EXPERIENTIAL FOOD INSECURITY MEASURES AND INCOME

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Master of Science

by

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ABSTRACT

Using a six year panel of results from the United Nation's Food and Agriculture Organization's Food Insecurity Experience Survey collected by Gallup World Survey, we investigate the relationship between food insecurity experiences and income. By applying Rasch modelling of context-specific item response and limited dependent variable econometrics, we estimate this relationship and draw comparisons across contexts. This is accomplished via analysis of the unobserved heterogeneity resulting from fixed effects, as well as country-group comparisons of what we define as a semi-elasticity of food insecurity experiences. Finally, we estimate the costs of alleviation for the moderate and severe food insecurity thresholds of food insecurity on a globally-comparable scale for 2017 and investigate differences in costs across countries in our sample. Our results are based on data surveyed with coverage of more than 90 percent of the world's population and is unique in its contribution to the body of comparative international food insecurity studies.

BIOGRAPHICAL SKETCH

Nick Grandstaff was born and raised on a farm in rural Iowa. Such an upbringing informed his interests and gave direction to his path of study. Currently, Nick is a M.S./Ph.D student at Cornell University's Dyson School of Applied Economics and Management with research interests of agricultural development, food security, and food markets in lower middle income contexts. His hobbies include running, rowing, thinking about food markets, and lunch. After completion of the M.S. degree, he will continue his time at Cornell as a Ph.D. student.

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1 Introduction

Food insecurity is present in all nations at all times. It manifests itself within households and among individuals in regions facing crisis as well as in times of transitory income loss or health shocks. Regardless of the depth or duration of an individual's experience with food insecurity, its effects on livelihoods keeps hunger alleviation a common policy priority amongst public and private institutions globally.

The United Nations' Food and Agricultural Organization (FAO) defines food security as a state in which "all people, at all times, have physical, social and economic access to sufficient, safe, and nutritious food that meet[s] their dietary needs and food preferences for and active and healthy life" (FAO 2021). Given the breadth of this definition, one cannot easily discern which metric may best capture the measurement of food security in its entirety. Meal frequency, caloric intake, nutrient intake, diet diversity, and anthropometric measurements all capture components of food insecurity, though limit researchers' scope of understanding if measured in isolation. Furthermore, many of these measures are costly and cannot be implemented much beyond one context at a time due to resource and organizational constraints.

Food insecurity then may be defined as a uni-dimensional latent variable–or one such that it can only be measured through mathematical models of other variables (Dodge 2003). Doing so, one may create a scale of "food insecurity experiences" reflecting the joint severity scaling of multiple food insecurity measures and revealed through itemized responses to experience-based questions. In 2014, the FAO partnered with Gallup World Poll (GWP) in 2014 to measure food insecurity experiences on latent scale as part of Gallup's ongoing global, nationally-representative survey (Ballard et al. 2014). Using an eight question, binary response food insecurity security experience scale (FIES), the FAO has collected data from randomly sampled individuals in more than 150 countries, with individuals sampled to represent over 90 percent of the world's population.

Using a Rasch model, we first model food insecurity experiences as a globally-standardized, one parameter item response variable. Such measurements have previously been undertaken but our contribution lies in the length of our panel and completeness of methodological applications. Our analysis extends further to estimate associations in responsiveness of this food insecurity experiences outcome variable and a contextually-comparable household income variable. From this, a semi-elasticity of food insecurity (SEFI) experiences can be derived, estimated, and compared across contexts. Then, we extract fixed effect parameter values by country and year, then estimate effects of country-year-level non-time-varying characteristics on these annual, country-level conditional means. Finally, we summarize estimates of alleviation costs of country-level moderate and severe food insecurity experiences and compare them across contexts with respect to food insecurity prevalence. In combination, we contribute a unique analysis of global food insecurity that allows for comparisons across countries and years.

2 Food Insecurity as a Latent Variable

Food insecurity, as it manifests among individuals and populations, is a difficult concept to measure due to the requisite dimensionality needed for its complete understanding. Food insecurity may stem from issues concerning of availability, access, and safety in one's food environment. This results in two constraints for researchers and policymakers: first, many measurements must be undertaken; and second, frequent measures are required. Regardless, either constraint suggests annual measurement of food insecurity experiences for any sizable share of a population would be a difficult and costly task.

To avoid the first of these problems, one may begin by defining food insecurity as a latent variable. Latent variable measurement has existed and developed since the 1950s with origins in the educational testing and psychometrics literature. One case of latent variable models is the Rasch model (Rasch 1960), a dichotomous response model modeled as a logistic function of one parameter: a difficulty, or severity, parameter. Derivation of this model may be found in the appendix.

For this study we use the food insecurity experiences scale (FIES) developed by Radimer et al. which conceptualized the latent variable into eight questions spanning the three recognized phases of food insecurity experiences with "quantitative, qualitative, psychological, and social components" (1990, 1992). Consistent with the Rasch model, the eight questions (here, interchangeably referred to as "items") visible in Table 1 elicit dichotomous responses for which respondents most closely associate with their experiences. While other Rasch-styled food insecurity scales have been developed, the Radimer et al. scale has been shown to be consistent with other scales' sub-constructs of food insecurity: uncertainty, compromising on dietary preferences or quality, eating less, and going hungry (Coates et al. 2006). In addition, the scale has been shown to be consistent with other food insecurity and poverty measures including the prevalence of undernourishment, percentage of children under five years of age who are underweight, the World Bank Poverty Rate, the Human Development Index, among others (Cafiero et al. 2018; Smith et al. 2017). Other food insecurity scales of varying item length and content have similarly been considered, but the Rasch scale has most recently risen to prominence.

After piloting the question battery in sub-Saharan Africa (Graham, Miller, & Viviani 2014; Brunelli, et al. 2014), the Food and Agricultural Organization (FAO) of the United Nations adopted the Radimer et al. (1992) scale to monitor global food insecurity status. Beginning in 2014, the FAO commissioned Gallup, Inc. to incorporate the eight questions into their annual Gallup World Poll (GWP) with broad coverage of the world's population (details of GWP sampling methods may be found in the appendix). This resolved the second constraints, frequency, while providing a sufficient sample size for annual, global measures which robustly capture the latent variable of interest: food insecurity experiences.

Table 1: Food Insecurity Experience Scale Questions

Item	Reference	During the last 12 MONTHS was there a time when:
1	WORRIED	You were worried you would not have enough food to eat because of a lack of money or other resources?
2	HEALTHY	You were unable to eat healthy and nutritious food because of a lack of money or other resources?
3	FEWFOODS	You ate only a few kinds of foods because of a lack of money or other resources?
4	SKIPPED	You had to skip a meal because there was not enough money or other resources to get food?
5	ATELESS	You ate less than you though you should because of a lack of money or other resources?
6	RANOUT	Your household ran out of food because of a lack of money or other resources?
7	HUNGRY	You were hungry but did not eat because there was not enough money or other resources for food?
8	WHOLEDAY	You went without eating for a whole day because of a lack of money or other resources?

Note: Questions translated to local languages by enumerators.

Given the outcome of interest is food insecurity experiences rather than food insecurity itself, some motivation is required in justifying the Rasch variable construction. By way of three assumptions, we present the ideas underlying the mechanism and how they can either be justified or tested.

First, uni-dimensionality of the latent variable construction is assumed for the variable constructed. This is discussed and justified further by Radimer et al. (1992) and Coates et al. (2006). Essentially, the latent variable can be mapped to the real line that it may be scaled. Second, the Rasch model assumes the probability of an item receiving a "yes" response (henceforth, "affirmed") is less likely for a relatively more severe item. Furthermore, the log-odds of such a probability may be modeled linearly by the difference in severity of the food insecurity condition experienced by the respondent and the severity reflected by the item. Both item location and experience location are located on the same uni-dimensional scale, with individuals, probabilistically, affirming items when their experience exceed the severity level of experience reflected by the item. And third, the logistic item severity model assumes that items discriminate equally for any level of probability. This provides that an item defined as less (more) severe may not become relatively more (less) severe as probability of item affirmation increases. Such an assumption is supported by the estimation of item-fit statistics, respondent-fit statistics, and inter-item conditional correlations–each being provided by the model estimating procedure via conditional maximum likelihood. Details on this procedure will follow. The final assumption is the defining characteristic between the one- and two-parameter item response mode and is especially important for cross-contextual transformations of Rasch scales. By construction of a one-parameter logistic model–that item severity but not discrimination change–this assumption is held. This idea is best visualized through item characteristic curves which present probability of item affirmation and scale severity or difficulty on a two dimensional plot. Additional information on these curves and Rasch models can be found in the text by Andrich (1988).

Such characteristics of a food insecurity measure are especially favorable for our purposes. Below, we estimate the association between experienced food insecurity and income globally. For such estimation to take place, our metric provide an estimation procedure by which one may reliably and comparably map individuals to a latent variable scale that may be transformed for similarity of scaling across contexts. Crucially, the Rasch model assumes no order of the items, but rather allows item response patterns by context to determine the item order and relative magnitude "distances" between items. This means our estimates of income's association with food insecurity across contexts may confidently be interpreted to show the relative magnitude one unit of income change may have on an individual's place within their context's distribution of food insecure individuals. Additionally, this lends itself to cross-context comparisons of severities by individuals and contexts across time and space.

3 Data Availability

To estimate this relationship between food insecurity experiences and household income, we rely on the Gallup World Poll for sociodemographic, income, and food insecurity data. In 2014 FAO introduced the FIES battery of questions to the GWP (Table 1) which has since. Sampling for these questions followed the same procedure as in the GWP above. Global coverage of the GWP in our data set includes 158 countries between 2014 and 2019. Respondents are sampled from countries representing more than 90 percent of the world's population. In 2018 a sizable portion of respondents were not asked the FIES questions on a country-level. These countries are omitted from our analysis. Data for our repeated cross section was provided to the authors in 2020, prior to the 2019 data being finalized (Gallup 2020). Table 2 summarizes the number of respondents in the repeated cross section by geographical region and income groupings by gross domestic product per capita. Though countries enter and exit the data set, there is a stable and sizeable number of respondents providing responses in any given year which provides us significant opportunity to better understand the relationship between income and food insecurity experiences across contexts.

Over the six year repeated cross section many countries enter and exit the data set. GWP coverage or inclusion of a country can vary for a number of reasons, but we will describe the sample by subsets of stable, repeated cross sections in which the panel country-units are balanced. For our purposes, we will use the full data set for summary statistics and regressions, unless otherwise noted. This subset, called "Full", contains

158 countries and contributes 751 country-years of data for which a country reports data from the FIES questions. This is the least restrictive of the data sets as it allows for countries to enter and exit freely. That said, we check robustness of our findings by creating and utilizing the next longest stable panel which is created by dropping 2014 and using countries that exist in the data for each of the years 2015 through 2019 (here, called "Drop 14"). This subset is comprised of 76 countries and approximately 38 percent of the sample. Compared with the "Drop 19" sample, the Drop 14 subset is larger by 150 thousand observations.

These subsets provide slightly different results to the Full sample with respect to item severity scaling and food insecurity prevalence. This is a consequence of the composition of countries and years drawn upon for the Drop 14 subset: countries where Gallup was willing to operate. The magnitudes of these differences were not large enough to cast aside over half of our sample.

Within years, our sample provides ample opportunity for international country groupings. In Table 2 we summarize two of these groupings. The first is by World Bank defined geographical regions and the second by World Bank defined income groupings organized by gross domestic product per capita. Summaries of included countries by geography may be found in the appendix. Income groupings are organized by income thresholds which vary by year, although all income is in constant terms. Country-level income groups are assigned to the data *post hoc* and we maintain these groups. Across years incomes vary which results in overlapping bin definitions. For many of the visualizations presented below, we often will use 2017 to present data by group and, as a result, here we summarize the group income levels. These 2017 groupings and the range of their median per capita GDP values include: high income ($14080, 85030), upper middle income ($3920, 14480), lower middle income ($1030, 4530), and low income ($180, 940) (here, groupings are inclusive).

Table 2 briefly presents the number of observations by region and year. Gallup's cluster sample design for non-institutionalized civilians over 15 years of age are nationally representative and probability based, but do leave out entire countries on occasion. In our data, country-level omissions are due to two reasons: danger posed to enumerators or late data-submission for 2019. This is evident for North America in 2019, when neither Canada nor the United States of America provided data before this study received the data. Regardless, our panel is representative of the countries from which it reports data and our study is among the largest of its kind to have collected a comparable food security metric across contexts for comparison.

4 Methods

Our analysis of the latent variable for food insecurity measurement is not without precedent, though many of the studies preceding ours rely upon binary thresholds of item affirmation "raw scores" set at three and

Table 2: Gallup World Poll Data Availability by Country Grouping

Grouping	2014	2015	2016	2017	2018	2019
East Asia & Pacific	13,039	17,298	17,448	19,356	14,168	15,079
Europe & Central Asia	47,077	46,261	48,626	44,566	33,098	29,124
Latin America & Caribbean	19,568	17,539	18,513	19,048	17,500	19,719
Middle East & North Africa	15,102	16,982	16,898	16,962	7,026	7,366
North America	2,048	2,030	2,048	2,018	1,009	-
South Asia	8,070	5,082	6,000	7,704	8,109	11,020
Sub-Saharan Africa	36,044	32,000	34,191	36,000	26,002	31,244
High Income	43,170	42,153	44,510	43,503	25,058	9,680
Upper Middle Income	36,583	39,378	41,450	39,718	28,727	42,639
Lower Middle Income	40,167	34,659	37,573	41,433	40,127	47,281
Low Income	20,028	20,002	19,191	20,000	12,000	12,872
Total Observations	144,449	140,192	147,724	148,654	108,912	113,552
Total Countries	143	136	140	141	101	90

Source: Gallup World Survey data requested in Fall 2019.

either seven or eight items affirmed (the second threshold varies by paper). These binary outcomes proxying for severity levels lend themselves to linear probability models, which may be estimated but are less accurate than what the data can provide. Here, we take interest in using the data's Rasch structure to form and understand a semi-continuous outcome variable. Next, we take cues from the literature and estimate the relationship between income and this outcome. Then, we compare this relationship across contexts. Finally, we estimate costs of food insecurity alleviation based upon the figures presented above.

4.1 Estimating the Rasch Model

To begin, we estimate the Rasch modelled outcome variable through the iterative process outlined by Cafiero et al. (2018) for our eight item, binary response scale. This process uses context-specific response patterns to map raw scores to relative magnitudes of severity, which are then normalized, scaled, and transformed to a globally-comparable reference scale. It should also be noted that individuals sampled within-country are probability weighted for population-level characteristics. These probability weights are utilized in any estimation of Rasch weights mentioned below. Here, we estimate these weights for our Full and Drop 14 samples of data and find the more stable sample to have relatively higher weights (shifting the distribution rightward), all else constant, than the Full sample due to the omission of countries excluded from the data set for a year. These lower weights reflect the included countries' stability and relatively lower food insecurity statuses. For those countries included in the Drop 14 sample severity reflected in lower ordered items is greater than in a sample where food insecurity is more pervasive. Similar trends are reflected in the Drop

19 and Cover 6 samples when a similar procedure is carried out.

Following Cafiero et al (2018) we maintain many of the same model settings from the R package they contributed, though vary the parameters to better understand the estimation method. In particular, a "tolerance" level of 0.4 is maintained throughout our analysis in the development of the Global Standardized Scale (GSS) with our data. Lower tolerance levels result in faster scale convergence and relatively higher item weights. Relatively higher tolerance levels slow convergence in the iterative process and result in more frequent omission of outlying countries, in terms of item response patterns. As a result, weights assigned by at a higher tolerance level are also consistently higher though by very small magnitudes. Individual-level probability weights collected by Gallup are used in all specifications of our CML model, as per Cafiero et al.

Cafiero et al. further outlines a Wald-statistic procedure to test scale and item stability. In other words, a test to determine if item interpretation varies in-context across years. We perform this procedure and find inconsistent results, which is likely caused by our longer panel and the ability of item meaning interpretation over time. When estimating these Rasch item weights with a country's data pooled across our panel or for each country-year to be estimated in kind, we find consistent results for both in the Full and Drop 19 samples. For simplicity, we assume stability over item interpretation for our study.

To better understand the estimated scale's fit to the data, several statistics and points of comparison are mentioned by Cafiero et al. We find similar conditional correlation and flat reliability statistics to the original study though we use a larger data set in terms of countries and observations. "Common items", as defined in the original paper, are also consistent in our samples. Unlike the original paper we do not drop countries from the sample with infit values above 1.4. An infit statistic reflects the in-sample fit of the item response curves to the data. Infit values above 1.4 are typically flagged and investigated further. We do this and conclude there is not sufficient reason for those countries' omission from our analysis. All are maintained.

The statistical package in question uses a conditional maximum likelihood (CML) function to fit the item responses to weights. Such method does not and cannot assign an item weight to individuals affirming zero items. As a consequence, individuals who do not affirm any of the questions (in other words, do not exhibit measureable food insecurity) are not mapped to the latent scale through this package. We do not assign these individuals a location on the latent scale because it would be misleading to assume they are homogeneous or that, across-contexts, we can accurately determine where further items might exist. Instead, we introduce the use of limited dependent variable econometrics in the next section estimate the relationship between food insecurity and income.

4.2 Modelling Food Insecurity Experiences on Income

For our study, we use Tobit regression (Tobin, 1958) to understand income's relationship with our semi-continuous, left-censored, Rasch modelled outcome variable. For robustness, we estimate a limited number of linear probability models on GSS-defined binary thresholds which we will call "Rasch thresholds" and are set with respect to locations on the latent distribution rather than a raw score. In all cases our regressions will use the individual-level probability weights provided by Gallup to ensure estimates are reflective of sample provided.

In our multivariate regression analysis we use Tobit in all cases. While Tobit does not account for possible asymmetries in our outcome variable, it does cater to several other characteristics of the data for which other methods cannot. Among these challenges, the first is the left-censoring of our dependent variable as previously discussed. Second is our desire to include and extract high dimension fixed effect coefficient (namely, on year and country). Third is the differential left-censor of our data by country resulting from the global-standardization process outliend by Cafiero et al. (2018). And fourth, we would like the correct distributional assumption on the dependent variable. Tobit caters to the first three characteristics while the fourth cannot be accommodated. Alternative methods including censored least absolute deviations, censored quantile regression, and symmetrically censored least squares but in all cases these options fail to accommodate our need for differing censor points and/or the extraction of fixed effects. As a result, we defer to Tobit and argue that asymmetries in the dependent variable distribution result in clustering of item-weight groupings and similar cross-context weighting of certain items (particularly, WHOLEDAY).

In the analysis that follows, we present model forms with varied sets of dependent and independent variables. Generally, the model may be thought of in the following form:

$$FS_{ijt} = \hat{\beta} INCOME_{ijt} + \theta T_t + \lambda_j + \varepsilon_{ijt} \tag{1}$$

where FS_{ijt} is a stand-in for our outcome food insecurity experience variables the continuous Rasch or the Rasch threshold outcomes. This term will vary throughout, but is always associated with a respondent i in a country j in a time t. Similarly, the independent variable $INCOME_{ijt}$ will take many forms throughout the analysis, but here it suffices to show its place in the general model with associated coefficient, β, which is this study's coefficient of interest. Given the repeated cross sectional format of our data, include fixed effects for country and year. Year, in this data set, is associated with the wave of GWP in which the questions are asked. The FIES questions of Table 1 reference a twelve month window before the survey is given. This captures food insecurity experiences not tied to any time of the year or a particular season occurring annually. The fixed effect for year is represented above by θT_t and the fixed effect for country is represented by λ_j. In all cases of the model, we include country and year fixed effects as binary independent variables. "Year", here, refers to the wave year of the survey. For Gallup, this corresponds to a time of year within a country, so that surveys collected in a country A occur at the same time of year, each year data is collected. This allows for the country-level fixed effects to assuage doubts concerning variable consumption seasonality within our panel.

Across samples the error term for this model is ε_{ijt} and is assumed to be conditionally independent, normally distributed, and associated with a respondent in a given place and time. That said, this is a strong assumption and the nature of our outcome variable results in a robustly negative error distribution suggesting our model overestimates the parameter returns on food insecurity experiences. By the Rasch methodology, all individuals surveyed weakly under-report their food insecurity status since they affirm the item that is weakly less severe than their location on the uni-dimensional latent scale. An individual affirms an item they deem consistent with their experiences, which is only true if their experiences are to the *right* of the item's location on the uni-dimensional scale.

To remove individual-specific variation in food insecurity experiences, we control for individual characteristics surveyed by Gallup.

$$FS_{ijt} = \hat{\beta} Income_{ijt} + \gamma X_{ijt} + \theta T_t + \lambda_j + \varepsilon_{ijt} \tag{2}$$

Equation 2 includes a term γX_{ijt} that includes a set of relevant covariates that are consistent with those used in the studies reviewed above. Such controls include: age, age squared, sex, greater than secondary education, marital status (married, separated, and widowed), household location (rural or urban), household size, and proportion of the household under 15 years old. These covariates are provided by Gallup, which, to an extent, limits our analysis and definition of categories. For that reason, sex in our study is treated as a binary.

While determining best model specification below, we will investigate whether functional form between income and food insecurity experiences differs by severity level. Are associations between income and food insecurity status stronger or weaker as more items are affirmed? To test this, we follow the Rasch methodology discussed above and in Cafiero et al. (2018), but also utilize Rasch thresholds, set at the item locations for *ATELESS* and *WHOLEDAY* on the GSS. These thresholds correspond with the phrasing *moderate & severe food insecurity* and *severe food insecurity* and may be used interchangeably.

Our independent variable, $Income_{ijt}$ is based on uniformly-surveyed income data where individuals were asked for their total monthly household income in local currency before taxes. This includes all wages, salaries, remittances from household members, and any other income source. When reported, this value is translated to annual household income and adjusted to 2016 U.S. dollars, purchasing power parity. We transform this variable to further test the functional form of income on food insecurity experiences. Consistent with the literature, we use log transformed income ($log(x + 1)$) throughout and present the results below.

As is characteristic of Gallup data collection procedure, no respondent is required to answer all questions and skipped questions are permitted. In our sample of Gallup data, approximately thirty-five percent of observations have incidence of at least one skipped question. That is for at least one of the covariates mentioned above, the respondent did not answer the question. In cases where this occurs, we impute the median values by corresponding country and year in an attempt to retain observations. We identify no patterns across non-responses. Individuals without a reported household income value comprise of less than one percent of the sample and are, in a majority case, surveyed in a country and year in which GWP did not collect the data. Finally, while 12,090 observations did not report income we find it to be due to omission from a country's question battery. Seven countries account for all but two of the income non-responses, having not reported income for at least one year. In our study we impute no income values and these observations are omitted from the analysis when regressions are performed

We specify our model to use fixed effects by country and year, but not their interaction. Such saturation of the model is tested and, though our dimensionality permits it, we do not observe much difference in our estimated parameters of interest as a result (less than a one percent magnitude change). In all specifications of our model, we report robust standard errors.

4.3 Understanding Food Insecurity and Income by Context

A key feature of our data is that it lends itself to uniform measurement of food insecurity experiences and incomes. To that end, we provide a two part analysis of this relationship. First we estimate SEFI values for country-groupings organized by GDP per capita levels by group-defined, country-level income tertiles. Comparing the SEFI across the contexts begins to unravel how food insecurity returns on income differ by region with respect to per capita GDP levels.

And while heterogeneity of SEFI is one aspect of this cross-contextual comparison, we also investigate what we will call the "baseline" levels of food insecurity by modelling the fixed effects of each country j. Here, we define the baseline value as the country fixed effect from our full regression over the repeated cross section. Above, this is represented by $\hat{\lambda}_j$ and represents the country-specific, non-time-varying unobserved heterogeneity. With these values, we regress our baselines on a set of country-level covariates to better understand what values are associated with these values. To allow for context-specific variation in our modelling of the fixed effects, two additional specifications of these baselines are tested. The first sums the original baseline value with the pooled coefficient on income multiplied by a country's median income for a given year, $\hat{\lambda}_{jt} + \hat{\beta} x_{jt}^{med}$. The second specification allows for the country-specific income coefficients by way of an interaction term between income and country. This takes the form of $\hat{\lambda}_{jt} + \hat{\beta}(x_{jt}^{med} * \hat{\lambda}_j) + \hat{\beta} x_{jt}^{med}$. The first alternate specification allows for variation in country income, while the second alternate specification accommodates variation in income and the SEFI by context. We defer to the second method for all of our analysis.

4.4 Estimating Costs

In the third part of our analysis, we estimate alleviation costs of food insecurity experiences which are estimated within each Gallup country-year sample and generalized to the population. With respect to a respondent's location on the latent distribution and two food insecurity thresholds on the GSS, we may use our estimates above to calculate costs and make further comparisons of contexts. This is done first through country-specific alleviation costs per capita across a country's population and, later, on a per capita beneficiary cost.

For the calculation of per capita alleviation costs, we use our SEFI estimates from the first section to estimate cost by the following:

$$\text{Per capita costs}_{jt} = \frac{1}{\mathbf{N}} \sum_{b=1}^{B} \sum_{n=1}^{N^b} (\mathbb{1}[l_{njt} > \tau_s] \cdot \frac{l_{njt} - \tau_s}{\hat{\beta}_{bjt}} \cdot \frac{Income_{njt}}{100}) \tag{3}$$

for which we use indices for country (j), year of data collection wave (t), and respondent (n). N^b refers to the total number of respondents in an income bin for a country and year, while $\mathbf{N}$ is the number of respondents for a country and year (bins pooled). The value $\mathbf{N}$ will take two values: either total respondents or total respondents above a food insecurity threshold. The second of these values lends itself to estimation of per capita costs by targeted individuals, in other words the estimated alleviation costs for each food insecure individual by context and in expectation. B refers to the total number of income bins by country groupings which we use to estimate SEFI values while b is an individual bin. On our latent distribution, l_{njt} is a respondents location, mapped onto the GSS in correspondence to country-level, scaled by country. Above, this location is used in an indicator function to identify respondents above a set severity threshold, τ_s, where the index s refers to the two thresholds used in separate cost calculations. Respondents affirming an item more severe than the threshold value take on an indicator function value of one. If a respondent does not affirm any items above the threshold, then their indicator function takes on a zero value. The two locational terms on the latent distribution are used in combination with the relevant SEFI value to estimate individual-specific costs of “moving” above-threshold respondents from their location, l_{njt}, on the GSS to the threshold, τ_s, by multiplying it with one percent of a respondent's per capita household income (here, represented by $Income_{njt}$).

Such a model relies on the assumptions that movements along the GSS are linear and that, regardless of distributional distance, income changes have constant effects on these movements. The aforementioned severity thresholds drawn from the GSS, so we further assume that our scaling of country-level Rasch measures via Cafiero et al (2018) provides us with a metric for which standardized, subjective experiences may be compared. Given these assumptions, we estimate one cost here using data from 2017 in the Full sample at two thresholds which correspond with the GSS items $ATELESS$ (-0.394, moderate and severe food insecurity) and $WHLDAY$ (1.649, severe food insecurity).

5 Descriptive Statistics

We collect descriptive statistics organized at the regional-level to quickly summarize geographical trends across the six year window of data. We defer to the global regions as defined by the World Bank: East Asia and the Pacific, Europe and Central Asia, Latin America and the Caribbean, Middle East and North Africa, North America, South Asia, and Sub-Saharan Africa. Furthermore, population-weighted descriptive statistics by per capita GDP groupings are reported. Details for which countries are included in each of these regions may be found in the appendix. We begin first with food security characteristics and then individual- and household-level characteristics.

For descriptive statistics of food insecurity experiences, we will use Rasch threshold values corresponding to positions associated with the previously mentioned ATELESS and WHOLEDAY items on the GSS. From those values, we further apply bin-level population weights for those countries included in the data set drawing from only 2017 data, for stability of our sample. The year 2017 was used here because it is near the middle of our sample and contains the largest number of observations. Tertile boundaries are set with respect to the incomes across these geographical regions as well as the per capita GDP groups. These cross-contextually comparable values are reported in Table 4 by geographies. In all cases higher income groups have less food insecurity than lower income groups. This is unsurprising, though it is worth noting the heterogeneity across geographies for which food insecurity prevalence rates decrease as an individual moves upwards in an income distribution. While the middle income bin in East Asia & Pacific region observes less than half of the food insecurity rate found in the lowest bin, Sub-Saharan Africa observes persistent food insecurity prevalence across their income distribution.

The “zero prevalence” case of North American food insecurity prevalence is due to its country's associated

Table 3: Food Insecurity Prevalence by Region 2017, by GSS Severity Thresholds

		Lowest		*Highest*	
Shares	*FIES Threshold*	First	Second	Third	Total
East Asia & Pacific	*Mod&Sev*	0.329	0.147	0.074	0.183
	Sev	0.017	0.006	0.001	0.008
Europe & Central Asia	*Mod&Sev*	0.238	0.118	0.064	0.141
	Sev	0.020	0.010	0.006	0.011
Latin America & Caribbean	*Mod&Sev*	0.584	0.441	0.261	0.428
	Sev	0.116	0.069	0.042	0.076
Middle East & North Africa	*Mod&Sev*	0.514	0.284	0.165	0.321
	Sev	0.076	0.034	0.019	0.043
North America	*Mod&Sev*	0.332	0.093	0.059	0.161
	Sev	0	0	0	0
South Asia	*Mod&Sev*	0.474	0.306	0.207	0.329
	Sev	0.002	0.001	0.000	0.001
Sub-Saharan Africa	*Mod&Sev*	0.803	0.740	0.624	0.722
	Sev	0.332	0.281	0.231	0.281
High Income	*Mod&Sev*	0.236	0.121	0.048	0.135
	Sev	0.007	0.003	0.002	0.004
Upper Middle Income	*Mod&Sev*	0.367	0.208	0.116	0.230
	Sev	0.049	0.026	0.016	0.030
Lower Middle Income	*Mod&Sev*	0.505	0.377	0.253	0.378
	Sev	0.063	0.051	0.042	0.052
Low Income	*Mod&Sev*	0.864	0.790	0.630	0.761
	Sev	0.159	0.134	0.110	0.135

Note: Prevalence refers to individuals above binary GSS thresholds at -0.394 and 1.649.

item weights. Even if an individual in this region reported going a day without food (as corresponds with the eighth item), the GSS threshold for severe food insecurity is higher than both the United State's and Canada's weight. Severe food insecurity prevalence in this region may be estimated by raw score. For Canada, 2.18 percent of 2017 respondents report having affirmed all items, while in the United States this figure is 3.36 percent.

Similarly, across per capita GDP groupings we observe no surprises. Food insecurity prevalence increases as income decreases in all contexts at both thresholds. Again, these prevalency rates are comparable across the groups and the population weighting for both sets of groups are defined by tertiles set with respect to either geography of per capita GDP, respectively.

As mentioned above, the GWP includes additional questions asked of all households which lend themselves for defining individual and household characteristics of the respondents. Here again we present the statistics by the geographical and per capita GDP groupings. Again, countries reporting these individual and household characteristics are reported by regional sampling weights so as to avoid within-region (group) bias due to relatively greater numbers of individuals sampled.

Among the individual characteristics we focus on age, gender, education, and marital status for our sample of GWP respondent data. Summary statistics presented in Table 5 are results of the pooled sample of data across years and countries–regardless of entrance and exits to the data. By nature of the GWP method, no individual under 15 years of age is surveyed. The mean age of respondents is varied with respect to global region, ranging from 34 years in Sub-Saharan Africa to 53 years in North America. These figures are consistent with estimates from World Bank (World Bank 2020). Across regions, respondents are equitably distributed by assigned sex at birth with the survey showing equitable participation with a global average of 54 percent of female participants. Secondary education completion rates–defined as proportion of population having completed at or above three years of tertiary education–is consistent across the sample with expectations by region (World Bank 2022). Marital status rates are are not remarkable for any one region, but it is worth noting "married" refers to respondents either married or in domestic partnerships; while "separated" refers to respondents either separated, divorced, or widowed.

Household characteristics of respondents available to us from the GWP are limited. We include in our analysis rural household status, number of household members and share of household under 15 years of age. Maintaining the regional conventions above, one observes the sample is largely rural for South Asia and sub-Saharan Africa, while respondents from countries in Latin America and the Caribbean are largely urban. Survey questions for North American respondents worded the "rural" question differently, splitting it from a binary outcome to four categories. Defining "rural" as "A rural area or on a farm" or "A small town or village", the share is 39 percent rural. Next, households from South Asia and Sub-Saharan Africa have,

Table 4: Individual-level Summary Statistics by Region, 2017

	Share of sample	Age	Female	HS≤	Marital Status	
	%	*Years*	%	%	*Married,%*	*Separated,%*
East Asia & Pacific	13.29	47.12	54.89	46.55	74.16	10.23
Europe & Central Asia	30.60	46.67	53.93	85.27	57.64	18.18
Latin America & Caribbean	13.08	42.85	60.77	62.39	45.46	18.72
Middle East & North Africa	11.65	37.74	46.79	67.93	63.66	7.64
North America	1.39	52.40	50.13	98.45	54.75	20.80
South Asia	5.29	37.11	51.62	34.51	73.73	6.27
Sub-Saharan Africa	24.72	33.42	48.74	54.12	46.88	11.22
High Income	30.07	50.30	50.81	90.82	57.49	17.44
Upper Middle Income	13.83	46.10	54.69	46.25	67.31	12.02
Lower Middle Income	28.64	37.54	52.72	48.11	66.74	8.53
Low Income	27.46	33.62	50.75	41.22	55.70	12.13

Note: Statistics reported with imputed medians for non-response.

on average, twice the membership of North American households. The proportion of household members is similarly distributed with South Asia and sub-Saharan Africa having the highest proportion of youth household members across the regions.

Table 5: Household-level Summary Statistics by Region

	HH Size	Share ≤ 15 years old	Rural %
East Asia & Pacific	3.11	0.398	50.97
Europe & Central Asia	2.81	0.222	13.19
Latin America & Caribbean	3.30	0.468	18.93
Middle East & North Africa	4.79	0.575	24.08
North America	2.75	0.205	-
South Asia	4.98	0.471	67.08
Sub-Saharan Africa	4.64	1.043	64.83
High Income	2.81	20.30	6.74
Upper Middle Income	3.05	40.39	42.50
Lower Middle Income	4.54	57.70	58.52
Low Income	5.38	103.78	75.60

Note: Statistics reported with imputed medians for non-response.

As is the case with nearly all summary statistics presented, here we observe few results inconsistent with expectation when countries are grouped and summarized by income levels. Higher per capita GDP is associated with lower levels of rural households as well as relatively older and smaller household sizes.

What we have is a highly heterogeneous, very large, repeated cross section sample of the globe. Given the literature and previous work on this data set, this study is well-positioned to contribute estimates for associative parameter estimates of income changes on food insecurity income experience status. Given the dimensionality of the factors defining our data, we defer to regression analysis to further understand the data. As outlined above, we begin by determining the best model to describe our relationship of interest.

6 Results

6.1 Specifying a Model

To understand the relationship between per capital household income and food insecurity status, we follow the model form presented above and progress through variations of the model by sample, specification, measure, and method. For all models described below, the models were specified with robust standard errors, year and country fixed effects, and individual-level probability weights by country and year (provided by Gallup).

Sample, the first of these considerations, is briefly discussed above with respect to overall goals of maximizing panel length and stability. The available GWP data has broad coverage, yet contains several instances of countries entering and exiting the data set for a variety of reasons. While we control for this to a degree using fixed effects, a balanced panel is more desirable than one that is unbalanced as it is subject to less unit heterogeneity. Here, we retain the Full sample and this associated noise, while use of subsets provides options of shorter–yet balanced–panels. Given data availability, no five year panel containing more than half of our data set is available; either for subset Drop 14 or Drop 19. For our purposes, this is not a salient trade-off.

We begin by testing saturation, or interactions of fixed effects, over year and country. While our sample provides us with sufficient sample size to expand the number of regressors without concern for degrees of freedom, we do not find it beneficial to include all interaction terms between country and year. Less than a one percent change in magnitude is recorded in the coefficient of interest (on logged income) so we do not maintain the practice.

We compare the same model with and without the inclusion of the individual and household controls listed above across binary severities. The additional covariates improve the amount of variation in the dependent variable explained by the model, so we include the covariates in all future specifications. Once these covariates are added, large amounts of attrition to the data is observed as a result of missing responses to the covariate questions. Gallup allows respondents to skip questions and we observe approximately 35 percent of our sample having skipped at least one of the covariate questions. Of the covariates most likely to be skipped, *age* and *rural* are each missed due to the question not being included in either a handful of countries or years. Household characteristics, like number of members and share of children, each have random non-response patterns (uncorrelated with observed, available characteristics) that are similar across the highest and lowest income quintiles by countries. To retain these observations, we impute the country-year median values for individuals who have skipped questions. This rule is applied to both categorical and continuous covariates.

It is worth noting here that individuals may also skip FIES questions, but this doesn't affect whether they are included in the data so long as at least one of the questions is answered. Since Rasch score assignment–for both binary and continuous cases–is dependent only upon the raw score, all individuals responding to a non-zero amount of items (responding either "yes" or "no" to one question) are retained and assigned a raw score consistent with their number of affirmed items. Non-response to the FIES questions is also uncorrelated with observed characteristics. GWP respondents are anonymous and informed of the fact which lends itself to high response rates in collection of otherwise sensitive data collection: less than one half of one percent of our sample live in a country-year context which surveyed the FIES questions but failed to respond to any of them.

The FIES survey model was developed to conform to Rasch model estimation and its assumptions, though much of the empirical literature uses the less-granular binary thresholds for two or three severity levels of food insecurity experiences based binary indicators of inequality with respect to raw scores or location on the uni-dimensional food insecurity experiences scale, as seen in Smith et al. (2017). FIES modelling with binary response variables allows for flexible estimation techniques that may easily incorporate panel methods and lend themselves to easy coefficient interpretation. But, they place assumptions on the error term that may not be justified. Both probit and linear probability models assume normal distributions about the error term, while logit estimation assumes its error term is dispersed by the logistic distribution. Due to downward response bias introduced by the threshold-based Rasch scale, this method similarly under-reports individual level severities and calls into question the distribution of the errors. For our specifications, we focus on the semi-continuous Rasch outcome variable, which similarly falls prey to a similar bias which cannot be corrected for. At best, the introduction of additional items can–in expectation–reduce this error by reducing the distance between one's place on the latent distribution and the nearest, lesser item. Practically speaking this is not feasible and earlier literature provides more insight as to why an eight item scale is preferred (see Coates et al. 2006).

The estimation of a Rasch modelled outcome variable maintains all of these regression settings, though calls for some adaptations. After application of the global standardized scale standardization procedure, outlined by Cafiero et al. (2018), three estimation challenges associated with this specific type of semi-continuous outcome variables reveal themselves. The first is the need for a censoring point for the distribution of Rasch scores estimated by sample. CML does not estimate a weight associated with no affirmed items, which results in nearly half of the sample not being assigned a weight. To focus on off-censor behavior and regressors' relationships with individuals who have affirmed at least one item, censored regression methods must be applied. Second, since CML is estimated by country and are assumed to be stable over the reference period, there is a different censor point for each country with approximately half of individuals in the sample reporting a censored Rasch score. This is important because we cannot assume or estimate where this "zero weight" might exist per country. And third, the distribution of Rasch scores is non-symmetric, non-parametric and, by extension, the estimation of a regression with such an outcome variable would violate the assumption of a normally distributed error term. Here, the distribution of Rasch scores reflects the three zones of food insecurity discussed in Coates et al. (2006) where items and individuals are clustered at the "worrying", "compromising on quality", and "compromising on quantity" zones of the item weights.

From these three estimation challenges, we then add our own list of priorities: an ability to estimate and extract coefficients for fixed effect by country and year. With these four priorities in mind, we consider several estimation methods before adding additional assumptions. Beginning with general censored methods, Tobit regression (Tobin 1958) comes to mind. The pioneering censor method splits estimation into two parts: one part for estimation of the binary-represented existence on the censor point and a second part for estimation in region off of the censored point(s). Tobit regression is able accommodate different censored point and fixed effects, which are two positive methodological aspects that trade-offs for the parametric assumption of a normally-distributed outcome variable. Next, censored quantile regressions or least absolute deviation methods may be considered. Censored quantile regressions would allow for the non-parametric estimation of the model, but do not accommodate different censored points and struggles to produce sensible fixed effect coefficients. Similarly, censored least absolute deviation methods, like Powell (1984), are not appropriate for the same reason. Being built upon the optimization techniques of censored quantile regression, CLAD similarly struggles with different censored points within the sample and fixed effects. Other methods, like Powell's symmetrically censored least squares (1986) is a two step estimator for censored data that, while accommodating of fixed effects and is semi-parametric, does not allow for different censor points and assumes a symmetric distribution. Liew's inequality constrained least squares estimation (1976) suffers similar shortcomings in our context.

Of the four priorities, one method provides us with a solution to three: Tobit regression. Each of the other methods considered introduces additional bias that is less tied to measurement and more tied to the methods' limits in construction. All other methods are less favorable, so we will proceed with the Tobit regression and impose the parametric assumption of normality over the dependent variable. The authors recognize such a strong assumption results in inconsistent estimation of regressors on food insecurity experiences, but the decision is a measured one. Consistent estimation of coefficients would be possible if we did not want to used fixed effect estimation, but this would sacrifice the ability to separate out country-level non-time-varying variance components.

We maintain the settings as above with covariates, non-saturated fixed effects, medians imputed, individual-level population weights, and the semi-continuous Rasch modelled outcome variable generated by the iterative GSS process set out by Cafiero et al. (2018) assuming item stability across time.

In Table 6 we apply these model specifications to our data and report context-specific coefficients and marginal effects of one percent income change with respect in-group income tertiles. For each of columns 1-5, one regression is run with interactions terms between log income and income tertile and coefficients for each interaction are estimated and reported in Table 6. Since we are using Tobit regression, coefficients reported are the marginal effects for the unconditional expected value of the dependent variable where the model predicts a value for the dependent variable, y^*, in expectation. Here, $y^* = max\{a, min\{y, b\}\}$ where a is our left censor point (varying by group) and b is some large value. This marginal effect is the sum of two other marginal effects which may be estimated individually, but are not presented here. The first is a marginal effect for the probability of being on the censor point–in such that a binary dependent variable is modelled. The second is the marginal effect for the expected value of the dependent variable off-censor. All coefficients presented in Table 6 are of the summed marginal effect and later results hinging on these values will be of similar calculation.

Consistent with *a priori* assumptions, relatively lower income contexts have more individuals experiencing more food insecurity. This is evident in the percentages of off-censor individuals reported in Table 6, ranging from nearly 85 percent off-censor in the high income groupings to approximately 26 percent in the low income group. As the share of individuals on-censor shifts, so to does the share of mean total response due to responses above the limit, or censor point. This proportional value and its importance in interpreting such coefficients and marginal effects is discussed further in McDonald & Moffitt (1980).

Each coefficient is statistically significant at above 95 percent confidence showing each group is distinct and well-defined. Tests of joint significance for equality of the interaction coefficients for tertiles 2 and 3 are rejected at 95 percent statistical confidence for each regression. With coefficients of the lowest tertile serving as a base for our interactions, we sum it with other tertile interaction coefficients to obtain the marginal effect values reported. In all cases these marginal effects are negative, robustly showing food insecurity experiences are inversely related with income across contexts. As above, we refer to these marginal effects as semi-elasticities of food insecurity experiences (SEFI). SEFI values are found to be lowest for relatively less wealthy individuals, highest for approximately median wealth individuals, and varying for the highest wealth individuals in a context. Interpretation of the values can be summarized as the marginal effect of one percentage change of income on standard deviations relative to mean on the uni-dimensional food insecurity experiences scale. Though an abstract dependent variable value, it is one that is comparable across contexts.

The lowest tertile values in columns 2-5 are all nearly identical in magnitude, which may be puzzling when considered alongside the existing literature of food and calorie elasticity research (Subrimarian & Deaton 1996; Colen et al. 2018; Salois et al. 2012; Ogundari & Abdulai 2013; among others). As is often reflected in the literature, low income individuals have relatively higher food elasticities as their marginal dollar of income is more often dedicated to food consumption than other expenses. Here, we find that food insecurity experiences do not have a similar relationship across income groups. This is a result of the broader range of experiences captured by FIES, relative to an objective measure of calorie consumption or food expenditures. Here, our SEFI values show the *ability* of a marginal dollar to be spent on food insecurity alleviating expenses. Low income individuals here have lower SEFI values than our middle and high income groups, for each per capita GDP grouping. This is likely a reflection of poor access to food insecurity alleviating expenditures, which may include more diverse food retail access or infrastructural investments that lessen food price fluctuations via arbitrage. In the second tertile, we observe the highest SEFI values across columns 2-5. This is a reflection of better access than in the first tertile, while still having relatively high demand for food insecurity alleviating expenditures. This conclusion is reflected in our estimates that show relatively higher middle tertile SEFI values in lower middle and low income countries than in high or upper middle income countries. Relatively wealthier individuals show similar trends in SEFI values as their counterparts in the middle tertile, though the magnitudes are muted by less need for food insecurity alleviating expenditures.

In column 1 we present the pooled SEFI results for all countries, which introduces significant noise to our estimation and mutes the magnitudes of SEFI values. It it likely due to this noise resulting from individuals with similar incomes pooled across widely different contexts that marginal effects are attenuated toward zero.

6.2 Modelling Fixed Effects

In specifying our model, we rely on country and year fixed effects to absorb the unobserved heterogeneity across units in our data. Next we extract and model the baseline values associated with country-level fixed effects and median incomes, as discussed above. Here we use a generalized model for SEFI values pooled in-country (no tertiles) and with slopes allowed to vary across countries. From this model we will briefly present the extracted baseline values by context then model the values via OLS with regressors chosen to elucidate which country-year level characteristics are most closely associated with the variance in these baseline values. Having used dummy variables for our fixed effects, we allow the United States and 2014 to be the omitted

Table 6: Semi-Elasticities of Food Insecurity

	(1) Pooled	(2) High	(3) Upper Middle	(4) Lower Middle	(5) Low
Coefficients on Log Income					
Tertile 1 *(Base)*	-0.019	-0.013	-0.020	-0.012	-0.015
	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)
Tertile 2	-0.082	-0.135	-0.233	-0.249	-0.205
	(0.002)	(0.010)	(0.011)	(0.013)	(0.020)
Tertile 3	-0.107	-0.044	-0.109	-0.174	-0.148
	(0.002)	(0.006)	(0.001)	(0.008)	(0.011)
Marginal Effects (SEFI)					
Tertile 1	-0.019	-0.013	-0.020	-0.012	-0.015
Tertile 2	-0.101	-0.148	-0.253	-0.260	-0.220
Tertile 3	-0.126	-0.057	-0.129	-0.185	-0.163
Tertile Bounds ($)					
Tertile 1 & 2	1,366	8,620	2,064	770	217
Tertile 2 & 3	5,959	18,036	5,213	2,075	701
On Censor (%)	59.0	84.9	63.1	45.7	25.9
Observations	788,010	207,308	228,136	236,068	98,947

Note: Population-weighted regressions; Tertiles defined by cross-country groupings of GDP per capita

values (or reference value) to which other estimates are relative. As a reference point, the baseline values for the four years of data the United States reports are from -2.21 to -2.24 units. It is otherwise difficult to characterize the variation of our baseline values practically beyond the basic description of income-adjusted unobserved heterogeneity in our base model.

Table 7: Baseline Values by Per Capita GDP Bins

	Mean	Standard Deviation
High Income	-2.899	0.405
Upper Middle Income	-1.996	0.757
Lower Middle Income	-1.428	0.765
Low Income	-0.677	0.757
Pooled	-1.909	0.992

As previously discussed, the baseline values summarized in Table 7 attempt to capture a country-specific reference value, or intercept, on the Rasch scale serving as a starting point for the addition of data by other regressors. Lower baseline values are associated lower starting values on the latent scale, or lower "starting" levels of food insecurity experiences. This is consistent with statistics calculated in Table 7 showing high income countries have higher baseline values relative to lower income countries. When pooled, these values are nearly symmetrical with a skewness of -0.184.

To model these baseline values, we will organize the regressors into two groups by the country-year level characteristics for which they try and explain: structural and food system. For structural characteristics, we use lagged gross domestic product per capita adjusted to parity 2016 U.S. dollars, share of population living in urban areas, share of population employed, and a standardized index for perception of political stability in one's own country collected by Gallup. For food system characteristics we include three year moving averages for availability of protein supply in grams per person per day, cereal dependency in share of cereal consumption imported, and share of a national diet (in calories) is comprised of cereals. In addition to the moving averages, we also include government expenditures on the agriculture, fishing, and forestry as a share of national expenditures, as well as indices of total factor productivity of inputs, labor, and capital endowments. In addition, we will test logged quantities of labor, capital, and machinery endowments. Data for these values are aggregated by the U.S. Department of Agriculture on a global scale, but is comprised of data products collected from across several U.N. agencies. For all regressions year fixed effects are included.

By these groups, we regress the structural and food system characteristics on our baseline values in simple and pooled regressions (within regressor group). To better understand the relative associations between these regressors and our dependent variable, we report marginal effects from OLS and standardized coefficients in Tables 8 and 9 (columns 1-5 in each table). In both tables, we use column 6 to collect the standardized coefficients from the simple regressions with the associated p-value in parentheses. Similarly for both tables, column 7 collects the standardized coefficients and p-values for the pooled regressor model.

Table 8: Modelling Baseline Values - Structural Regressors

						Standardized Coefficients	
						Simple	All
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Urban Population (%)	-0.024					-0.535	-0.192
	(0.001)					(0.000)	(0.000)
Lagged per capita GDP		-0.000				-0.614	-0.319
		(0.000)				(0.000)	(0.000)
Total Investment (% GDP)			-0.005			-0.040	-0.013
			(0.005)			(0.292)	(0.653)
Employment Rate (%)				-5.360		-0.476	-0.193
				(0.369)		(0.000)	(0.000)
Political Stability Index					-0.554	-0.534	-0.167
					(0.033)	(0.000)	(0.000)
R-squared	0.289	0.372	0.010	0.231	0.291	-	0.500
Observations	725	722	695	725	725	-	682

Note: Standard errors reported are not robust to accommodate the calculation of standardized coefficients.

In Table 8 we see that all regressors but total investment in the agricultural sector is significant in explaining the variation in the baseline values for both simple and pooled models. Among the group of five, the beta coefficients in the pooled model and the R-squared values of the bivariate models suggest lagged per capita GDP is most closely associated with the baseline values (albeit, with the smallest of coefficient magnitudes) followed by share of urban population, the employment rate, and political stability in context. While none of these results are surprising, it is worth showing that a country's macro indicators are associated with the unobserved heterogeneity in our model.

Table 9: Modelling Baseline Values - Food System Regressors

						Standardized Coefficients	
						Simple	Pooled
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Protein Supply (g/day)	-0.035					-0.740	-0.275
	(0.001)					(0.000)	(0.000)
Cereal Dependency (%)		0.003				0.222	0.018
		(0.000)				0.000	(0.445)
Cereals, Roots, Tubers (%)			0.050			0.736	0.149
			(0.002)			(0.000)	(0.001)
TFP - Inputs				0.019		0.134	0.086
				(0.008)		(0.015)	(0.014)
TFP - Labor				0.017		0.145	-0.008
				(0.005)		(0.000)	(0.762)
TFP - Capital				0.006		0.070	-0.091
				(0.005)		(0.224)	(0.013)
Log Labor Endowments					0.319	0.652	0.359
					(0.012)	(0.000)	(0.000)
Log Capital Endowments					-0.140	-0.252	-0.128
					(0.022)	(0.000)	(0.004)
Log Machinery Endowments					-0.171	-0.481	-0.322
					(0.013)	(0.000)	(0.000)
R-squared	0.549	0.050	0.542	0.069	0.641	-	0.713
Observations	595	611	595	721	721	-	585

Note: Standard errors reported are not robust to accommodate the calculation of standardized coefficients.

Next, in Table 9, we consider food system regressors which are more closely associated with consumption habits and productivity within the food system. We observe consistently strong associations between levels of protein, cereals, roots, and tubers consumed in context with the baseline values. Again, this is not a surprising finding, as the measures should, logically, be negatively correlated with the FIES scale for severities. Next, it see weak association between cereal dependency and the baseline values, suggesting attainment of a lower baseline value has a weak relationship with fluid agricultural trade within a context. Similarly, we see a weak relationship between all types of factor productivity and the baseline values. This is in contrast with logged endowments, which have a strong association and suggest labor, capital, and machinery access has relative import to the quality or efficacy of said factors.

While our set of regressors is not exhaustive, those included do give some indication as to what national-level characteristics may also be associated with the unobserved country and year variation captured by the fixed effects. Since our model uses individuals and their individual-level experiences with food insecurity as a response variable, it makes sense that the best regressors more closely aligned with a household's ability to satisfy conditions associated with relatively lower baseline values. Lagged GDP, cereal dependency, and total factors of productivity do little to explain the variation in the dependent variable. Our modelling of the fixed effect gives indication that labor and machinery endowments of a context have a strong association with these baseline values, while trade and GDP have less say in explaining these quantities.

6.3 Estimating Costs

The contextual comparability of our model further lends itself to the estimation of comparable costs associated with food insecurity alleviation by context. For the following "costing" exercise, we use the sampled data from 2017 to estimate one year costs of alleviating moderate and severe Food insecurity (*Mod&Sev FI*). We use data from one year along with the marginal effects presented in Table 6 to simply estimate a per capita cost of general cost incidence and targeted incidence (costs per capita for beneficiaries). The unique nature of our data makes these figures doubly interesting as they estimate comparable costs across contexts, allowing one to begin to understand the costs associated with alleviating food insecurity experiences in one context versus the next.

Again, the dimensionality of our repeated cross section makes it difficult to present a country-level analysis of these costs. Instead, we again present group averages of the costs by the geography and per capita GDP groups used above. These averages are used for food insecurity prevalence estimations, as well as the costing itself.

In Table 10 we show rates of moderate and severe food insecurity alongside the per capita costs of alleviating this level of food security if the cost is shared amongst the population, as well as per capita costs if they were to be shared only amongst the people existing above the GSS threshold and deemed food insecure. While total costs are subject to two varying quantities (food insecurity rates, and SEFI values), we are able to control for food insecurity rates in the targeted column. Values in the targeted costs column estimate the value of a per-person transfer in expectation used to shift an average food insecure individual from their place on the GSS to the threshold. Doing so is shown to be relatively more expensive in wealthier contexts.

We may take these results and method and then extend it to accommodate a general increase of five and

Table 10: Costing Moderate and Severe Food Insecurity Experiences, 2017

	Prevalence Mod&Sev FI	Per Capita Costs		Countries
	Share	Total	Targeted	
East Asia & Pacific	0.162	82.54	1,007.92	15
Europe & Central Asia	0.103	101.95	1,489.12	45
Latin America & Caribbean	0.338	159.75	531.42	20
Middle East & North Africa	0.200	165.23	1,325.99	16
North America	0.105	391.93	3,862.68	2
South Asia	0.323	42.30	158.78	5
Sub-Saharan Africa	0.582	140.02	224.57	36
High Income	0.077	178.96	2404.86	43
Upper Middle Income	0.224	122.03	419.42	37
Lower Middle Income	0.383	102.68	249.83	38
Low Income	0.595	79.45	107.80	20

Note: Population data is from 2017 and sourced from the World Bank.

ten percent general increases of income in-country. Such increases would (in our model) lead to a proportion of individuals near the threshold having access to sufficient income and prevalence to drop. Further more, these estimations change what a percent of income is for the individuals of our sample from 2017. In Table 11 we show these results, beginning with the adjusted prevalence rates and followed by per capita costs as calculated in Table 10. With a five percent increase in incomes, moderate and severe food insecurity decreases and per capita costs also decrease. This remains the pattern with a ten percent increase in incomes and is not a surprising results by any means. In either case, targeted per capita costs are higher in high income contexts and is, generally, lower in low income contexts.

Table 11: Costing Moderate and Severe Food Insecurity Experiences with Income Shifts, 2017

	Prevalence Mod&Sev FI		Per Capita Costs, +5%		Per Capita Costs, +10%	
	Share, +5%	Share, +10%	Total	Targeted	Total	Targeted
East Asia & Pacific	0.054	0.047	15.82	295.68	10.79	208.22
Europe & Central Asia	0.020	0.013	4.13	252.68	1.48	82.40
Latin America & Caribbean	0.153	0.118	37.45	299.68	19.93	194.24
Middle East & North Africa	0.042	0.032	12.15	351.83	5.46	133.82
North America	0.007	0.003	3.69	412.23	0.50	134.22
South Asia	0.095	0.082	23.68	272.12	17.69	243.29
Sub-Saharan Africa	0.277	0.257	45.34	204.05	42.87	176.09
High Income	0.011	0.007	3.88	362.52	0.69	102.92
Upper Middle Income	0.088	0.055	25.15	234.11	9.12	119.44
Lower Middle Income	0.173	0.158	51.12	302.10	41.54	271.19
Low Income	0.222	0.219	20.43	88.25	20.08	90.82

Note: Population data is from 2017 and sourced from the World Bank.

One interesting finding in Table 11 is the relationship between costing, incomes, SEFI values, and proportion of a context that is food insecure. Targeted costs in the income-country bins show the costs associated with the Lower Middle Income are relatively higher than in the bins above and below it. This is a reflection of the nonlinearity of SEFI values across the income distribution, but also reflects access and the FIES scale. Costs associated with access prove to be very expensive and lead to per capita costing variation across groups that might, by assumption, be decreasing with income level. This is not the case here, as income's evolving relationship with food security across the distribution allows for relatively high-valued costing in high income contexts (due the prices for additional access-bolstering investments), as well as in low income contexts where access bolstering investments may be non-existent. In either case, costing is an exercise aimed at showing how these barriers to improves FIES scores can be expensive for very different reasons. Regardless, the FIES metric focusing on experiences allows us to comparably view these costs and, later, spend time investigating what contributes to this heterogeneity.

7 Conclusions and Subsequent Work

Food insecurity experiences vary globally and the semi-elasticities relating income with these experiences are similarly heterogeneous. Above we create a globally-comparable latent scale for food insecurity experiences and describe its relationship with household incomes by context. Though an experiential measure for food insecurity is unique and cannot easily be compared to previous non-Rasch-based work, the patterns we identify are consistent with previous research using similar measures. In addition, we extend the literature to better understand contextual differences and then exploit these differences to estimate food insecurity alleviation costs by region and income group. These costs are calculated with respect to differing food insecurity prevalence rates by country. In monitoring the Sustainable Development Goals, research offering estimates of comparable progress metrics will become increasingly valuable. Our research fits in this space and next steps should take similar care in contextual-comparability so as to lend itself to further monitoring of goals of shared global importance.

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9 Appendix

9.1 Derivation of Rasch Model

A Rasch model is based on three assumptions which allow a researcher to measure a latent variable existing on a continuous scale alongside items, or indicators (or questions), on a measured scale (Nord 2014). If the data is consistent with these assumptions, a Rasch model may be applied and, in our context, a contextually-comparable parameter may be estimated. These assumptions include: uni-dimensionality, for the underlying scale; conditional independence, for the items on the scale; and monotonicity, of the responses to items. Uni-dimensionality refers to the latent variable being measured (food insecurity) existing on the same scale as the items (our FIES questions). The conditional independence assumption refers to the fact that each item presented evokes a response that is independent from other responses to other items. For example, an earlier item asked (regardless of underlying severity) does not necessarily imply another also must occur. Experiences stand alone. Finally, the items do have an underlying distribution, such that some items are affirmed more often than others.

Given that our data adheres to these assumptions (as validated by numerous earlier studies), we may obtain Rasch scores by the following method for single-parameter logistic models. From the above, the model assumes the "log-odds of a household affirming an item is proportional to the difference between the 'true' severity level of the household and the 'true' severity level of the item." (Nord 2014) So, the odds that a respondent will affirm an item contributing to the raw score is set on a scale bounded below by zero and unbounded above. The probability that an item, i will be affirmed is P, whereas its complement is $Q = (1 - P)$. The probability Q may also be thought of as a probability that the item will *not* be affirmed. The latently-observed food insecurity severity measure is h.

Therefore, we have that

$$\frac{P}{Q} = e^{h-i}$$

is the odds-ratio for affirmation. Intuitively, increases in this ratio are associated with greater confidence, or probability that an item i will be affirmed–revealing the true nature of latent h. To obtain the probability of affirming an item, i, one may rearrange the first equation to

$$P = \frac{e^{h-i}}{1 + e^{h-i}},$$

which can be simplified further to

$$P = \frac{1}{1 + \frac{1}{e^{h-i}}}.$$

From these estimated parameters, we may set thresholds on a continuous, closed interval that provide likelihoods for affirmations of certain items on the FIES questions. From these contextually-dependent, estimated parameters, country-level food insecurity may be compared cross-context. Food security experiences may be made comparable across context by separating three domains or experiential structures, as proposed by Coates et al. (2006). These structures include respondent perceptions (experiences with) of food uncertainty and worry, inadequate food quality and quantity, and hunger.

9.2 Gallup World Poll Sampling Method Details

Repeated, annual cross sections of data at the country level were collected in hour-long face-to-face surveys administered in a country's major conversational languages. Respondents are asked a core battery of questions alongside a set of region- or country-specific questions. The sample of individuals changes yearly, but by-country the surveys are asked at the same time each year. These questions typically have binary, "Yes/No" responses while some, including socio-demographic data, will evoke short responses–each to the end of data for cross-country comparisons.

Gallup collects approximately 1,000 responses from each country per year with China (4,000), India (3,000), and Russia (2,000) often being over-sampled in the reported data to provide a more complete characterization of these contexts across all GWP metrics. In some cases respondents from urban areas comprise of a larger share of a context's sample than what reflect the truth. The data is weighted at the individual and household level based upon national rates and the surveyed characteristics. Gallup's methodology for data collection is "probability based and nationally representative of the resident adult population" (World Poll Methodology). Furthermore, Gallup reports coverage area is "the entire country including rural areas, and the sampling frame represents the entire civilian, non-institutionalized, aged 15 and older population" while areas in conflict or otherwise putting Gallup staff at risk are not reported upon.

While Gallup does administer a shorter phone survey, face-to-face data collection is the norm and population-weighted stratified samples are taken with the aim of 100 to 125 clusters being drawn then surveyed. Within clusters, eight to ten individuals are surveyed via random route procedures. This is where an initial household is surveyed by a Gallup field manager with subsequent surveys administered to the households three, occupied dwellings to the left (facing the initial household, excluding present dwelling). Surveyors identify households on the basis of whether they have cooking facilities. If for any households initially selected cannot be surveyed and do not directly refuse, three attempts are made per household to collect a response before the household is replaced by similar procedure. It is worth noting that group housing, i.e. dormitories or barracks, are not counted.

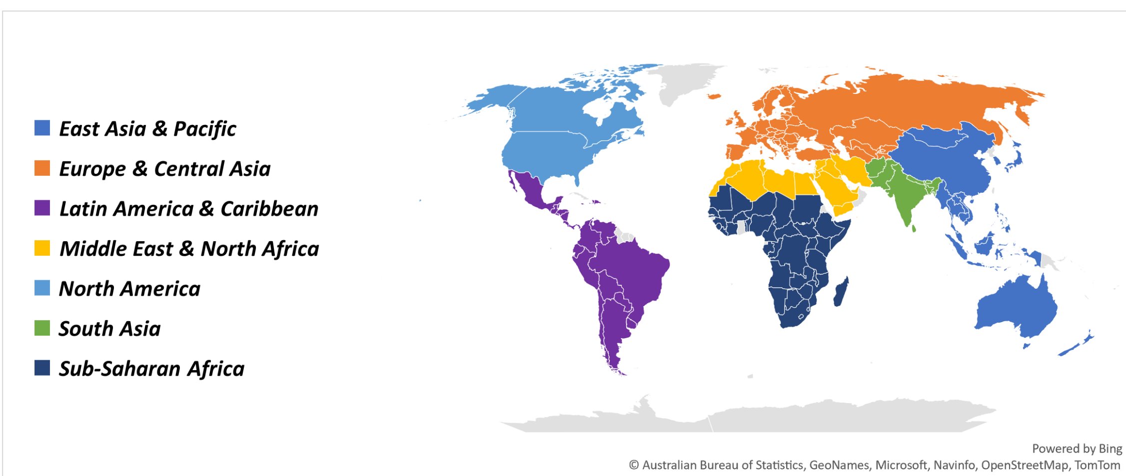
Within the household, individuals over the age of 15 are eligible to complete the survey and, within the household, the interviewer uses a computer assisted personal interviewing system to select one respondent amongst the qualified household members. If gender matching is an issue due to cultural norms, interviewers randomize the survey administration among household members of similar gender.

For phone surveys, random digit dialing methods are used to contact potential respondents from a nationally-representative list of phone numbers. Once contacted, eligible household members with the next birthday are surveyed. Here, five attempts on different days are made per household. Note, phone surveys are only conducted in countries where coverage/penetration is greater than 80 percent.

Since 2005, the Gallup World Survey collects information on characteristics and beliefs held by individuals from nationally-representative samples. In 2014, with support from the United Kingdom's Department for International Development (DfID) and the Kingdom of Belgium, FAO introduced an additional eight question extension to the GWS with a focus on food security to the end of quick, nationally-comparable statistics on food insecurity. This study leverages these data from a five year unbalanced panel, with motivation from an existing literature developing, validating, and applying methods to subsets of the GWS Food Insecurity Experience Survey (FIES) questions.

9.3 World Bank Geographical Groupings

Figure 1: Data Sample Subsets



East Asia & Pacific: Australia (5,010), Cambodia (6,600), China (20,138), Hong Kong (3,025), Indonesia (5,001), Japan (5,012), Laos (4,577), Malaysia (3,013), Mongolia (6,070), Myanmar (6,760), New Zealand (5,015), Philippines (7,090), Singapore (6,040), South Korea (5,016), Thailand (6,001), and Vietnam (7,053)

Europe & Central Asia: Albania (6,078), Armenia (4,002), Austria (5,001), Azerbaijan (5,081), Belarus (6,351), Belgium (5,050), Bosnia and Herzegovina (6,081), Bulgaria (6,081), Croatia (6,080), Cyprus (5,070), Czech Republic (5,009), Denmark (5,006), Estonia (6,080), Finland (5,001), France (5,001), Georgia (6,080), Germany (5,003), Greece (6,080), Hungary (6,083), Iceland (1,628), Ireland (5,001), Italy (5,001), Kazakhstan (6,080), Kosovo (6,089), Kyrgyzstan (6,080), Latvia (6,125), Lithuania (5,001), Luxembourg (5,001), Macedonia (5,137), Moldova (5,081), Montenegro (6,080), Netherlands (5,007), Norway (5,006), Poland (5,081), Portugal (5,040), Romania (6,083), Russia (8,002), Serbia (6,080), Slovakia (6,080), Slovenia (5,020), Spain (5,001), Sweden (5,002), Switzerland (4,504), Tajikistan (8,080), Turkey (7,063), Turkmenistan (6,089), Ukraine (6,080), United Kingdom (4,002), and Uzbekistan (6,080)

Latin America & Caribbean: Argentina (6,060), Belize (509), Bolivia (6,000), Brazil (8,013), Chile (4,082), Colombia (6,000), Costa Rica (6,000), Dominican Republic (6,078), Ecuador (6,000), El Salvador (6,080), Guatemala (6,100), Haiti (2,517), Honduras (6,000), Jamaica (1,012), Mexico (6,083), Nicaragua (6,080), Panama (6,080), Paraguay (6,079), Peru (6,000), Uruguay (6,080), and Venezuela (6,080)

Middle East & North Africa Algeria (5,120), Bahrain (4,080), Egypt (7,070), Iran (5,009), Iraq (5,024), Israel (5,011), Jordan (6,015), Kuwait (5,011), Lebanon (6,040), Libya (4,020), Malta (5,040), Morocco (6,080), Saudi Arabia (5,035), Syria (1,007), Tunisia (5,060), United Arab Emirates (8,466), and Yemen (6,140)

North America: Canada (5,063) and United States (5,096)

South Asia Afghanistan (6,127), Bangladesh (3,075), Bhutan (2,044), India (18,644), Nepal (6,145), Pakistan (5,601), and Sri Lanka (4,360)

Sub-Saharan Africa Angola (1,005), Benin (6,000), Botswana (6,116), Burkina Faso (5,001), Burundi (2,004), Cameroon (6,000), Central African Republic (2,004), Chad (5,001), Comoros (1,005), Congo (Kinshasa) (4,002), Congo Brazzaville (6,090), Ethiopia (7,226), Gabon (6,078), Gambia (3,123), Ghana (6,010), Guinea (5,001), Ivory Coast (6,000), Kenya (6,001), Lesotho (3,003), Liberia (5,001), Madagascar (5,009), Malawi (6,000), Mali (5,001), Mauritania (6,100), Mauritius (4,002), Mozambique (4,002), Namibia (4,009), Niger (6,008), Nigeria (8,000), Rwanda (6,000), Senegal (6,000), Sierra Leone (6,141), Somalia (3,194), South Africa (6,060), South Sudan (4,002), Sudan (1,005), Swaziland (2,114), Tanzania (6,008), Togo (6,130), Uganda (6,000), Zambia (6,000), and Zimbabwe (6,082)

9.4 Development of Experiential Food Insecurity Scales

The Voices of the Hungry project began global roll-out of the FIES questions as part of the GWP in 2014 and was initially started in 2013. The battery of FIES questions is based upon a body of literature of experiential food security measures that precede it. This body of work is, in turn, based upon another body of literature developing experiential measures and Rasch measurement.

To begin, one must first note the paper at the basis of the literature applying one parameter logistic models to experiential measures: Rasch, 1960. The model by Georg Rasch put forth a model assuming the "probability of a correct response to a certain test question–often called an item–by human respondent[s] depends on only two qualities, one that quantifies the difficulty of the item and one that quantifies the ability of the respondent to solve the item." (von Davier 2014; Rasch 1966) The model rests on three assumptions, which I will reiterate here:

1. The number of affirmed items may serve as a sufficient statistic for the location of a respondent on a uni-dimensional scale.

2. The probability that a respondent affirms an item increases with their own, unobserved place on the underlying distribution.

3. Items are independent and affirmation to one item does not influence answers a respondent provides to other items.

From these assumptions, models have since been developed with variable numbers of questions (items) measuring providing estimates for respondents' placements on several underlying distributions. While applications in educational testing tend to include more items (e.g. Fisher 1991; Aryadoust et al. 2020), medical literature tends to have fewer items (e.g. Leung et al 2014). This is a function of each application, where educational testing literature uses Rasch models to rank students while health measures need only uncover respondents' placements in reference to themselves and the scale of interest.

Following the example of health-based Rasch models, Radimer et al. (1992) developed an experiential household food insecurity scale which developed and tested the list of questions presented in Table 1. The Radimer et al. scale of seven items were selected to reveal respondent characteristics associated with the three phases of hunger identified by Radimer et al. (1990). The work of Radimer et al. was validated by Frongillo (1997) and preceded later work for another eighteen-item food insecurity experience scale developed by the United States Department of Agriculture in 1995, the Household Food Security Survey Module (HFSSM) (Bickel et al. 2000). The items used in the HFSSM were validated by Carlson et al (1999) and further shown to be valid in other contexts–meaning the questions regarding food insecurity could reliably be translated and item parameters estimated outside of the United States (Rafiei et al. 2009; Butcher et al. 2019). Following this pattern, the HFSSM was validated to fifteen questions for households in Brazil (Perez-Escamilla et al. 2004). These developments, along with contributions of food insecurity experiential scales such as the Brazilian Food Insecurity Scale and the Household Food Insecurity Access Scale (HFIAS) (Coates, Swindale & Bilinsky 2007) gave rise to another experiential food insecurity scale: the Latin America and Carribean Food Security Scale (*Escala Latinoamericana y Caribeña de Seguridad Alimentaria* - ELCSA). This scale, again adapted to sixteen items, was validated in Mexico (Perez-Escamilla et al. 2008a) and southern Haiti (Dessalines et al. 2008).

Coates et al. (2006) compared these experiential food insecurity scales, drawing comparisons between the three regions of food insecurity experience: worry, compromising quality, and compromising quality. Each of eighteen experiential scales were compared with the conclusion that food insecurity experiences exists on a uni-dimensional scale. Among these studies, the ELCSA was then shown to be comparable across countries, Mexico and Uruguay, by Perez-Escamilla et al. (2011). Among these studies, the Voices of the Hungry deemed the eight question FIES survey module from Radimer et al. (1992) the preferred measure of choice for monitoring SDG 2.1.2 (Ballard et al. 2013).

As stated earlier, the strength of the FIES model is its flexibility to context. No item has an associated order in any context. Items are not compared across context, instead the population-level distributions of food insecurity experiences in a population and respondents' places on these distributions are compared. Wesselbaum et al (2022) and Smith & Wesselbaum (2023) take advantage of these characteristics in two analyses of the repeated cross-section, focusing on regressions that attempt to explain the conditional second moment.

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