Increasing Sedentary Time, Minimum Dietary Energy Requirements and Food Security Assessment

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Increasing Sedentary Time, Minimum Dietary Energy Requirements and Food Security Assessment

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Abstract: We compute corrections for sedentary behavior in physical activity levels (PALs) and incorporate them along with corrections for over estimation of basal metabolic rates (BMRs) into threshold caloric intakes, known as Minimum Dietary Energy Requirements (MDERs). Using these modified MDERs, we compute new estimates of food insecure populations using USDA-ERS International Food Security Assessment (IFSA) model for the 83 countries covered by IFSA for 2023. We compute moderate upward biases in the FAO's MDERs due to sedentarism of 3.52% or 57.49 kcal a day, leading to an average of 1720 caloric MDER, which translate to reductions in the estimate of food insecure population of 71.3 million in the 83 IFSA countries. With both BMR and PAL corrections, the MDER falls to 1638 kcal on average and the food insecure population estimate falls by 173.6 million. Relative to USDA-ERS' 2100-calorie threshold estimating 1.056 billion food-insecure, the 1638 kcal per capita per day accounting for BMR and PAL corrections would result in 711.7 million reductions. Robustness checks using a lognormal distribution approach with FAO data confirm similar large responses of food insecure population estimates to the MDER corrections for the same countries. Beyond the correction for systematic upward bias, estimating more precise MDERs will lead to more precise food insecure estimates.

Keywords: Food Security, Minimum Dietary Energy Requirement (MDER), sedentarism, prevalence of undernourishment.

JEL codes: I3, Q18

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Increasing Sedentary Time, Minimum Dietary Energy Requirements and Food Security Assessment

Introduction

Estimates of global food insecurity play an important role in informing policy decisions, such as those surrounding COVID-19 (Balistreri et al., 2022) or the EU's Farm to Fork Strategy (Beckman et al., 2020). Yet, despite the important role they play, issues of inconsistencies and disparities in the estimates provided by food security indicators have been identified (Barrett 2010, de Haen et al. 2011, Henry 2005, Poudel and Gopinath 2021, Swaminathan et al. 2018, Svedberg 2002, among others). We address two major sources of upward bias in food security indicators as explained below.

Poudel and Gopinath (2021) examine global food security indicators on the Prevalence of Undernourishment (PoU) from the Food and Agriculture Organization (FAO), the International Food Policy Research Institute (IFPRI), the United Nations Development Programme (UNDP), and the United States Department of Agriculture (USDA). They find that the variation within the indicators is explained by economic growth, literacy, urbanization, and internet access. They further employ meta-regression analysis to examine the sources of variability between indicators, with significant findings regarding study characteristics such as primary data use, experience of the agency in food security analysis, and the number of countries examined, among others.

De Haen et al. (2011) examine the FAO PoU indicator as compared to two other approaches to food insecurity assessment, household consumption surveys, and childhood anthropometrics. They provide overall assessments of each approach in terms of strengths and weaknesses, while pointing out conflicting results from the three approaches, and provide options for improving these indicators. They conclude that the estimates of food insecurity are inaccurate, but do not identify a systematic bias below or above the FAO estimates.

The methods of assessing the prevalence of undernourishment rely upon a minimum dietary energy requirement (MDER), which is given in kcal per person, per day. This MDER forms a critical average daily caloric threshold for which a typical lightly active individual would be considered undernourished calorically, should they fall below the threshold. FAO provides yearly revised estimates of MDERs for the set of nations included in its annual report, The State of Food Security and Nutrition in the World (SOFI). The MDER used in PoU estimation is updated for small demographic changes occurring over time such as the sex and age composition of the population; it is otherwise static over time (FAO et al., 2023). We elaborate on this point in section 2.1.

The MDER is a summation across population strata, based on sex and age subgroups, which form weights that are multiplied by a minimum daily energy requirement of the specific population subgroup in question. The subgroup energy requirement estimates used in the MDER are multiple decades old, dating back to at least 1985 (FAO, 2005). There is no adjustment made for changes in caloric needs of the population due to other factors. We further note that the MDER cutoff used in the annual USDA International Food Security Assessment (IFSA), is a fixed value of 2,100 kcal per person a day.

Another contention pertains to the Basal Metabolic Rate (BMR) values estimating the caloric needs of the population subgroups based on age and sex which are aggregated into the MDER. Swaminathan et al. (2018) examined the estimated BMRs used in the FAO PoU. They found that for Indian adults, the BMR was overestimated between 5 and 12%. With an overestimated BMR value used, PoU estimates will be biased upwards and overstate the true level of food insecurity. Svedberg (2002) also examines the issue of BMR inflation, noting a 10% overestimation in the BMR for people living in the “tropics.” He constructs a revised alternative modeling approach and finds overestimation and underestimation effects in the FAO PoU approach, with a net effect of overestimation. In checking his PoU values against anthropometric indicators, he finds better agreement in most regions modeled with his revised PoU methodology.

Henry (2005) summarizes past criticisms of the equations and data utilized in the FAO SOFI methodology for estimating PoU. The current FAO PoU methodology utilizes what are called the “Schofield equations” to compute BMRs. Henry (2005) created revised equations, the “Oxford equations” utilizing more recent data that better represents developing economies. He finds notable inflation in the estimated BMR from the Schofield equations compared to his revised Oxford equations. BMR inflation is important to examine since BMR inflation has an elasticity of one in the MDER, causing upward bias when the BMR is inflated.

These shortcomings strongly suggest the need to revise estimates of the PoU, which we address in this paper. First, changes for sedentarism and BMR inflation are accounted for in revised MDERs and then we look at their implications for estimates of food insecurity such as those provided by the FAO’s SOFI and the USDA’s IFSA. Further, we assess the sensitivity of food insecurity estimates to the revised caloric cutoffs used. More precise cutoffs may be key to reduce the inaccuracy of PoU estimates.

Michels and Beghin (2024) address bias in the FAO PoU indicator sourced from changes in sedentarism worldwide over time. Here, we employ and update the methods of Michels and Beghin (2024) to provide revised estimates of food insecurity for the set of 83 nations in the annual IFSA report. To accomplish this, we construct revised MDER cutoffs, adjusted for sedentarism and BMR inflation. We model various constructed MDER values through the use of the IFSA model and its corresponding dataset applying, but also via the Lognormal approach of

FAO as a robustness check. The IFSA model uses elements of the Lognormal approach to calibrate the average caloric intake of the bottom decile, but relies on an empirical distribution for the other nine deciles based on income distribution data. Our results show substantial implications for food security and estimations, while highlighting the sensitivity of estimates of undernourishment to the MDER cutoffs used.

Based off our findings, we compute multiple elasticity values of the estimates of food insecurity to the MDER cutoff for each nation in our dataset. The elasticity results show notable heterogeneity between nations, but homogeneity in values for a given nation, suggesting the elasticity for a given nation isn't highly sensitive to the particular MDER used. We find that the elasticity is sensitive to which nation is under consideration, that the PoU itself is sensitive to the MDER cutoff, and that the estimates of undernourishment utilizing the PoU are sensitive to small PoU errors, particularly for high population nations. Hence getting MDERs right is pivotal.

2. Methods

In the following section we first introduce the MDER and the proposed correction to account for increased sedentarism. Then we describe two main modeling approaches to assess food insecurity, the USDA IFSA model, and the lognormal approach used in FAO's SOFI assessment. We also formalize the link between the correction in the MDER and its impact on the prevalence of undernourishment and food insecure population.

2.1 Correction of the MDER

FAO uses a lognormal approach to compute its PoU indicator. The PoU is written as:

$$PoU = \int_{x<MDER} f(x \mid \theta)dx. \quad (1)$$

Function $f(x \mid \theta)$ is the assumed lognormal probability density function describing a population's representative average individual's habitual dietary energy intake levels (FAO 2014).[1] The energy intake is given by x, which is expressed in kcal per day, per person. Parameters θ are the mean dietary energy consumption and the coefficient of variation of the lognormal distribution, from which a standard deviation is implied. The cumulative probability of the representative individual's habitual dietary energy intake falling under the kcal cutoff, given by the MDER, is one interpretation of the PoU. The MDER represents the caloric requirement for a lightly active lifestyle. Another use and interpretation of the PoU is to estimate the proportion of the population that is undernourished. For a given nation's population, the following relationship holds (Wanner et al. 2014) to derive the food insecure population in a country, *FIP*:

$$FIP = PoU * Population \quad (2).$$

FAO constructs the PoU to be nation specific and it is computed as an aggregation utilizing weights P_{ij} consisting of the share of the population that a constructed sex and age group of the nation represents. More formally:

$$MDER = \sum_{ij} MER_{ij} * P_{ij}$$, across sex *i* and age groups *j,* (3)

where MER_{ij} is the minimum daily energy requirement per person in the *ij* group and P_{ij} is the population share of sex *i* and age group *j* (FAO 2008). Formerly, a pregnancy allowance was also included, and which has been omitted since in FAO et al. (2023). Each group has a specific minimum energy requirement based upon its basal metabolic rate (BMR) and a physical activity level (PAL) (FAO 1985 and 2005). These BMRs and PALs were established in 1985 for FAO from older data using the so-called Schofield BMR equations (Schofield, 1985). Based on available data from the UN Department of Economic and Social Affairs, these population

[1] This individual is representative of the population in the sense that they are of average physical activity level, age, stature, and sex. (FAO, 2014).

weights are adjusted over time (FAO et al., 2023). These demographic weights are the only time-varying elements of the FAO MDER.

Various kcal cutoffs for modeling undernourishment are possible. The MDER values computed by FAO and discussed above are one such possibility. An alternative used by the USDA ERS in their modeling work in the annual IFSA report instead utilizes a constant 2,100 kcal per person per day cutoff. Here, we seek to adjust the MDER values from FAO for changes in sedentarism around the world to create revised MDERs to derive revised PoU estimates. Our methodology allows for revised MDERs that are time and country specific, include current population weights, and account for current country-specific sedentarism. The timespan we consider for the revised MDERs in this paper is from 1985 to the latest available data, 2022/23. In the current application, we use the aforementioned approach in conjunction with covariate data we collected to allow for revised MDERs that are adjusted for sitting time changes.

Our methodology relies upon and extends Michels and Beghin (2024), which established the methodology for accounting for rising sedentarism based on a conceptual model of labor allocation decisions faced by a representative household with physical and intellectual labor types, selling these to labor markets and using them to produce non-market goods such as leisure activities. They showed that increasing productivity and wages to sedentary activities, called "cognitive human capital intensive," lead to more time allocated to these activities, rationalizing the labor allocation towards more sitting time. Their empirical implementation translates the conceptual model into regression models of sitting time using a pseudo panel dataset. Sitting time is determined by covariates which explain the progression away from physical labor toward cognitive and sedentary activities with improvements in productivity and returns in the latter.

Among covariates, the proportion of the population using the internet, x_{web}, reflects the changing relative productivities of cognitive vs physical human capital types. It captures access to and intensity of information during both work and leisure activities, and the increasing digitization of occupations. Gains in cognitive human capital, x_{educ}, are represented by upper-secondary education completion rates. The rural share of population, x_{rural}, traces changes in the physical human capital type as urban occupations tend to be more sedentary. Income inequality, x_{theil}, as measured by the Theil index of inequality reflects heterogeneity in human capital and returns. The greater the inequality, the less sedentary, all else equal as less remunerated activities tend to be physical. GDP per capita, x_{gdp}, encapsulates economic development and more sedentarism.

Their econometrically estimated transfer functions predict changes in national average sitting time, y_{sit}, (serving as a proxy for sedentarism), for a country and year as determined by these five covariates, which are time varying and make use of population weights in the regressions, and by a few fixed effects, d, reflecting some data imputations. They select five preferred specifications based on goodness of fit and consistency with the predictions of the conceptual model. The coefficients were then aggregated in both slope and elasticity forms, applying the necessary transformations across the functional forms to allow for aggregation of the estimated coefficients via meta-analysis methods. Eight transfer functions were constructed.

Equations (4)-(7) give the form of all eight but we have omitted the version of each with the squared proportion on the web covariate for brevity. Equations (4) and (5) give the 1^{st} order Taylor approximation models that utilize deviations from the mean in slope and elasticity forms, respectively. Equation (6) is an aggregated regression form model utilizing slopes (β) and (7) gives the aggregated multiplicative model using elasticities (δ).[2]

$$y_{sit\_prediction} = \bar{y}_{sit} + (x_{web} - \bar{x}_{web})\hat{\beta}_{web} + (x_{rural} - \bar{x}_{rural})\hat{\beta}_{rural} + (x_{theil} - \bar{x}_{theil})\hat{\beta}_{theil} \\ +(x_{educ} - \bar{x}_{educ})\hat{\beta}_{educ} + (x_{gdp} - \bar{x}_{gdp})\hat{\beta}_{gdp} + (d_{theil\_imp} - \bar{d}_{theil\_imp})\hat{\beta}_{theil\_imp} \quad (4)$$

$$y_{sit\_prediction} = \bar{y}_{sit} + \bar{y}_{sit}[\sum_{\substack{j=web,\\ educ,\\ rural,\\ theil,\\ gdp}} \frac{\hat{\delta}_j}{\bar{x}_j}(x_j - \bar{x}_j) + \exp\{\hat{\delta}_{theil\_imp} d_{theil\_imp} - \hat{\delta}_{theil\_imp}\bar{d}_{theil\_imp}\} - 1], \quad (5)$$

$$y_{sit\_prediction} = \hat{\beta}_0 + \hat{\beta}_{web}x_{web} + \hat{\beta}_{educ}x_{educ} + \hat{\beta}_{rural}x_{rural} + \hat{\beta}_{theil}x_{theil} + \hat{\beta}_{gdp}x_{gdp} + \hat{\beta}_{theil\_imp}d_{theil\_imp}, \quad (6)$$

$$y_{sit\_prediction} = \exp\{\hat{\delta}_0\} * x_{web}^{\hat{\delta}_{web}} * x_{educ}^{\hat{\delta}_{educ}} * x_{rural}^{\hat{\delta}_{rural}} * x_{theil}^{\hat{\delta}_{theil}} * x_{gdp}^{\hat{\delta}_{gdp}} * \exp\{\hat{\delta}_{theil\_imp} d_{theil\_imp}\}. \quad (7)$$

Predicted sitting time changes were used to construct revised physical activity levels (PALs) by adjusting the time allocation to activities in the factorial calculation used, see Table 1 and its notes. Our methodology builds on their proposed method of updating the total energy expenditure calculation.

<Table 1 about here. FAO example factorial calculation and revised factorial calculation>

The variable "SC" in the sixth column stands for the predicted change in sitting time from 1985 to 2022/23 from the transfer functions. The sixth column of Table 1 shows how we adjust downward the household chores and walking time allocations and adjust up the leisure time allocations for the changes in predicted sitting time in the factorial calculation. The computed time allocations are then multiplied by their energy costs, then these values are summed and normalized by 24 (1 day), similar to what is done in the original example calculation in the fourth column of Table 1 and the bottom cell of the fifth column of Table 1. The resulting revised PALs are then used to rescale the FAO MDER values for changes in sitting

[2] Model (7) is unused due to a zero value for the proportion on the web covariate in 1985. The outputs of the other six models are averaged to make sitting time predictions. Upper bars designate average values, hats designate estimated coefficients.

time, generating new MDER cutoffs to use in food insecurity modeling such as the lognormal approach of FAO or the USDA IFSA approach.

Revisions of MDERs can be carried out using the construction of FAO's MDER. Recall that: $MDER = \sum_{ij} MER_{ij} * P_{ij}$. The MER_{ij} term is further broken out to $1.55 * BMR_{ij}$. The 1.55 value is the PAL used by FAO, which is common to all subgroups of the population used. The BMR is the source of variability by subgroup. Hence we can rescale the old MDER by our new revised PAL value divided by 1.55. Thus, we have that:

$$MDER_{Revised} = \frac{PAL_{Revised}}{1.55} * MDER_{FAO}. \quad (8)$$

The revised MDERs capture several time-varying determinants. First, the composition of the population by age and sex categories changes, which is built into the original MDER values FAO computes. Caloric needs are modeled by FAO based on age, sex, and weight (FAO et al., 2023). Secondly, sedentary behavior drives the PAL, which we capture with our covariates that proxy for the levels of and changes in the productivity and returns to sedentary vs more physically demanding activities. The makeup of the economy and state of advancement plays a role here, more advanced economies are expected to be more sedentary by influences of technology and urbanization and often reduced income inequality. Lastly, the effects of time play a role. Both the composition of the population and the sedentary behavior are time varying. FAO adjusts MDERs for the compositional makeup changes of the population regarding age and sex, but our work here also adjusts MDERs for changes over time in technology, urbanization, and the economy overall, which is reflected in our covariates. Finally, a uniform proportional reduction in BMR can be imposed on the revised MDER (8) by scaling down the right-hand side of the equation. We choose a conservative 5% inflation of the BMR downward adjustment of the BMR (a scalar of 0.9528 in (8)).

2.2 IFSA Model Summary

This section provides a succinct description of the key characteristics of the USDA's IFSA model, avoiding formal equations. Readers interested in the full mathematical details and calibration approach can refer to Appendix A of Zereyesus et al. (2023). This section heavily draws upon their work. The IFSA model projects food demand access, and food gaps for 83 low- and middle-income countries by 10 income deciles over ten-year horizons (Zereyesus et al. 2023). Each country's food security metrics are estimated and calibrated to 2020-2022 data for the 2023 estimation and projected to 2033. Food consumption is categorized into four groups, two of which are country-specific for grains. The four groups encompass the entire food consumption spectrum. They are the major (caloric) grain (determined by calorie share), other grains, root and tuber crops, and an aggregate of all-other-foods. The modeling projections of food demand are expressed in a grain equivalent based on each food group's caloric content to allow aggregation across food groups, which allows this grain equivalent to be easily expressed in kilogram calorie per days (kcal/day).

The food security of a country is evaluated by comparing estimated domestic food consumption (food demand) with a caloric threshold necessary to sustain life at a level of activity. This threshold varies depending on the model used. For example, the USDA IFSA model uses 2,100 kilocalories (kcal/day) per capita.

Three food security indicators are estimated: (1) the population share of food insecure: This indicator represents the proportion of the total population unable to reach the reference caloric threshold of 2100 kcal/day. This threshold is higher than both the FAO's MDER and our corrected MDERs, as mentioned below. (2) the number of food insecure people; and (3) the food gap, this indicator represents the total amount of additional food (measured in calories) needed to bring all individuals below the 2100 kcal/day threshold up to that level.

The centerpiece of the IFSA model is a food demand system included in a multi-market partial-equilibrium model for each country in the assessment. World prices reflecting USDA's world outlook feed into localized domestic prices via price transmission equations, determining local demand and then grain supply and imports. Beghin et al. (2015) introduced the methodology, and Beghin et al. (2017) provided more detail on price transmission and food security projections.

The demand system for the four food groups employs a simplified price-independent generalized log-linear (PIGLOG) (Deaton & Muellbauer,1980; Muellbauer 1975). This model captures own-price and income responses but excludes cross-price responses, which are often difficult to obtain. Importantly, the PIGLOG system allows for exact aggregation of decile demands into an aggregate average demand, accounting for both average income and the income distribution. For the 2023 estimation, the model is calibrated on a 3-year-average of prices and incomes (2020–22), along with observed consumption levels, a measure of inequality, and a combination of consensus and estimated income and price elasticities. This calibration process involved adjusting free parameters within the demand system to allow imposition of plausible patterns of price and income responses across income deciles. The model assumes decreasing income and price sensitivity of food demand as decile-income rises. For further details on the calibration, refer to Beghin et al. (2015) of.

The model accounts for quality differentials within each of the four food categories. Poorer deciles face lower quality at lower prices and richer deciles do the opposite. By aggregation, the consumption weighted average equality is equal to one to be consistent with aggregate data. The quality of the bottom decile is calibrated to match the caloric consumption pattern of the bottom decile implied in FAO's SOFI assessment under its lognormal approach. The focus here is on the decile most likely to contain food insecure populations.

IFSA has two ways to assess the PoU and food-insecure population. First, it compares each decile's total average caloric intake and counts the deciles that fall below the 2,100-kcal threshold. In that case, the changes in food-insecure population are by decile increments of a population. The second way to predict food insecure population is to use the estimated mean aggregate caloric intake projected by the model and use this as the lognormal mean availability along with the coefficient of variation of published by FAOSTAT and assume a lognormal distribution mimicking SOFI but centered on USDA's projection of the total caloric availability. As noted above, the trade-off with this second approach is that the projected decile distribution might not be consistent with the lognormal distribution for its entirety, but it allows one to refine the estimate of the food insecure population beyond the decile-based variation. Here we report results based on this second approach.

2.3 Scenario-IFSA Calibration with Different MDERs

In our analysis, we calibrate the IFSA model on the original FAO MDER and then our corrected MDERs along with the 2,100-kcal threshold.[3] We do not use the projection element of the IFSA, but rather focus on estimates of food insecurity in the calibrated 2020-2023 and compare the implications of using different MDERs on food insecurity estimates. The IFSA model uses slightly different caloric availability than that shown in the Food Balance Sheets of FAOSTAT. It combines and reconciles information for grain production data from USDA, Foreign Agricultural

[3] The IFSA model calibrates the food availability of the bottom decile using a quality adjustment factor increasing consumption and decreasing prices, holding expenditure constant, that matches the FAO's first decile food availability. The adjustment factor evolves; as deciles become richer, quality increases. By aggregation, it leads to the original food availability for a nation (Beghin et al. 2017).

Service's Production, Supply and Distribution (PSD) database, and from the Food and Agriculture Organization of the United Nations (FAO).

2.4 Lognormal Approach

On top of utilizing the IFSA model for estimates of the undernourished, we also use our revised MDERs in the FAO PoU framework to re-estimate the PoU to adjust for sedentarism. FAO uses the total food availability per person to represent the mean dietary energy consumption that is required for its lognormal modeling approach. This data is available through FAOSTAT along with the CV needed for the lognormal computations.[4] To obtain the parameters of the lognormal distribution, the following two equations are used (FAO, 2008) with

$\sigma_x = [\ln(CV^2 + 1)]^{1/2}$, and $\mu_x = \ln(\bar{x}) - \frac{\sigma_x^2}{2}$, with $\bar{x}$ being the mean dietary energy consumption, approximated here by the total food availability per person. Then, we use the standard normal cumulative distribution function $\Phi(\cdot)$ to compute $\Phi[\frac{(\ln(MDER) - \mu_x)}{\sigma_x}]$ that gives the PoU. Then, we use (2) to estimate the food-insecure population.

2.5 The MDER Elasticity of the Prevalence of Undernourishment

Based upon the lognormal modeling approach of FAO, we find that the MDER elasticity of the PoU can be readily computed. Food insecurity estimates for a given country using the PoU are computed using equation (2). Using FAO (2008) and inserting the PoU from the lognormal distribution, we have: $FIP = \left[\int_{-\infty}^{\frac{\ln(MDER)-\hat{\mu}}{\hat{\sigma}}} \frac{1}{\sqrt{2\pi}} \exp\left\{ \frac{-x^2}{2} \right\} dx \right] * Population.$

[4] https://www.fao.org/faostat/en/#data/FBS and https://www.fao.org/faostat/en/#data/FS for the total food availability and CV, respectively. 2021 and 2022 were the latest years available during our analysis for total food availability and CV values. We also include FAO's food waste estimate to obtain the average caloric availability "utilized."

The implied elasticity of the food insecure population with respect to the MDER is:

$$\frac{d\ln(FIP)}{d\ln(MDER)} = \exp\left\{-\frac{(\ln(MDER)-\hat{\mu})^2}{\hat{\sigma}^2}\right\} * \left[\int_{-\infty}^{\frac{\ln(MDER)-\hat{\mu}}{\hat{\sigma}}} \frac{1}{\sqrt{2\pi}} \exp\left\{\frac{-x^2}{2}\right\} dx\right]^{-1} * \frac{1}{\hat{\sigma}}.$$ [5]

The lognormal model lends itself to a relatively simple equation for computing the elasticity. In the case of the IFSA model the implied caloric intake distribution of the population is more empirical as explained above, combining a log-normal assumption for the first decile, and an empirical distribution based on income distribution for the other deciles. We make use of arc elasticities instead, using the formula:

$$\frac{d\ln(FIP)}{d\ln(MDER)} \approx \frac{(PoU_i - PoU_{FAO})(MDER_i + MDER_{FAO})}{(PoU_i + PoU_{FAO})(MDER_i - MDER_{FAO})},$$

where the subscript *i* denotes any of the three revised MDERs and PoU estimates based on them, the PAL Revised, BMR Deflated, and PAL and BMR Revised MDERs. All arc elasticities are computed from the FAO original MDER value to a revised MDER point. Similar arc elasticities can be computed for the results from the lognormal model, but for that model elasticities computed using the method described above are preferred since it yields exact point elasticities.

3. Data Discussion and Results on Corrected MDERs

3.1 Data and Covariates

We construct the necessary dataset, which covers the 83 nations included in the annual USDA IFSA report. The necessary covariates to predict the new MDERs are collected from the same sources as in Michels and Beghin (2024) shown in Table 2. Table 2 provides summary statistics

[5] From the Food Insecure Population definition above, differentiate each side with respect to the MDER, apply the Fundamental Theorem of Calculus and the Chain Rule. Then, construct the elasticity, cancelling terms and simplifying to arrive at our given equation. Without canceling constants, the right-side expression can be written with the Inverse Mills Ratio.

for our covariates.

<Table 2 about here Data Sources and Years of Variables>

Following the order of Table 2, we collected 2023 MDERs from FAOSTAT, which serve as the base upon which our BMR and PAL revisions to the MDER build. Our covariates are collected for as close to those years as was available for each nation in order to compute our revisions to the original FAO MDERs. Data availability by year varies, see Table 2 and the online supplementary materials for more details. In some cases, covariate values needed to be imputed for some countries and years. An Excel workbook documenting the steps taken for the covariates is available online in the supplementary materials for the paper. We observe large heterogeneity, in some cases, in the changes to the covariate values for the included set of nations over time.

The proportion of the population in 2022 with internet access varies from a very low level in the Democratic People's Republic of Korea, estimated to be only a matter of thousands with internet access, up to over 88% in Morocco. Further, Angola saw over a 37-percentage point drop in the rural population percentage over the time period we examine, while five nations actually experienced an increase in the share of rural population. Income inequality over time exhibits large decreases in some cases but also significant increases as well, although the average inequality trends downward. Upper secondary education completion rates rose in all countries, at least marginally, except in Zimbabwe where they actually declined a bit over 3.3 percentage points. Lastly, GDP per capita rose in most countries, sometimes by large percentage increases, but fell in 15 nations of our 83 countries included in the IFSA. Sizeable covariate changes may translate to sizeable changes in predicted sitting time and in our revised PAL, and revised MDERs we compute, and ultimately larger changes in the PoU.

We include kernel density estimates (KDE) of the distributions of the covariates in the two time periods in our appendix figures, which allow for some informative visualization of the changes in the distributions of the covariates over time. In Appendix Figure 1, the KDE of the proportion of the population using the internet in 2022 reveals a bimodal distribution, indicating a trend towards nations having largely connected online and others with only some web connection. Appendix Figure 2 illustrates the overall decline in the rural population percentage; Appendix Figure 3 tells a story of a generally declining Theil index, with higher concentration around the 0.25 range. Appendix Figure 4 shows an overall improvement in upper secondary completion rates, with the distribution shifting up and the upper tail gaining mass. Finally, Appendix Figure 5 shows a similar pattern for GDP per capita.

3.2 Results on Sitting Times, Physical Activity Levels, and MDERs

Figure 1 gives the KDE of the distribution of the change in predicted sitting time of the 83 nations in our dataset. All nations had positive changes in sitting time. In some cases, the changes were quite large, as high as 1.848 hours a day for Tunisia, and some as small as 0.103 hours a day, as for Niger. There is a clustering of countries around 0.5 hours a day increase, but still a significant portion of nations with as high as a 1-hour a day increase.

<Figure 1 about here>

Figure 2 gives the KDE of the distribution of the revised PALs we have constructed from the predicted changes in sitting time. Recall that FAO uses a PAL of 1.55 in its MDER calculation. We see the shift of the values downwards, with a large proportion falling in the 1.5 to 1.525 neighborhood, roughly speaking. Since all predicted changes in sitting time are positive, all revised PALs are below 1.55. The largest value is Niger at 1.543, while the smallest is Tunisia at 1.427. These values make good sense based on these two nations having the smallest and largest predicted changes in sitting time, respectively.

<Figure 2 about here>

In Figure 3, KDEs of the distributions of the original 2023 FAO MDERs are visualized in dark grey. Furthermore, we have KDEs of the 5%-BMR deflated MDER, visualized in blue, the PAL-revised MDER, visualized in grey, and the PAL-and-BMR-revised MDER, visualized in orange. We see a shift downwards of the distribution in all cases, with the 5% revision in BMR MDER shifting further on average than the PAL revised MDER, and the BMR and PAL revised having the furthest left distribution. There does appear a tendency of the PAL revision to reduce the dispersion of the distribution, with the mass somewhat more concentrated. Lastly, we should note that the nations of India, Indonesia, and Nigeria all saw large predicted sitting time changes, translating to large changes in revised MDERs, and are ultimately expected to have significant implications for the revised PoU. These nations are important to note due to their large populations, which combined equal over 1.9 billion people for 2022 (World Bank, 2023). Descriptive statistics for the MDERs (including our revised MDERs), our revised PAL and estimated changes in sitting time appear in Table 3.

<Figure 3 about here>

<Table 3 about here>

4. Results on Estimates of Undernourished populations

We examined the changes in FAO MDERs published, as of January 2024. This is of interest as it makes a nice comparison of what occurred over time with the FAO MDERs vs. changes induced by our adjustments for sedentarism and the assumed 5% bias in BMR in MDERs. We downloaded FAO's published MDER values and computed the percentage change from 1985 to 2023, when available, and in other cases used the oldest available data when it was not available back to 1985.[6] Summary statistics appear in Table 4, column 2, while a histogram of the percentage changes appears in Appendix Figure 6. It should be noted that the change in the FAO MDERs over time is driven by the demographic changes of the population; FAO adjusts for age and sex changes in the populations.

<Table 4 about here>

Inspection of the revisions to FAO's MDERs over time compared to our adjustments from 1985 to 2023 showed some opposite signs occurring. Upon trimming the country list of FAO to match that of the IFSA, which is the nation set we apply our PAL correction to for the MDER, we observe a modestly strong -0.4283 simple correlation between the percentage change of the FAO MDER over time compared to our PAL sedentarism adjustment percentage change over time. Only 12 of 205 FAO MDER percentage changes over time are negative and tend to be those of more developed economies. All the rest are positive, and in some cases quite large, as seen in Table 4 above, the maximum is 14.469% and the 75th percentile 6.703%, while the mean is a 4.603% increase.

Table 4 also shows in columns 3 and 4 descriptive statistics for the percentage changes in our PAL revised MDERs and the PAL and BMR revised MDERs, computing percentage change as (New MDER/Old MDER)-1. Note that the MDERs that had the 5% BMR deflation applied computes to a 4.762% decrease in all cases. We find mean downward percentage revisions of 2.929 and 7.552%, respectively, when we adjust for only the PAL and when we adjust for the PAL and the BMR inflation. All revisions are downward and in some cases for PAL only, quite small, at only -0.443% for Niger.

[6] Some computed values are artificially small due to a smaller timescale involved due to data limitations. 178 out of 205 (86.83%) nations had data back to 1985.

We compare the MDERs that have the PAL and BMR adjustments both applied as to the original FAO MDERs. We break down the MDER inflation to examine how much is attributable to the PAL adjustment, the BMR adjustment, and their interaction effect. Table 5 contains the four different MDER cutoffs, the FAO MDER, our PAL Revised BMR, our BMR Deflated MDER (5%), and the PAL and BMR Revised MDER.

For the five nations with the highest number of food insecure individuals, we have broken down the inflation in the MDER into its components in both absolute kcal terms and percentage.[7] Examining the PAL inflation alone, we see that for Nigeria it is as high as 6.449%, higher than the assumed BMR inflation, but for three of the five selected nations it is within 1-2%. However, we will see next that even relatively small amounts of bias are meaningful due to the high elasticity of the food insecurity estimates with respect to the MDER cutoff used.

<Table 5 about here>

The posited BMR inflation is often higher than the PAL inflation for this small subset of nations. The interaction effects of the PAL and BMR are generally smaller, but the total inflation with an assumed 5% BMR inflation, which is on the conservative end from the literature, is as high as 11.771% for Nigeria. Regardless, even without any assumed BMR inflation, there are meaningful implications for the estimates of the food insecure due to the sensitivity of the methodology to the kcal cutoff chosen (MDER). Assuming some BMR inflation serves as an exercise to show the impacts on food security assessment, compounding the bias from sedentarism over time.

Table 6 provides descriptive statistics of the inflation in kcal and percentage for the whole set of 83 IFSA nations we consider. Table 6 provides some information on the distribution of

[7] The FAO Lognormal approach predicts a different list of five nations as the top food insecure than the IFSA model predicts. We use the former.

these PAL and BMR inflations. We see the PAL inflation varies from a minimum of about 7 kcal to a maximum of about 137 kcal. The total inflation percentage shown in the last column ranges from 5.5% to just over 14%.

<Table 6 about here>

Table 7 shows the implications of the varying MDER cutoffs we have computed, for the five nations mentioned above, when utilized in the USDA IFSA model. We see for the original FAO MDER, India has an estimated 90 million (rounded) undernourished, but this number declines dramatically as each alternative MDER is substituted in, down to 45 million for the PAL and BMR Revised MDER, while the 2,100-kcal cutoff of the ERS gives a higher 270 million undernourished in India. The PAL Revised MDER alone implies 22 million fewer undernourished. Swaminathan et al. (2018) found that the current methodology used to estimate BMR overestimates the BMR of Indians by 5 to 12%, so the PAL and BMR Revised MDER values for India are plausible. For just these five nations, the differences between the FAO MDER and our revised MDERs translate in decreases of 37, 56, and 84 million people (rounded) who are food insecure, for the PAL Revised, BMR Deflated, and PAL and BMR Revised MDERs. The difference becomes starker when all 83 nations of the IFSA are included in the world aggregate row at the bottom of the table.

<Table 7 about here>

Estimation with the 2,100-kcal cutoff of ERS results in an aggregate value of 1056 million (rounded) undernourished, as compared to using the IFSA model and the FAO MDER cutoff which estimates a total of 518 million (rounded) undernourished. The difference between the FAO MDER cutoff and our revised MDERs are 71, 118, and 174 million (rounded), for the PAL Revised, BMR Deflated, and PAL and BMR Revised MDERs, respectively. Again, even without assuming any BMR inflation and only examining the PAL revised numbers, we see a difference of over 71 million people, a substantial population. Small revisions to the MDER values amount to large changes in the estimates of the undernourished. These values are only for the 83 nations considered in the IFSA, FAO includes a larger set of nations in the annual SOFI, which means their total undernourished population estimates would fall by a larger amount than suggested here.

The results shown in Table 8 show a sensitivity in the PoU estimates to the MDER cutoff used. We present arc elasticities for the same set of five nations and the results from the IFSA model. The elasticities are computed from the original FAO MDER value to each of our revised MDERs. For these five nations, we see a range of elasticities from around 2.7 to over 8.1, showing notable variability between nations, but high sensitivity for some to the MDER threshold used for the PoU estimation. Further, for a given nation, all three elasticity values are relatively similar. For a given nation, which MDER cutoff used doesn't mean a large difference in elasticity value, but the PoU itself is sometimes highly sensitive to the MDER. It would be inappropriate to use an average elasticity value as an approximation for all countries as the fit would be very poor in some cases.

<Table 8 about here>

Table 8 also shows descriptive statistics of the arc elasticities calculated from the IFSA modeling results but for all 83 nations of the dataset showing notable heterogeneity between nations (from 1.681 to 12.013), but small variations for any given nation.

We also present in Table 9 results for the same set of five nations for PoU estimates utilizing the Lognormal model with our various MDER cutoffs, including the 2,100-kcal cutoff used by ERS, which is similar in spirit to Table 7. Comparing these two tables, we see the

Lognormal model predicts much higher levels of undernourishment in India (by over 100 million in one case), slightly higher in DRC, Nigeria, and Ethiopia. The IFSA model predicts higher undernourishment in Pakistan. Typically, the Lognormal model predicts notably higher world aggregate levels of undernourishment in the set of 83 nations considered in this work, with the exception of the 2,100-kcal cutoff scenario.[8]

<Table 9 about here>

Point estimates of the PoU elasticities from the Lognormal approach for a given MDER cutoff are shown in Table 10 for the same top five food insecure nations. For India, the Lognormal point elasticities are lower than those from the IFSA model (5.6-6.5, roughly, compared to 8 to 8.13). However, the values for Pakistan are nearly similar in both methods; DRC's elasticities are actually higher in the Lognormal approach; Nigeria's elasticities are higher in the IFSA approach, as well as Ethiopia's. Regardless of the model used, the values are usually consistent across MDER cutoffs for a given nation; they are all large and with notable heterogeneity across nations.

Table 10 also shows descriptive statistics for the point elasticities from the Lognormal model for the full 83 nation set. They range from 2.795 to 16.159, showing extreme sensitivity to the MDER value used in the PoU at the upper end. This underscores the importance of obtaining the best data possible to generate more precise estimates of the PoU. Similarly, noisy estimated values used as inputs (the CV used and the total food availability as discussed in section 2.4) to the modeling work of the PoU could introduce large errors in the estimated PoU at these high elasticity values. However, even a more moderate elasticity value, such as those for India around 6, when considering its large population, the PoU will be multiplied against, again translates into

[8] FAO food supply values were not available for Eritrea and Somalia. We created synthetic population weighted estimates using Ethiopia, Djibouti, and Sudan for Eritrea, and Ethiopia, Djibouti, and Ethiopia for Somalia.

large possible errors in the estimate of the undernourished.

<Table 10 about here>

5. Conclusion and Implications

Our work addresses an important aspect of food insecurity assessment in adjusting estimates of the PoU for changes in sedentarism over time. We apply and update the approach of Michels and Beghin (2024) to adjust MDERs for sedentarism by adjusting the PAL used in the calculation of the MDER for changes in sedentarism, proxied by changes in estimated sitting time, along with allowing for a deflation of the MDER for bias in the calculated BMRs used in the MDERs by FAO. We collected data from 1985 to 2022/23 for the 83 nations included in the yearly USDA ERS IFSA report to apply our revision methodology to. The results from either modeling approach, that of the IFSA or the Lognormal approach used by FAO, show significant declines in the number of undernourished in this set of 83 nations considered. The estimated PAL bias is positive and all MDERs were revised downwards.

The IFSA model with the 2,100-kcal cutoff of ERS reported 1056.248 million undernourished in the 83-nation aggregate, while the 2,100-kcal cutoff implemented into the Lognormal model results in a higher 1,226.394 million estimate. Use of the FAO MDERs in the IFSA model resulted in 518 million (rounded) undernourished, 447 million using our PAL Revised MDERs, 400 million for the BMR Deflated MDERs, and 345 million for the PAL and BMR Revised MDERs. These are staggering differences confirmed in the robustness check using the FAO's Lognormal approach.[9] The Lognormal model estimated 589, 507, 459, and 393 million undernourished for the FAO MDER, the PAL Revised MDER, the BMR Deflated

[9] We applied food waste & loss percentages from FAOSTAT to the FAO MDERs in an attempt to match FAO's estimated PoU values. Significant discrepancies remain as compared to the estimates FAO has published in the latest SOFI report. The SOFI uses 3-year averages but the discrepancies we encounter tend to be larger than this adjustment.

MDER, and the PAL and BMR Revised MDER, respectively. These numbers, from either modeling approach, suggest a high sensitivity to the MDER value used in the modeling approach.

The elasticities of PoU with respect to the MDER are high (all above 1) but heterogeneous across nations with some extreme values as high as 16. For India, with elasticity values around 6 to 8, a small adjustment to the MDER can imply drastic changes in the estimate of the undernourished, meaning tens of millions fewer undernourished people with a seemingly small change in the MDER cutoff. The heterogeneous elasticities computed across the 83 nations considered show the importance of deriving more accurate MDERs and their underlying elements (PAL, BMR) for each food insecure country.

These results above highlight the importance of obtaining the best data possible as inputs to these modeling approaches and reducing sources of noise whenever possible. Small errors in the inputs of these modeling approaches, such as the mean dietary energy consumption and the CV, can translate to large errors in the output estimates of undernourished. While it is impossible to eliminate these issues entirely, the adjustment for sedentarism via the PAL over time helps to account for an important bias and generate more accurate estimates of undernourishment to make better informed policy decisions.

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Table 1. FAO example factorial calculation and revised factorial calculation

	FAO Example Factorial Calculation (FAO/WHO/UNU 2001)				Revised Factorial Calculation	
Main daily activities Sedentary or light activity lifestyle	Time allocation hours	Energy cost PAR	Time × energy cost	Mean PAL multiple of 24-hour BMR	Time allocation hours	Adjustment Factor (AF)
Sleeping	8	1	8		8-0.25*AF	0.4424
Personal care (dressing, showering)	1	2.3	2.3		1+0.2*AF	
Eating	1	1.5	1.5		1-0.25*AF	
Cooking	1	2.1	2.1		1+0.2*AF	
Sitting (office work, selling produce, tending shop)	8	1.5	12		8-0.25*AF	
General household work	1	2.8	2.8		1+0.2*AF-0.5*SC	
Driving car to/from work	1	2	2		1+0.2*AF	
Walking at varying paces without a load	1	3.2	3.2		1+0.2*AF-0.5*SC	
Light leisure activities (watching TV, chatting)	2	1.4	2.8		2-0.25*AF+SC	
Total	24		36.7	36.7/24 =1.53		

Notes: FAO uses the factorial method to estimate total energy expenditure. The approach allocates time in hours per day to various daily activities (components of the calculation, called "factors"), each of which is assigned an energy cost as a multiple of BMR, and aggregates across activities to estimate an overall PAL value (FAO, 2008). We utilized an adjustment factor of 0.4424 to add and subtract from the time allocation of each activity, based on whether the energy cost in PAR is above or below 1.55. This was done to bring the *approximate* value of 1.53 in the table above in line with the 1.55 value used by FAO. Their exact factorial calculation is unknown to us. We also adjusted the factorial calculation using Solver in Excel utilizing constraints on time allocations and minimizing the sum of the squared deviations from the time original allocations. The results were overall similar to the above method, with only some minor differences.

Table 2. Data Sources and Years of Variables

Variable	Source	Years	Mean	Standard Deviation	Minimum	Maximum
MDER	FAOSTAT	2023	1774.70	62.15	1655.00	1933.00
Proportion of Population Using the Internet	World Bank WDI	1985, 2022	2022: 46.62	2022: 23.77	2022: 0.00	2022: 88.13
Rural Population Percentage	World Bank WDI	1985, 2022	1985: 66.38 2022: 51.74	1985: 17.34 2022: 18.05	1985: 20.58 2022: 10.74	1985: 94.94 2022: 85.58
Theil Index	World Bank Poverty and Inequality Platform, World Bank World Development Report 1999, LM-WPID dataset from Lakner and Milanovic (2013)	1985, 2022	1985: 0.33 2022: 0.26	1985: 0.17 2022: 0.11	1985: 0.10 2022: 0.10	1985: 1.03 2022: 0.64
Upper Secondary Education Completion Rate	UNESCO	1990, 2023	1985: 0.21 2023: 0.40	1985: 0.22 2023: 0.29	1985: 0.01 2023: 0.02	1985: 0.93 2023: 0.99
GDP Per Capita in 2015 USD	World Bank WDI	1985, 2022	1985: 1445.12 2022: 2437.02	1985: 1094.08 2022: 1915.51	1985: 172.92 2022: 262.18	1985: 4704.06 2022: 8732.08

Notes: Web use is zero in 1985 in all nations. For the Theil Index the nearest values to 1985 and 2022 available were used when data availability was limited. For the upper secondary education completion rate, 2023 is the latest data available.

Table 3. Descriptive Statistics of Output Variables and MDERs

Variable	Mean	Standard Deviation	Minimum	Maximum
Predicted Change in Sitting Time (hours/day)	0.68	0.36	0.10	1.85
New Physical Activity Level (PAL) unitless	1.50	0.02	1.43	1.54
FAO MDER (kcal/day)	1774.70	62.15	1655.00	1933.00
BMR Deflated MDER (kcal/day)	1690.19	59.19	1576.19	1840.95
PAL Revised MDER (kcal/day)	1722.30	54.23	1614.86	1877.26
PAL and BMR Revised MDER (kcal/day)	1640.28	51.64	1537.97	1787.87

Note: Population weighted averages of the PAL Revised MDER and PAL and BMR Revised MDER are 1720 and 1638, respectively, as presented in the abstract, counter to the arithmetic means presented above.

Table 4. Descriptive Statistics of FAO MDER vs PAL Revised MDER and PAL and BMR Revised MDER Percentage Changes Over Time

	FAO MDER Percentage Changes Over Time via demographic change	PAL Revised MDER Percentage Changes Over Time	PAL and BMR Revised MDER Percentage Changes Over Time
Mean	4.603%	-2.929%	-7.552%
Minimum	-2.355%	-7.949%	-12.333%
25th Percentile	1.749%	-3.700%	-8.286%
Median	4.470%	-2.578%	-7.218%
75th Percentile	6.703%	-1.758%	-6.436%
Maximum	14.469%	-0.443%	-5.184%
Std. Dev.	3.457%	1.530%	1.457%

Table 5. MDER Inflation for Top Five Food Insecure Nations

Country	FAO MDER (kcal)	PAL Revised MDER (kcal)	5%-BMR Deflated MDER (kcal)	PAL & BMR Revised MDER (kcal)	Inflation Via PAL (kcal)	Inflation Via BMR (kcal)	Inflation Interaction (kcal)	Total Inflation (kcal)	PAL Inflation (%)	BMR Inflation (%)	Interaction Inflation (%)	Total Inflation (%)
India	1806	1744.462	1720.000	1661.393	58.607	83.070	2.930	144.607	3.528%	5.0%	0.176%	8.704%
Pakistan	1740	1713.984	1657.143	1632.366	24.777	81.618	1.239	107.634	1.518%	5.0%	0.076%	6.594%
Dem. Rep. of Congo	1655	1625.932	1576.190	1548.507	27.684	77.425	1.384	106.493	1.788%	5.0%	0.089%	6.877%
Nigeria	1719	1614.865	1637.143	1537.966	99.177	76.898	4.959	181.034	6.449%	5.0%	0.322%	11.771%
Ethiopia	1739	1717.923	1656.190	1636.117	20.073	81.806	1.004	102.883	1.227%	5.0%	0.061%	6.288%

Table 6. Descriptive Statistics on the MDER Inflation for 83 IFSA Nations

	Inflation Via PAL (kcal)	Inflation Via BMR (kcal)	Inflation Interaction (kcal)	Total Inflation (kcal)	PAL Inflation (%)	BMR Inflation (%)	Interaction Inflation (%)	Total Inflation (%)
Mean	49.9064	82.0141	2.4953	134.4159	3.043%	5.000%	0.152%	8.195%
Minimum	7.0566	76.8983	0.3528	86.6756	0.445%	5.000%	0.022%	5.467%
25th Percentile	28.9318	80.4184	1.4466	112.1831	1.789%	5.000%	0.089%	6.879%
Median	44.4597	81.6352	2.2230	128.1719	2.647%	5.000%	0.132%	7.779%
75th Percentile	65.0272	83.4535	3.2514	152.6989	3.842%	5.000%	0.192%	9.034%
Maximum	137.8652	89.3933	6.8933	224.5795	8.636%	5.000%	0.432%	14.068%
Std. Dev.	26.7719	2.5822	1.3386	28.3398	1.646%	0.000%	0.082%	1.728%

Note: Population weighted averages for the Inflation Via PAL and PAL Inflation are 57.49 and 3.52%, as reported in the abstract, counter to the arithmetic means of 49.9064 kcal and 3.043% as shown in the table above.

Table 7. Top Five Countries and World Aggregate of Undernourished Population Utilizing IFSA Model (millions)

Country	FAO MDER	PAL Revised MDER	BMR Deflated MDER	PAL and BMR Revised MDER	ERS 2100 (2020-22 Calibrated)
India	90.457	68.270	60.580	44.633	270.242
Pakistan	48.713	45.268	38.124	35.188	80.278
Dem. Rep. of Congo	30.893	29.427	26.946	25.583	54.341
Nigeria	27.593	18.476	20.249	13.107	64.562
Ethiopia	16.696	15.514	12.319	11.368	36.310
World Aggregate (83 countries)	518.202	446.875	400.201	344.583	1,056.248

Table 8. Arc Elasticities of IFSA PoU Results Top Five Nations

Country	PAL Revised MDER	BMR Deflated MDER	PAL and BMR Revised MDER
India	8.065	8.110	8.134
Pakistan	4.867	5.000	5.051
Dem. Rep. of Congo	2.743	2.798	2.828
Nigeria	6.335	6.293	6.403
Ethiopia	6.015	6.184	6.227
World Aggregate (83 countries) Descriptive Statistics			
Mean	6.213	6.283	6.291
Minimum	1.681	1.770	1.803
25th Percentile	4.147	4.280	4.394
Median	6.335	6.339	6.403
75th Percentile	7.956	8.011	7.931
Maximum	12.824	12.833	12.013
Std. Dev.	2.434	2.406	2.327

Table 9. Top Five Countries and World Aggregate of Undernourished Population Utilizing the Full Lognormal Model (millions)

	FAO MDER	PAL Revised MDER	BMR Deflated MDER	PAL and BMR Revised MDER	2,100 kcal
India	191.558	156.554	143.696	115.421	401.519
Pakistan	39.717	37.017	31.420	29.117	82.927
Dem. Rep. of Congo	32.841	31.071	28.069	26.419	58.389
Nigeria	31.472	22.646	24.409	17.115	73.052
Ethiopia	24.427	23.257	19.957	18.928	46.403
World Aggregate (83 countries)	589.360	507.093	459.318	392.664	1,226.394

Table 10. Point Elasticities of Lognormal PoU Results Top Five Nations

	FAO MDER	PAL Revised MDER	BMR Deflated MDER	PAL and BMR Revised MDER
India	5.645	5.997	6.141	6.500
Pakistan	4.614	4.730	4.993	5.112
Dem. Rep. of Congo	3.073	3.178	3.365	3.473
Nigeria	5.006	5.530	5.414	5.948
Ethiopia	3.985	4.064	4.301	4.381
World Aggregate (83 countries) Descriptive Statistics				
Mean	6.057	6.560	6.381	6.890
Minimum	2.795	3.043	2.877	3.128
25th Percentile	3.914	4.252	4.031	4.356
Median	5.441	5.933	5.641	6.013
75th Percentile	7.770	8.289	8.178	8.789
Maximum	14.247	15.386	15.109	16.159
Std. Dev.	2.635	2.828	2.822	3.016

Figure 1. Change in Predicted Sitting Time Distribution

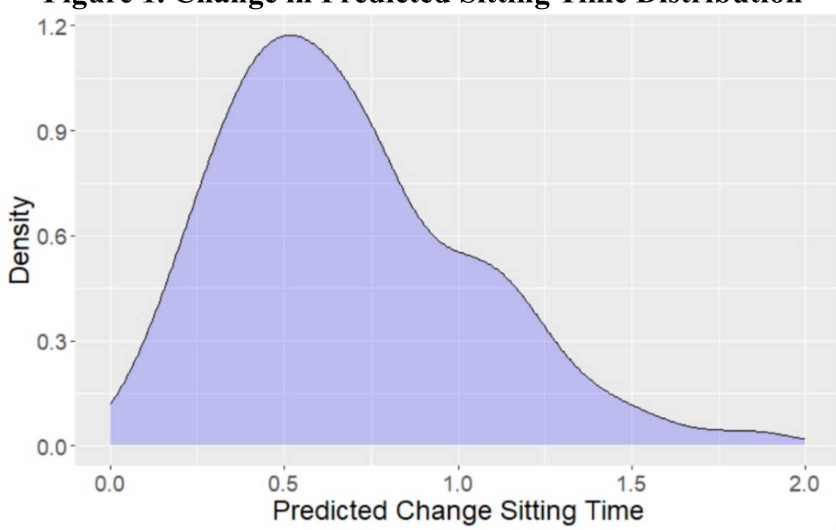


Figure 2. Revised Physical Activity Level Distribution

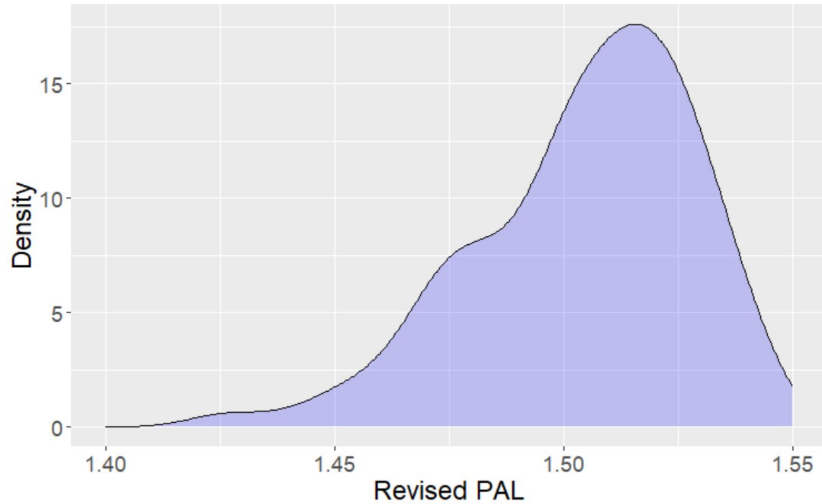
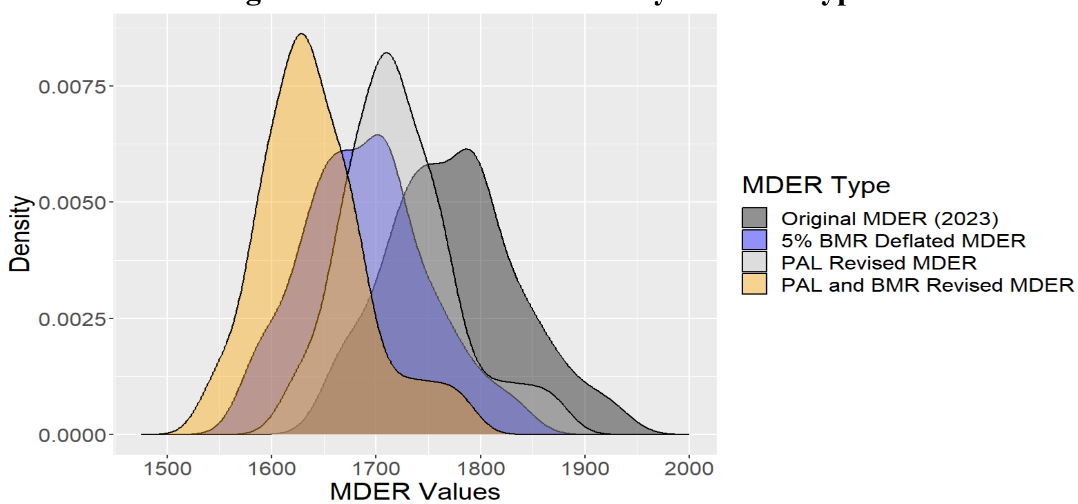
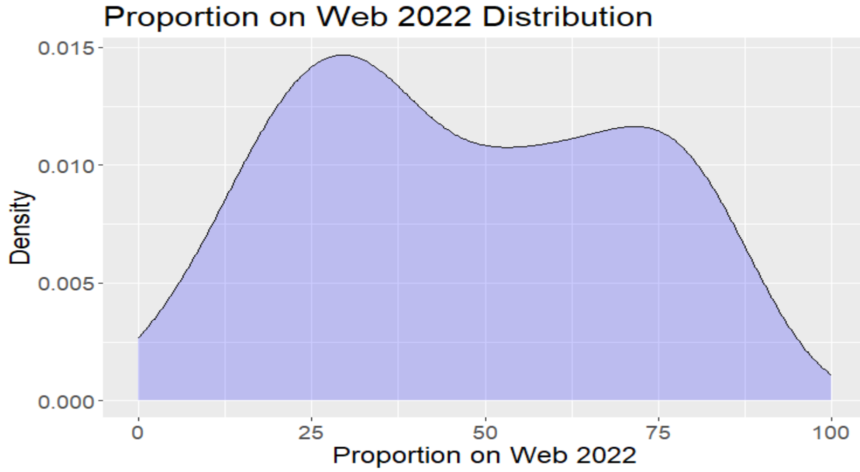


Figure 3 . MDER Distribution by Revision Type

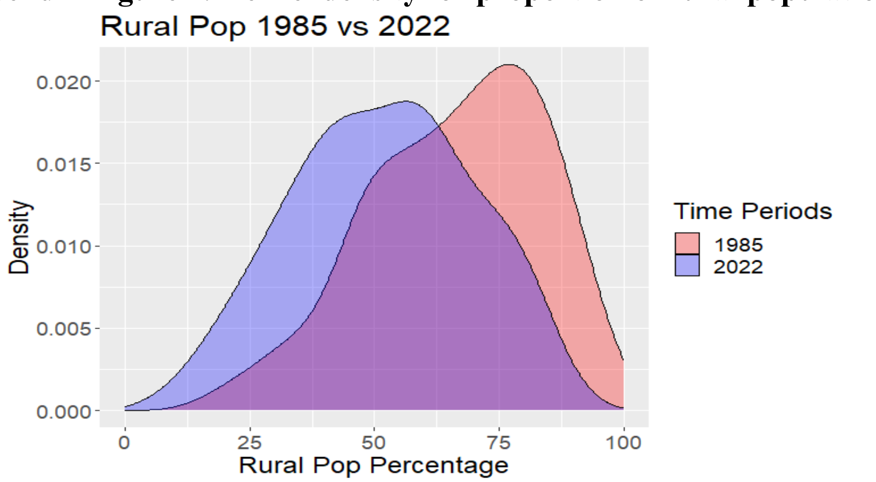


Appendix

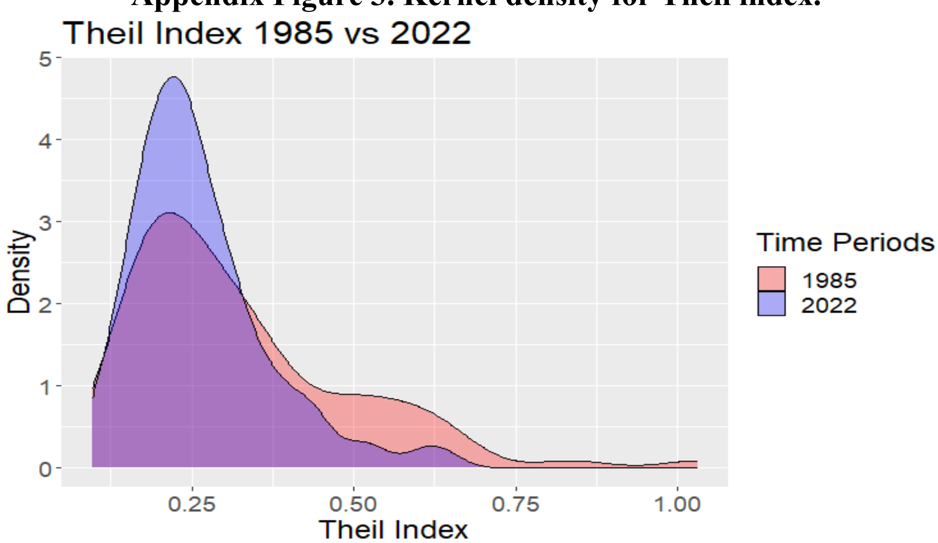
Appendix Figure 1. Kernel density for proportion on the web.



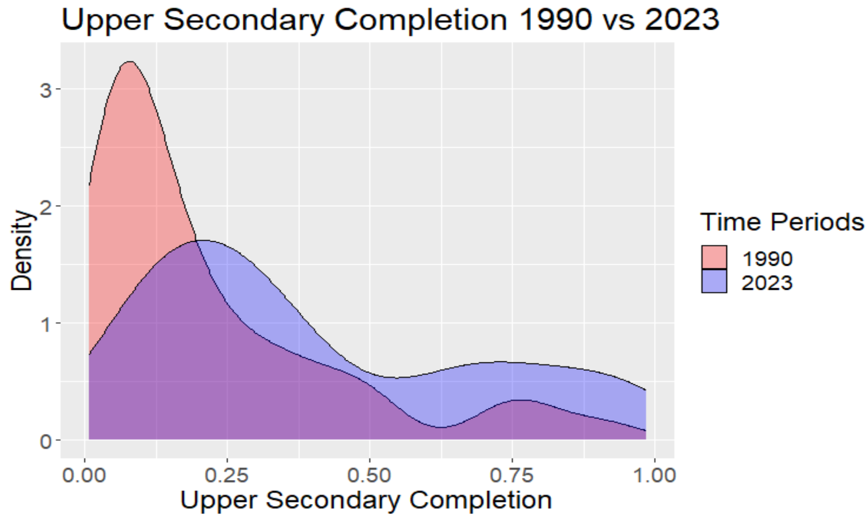
Appendix Figure 2. Kernel density for proportion of rural population.



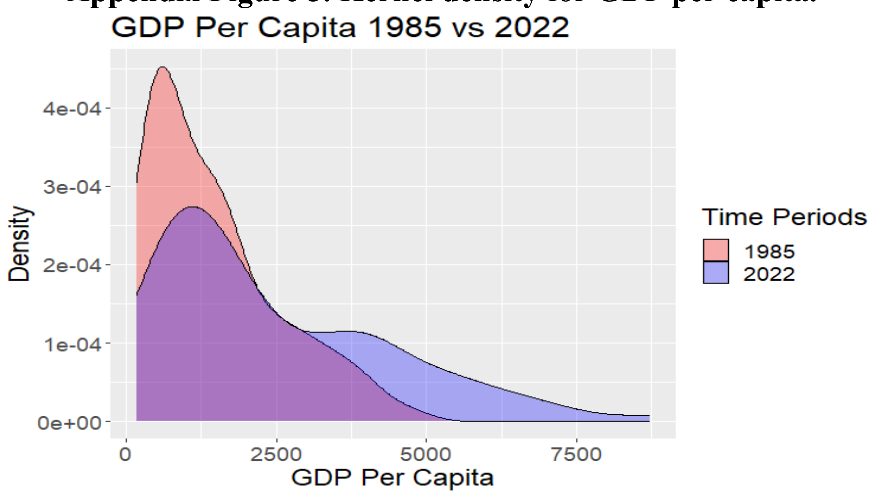
Appendix Figure 3. Kernel density for Theil index.



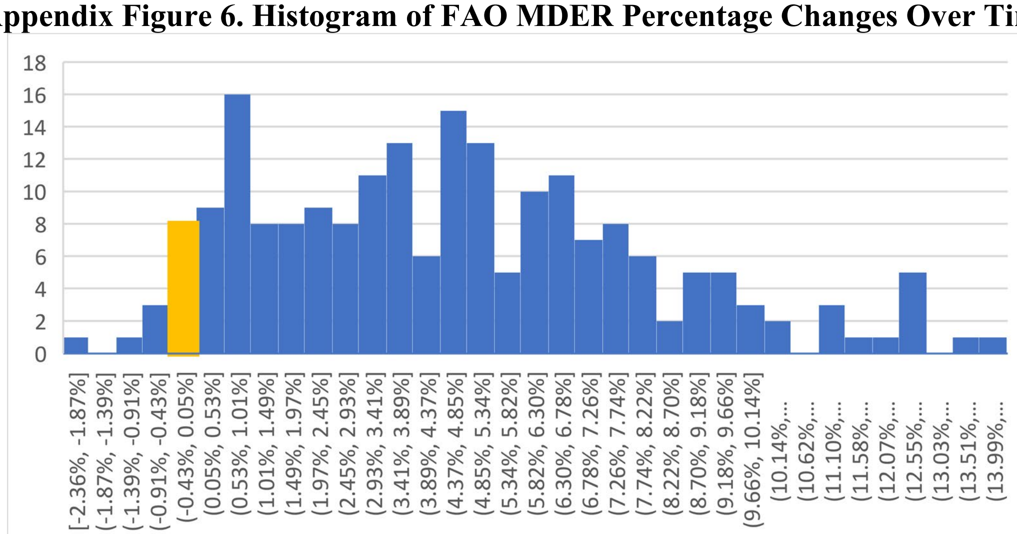
Appendix Figure 4. Kernel density for upper secondary completion



Appendix Figure 5. Kernel density for GDP per capita.



Appendix Figure 6. Histogram of FAO MDER Percentage Changes Over Time



Appendix Table A1. Estimates of Undernourished Utilizing IFSA Model (in millions)

Country	FAO MDER	PAL Revised MDER	BMR Deflated MDER	PAL and BMR Revised MDER	ERS 2100 (2020-22 Calibrated)
Afghanistan	16.979	15.847	13.874	12.811	18.467
Algeria	1.168	0.737	0.784	0.481	2.583
Angola	6.449	5.547	5.004	4.246	13.752
Armenia	0.060	0.046	0.035	0.026	0.173
Azerbaijan	0.108	0.056	0.057	0.028	0.388
Bangladesh	9.677	7.532	6.504	4.960	33.198
Benin	1.063	0.915	0.767	0.654	2.644
Bolivia	1.555	1.110	1.092	0.753	3.599
Burkina Faso	4.439	4.133	3.691	3.420	6.818
Burundi	7.732	7.589	6.809	6.662	9.920
Cabo Verde	0.058	0.040	0.041	0.027	0.192
Cambodia	1.089	0.857	0.747	0.577	3.466
Cameroon	2.216	1.829	1.561	1.270	5.972
Central African Republic	2.807	2.696	2.394	2.287	4.317
Chad	6.558	6.435	5.623	5.507	8.939
Colombia	1.668	1.148	1.091	0.731	5.178
Congo	2.340	2.173	1.914	1.759	3.048
Cote d'Ivoire	2.965	2.413	2.346	1.886	5.991
Democratic People's Republic of Korea	10.736	10.401	8.848	8.534	14.507
Democratic Republic of the Congo	30.893	29.427	26.946	25.583	54.341
Djibouti	0.100	0.086	0.074	0.063	0.193
Dominican Republic	0.290	0.150	0.177	0.087	0.918
Ecuador	1.649	1.359	1.082	0.874	4.010
Egypt	8.359	6.782	6.168	4.932	16.207
El Salvador	0.501	0.426	0.345	0.289	1.250
Eritrea	2.536	2.317	2.086	1.882	3.709
Eswatini	0.150	0.127	0.107	0.089	0.292
Ethiopia	16.696	15.514	12.319	11.368	36.310
Gambia	0.157	0.119	0.108	0.080	0.735
Georgia	0.224	0.164	0.145	0.104	0.537
Ghana	1.037	0.706	0.688	0.456	2.589
Guatemala	2.093	1.736	1.565	1.278	4.932
Guinea	1.019	0.881	0.758	0.648	2.665
Guinea-Bissau	0.510	0.454	0.401	0.353	0.964

Haiti	5.605	5.268	5.125	4.793	6.740
Honduras	1.170	0.934	0.878	0.688	2.548
India	90.457	68.270	60.580	44.633	270.242
Indonesia	16.502	13.158	11.445	8.971	41.605
Iran	0.773	0.429	0.463	0.248	9.229
Jamaica	0.229	0.169	0.151	0.108	0.402
Kenya	16.204	14.398	12.729	11.153	25.057
Kyrgyzstan	0.166	0.122	0.103	0.074	1.124
Laos	0.667	0.508	0.450	0.334	2.382
Lebanon	0.431	0.290	0.298	0.194	1.125
Lesotho	0.664	0.581	0.534	0.460	0.988
Liberia	1.805	1.742	1.566	1.507	3.023
Madagascar	12.141	11.417	10.182	9.499	19.423
Malawi	2.842	2.500	2.162	1.882	6.059
Mali	1.848	1.550	1.363	1.128	3.685
Mauritania	0.240	0.186	0.170	0.129	0.746
Moldova	0.103	0.085	0.059	0.048	0.318
Mongolia	0.201	0.136	0.138	0.090	0.464
Morocco	1.994	1.480	1.423	1.035	2.955
Mozambique	11.596	10.967	9.813	9.227	17.372
Myanmar	5.434	4.730	3.858	3.319	10.029
Namibia	0.450	0.332	0.319	0.227	0.827
Nepal	1.223	0.939	0.798	0.600	4.485
Nicaragua	1.083	0.957	0.856	0.749	1.924
Niger	3.304	3.236	2.611	2.553	8.200
Nigeria	27.593	18.476	20.249	13.107	64.562
Pakistan	48.713	45.268	38.124	35.188	80.278
Peru	2.641	1.540	1.826	1.018	6.587
Philippines	9.077	6.731	6.646	4.824	23.895
Rwanda	2.657	2.463	2.098	1.931	5.188
Senegal	1.104	0.880	0.737	0.576	3.526
Sierra Leone	2.078	1.935	1.757	1.626	3.115
Somalia	12.094	11.830	11.093	10.816	13.861
South Sudan	6.531	6.416	5.804	5.686	6.501
Sri Lanka	2.142	1.487	1.453	0.975	3.970
Sudan	3.959	3.481	2.875	2.503	15.136
Syria	1.989	1.768	1.384	1.218	4.361
Tajikistan	1.831	1.709	1.422	1.319	2.587
Tanzania	13.739	12.819	11.386	10.568	23.847
Togo	1.192	1.034	0.881	0.755	2.718
Tunisia	0.344	0.170	0.230	0.109	0.638
Turkmenistan	0.152	0.139	0.093	0.084	0.547
Uganda	16.730	15.844	14.132	13.309	24.218

Ukraine	4.837	3.688	3.170	2.344	4.127
Uzbekistan	0.591	0.343	0.343	0.190	1.797
Vietnam	2.467	1.597	1.626	1.024	8.483
Yemen	17.883	16.752	15.653	14.515	21.927
Zambia	6.919	6.650	6.034	5.780	9.129
Zimbabwe	7.921	7.717	6.962	6.760	11.491
Total	**518.202**	**446.875**	**400.201**	**344.583**	**1056.248**

Appendix Table A2. Estimates of Undernourished Utilizing Lognormal Model (in millions)

Country	FAO MDER	PAL Revised MDER	BMR Deflated MDER	PAL and BMR Revised MDER	2100 kcal Cutoff
Afghanistan	13.162	12.495	11.341	10.719	22.763
Algeria	0.823	0.499	0.534	0.314	2.835
Angola	7.808	6.959	6.435	5.682	15.855
Armenia	0.017	0.012	0.008	0.006	0.076
Azerbaijan	0.047	0.023	0.023	0.011	0.196
Bangladesh	18.088	14.566	12.824	10.126	45.126
Benin	1.349	1.190	1.026	0.897	3.380
Bolivia	2.581	2.042	2.019	1.562	5.129
Burkina Faso	3.716	3.425	3.009	2.757	7.308
Burundi	6.173	6.033	5.290	5.153	9.909
Cabo Verde	0.070	0.047	0.049	0.032	0.138
Cambodia	0.658	0.484	0.406	0.291	2.470
Cameroon	1.526	1.226	1.023	0.808	5.153
Central African Republic	2.649	2.549	2.278	2.181	4.276
Chad	5.445	5.335	4.620	4.519	9.460
Colombia	3.585	2.705	2.602	1.925	7.806
Congo	2.058	1.943	1.764	1.657	3.249
Cote d'Ivoire	2.241	1.736	1.676	1.276	5.743
Democratic People's Republic of Korea	12.383	12.042	10.432	10.102	17.178
Democratic Republic of the Congo	32.841	31.071	28.069	26.419	58.389
Djibouti	0.119	0.102	0.088	0.075	0.232
Dominican Republic	0.711	0.441	0.496	0.296	1.576
Ecuador	2.442	2.118	1.794	1.536	5.404
Egypt	8.853	7.289	6.675	5.425	18.126

El Salvador	0.566	0.489	0.405	0.346	1.393
Eritrea*	0.399	0.340	0.283	0.238	1.116
Eswatini	0.119	0.100	0.083	0.068	0.302
Ethiopia	24.427	23.257	19.957	18.928	46.403
Gambia	0.454	0.375	0.351	0.285	0.954
Georgia	0.130	0.094	0.082	0.058	0.305
Ghana	1.449	1.031	1.007	0.701	4.061
Guatemala	2.011	1.710	1.565	1.315	4.650
Guinea	1.405	1.245	1.100	0.968	3.174
Guinea-Bissau	0.670	0.618	0.567	0.519	1.094
Haiti	4.480	3.993	3.791	3.335	6.584
Honduras	1.971	1.696	1.628	1.386	3.365
India	191.558	156.554	143.696	115.421	401.520
Indonesia	14.208	11.249	9.743	7.583	39.732
Iran	4.598	2.887	3.065	1.856	11.411
Jamaica	0.189	0.141	0.127	0.092	0.346
Kenya	13.820	12.417	11.118	9.883	25.669
Kyrgyzstan	0.314	0.232	0.197	0.142	1.059
Laos	0.262	0.180	0.152	0.101	0.947
Lebanon	0.490	0.354	0.362	0.255	1.020
Lesotho	0.885	0.798	0.748	0.666	1.371
Liberia	1.838	1.768	1.576	1.510	2.965
Madagascar	10.492	9.843	8.748	8.148	18.403
Malawi	3.181	2.883	2.580	2.323	6.619
Mali	2.864	2.509	2.278	1.978	6.322
Mauritania	0.395	0.323	0.301	0.243	0.911
Moldova	0.033	0.027	0.017	0.013	0.103
Mongolia	0.043	0.024	0.024	0.013	0.210
Morocco	2.006	1.538	1.486	1.121	4.041
Mozambique	7.430	6.863	5.860	5.370	16.380
Myanmar	2.069	1.713	1.299	1.059	7.016
Namibia	0.435	0.354	0.344	0.275	0.816
Nepal	1.261	0.989	0.851	0.656	4.117
Nicaragua	1.106	0.982	0.882	0.776	2.069
Niger	3.879	3.804	3.103	3.038	9.000
Nigeria	31.472	22.646	24.409	17.115	73.052
Pakistan	39.717	37.017	31.420	29.117	82.927
Peru	1.808	1.003	1.208	0.640	5.409
Philippines	5.303	3.615	3.557	2.356	18.177
Rwanda	3.533	3.322	2.917	2.728	6.370

Senegal	0.829	0.658	0.550	0.429	2.730
Sierra Leone	2.105	1.941	1.740	1.594	3.730
Somalia*	3.390	3.203	2.726	2.563	7.179
South Sudan	1.638	1.569	1.241	1.184	3.910
Sri Lanka	0.573	0.352	0.341	0.201	2.313
Sudan	4.210	3.702	3.056	2.660	11.933
Syria	5.230	4.914	4.317	4.034	8.155
Tajikistan	0.687	0.624	0.482	0.435	1.872
Tanzania	13.048	12.114	10.669	9.848	27.153
Togo	1.328	1.181	1.034	0.910	2.839
Tunisia	0.294	0.149	0.199	0.097	0.808
Turkmenistan	0.212	0.194	0.131	0.120	0.770
Uganda	16.208	15.478	14.057	13.369	25.827
Ukraine	1.689	1.235	1.039	0.740	3.746
Uzbekistan	0.542	0.331	0.331	0.195	1.867
Vietnam	4.050	2.724	2.769	1.813	11.814
Yemen	10.078	9.270	8.523	7.782	17.498
Zambia	5.117	4.834	4.202	3.948	9.643
Zimbabwe	5.517	5.304	4.544	4.349	9.443
Total	**589.360**	**507.093**	**459.318**	**392.664**	**1,226.394**

Note: * denotes the food supply per day in kcal was imputed for this nation using the three nearest neighbors by population weighted average.

Appendix Table A3. Arc Elasticities of IFSA Modeling from FAO MDER Origin Point

Country	PAL Revised MDER	BMR Deflated MDER	PAL and BMR Revised MDER
Afghanistan	3.946	4.127	4.224
Algeria	8.058	8.055	7.944
Angola	5.101	5.173	5.264
Armenia	10.801	10.813	10.682
Azerbaijan	12.824	12.833	12.013
Bangladesh	7.988	8.041	8.059
Benin	6.535	6.618	6.661
Bolivia	7.164	7.173	7.283
Burkina Faso	3.702	3.772	3.814
Burundi	2.442	2.603	2.634
Cabo Verde	7.186	7.172	7.240

Cambodia	7.580	7.633	7.663
Cameroon	7.034	7.106	7.151
Central African Republic	3.111	3.255	3.305
Chad	3.028	3.148	3.165
Colombia	8.576	8.583	8.510
Congo	3.940	4.102	4.198
Cote d'Ivoire	4.762	4.774	4.844
Democratic People's Rep of Korea	3.749	3.952	3.993
Democratic Rep of the Congo	2.743	2.798	2.828
Djibouti	6.044	6.127	6.186
Dominican Republic	9.919	9.949	9.549
Ecuador	8.378	8.510	8.559
Egypt	6.143	6.183	6.238
El Salvador	7.483	7.588	7.628
Eritrea	3.865	3.992	4.103
Eswatini	6.716	6.833	6.914
Ethiopia	6.015	6.184	6.227
Gambia	7.485	7.520	7.555
Georgia	8.725	8.756	8.726
Ghana	8.296	8.300	8.232
Guatemala	5.866	5.923	6.001
Guinea	5.963	6.030	6.074
Guinea-Bissau	4.785	4.894	4.987
Haiti	1.811	1.833	1.883
Honduras	5.808	5.842	5.933
India	8.065	8.110	8.134
Indonesia	7.365	7.419	7.451
Iran	10.274	10.298	9.853
Jamaica	8.389	8.437	8.467
Kenya	4.802	4.924	5.035
Kyrgyzstan	9.533	9.553	9.464
Laos	7.924	7.982	8.030
Lebanon	7.491	7.481	7.518
Lesotho	4.348	4.432	4.564
Liberia	2.824	2.905	2.933
Madagascar	3.463	3.598	3.672
Malawi	5.487	5.575	5.637
Mali	6.132	6.194	6.250
Mauritania	6.997	7.028	7.060
Moldova	10.962	11.041	10.977

Mongolia	7.651	7.646	7.650
Morocco	6.843	6.855	6.883
Mozambique	3.309	3.414	3.467
Myanmar	6.840	6.955	7.005
Namibia	6.957	6.985	7.129
Nepal	8.597	8.639	8.618
Nicaragua	4.726	4.798	4.869
Niger	4.675	4.804	4.814
Nigeria	6.335	6.293	6.403
Pakistan	4.867	5.000	5.051
Peru	7.521	7.478	7.473
Philippines	6.335	6.339	6.401
Rwanda	4.704	4.825	4.877
Senegal	8.095	8.168	8.194
Sierra Leone	3.356	3.430	3.484
Somalia	1.681	1.770	1.803
South Sudan	2.276	2.417	2.443
Sri Lanka	7.846	7.855	7.905
Sudan	6.411	6.507	6.549
Syria	7.218	7.358	7.397
Tajikistan	5.012	5.160	5.209
Tanzania	3.761	3.840	3.884
Togo	6.060	6.163	6.232
Tunisia	8.164	8.196	7.917
Turkmenistan	9.835	9.955	9.942
Uganda	3.344	3.451	3.502
Ukraine	8.449	8.538	8.607
Uzbekistan	10.913	10.913	10.515
Vietnam	8.427	8.426	8.306
Yemen	2.631	2.727	2.826
Zambia	2.722	2.801	2.833
Zimbabwe	2.519	2.643	2.676

Appendix Table A4. Point Elasticities of Lognormal Model

Country	FAO MDER	PAL Revised MDER	BMR Deflated MDER	PAL and BMR Revised MDER
Afghanistan	2.926	3.016	3.179	3.271
Algeria	8.610	9.232	9.151	9.779

Angola	3.809	3.996	4.121	4.312
Armenia	14.247	14.834	15.386	15.980
Azerbaijan	14.046	15.109	15.086	16.159
Bangladesh	6.739	7.137	7.363	7.769
Benin	5.404	5.588	5.799	5.985
Bolivia	4.795	5.249	5.270	5.736
Burkina Faso	4.172	4.292	4.478	4.600
Burundi	2.952	3.017	3.378	3.447
Cabo Verde	6.800	7.530	7.469	8.214
Cambodia	9.504	10.038	10.334	10.876
Cameroon	7.875	8.233	8.520	8.884
Central Afri. Rep.	2.890	2.995	3.291	3.401
Chad	3.219	3.257	3.515	3.554
Colombia	6.341	6.742	6.795	7.202
Congo	3.017	3.127	3.306	3.420
Cote d'Ivoire	5.753	6.106	6.153	6.511
Dem. People's Rep. of Korea	3.266	3.350	3.765	3.854
Dem Rep of Congo	3.073	3.178	3.365	3.473
Djibouti	5.862	6.102	6.334	6.579
Dominican Republic	7.125	7.854	7.680	8.421
Ecuador	6.032	6.299	6.601	6.875
Egypt	5.601	5.863	5.979	6.245
El Salvador	6.575	6.818	7.121	7.368
Eritrea*	6.713	7.009	7.336	7.639
Eswatini	7.125	7.463	7.801	8.146
Ethiopia	3.985	4.064	4.301	4.381
Gambia	5.050	5.392	5.506	5.855
Georgia	8.985	9.497	9.694	10.212
Ghana	7.203	7.666	7.696	8.165
Guatemala	4.975	5.203	5.325	5.557
Guinea	4.850	5.008	5.168	5.328
Guinea-Bissau	3.258	3.410	3.568	3.725
Haiti	3.240	3.501	3.615	3.887
Honduras	3.782	3.998	4.056	4.276
India	5.645	5.997	6.141	6.500
Indonesia	7.451	7.802	8.012	8.367
Iran	7.991	8.730	8.638	9.388
Jamaica	7.870	8.382	8.561	9.081
Kenya	4.244	4.461	4.677	4.901
Kyrgyzstan	9.159	9.698	9.983	10.532
Laos	10.612	11.309	11.608	12.317
Lebanon	5.996	6.479	6.445	6.935

Lesotho	3.261	3.496	3.637	3.882
Liberia	3.010	3.085	3.300	3.377
Madagascar	3.522	3.668	3.930	4.082
Malawi	4.141	4.281	4.434	4.575
Mali	4.535	4.718	4.847	5.033
Mauritania	5.376	5.641	5.733	6.002
Moldova	13.002	13.399	14.127	14.529
Mongolia	11.354	12.247	12.209	13.111
Morocco	5.970	6.294	6.335	6.663
Mozambique	4.632	4.792	5.102	5.267
Myanmar	9.170	9.486	9.935	10.255
Namibia	4.611	4.948	4.990	5.334
Nepal	7.770	8.124	8.335	8.693
Nicaragua	4.460	4.641	4.801	4.986
Niger	4.417	4.446	4.742	4.772
Nigeria	5.006	5.530	5.414	5.948
Pakistan	4.614	4.730	4.993	5.112
Peru	7.950	8.881	8.596	9.541
Philippines	7.887	8.467	8.491	9.079
Rwanda	3.755	3.866	4.095	4.210
Senegal	8.094	8.464	8.742	9.118
Sierra Leone	3.740	3.880	4.064	4.208
Somalia*	4.295	4.389	4.649	4.746
South Sudan	5.441	5.519	5.933	6.013
Sri Lanka	10.212	11.004	11.053	11.855
Sudan	6.310	6.518	6.819	7.031
Syria	3.773	3.880	4.098	4.208
Tajikistan	6.971	7.125	7.524	7.681
Tanzania	3.969	4.087	4.284	4.405
Togo	4.938	5.132	5.345	5.542
Tunisia	7.770	8.576	8.243	9.056
Turkmenistan	9.408	9.550	10.176	10.320
Uganda	2.795	2.877	3.043	3.128
Ukraine	9.543	10.085	10.373	10.924
Uzbekistan	9.790	10.461	10.460	11.138
Vietnam	7.527	8.077	8.055	8.612
Yemen	3.287	3.437	3.584	3.739
Zambia	3.860	3.967	4.221	4.330
Zimbabwe	3.758	3.850	4.199	4.294

Note: * denotes the food supply per day in kcal was imputed for this nation using the three nearest neighbors by population weighted average.