, and a_{io} as a function of the free parameter. Once these three parameters are recovered, the

decile demands and their corresponding elasticities are computed based on the decile income levels and the aggregate elasticities. This step relies on the four parameters (one free parameter and three calibrated) and equation (2) with $A_i(p_i)=a_{io} + a_{i1}\, p_i$, and $B_i(p_i)=b_{io}+b_{i1}\, p_i$ for the demands and (3) and (4) for each decile elasticities.

The calibration is recursive. Four steps are involved:

1. We pin down b_o such that the ratio of calibrated price elasticities for the bottom and top deciles equal to the ratio of the natural logarithm of their national income shares in the base year. Else, there is range of values of b_o that satisfy the calibration. This ratio is 2.932 for Tanzania.

2. Parameter b_{i1} is then recovered from the income elasticity estimate $\hat{\varepsilon}_{q_i\bar{x}}$ and for a given value of $\hat{b}_{io}$, both denoted by hats, that is,

$$\hat{\varepsilon}_{q_i\bar{x}} = 1+(B_i(p_i)/\bar{w}_i) = 1+[(\hat{b}_{io}+b_{i1}p_i)/\bar{w}_i],$$

leading to

$$\tilde{b}_{i1} = [\bar{w}_i(\hat{\varepsilon}_{q_i\bar{x}}-1)-\hat{b}_{io}]/\,p_i.$$

Tildes denote calibrated values.

3. Next, the calibrated value of the a_{i1} parameter is recovered, given calibrated parameter $\tilde{b}_{i1}$, an estimate of the own-price elasticity of the aggregate average demand for good i $\hat{\varepsilon}_{q_ip_i}$, and the observed average income and Theil index z. The expression for the calibrated value of parameter a_{i1} is

$$\tilde{a}_{i1} = \bar{w}_i(\hat{\varepsilon}_{q_ip_i}+1)-\tilde{b}_{i1}(\ln(\bar{x})+\ln(10/z)).$$

4. The calibrated value of the last parameter a_{io} is recovered from the average share of expenditure (9),

$$\tilde{a}_{i0} = \bar{w}_i - \left(\tilde{a}_{i1} p_i + (\hat{b}_{i0} + \tilde{b}_{i1} p_i)(\ln(\bar{x}) + \ln(10/z))\right).$$

Parameters $\tilde{a}_{i0}, \tilde{a}_{i1}, \hat{b}_{i0}$, and $\tilde{b}_{i1}$, along with income x^h and price p_i are used to generate the consumption level of good *i* for each decile. Similarly, one can compute the associated decile-specific elasticities of demand with respect to income and price using equations (2)–(4). Again, in this initial calibration, the quality of any good *i* is assumed constant across deciles.

Step 4 completes the calibration and characterization of each decile's consumption of any given good *i*, and assuming that quality remains the same across all deciles. The four-step process illustrates the link between decile demand and aggregate market demand. It also demonstrates the correspondence between income and price responsiveness of the average and individual per-capita demands through aggregation over individual decile demands. In the context of the food security outlook, the same sequence of steps is undertaken for four categories of food in Tanzania (corn as the staple grain, other grains, R&T, and all-other-foods aggregate). An example of such calibration is provided in the Excel files previously mentioned along with the calibration for the four good types and the decile consumption in the base year of 2012. The four categories will be common to all potential countries included in the assessment; but the staple grain is country-specific, and the composition of "other grains," R&T, and "all other foods" will also be country specific but all expressed in gran equivalent.

Price index for aggregate category

Three of the goods (other grains, R&T, and aggregate all other foods) include several commodities. For goods with international and/or domestic price data available (i.e., grains), we use a weighted (by share of consumption) price index aggregating prices of various grains into a grain composite price index. For other products (R&T and all other foods), this approach does not appear sound, as nutritional content per unit of weight varies dramatically over goods (i.e.,

dairy, meat, oils, vegetables). Their aggregation is done on a grain-based equivalence.

For R&T, the international price of cassava is used as a representative world price and is linked to local prices of R&T such as yam or manioc from FAO GIEWS whenever available for 2012. All prices are in grain equivalent. The price of vegetable oil in grain equivalent is used as a representative price for "all other food." This is not ideal, but oil tends to be an important component of other foods in most countries and its international price is readily available. Other "representative" commodities could be used.

Synthetic price transmission equations are used to link the world and domestic prices expressed in grain equivalent. These are explained in detail in the next section. The transmission equation includes tariffs and transportation costs from world markets to the domestic market as well as the effect of the real exchange rate. They also assume a less than perfect transmission between world and domestic prices.

Aggregation over the four types of goods

Next, the aggregation of the four food types is considered to derive a calorie or grain equivalent to the estimated demands. The aggregation is feasible because the four food categories are expressed in calorie-equivalent as done in FAO's food balance sheets and can be easily expressed in grain-equivalent (or any food item equivalence) from calorie-equivalent. Each food category is characterized by a grain or calorie energy intake per unit of consumption. Naturally, the 4 demands can be aggregated to a total grain or calorie equivalent, which in turn responds to price and income via the economics underlying each of the four food demand components (major grain, other grains, R&T, and all other foods). Table 2 shows the calibration for corn per decile for Tanzania.

5. Price transmission equations

Following the work of Mundlak and Larson (1992), Campa and Goldberg (2005) and others, the price transmission equation links the local real consumer price of good *i* to the corresponding world market price and embodies the influence of world prices, international transportation, exchange rates, trade policy, and other transaction costs arising from bringing commodities to local markets. Each real consumer price for any tradable importable commodity *i* is linked to the corresponding world market price as follows:

$$p_i = (\theta ER\ (wp_i(1+trc_{\text{int}}/\theta)(1+tariff/\theta)+trc_{\text{dom}})/P, \qquad (12)$$

where θ is the slope indicating the strength of transmission between the world price and the domestic price, *ER* is the nominal exchange rate in local currency units per U.S. dollar, wp_i is the FOB price of commodity *i*, *trc* denotes trade and transportation costs in the international market (*int* subscript) in ad valorem form and in the domestic market of the importing country in specific form (*dom* subscript); *tariff* denotes the sum of all specific and ad valorem tariffs imposed on the good and expressed in ad valorem form, and where *P* is the CPI deflator (or GDP deflator) in the importing country as defined previously. Trade and transportation costs can be commodity specific. In a world of perfect transmission, θ is equal to 1.

Note that (12) can equivalently by expressed with world price *wp* expressed as a real world price *rwp* (real constant US dollars/mt), real exchange rate *RER* (real local currency units (LCU) per real US dollar), and real trade costs *rtrc* other than tariffs and international transportation cost in real LCUs, and then not further deflating by the local CPI deflator *P*. This step yields:

$$p_i = (\theta RER\ (rwp_i(1+trc_{\text{int}}/\theta)(1+tariff/\theta))+rtrc_{\text{dom}}). \qquad (12')$$

Other specifications than (12) or (12') are possible, especially if econometric estimates of price

transmissions are available. An intercept can be added, or a slope coefficient to (12) to reflect the econometric estimates of a regression of the type (p = a + b wp). The additive form of (12) and (12') provides a price-transmission elasticity (dln$p$/dlnrwp), which is less than one by construction as long as some additive tariff or trade costs are present and can be further lowered by setting the slope parameter θ to a value smaller than 1.For example in the Tanzania illustration we assume a slope θ of 0.7.

For the implementation of the price transmission equation, there are two cases: (*a*) both domestic and international prices are available, and an intercept (which subsumes all trade costs between world and domestic markets) can be derived to link the two prices expressed in similar real LCUs; or (*b*) only the international price is available and a synthetic domestic price is estimated using the price transmission described in (12). To compute (12), tariffs are obtained from the WTO website (WITS and/or Macmap databases are also alternatives); the CPI deflator *P* is available from the USDA-ERS macro database; FOB/CIF ratios are estimated at 1.10 in ad valorem form for importable goods and not accounted for in the case of exportable. Similarly tariffs are not included for exportables since the price signal at the margin is in the export market. Domestic trade costs are assumed to be $20 per metric ton of grain equivalent (2005 real prices). World price data are obtained from USDA's world outlook which allows making 10-year projections. These transmission equations are shown in table 1 with the implied intercept between world and domestic price expressed in similar real LCUs. See the Excel files for further details.

6. Quality scaling

Consistent with real-world observation, it is assumed that the quality of good *i* increases with

income and that its price is also increasing with quality. Therefore, low-income consumers consume cheaper quality purchased at a lower price and vise-versa for higher income consumers. We posit that quality is represented by a scaling factor $\mu(x)$ which, when normalized appropriately over all deciles, is equal to 1. The scaling factor scales quality and prices down such that the product of quality-adjusted quantity consumed and prices remain constant (quantity adjusted for quality and price move in opposite directions such that the estimated expenditure share is invariant to quality. The quality-scaling approach can be rationalized using the framework of Cox and Wohlgenant (1986) of hedonic prices in which households in different income deciles chose quality as part of their utility maximization problem. We do not attempt to model this hedonic choice explicitly here, however.

Using equation (2) and a definition of the scaling factor μ we have a quantity consumed with variable quality for any good i and decile h

$$q^h_{i\,adj} = q^h_i / \mu^h_i = (x^h / \mu^h_i p_i)\left(A_i(p_i) + B_i(p_i)\ln(x^h)\right), \qquad (13)$$

with

$$\mu^h_i > 0 \ \forall h, \text{ and } \sum_{h=1}^{10}(q^h_i / \mu^h_i)/10 = \overline{q}_i. \qquad (14)$$

Low-income deciles consume goods of cheaper quality in greater abundance ($q^h_{iadj} \geq q^h_i$ with μ^h smaller than unity) and richer consumers do the opposite by consuming higher quality goods in smaller amount once expressed in quality-adjusted units ($q^h_{iadj} \leq q^h_i$ with μ^h larger than unity).

The scaling is calibrated such that on average over deciles, the mean of the variable-quality consumption levels is equal to the mean consumption per capita holding quality constant as expressed by equation (14). Expenditures are invariant to scaling since the price and quantity are inversely scaled and offset each other. One can think of consumption in average-quality

equivalent (in equation (2) or in variable-quality units in equation (13)). To compute calorie availability, equation (13) is used. To calibrate the demand system, equation (2) is used and then we impose the scaling on top of the original demand calibration. To do so, a reference consumption level is established in variable-quality units for the first (lowest) decile, which is represented by $q^1_{iadj\min}$ in equation (15) below.

The scaling parameter μ for good *i* and decile *h* is derived using the adjusted consumption level as follows:

$$q^h_{iadj} = (\alpha + \beta q^h_i), \text{ or}$$

$$\mu^h_i = q^h_i / (\alpha + \beta q^h_i), \qquad (15)$$

with

$$\beta = (\overline{q}_i - q^1_{iadj\min}) / (\overline{q}_i - q^1_i) \text{ and } \alpha = q^1_{iadj\min} - \beta q^1_i.$$

For the Tanzanian model illustration we use the 1st decile per capita availability implied by FAO-IFAD's *State of Food Insecurity* (*SoFI*) in 2014 and updated data on food availability as explained in the paper appendix. This availability for the 1st decile is 138.1 kg of grain equivalent (rounded) per year in Tanzania, or equivalently 1239 calories per day. Each of the four goods contributes proportionally to the first decile's reference consumption level and each is scaled up to sum up to the aggregate reference consumption level. The constraint of having the mean quality equal to 1 over all deciles provides a second equation to establish how quality evolves over deciles in any given year. The demand-weighted-average scaling factor is equal to 1, such that the scaling does not "create" consumption in the aggregation over decile. The sum of all consumption over deciles with variable quality sums up to the same food volume estimated assuming constant average quality.

Over time, this minimum consumption in adjusted units is allowed to grow slowly

following the projected distribution of food availability in the country as explained in the appendix. To illustrate with Tanzania, quality increases are included by first scaling up each consumption for the four categories to achieve a minimum aggregate calorie intake of 1,239 calories per day for the lowest decile in the base year. We derive a proportional minimum consumption and scaling schedule for each of the 4 food types (corn, other grains, R&T, all other foods) so that aggregation holds through to reach 138.1kg/year. The quality scaling for corn is shown per decile in Table 2 (see column labelled "quality scale") for the base year.

The quality scaling structure in the base year is illustrated in the Figure 1 for the four goods included in the Tanzanian model. The figure shows how the scaling evolves as income changes, moving across deciles in any given year.

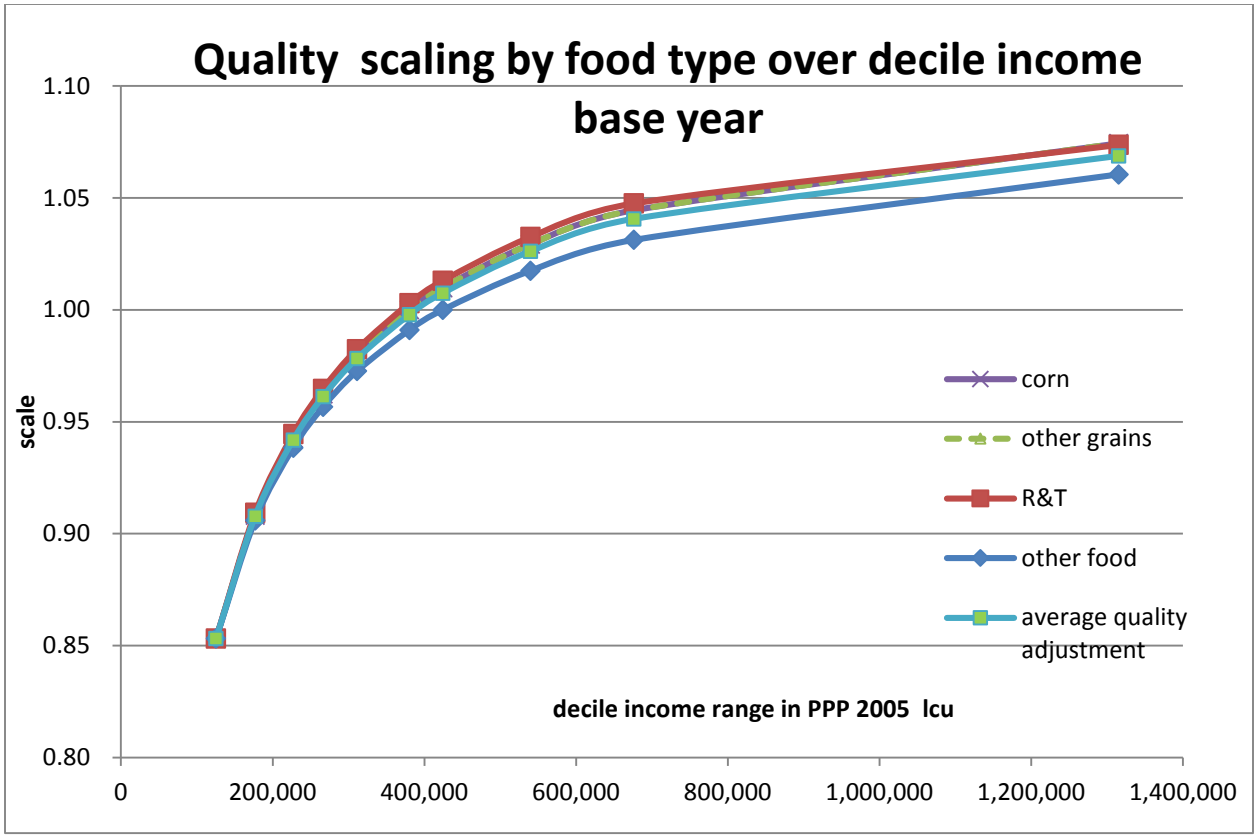

Figure 1

Over time as income increases, the lowest decile's consumption grows with income. We let quality increase as well (the scaling factor slowly increases, but remains below 1 for the lowest income groups), which translates into a net increase in the lowest-decile consumption when quality is accounted for. Conversely, for deciles starting with above-average quality (scaling factors larger than 1 in the base year), as income progresses, quality adjustments relative to the mean quality eventually decrease and even cease if the non-adjusted availability of the good for the 1st decile is at least as large as the minimum implied by the variable-quality approach. The range of quality differences across deciles shrinks over time as average income increases. This feature is a consequence of imposing the demand-weighted average quality equal to 1 in all years. There is some intuition to this feature—quality dispersion decreases when everyone's income rises.

As the population average of food availability increases in the projected period, the availability of calories also increases for the bottom decile. We then use this projected bottom decile availability to calibrate quality as explained in previous paragraphs and we do so for every year from 2012 to 2023.

Figure 2 illustrates this change over time in scaling for the 1st decile in the Tanzanian model and for the quality adjustment averaged over the 4 food types.

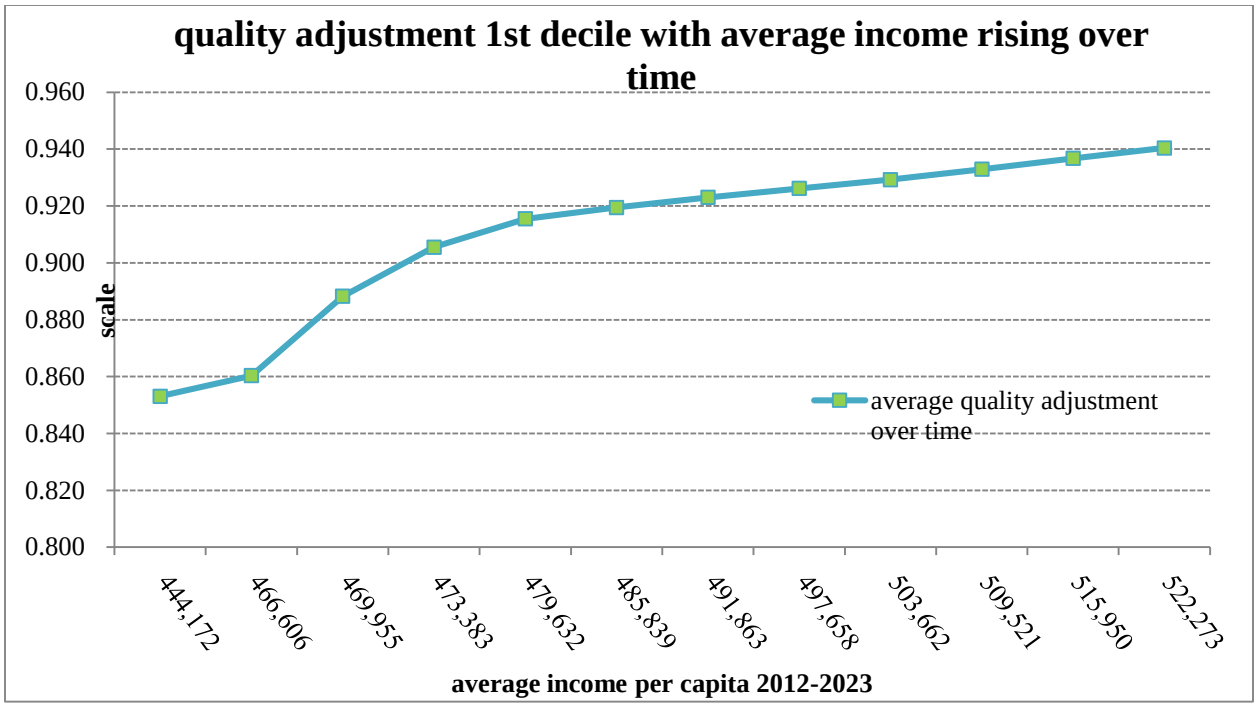

Figure 2.

7. Decomposition of projected demand by its determinants

In this section, a decomposition of the projected growth of demand is illustrated from 2012 to 2023 induced by changes in its determinants. Total demand growth is decomposed into per capita demand growth and population growth. Then, per capita demand growth is further decomposed in terms of the income response and the price response, which itself is decomposed into a real world price response and real exchange rate response. The growth of projected total demand is then approximated by linearization as in Dong, (2006), Heien and Wessells (1988), and Shui et al. (1993). The decomposition for infinitesimal changes is

$$d\ln(totQ_i(pop, rwp, RER, \bar{x})) = d\ln(pop) + d\ln(\bar{q}_i)) = d\ln(pop) + \varepsilon_{q_i p_i}\varepsilon_{p_i rwp_i}(d\ln(rwp) + d\ln(RER)) + \varepsilon_{q_i \bar{x}} d\ln(\bar{x}),$$

discretely approximated by

$$\frac{\Delta totQ_i}{totQ_i} \approx \left(\frac{\Delta pop}{pop} + 1\right)\left(1 + \varepsilon_{q_i p_i}\varepsilon_{p_i rwp_i}\left(\frac{\Delta rwp}{rwp} + \frac{\Delta RER}{RER} + \frac{\Delta rwp}{rwp}\frac{\Delta RER}{RER}\right) + \varepsilon_{q_i \bar{x}}\frac{\Delta \bar{x}}{\bar{x}}\right) - 1, \qquad (17)$$

with $totQ_i$ denoting total food demand for commodity i, pop denoting population of the country,

and with $\varepsilon_{p_i rwp_i}$ being the price transmission elasticity. The growth rates ($\Delta x/x$)) are taken from 2012 to 2023. Note that second equation in (17) is an approximation since the elasticities are endogenous and vary with price, quantities, and income. The price transmission elasticity for corn in Tanzania is 0.549 evaluated in 2012 prices. We compute the effects as follows. For the domestic price effect on per capita demand, we look at $\left(\frac{\bar{q}(p_{2023},\bar{x}_{2012})}{\bar{q}(p_{2012},\bar{x}_{2012})}-1\right)$ with real domestic price *p(rwp, RER*) defined as in equation (12'). This effect is then allocated proportionally to the relative changes in the *RER* and *rwp* between 2012 and 2023. For the income effect on per capita demand, we look at $\left(\frac{\bar{q}(p_{2012},\bar{x}_{2023})}{\bar{q}(p_{2012},\bar{x}_{2012})}-1\right)$.The sum of the two effects (domestic price and income) are then summed up to approximate the relative change in per capita demand induced by the price, exchange rate, and income changes.

The decomposition is shown in Table 3. Based on the calibrated demands, total food demand for corn in Tanzania national demand for corn/maize is projected to increase by nearly 76% in the projected decade given the trajectory of projected real income per capita (+18%), real world price for corn (-49%) real exchange rate (-22%), and population (+35%). Per capita demand is projected to grow by 30% based on the calibrated demand per capita (equation (8)). The interaction of population growth and that of per capita demand is responsible for 11% growth of total demand (76% = 35% + 30% + 11%). Again, the latter figures are obtained using the calibrated demand.

The decomposition of the demand growth per capita shows that the change in the real world price after being scaled by the own-price elasticity and the price transmission elasticity is the most important contributor to per capita demand growth (14% growth of per capita demand). The real appreciation of the Tanzanian currency, after proper scaling by elasticities, leads to 6% of per capita demand growth. Finally, income growth contributes 9% growth of per capita

demand. The approximation of per capita demand growth is not perfect, of course, and misses a bit less than 1% of projected growth of per capita demand. The unaccounted change come from interaction between price and income changes and from the linear approximation implied in equation (16). The latter shortfall is slightly accentuated in the total demand projection, which is about 2.56% of growth short of the projected change (75.88% versus 73.39%). Similar decompositions could be computed by decile for which an additional factor could be added, that is, the quality scaling and its evolution over time. Since the quality scaling is normalized to 1 for aggregate demand in every year, the growth of total food demand is invariant to quality scaling.

8. Food security assessment

8.1. Indicators

Two food insecurity indicators are estimated for the current year as well as ten years out: the number of food insecure people and the distribution gap, explained below. The main focus and contribution of the *Assessment* model is its projection of food demand by income group, as described in detail in the preceding sections of this paper. This focus on individual income groups allows for the analysis of the access dimension of food security, which looks at the question of whether households have sufficient purchasing power to buy the food they need. For this purpose, we use the decile food demands, subject to income constraints and responding to price signals for the 10 income groups. This decile food demand is then compared with a nutritional target to determine whether a given income group would be considered food secure.

We use two nutritional targets, based on a daily caloric intake standard of 1800 and 2,100 calories per capita per day. The caloric target is converted into grain equivalent quantities using conversions which are similar to those used in the construction of the food availability data.

USDA has used the 2,100-daily calorie target (234 kg of grain equivalent per year for Tanzania). The 1,800-calorie target represents an alternative for sedentary people. There is no universal standard for food security but these two targets are plausible and provide a range.

We use two approaches to the distribution of income, one based on the decile distribution of income, the other based on a recovered lognormal distribution of food intake from *SoFI*. Using the decile approach, if the estimated decile food demand falls below the target level, the entire income group (decile) is counted as food insecure. Aggregating the people in these food-deficit income groups provides one of our food insecurity indicators—the number of chronically food-insecure people. Still under this decile approach and to provide an indication of the depth of food insecurity, we look at food gaps between the estimated food consumption level of food insecure groups and the target level. This gap can be expressed on a per capita basis in daily calories. The objective is to allow each income decile to reach the nutritional target. If food demand based on incomes and prices in a given income decile is lower than this target, that difference is part of the gap for this country. The gaps for all income deciles are added up to determine the gap for a given country in volume of grain equivalent in 1000 metric tons. The latter gap measure can be expressed as the total amount of food required to allow each income decile to reach the nutritional target (1800 or 2100 calories/day).

For the second approach to the distribution of income, we rely on *SoFI* data to estimate the distribution of calorie availability which is a monotonic transformation of the income distribution. *SoFI* provides information on the distribution of food intake for 170 countries. It indicates the shape of the distribution (lognormal, normal) and provides the mean caloric intake and the coefficient of coefficient of variation of the calorie availability. The coefficient of variation is based on income variation estimated from surveys. We use this information, slighted

updated, to characterize consumption as distributed with a mean *m* and variance *v*. We explain this in details the attached appendix. The coefficient of variation (*CV*) of food availability for each country is $CV=\left(\frac{\sqrt{v}}{m}\right)$, where *v* is the variance of the empirical distribution which can recovered given the mean and the *CV* as indicated in the appendix for the base year. Assuming food availability q_{cal} is distributed lognormal, then $\ln(q_{cal})$ is distributed $N(\mu,\sigma^2)$ with $\mu = \ln(m^2/\sqrt{v+m^2})$ and $\sigma^2 = \ln(1+(v/m^2))$. Once μ, and σ^2 are computed, we can recover the proportion of the population that falls below the calorie target (1800 in the next equation) using the equation

$$\Phi^{insecure} = \Phi((\ln(1800-\mu)/\sigma) = \int_{-\infty}^{(\ln(1800)-\mu)/\sigma} 1/\sqrt{2\pi}e^{(\ln(1800)-\mu)^2/2\sigma^2)}\,\mathrm{d}\,q_{cal}. \quad (18)$$

A similar equation holds for 2100 calories. Function Φ indicates the CDF of the standard normal distribution, and $\Phi^{insecure}$ indicates the proportion of the population that is food insecure. Next the average food intake of food insecure people, $q_{cal\ average}^{food\ insecure}$, can be recovered using the partial mean of the calorie availability below the target (1800 here in the equation), which is obtained using

$$E\left(\ln(q_{cal}^{food\ insecure}) \mid \ln(q_{cal}) < \ln(1800)\right) = \mu - \sigma[\phi((\ln(1800)-\mu)/\sigma)/\Phi((\ln(1800)-\mu)/\sigma)], \quad (19)$$

and leading to

$$q_{cal\ average}^{food\ insecure} = e^{\mu-\sigma/\Phi^{1800}[\phi((\ln(1800)-\mu)/\sigma)]} \quad (19'),$$

where ϕ is the standard normal density function. The food gap can be computed by looking at the difference between the target and the average calorie availability for food insecure consumers. This provides a gap in calories per day per insecure person. The latter can be

multiplied by the population at risk and converted in grain equivalent per year to yield a gap indicator based on annual grain volume as under the decile-approach.

Note that with this second approach to the distribution of income, the mean caloric availability for the country increases over time. If the *CV* is maintained constant, then the Theil index for that distribution is assumed constant as in the *Assessment.* Both mean and standard deviation are growing at the same growth rate to keep the income ratios (decile income/average income) constant in the Theil index. However, here we are dealing with the Theil index of calorie availability which is slightly different than the Theil index of income, given that income elasticities decrease as income increases across deciles. We abstract from this possibility here.

8.2. Assessment

The assessment of food security is shown in Tables 4 and 5. Table 4 presents the projected population at risk for the 2 targets (1800 and 22100 calories/day) and the two approaches to income distribution and for projections over the decade (2012, 2013, 2018, and 2023)). Table 5 shows the implied projected food gaps for similar years.

In the decile method, if an estimated decile food demand falls below the target, the entire income decile is counted as food insecure. Aggregating the people in these food-deficit income deciles provides the number of food-insecure people. Hence, the variation in food-insecure population changes by 10%-increments when population deciles come in or out of food insecurity. The method is informally illustrated in Figure 3. All deciles falling below the red line of 234 kg (2100 calories/day) are deemed food-insecure. One can also gauge the food gap between the target and consumption level by decile from the figure. The gap provides an indication of the depth of the insecurity.

Both approaches concur that population in the first decile will remain food insecure even under the low threshold of 1,800 calories. Under the more stringent criterion of 2,100 calories, people in the two bottom deciles will remain food insecure in 2023. In those later years, the decile approach overstates the share of population (20%) that is food insecure compared to the distribution-based estimate of 13%.

Table 5 shows that the 180 calorie target is more modest and provides a calorie gap that are smaller than under the more stringent calorie target of 2100 calories. It also shows that the lognormal approach tends to projects less pronounced decreases in the calorie gap per insecure person over time, as compared to the decile-approach. Both approached provide comparable estimates of annual good gaps ingrain equivalent of about 1 million metric tons in the base year with the 2100-calorie target and roughly half of that volume with the 1800-calorie target. The annual grain gaps fall by more than two thirds by 2023 to around 300 thousand tons per year with the high target, and by more than three quarters to roughly 100 thousand ton with the 1800-calorie target. The rapid decrease is caused by the projected income growth and increase in average food availability over time.

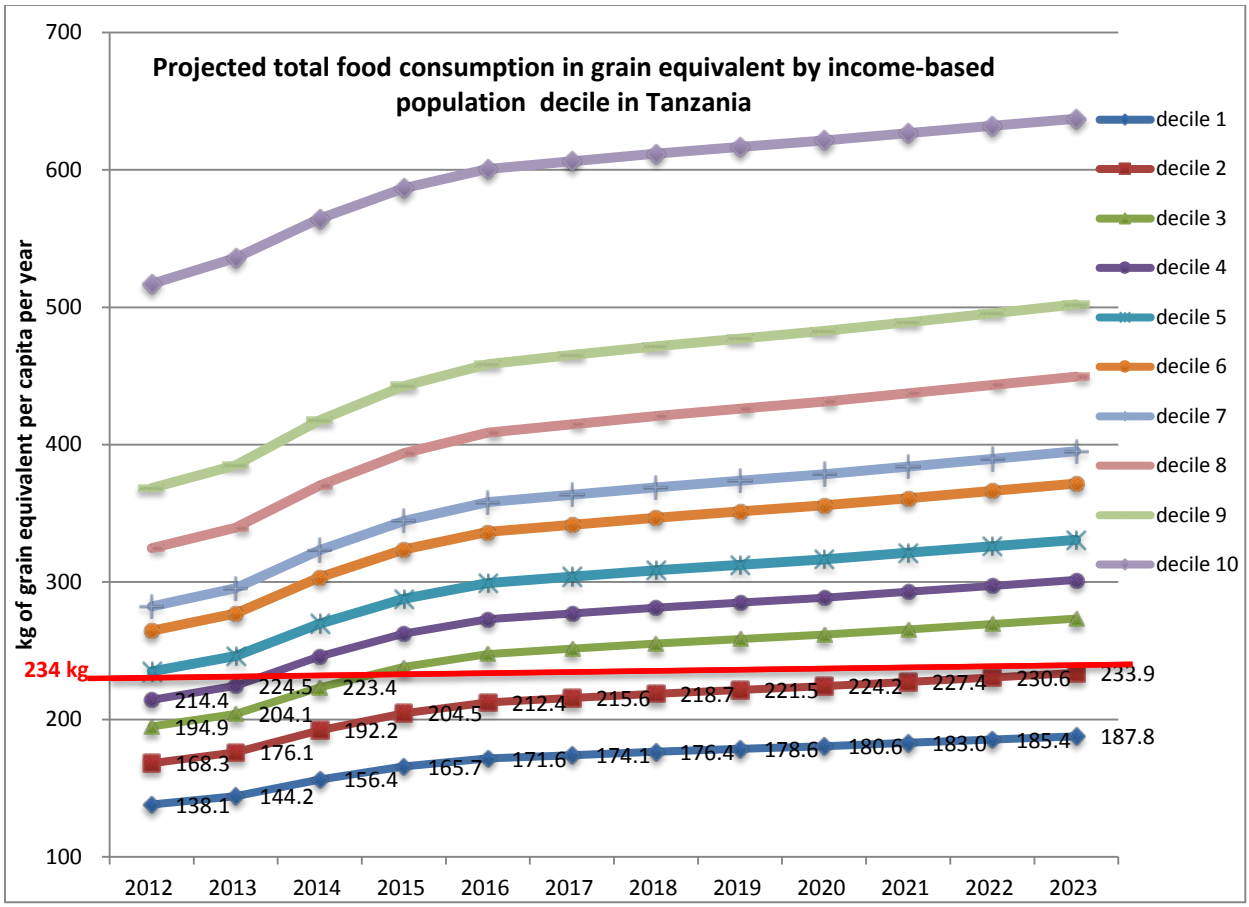

Figure 3. **Redline at 234 kg indicates the cutoff for food insecurity of 2100 calories/day**

9. Summary and concluding remarks

This paper presented a parsimonious modeling approach to incorporate price effects, quality variation, and consistent aggregation over income classes and food qualities in a food demand system. The approach can be used to assess calorie intake per decile, to investigate income, price, and exchange rate shocks, and could be applied to improve USDA's *International Food Security Assessment* model.

The approach is based on a simple PIGLOG demand approach for four food categories (major grains, other grains, R&T, and an aggregate all other food). The approach relies on the existing sparse data available for these assessments, which is a desirable feature. The proposed

approach was illustrated for Tanzania. The calibration was then used to decompose the impact of changes in population, income, world price, and real exchange rate on food demand over the 2012–2023 projection period. Finally, we projected the population that would be food insecure and the associated food gaps.

The methodology provides estimates of chronic food insecurity, but it could also be used to analyze the consequences of shocks in income, world prices and exchange rates on food security such as those that have occurred in the last decade. As proposed in this paper, the combination of USDA's *Assessment* with *SoFI* information on the distribution of food availability provides an outlook of food security anchored in the most up-to-date information of *SoFI* and which incorporates food demand responses to projected populations income and price changes to project future food insecurity.

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Table 1. Price transmissions in Tanzania and supporting data used for 2012

Price transmission in Tanzania (prices are per metric ton)							
		exportable/importable	**observed or synthetic**	**Domestic price in Real LCU in grain equivalent**	**International price in Real LCU in grain equivalent**	**International price location from USDA Commodity Outlook**	**Implied intercept (DP-θWP)**
Major grain (maize)	Maize/corn	importable	obs	2864045	224806	USDA	129040
All other grains	Rice	importable	obs	938911	465782	USDA Thailand	612864
	Wheat	importable	syn	287,338	236094	USA hard red winter USDA	122072
	Sorghum	importable	syn	218,461	214927	USA sorghum USDA	68013
	Millet	exportable	syn	166,265	214927	US sorghum USDA	15816
	Barley	importable	syn	247,308	213216	USDA Rouen barley price	98057
grain index price				555,363	331955	computed	322995
R&T	Cassava	importable	syn	1,316,778	1198254	USDA: Internat. cassava	478000
Other food	soy oil	importable	syn	342,712	357543	USDA: Soy oil	92432

RER	929.70
CPI us	117.56
CPI Tanzania	197.07
CIF/FOB	10%
Taxes: AHS wheat	0.31
Taxes: AHS Sorghum	0.13
Taxes: AHS Millet	0.25
Taxes: AHS Barley	0.25
Taxes: AHS Maize	0.33
Taxes: AHS Rice	0.29
Taxes: Soy oil	0.1
Taxes: Cassava	0.25
Slope of transmission θ	0.7

Table 2. Demand calibration and quality adjustment per income decile for corn demand in Tanzania

Data and parameters used to calibrate the PIGLOG demand 2012 base year	value	unit
average income data	444171.9	real lcu/ capita
average corn quantity consumed (data)	74.580	kg/capita
aggregate income elasticity (data)	0.563	unitless
aggregate price elasticity (data)	-0.413	unitless
consumer price major grain (data)	286.4048	real lcu/kg
Thiel index (ln(10/z)) computed from decile data	0.229018	unitless
average expenditure share (data)	0.04809	unitless
bo free parameter (set freely)	-0.01648207	
b1 (computed)	-0.00001583	
a1 (computed)	0.00030801	
ao (computed)	0.23796806	

decile	income shares by decile in %(data)	calibrated decile average demands kg per capita	computed decile income elasticities	computed decile price elasticities	computed decile expenditure share	implied daily calories from maize	quality scale	annual consumpt. corrected for quality	daily calorie adjusted for quality
1	2.82	34.77	0.74	-0.56	0.080	311.98	0.85	40.76	365.77
2	3.98	44.60	0.71	-0.54	0.072	400.22	0.91	49.11	440.74
3	5.11	53.11	0.69	-0.52	0.067	476.54	0.94	56.34	505.59
4	6.00	59.21	0.67	-0.50	0.064	531.28	0.96	61.52	552.10
5	7.00	65.58	0.65	-0.49	0.060	588.43	0.98	66.93	600.66
6	8.56	74.56	0.63	-0.47	0.056	668.97	1.00	74.56	669.10
7	9.55	79.78	0.61	-0.45	0.054	715.79	1.01	78.99	708.88
8	12.15	91.98	0.57	-0.42	0.049	825.31	1.03	89.36	801.94
9	15.22	104.04	0.52	-0.38	0.044	933.48	1.04	99.61	893.85
10	29.61	138.18	0.30	-0.19	0.030	1239.80	1.07	128.61	1154.13

Table 3. Decomposition of projected corn demand in Tanzania

Decomposition of projected total demand in terms of growth of population, income per capita, world price, and real exchange rate between 2012 and 2023			
Variable	**2012-2023 projected rate of change**	**Approximated effect on demand in %**	**Explanation**
Population (1)	35.27%	35.27% (total demand)	population shift, holding per capita demand constant.
Real PPP income (2)	17.58%	9.26% (per capita demand)	income shift of per capita demand using arc elasticity of income, other things constant
Real world price (real US $) (3)	-48.73%	13.99% (per capita demand)	price response of per capita demand to world price change
Real exchange rate (3) (the cost of a real $)	-22.29%	6.40% (per capita demand	price response of per capita demand to change in real exchange rate
Projected per capita demand (5) as per calibration	30.02%	29.65% (per capita demand)	sum of income, world price, exchange rate effects on per capita demand. Linearized approximation
Projected total national demand (6) as per calibration and projection	75.88%	75.39%	combined estimated per capita and population effects (sum + product of relative changes). Note the approximation misses 0.49% of the projected change (75.88% versus 75.39%)

Table 4. Projected food insecure population in Tanzania. (Estimated with 2 food security targets and 2 methods)

Year	Food insecure population 1800 calorie target Lognormal approach	Percent of population falling below 1800 calorie/day Lognormal approach	Food insecure population 1800 calorie target USDA decile approach	Percent of population food insecure 1800 calorie/day USDA decile approach	Food insecure population 2100 calorie target Lognormal approach	Percent of population falling below 2100 calorie/day Lognormal approach	Food insecure population 2100 calorie target USDA decile approach	Percent of population food insecure 2100 calorie/day USDA decile approach
2012	11,571,381	24.67%	14,073,830	30%	18,944,397	40.38%	18,765,107	40%
2013	10,088,020	20.90%	9,652,388	20%	17,198,274	35.64%	19,304,777	40%
2018	4,581,702	8.26%	5,545,134	10%	9,541,100	17.21%	11,090,269	20%
2023	3,718,825	5.86%	6,346,112	10%	8,267,888	13.03%	12,692,225	20%

Table 5. Food gap in calorie/day per insecure person and total annual food gap in grain equivalent (1000 metric tons)

1800-calorie target

Year	Average per capita daily calorie intake (projected for the whole population)	Food gap in calorie/day per insecure person lognormal approach	Total annual food gap in 1000 mt of grain equivalent lognormal approach	Food gap in calorie/day per insecure person decile approach	Total annual food gap in 1000 mt of grain equivalent decile approach
2012	2430	337.1	435	300.6	471.4
2013	2538	322.3	362	362.9	390.4
2018	3105	264.9	135	216.8	133.9
2023	3306	250.3	104	114.7	81.1

2100-calorie target

Year	Average per capita daily calorie intake (projected for the whole population)	Food gap in calorie/day per insecure person lognormal approach	Total annual food gap in 1000 mt of grain equivalent lognormal approach	Food gap in calorie/day per insecure person decile approach	Total annual food gap in 1000 mt of grain equivalent target decile approach
2012	2430	464.2	980.0	494.5	1034.0
2013	2538	442.5	848.1	419.8	903.1
2018	3105	358.4	381.2	327.1	404.2
2023	3306	337.1	310.7	208.0	294.2

Appendix. Estimating the average caloric intake for the first decile using *SoFI*

We rely on *SoFI* data to estimate the caloric intake of the bottom decile and then the food insecure population and food gaps. The caloric intake estimate for the 1s decile is then used to calibrate the 4 consumption levels for that decile and the quality adjustment for the 4 food items. *SoFI* indicates the shape of the distribution (lognormal, normal) and provides the mean caloric intake and the coefficient of variation of the caloric intake. This information, somewhat updated allows us to characterize consumption as distributed (m, v). Mean caloric availability m is given in *SoFI* but it relies on slightly older data on food availability. We obtain the most recent availability data from FAO and use those as the mean caloric availability. *SoFI* also provides the coefficient of variation of food availability for each country ($CV=(\sqrt{v}/m)$), where v is the variance of the empirical distribution which can recovered given the mean and the CV as indicated in the appendix table below for 2012 the base year. Assuming food availability q_{cal} is distributed lognormal, then $\ln(q_{cal})$ is distributed $N(\mu,\sigma^2)$ with $\mu = \ln(m^2/\sqrt{v+m^2})$ and $\sigma^2 = \ln(1+(v/m^2))$. (A.1)

Once μ, and σ^2 are computed as shown in the appendix table, we can recover the upper bound of the bottom decile's consumption (in calories) for which the probability mass is 0.1. That is, $q^1_{cal\ upb} = e^{(\mu+\Phi^{-1}(0.1)\sigma)}$, where $q^1_{cal\ upb}$ indicates the upper-bound consumption level (in calories) for the 1st decile, Φ indicates the CDF of the standard normal distribution and Φ^{-1} is the inverse function of that CDF used to recover the caloric level equal to the upper bound of the nutrition interval corresponding to a probability mass of 0.1 (10% of the population of the bottom decile).

These values are shown in the appendix table as well (see 2012 year). Once this upper-bound level of calories is recovered, one can compute the mean availability of calories for the 1st

decile going from (0, to $q^1_{cal\ upb}$), that is, in terms of logarithms, the interval (-∞, ln($q^1_{cal\ upb}$)) .

This partial mean of the calorie availability in the 1st decile, $q^1_{cal\ average}$, is

$$E\left(\ln(q^1_{cal}) \mid \ln(q^1_{cal}) < \ln(q^1_{cal\ upb})\right) = \mu - \sigma[\phi((\ln(q^1_{cal\ upb}) - \mu)/\sigma) / \Phi((\ln(q^1_{cal\ upb}) - \mu)/\sigma)] \quad \text{(A.2)},$$

or

$$q^1_{cal\ average} = e^{\mu - \sigma/0.1[\phi((\ln(q^1_{cal\ upb}) - \mu)/\sigma)]} \quad \text{(A.3)},$$

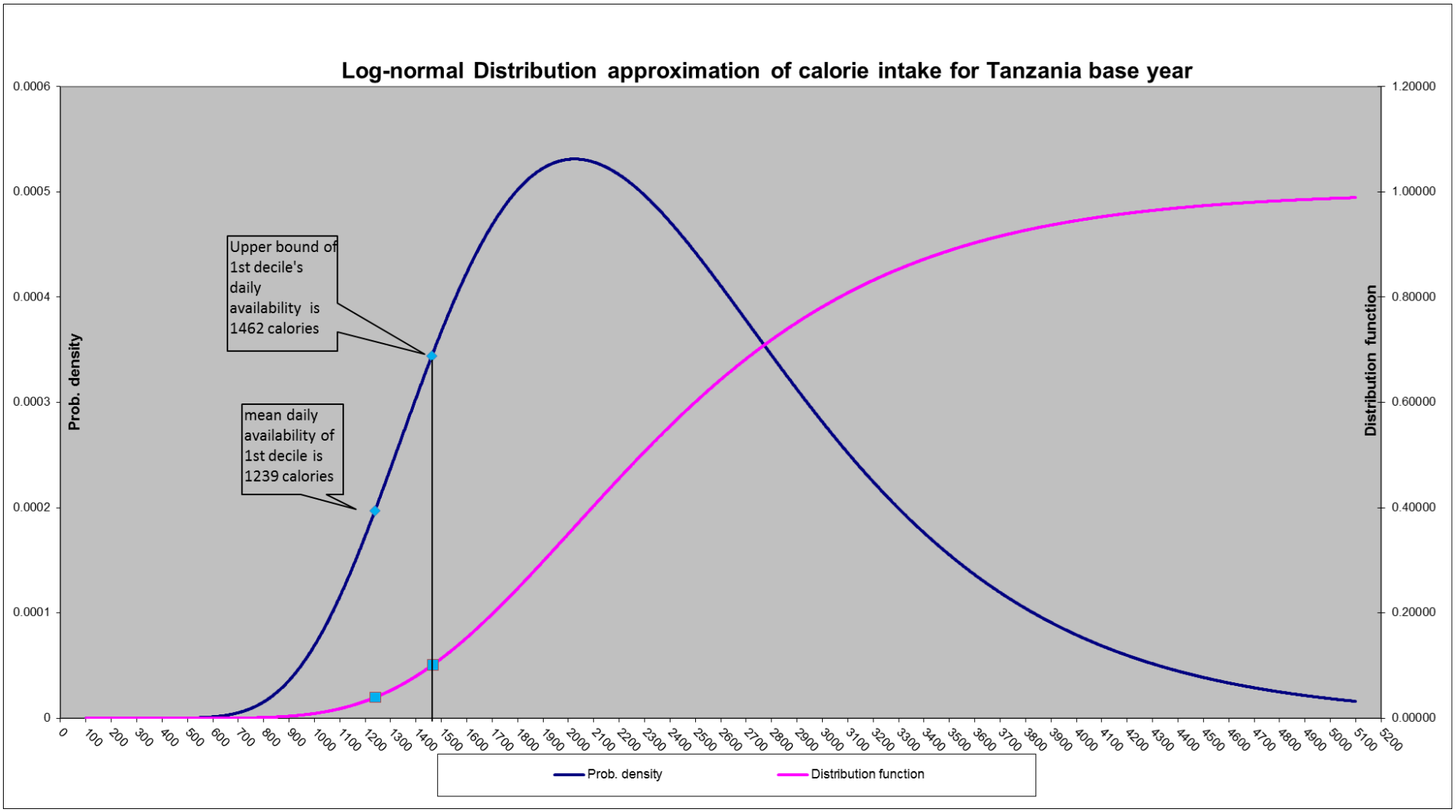
where ϕ is the standard normal density function. These values are shown for 2012 in the second to last column in daily calories and then in kg of grain equivalent per year.

In our application for Tanzania, updated *SoFI* data indicate a population average caloric availability equal to 2430 calories for Tanzania, with a *CV* of caloric availability of 0.36. These values lead to lognormal parameter values μ =7.735, and σ = 0.3491. Then the computed upper bound for the 1st decile is 1462 calories and the mean caloric availability for the same decile is 1239 calories for 2012. Appendix Figure1 illustrates the approach.

To project the bottom decile caloric availability for 2013-2023 we then use our projected population mean caloric availability and maintain the CV constant, which is equivalent to maintaining the variance of the normal distribution (ln(availability)) constant as shown in the Appendix table. As the population average increases in the projected period, the availability of calories also increases for the bottom decile. We then use this projected bottom decile availability to calibrate quality as explained in the main text and we do so for every year from 2012 to 2023.

Appendix Table 1. Estimation of the average daily caloric availability of the bottom decile in Tanzania to calibrate quality scales

year	Coefficient of Variation from *SoFI*	mean daily caloric availability projected by Tanzania model	Implied standard deviation of daily caloric availability	Standard deviation of Normal distribution (ln(availability))	Mean of Normal distribution (ln(availability))	upper bound of caloric availability decile 1	average decile 1 daily caloric availability	average decile 1 availability in grain equivalent kg/year
2012	0.36	2430	875	0.349	7.735	1462	1239	138
2013	0.36	2538	914	0.349	7.778	1527	1294	144
2014	0.36	2752	991	0.349	7.859	1656	1403	156
2015	0.36	2917	1050	0.349	7.917	1754	1487	166
2016	0.36	3021	1088	0.349	7.952	1817	1540	172
2017	0.36	3064	1103	0.349	7.967	1843	1562	174
2018	0.36	3105	1118	0.349	7.980	1868	1583	176
2019	0.36	3143	1131	0.349	7.992	1890	1602	179
2020	0.36	3179	1144	0.349	8.003	1912	1621	181
2021	0.36	3220	1159	0.349	8.016	1937	1642	183
2022	0.36	3263	1175	0.349	8.029	1963	1664	185
2023	0.36	3306	1190	0.349	8.042	1988	1685	188



Appendix Figure 1.