Food insecurity and subjective well-being: an exploratory analysis of global heterogeneity

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ABSTRACT

This study uses Gallup World Poll data to estimate the impact of food insecurity on SWB, and the extent to which it has different impacts across the world. We focus on a simple but potent food access question: "Have there been times in the past 12 months when you did not have enough money for food?" A negative answer to this question is associated with devastatingly low levels of SWB, particularly when SWB is measured asan overall life evaluation (Cantril ladder scale) and, to a lesser extent, when SWB is measured on the basis of negative experiencesin the last 24 hours. In addition we explore heterogeneity among 10 broad regions of the world, 126 countries and individuals within a multilevel framework. We identify significant heterogeneity across regions and countries, with greater impact in regions and countries with low levels of SWB. An analysis of income levels at purchasing power parity for the food insecure in different parts of the world suggests that individuals in richer areas may interpret the item in terms of general economic hardship, whereas individuals in poorer areas respond to the food insecurity question in a more literal sense. Future studies should further explain the multilevel structure identified in our exploratory analysis, particularly geographic variation in impacts of food insecurity and the extent to which this variation is due to measurement inequivalence or cultural differences.

Keywords: Food Insecurity, Subjective Well-Being, Gallup World Poll

1. Introduction

Food insecurity is a many-headed hydra that arises from a network of complex interactions between stable factors such as markets, climate, or infrastructure, and unpredictable factors such as natural disasters or wars. Likewise, the consequences of food insecurity are multi-pronged. Most research has focused on its deleterious effect on health (e.g. Olson, 1999), and the costs that negative health outcomes represents throughout an individual's lifetime, as well as society at large. Food is one of the basic needs that must be met before advancing to higher levels of self-actualization (Maslow, 1943). From the wider perspective of human motivation theory, Tay & Diener (2011) identified basic needs, including food and shelter, as a major determinant of life evaluation, even if the impact on SWB of each need was independent of whether other needs were fulfilled, in contradiction with Maslow's hierarchical model.

Even though there is a wide body of literature on the relationship between human needs and SWB, few studies to date have focused specifically on the impact of food insecurity on subjective well-being (SWB). Akpalu, Christian, & Codjoe (2015) recently conducted one such study using data from three urban poor communities in Accra – Ghana, finding a weak correlation between food security and household income. The study also found that income compensating differentials are greater for food insecure households than food secure households, suggesting that the deleterious effect of food insecurity on subjective well-being goes above and beyond the effect of poverty.

A broader study was conducted more recently by Guardiola & Rojas (2016), this time focusing on the relationship between food deprivation and SWB in Latin America. Their findings corroborate those by Akpalu et al. (2015) regarding the greater impact of food deprivation relative to income. The authors also identify several sources of heterogeneity suggesting that religion and relational goods may enhance SWB in Latin America relative to other regions, even among the food insecure. Tsai & Senah (2014) identify additional individual-level sources of heterogeneity in their sample of Ghanaian households, concluding that male heads of household give greater importance than females to usage of land, owning of livestock and amount of food spending.

The current study aims to build on these prior local and regional-level efforts, and expand them to an international level. More specifically this study aims to estimate the average global impact of food insecurity on SWB, and whether the size of this impact varies by country, age group, educational attainment and urban vs. rural setting.

2. Methods

All data come from the Gallup World Poll (GWP), a global research project conducting nationally representative surveys annually since 2006, in more than 160 countries and more than 140 languages. In most of the developing world, GWP surveys are conducted using in-person interviewing and an area sampling frame design. In the developed world, random-digit-dialling or a nationally representative list of phone numbers is used, generally including landline and mobile phones stratified by region. With some exceptions, all surveys, either telephone or face-to-face, are probability based and nationally representative of the resident non-institutionalize population aged 15 and older[1].

[1] See http://www.gallup.com/178667/gallup-world-poll-work.aspx for further methodological details

We consider in this study cognitive and affective measures of SWB (Diener, 2000): Life Evaluation and Experienced Well-Being. Life evaluation (LE) are measured with the Cantril Self-Anchoring Striving Scale (Cantril, 1965). The question uses a scale from 0 to 10 and asks respondents:

> *Please imagine a ladder with steps numbered from zero at the bottom to ten at the top. Suppose we say that the top of the ladder represents the best possible life for you, and the bottom of the ladder represents the worst possible life for you. On which step of the ladder would you say you personally feel you stand at this time, assuming that the higher the step the better you feel about your life, and the lower the step the worse you feel about it? Which step comes closest to the way you feel?*

Experienced Well-Being is created using experiential measures of emotions, including two positive experience questions (smile or laugh, enjoyment) and three negative experience questions (worry, sadness, anger). These measures were selected out of a larger list of affect measures in the GWP on the basis of providing the largest possible number of country/year observations while maintaining a balanced list of positive and negative measures. The questions are introduced as follows:

> *Now, please think about yesterday, from the morning until the end of the day. Think about where you were, what you were doing, who you were with, and how you felt:*

The positive affect questions are:

1. *Did you smile or laugh a lot yesterday?*
2. *Did you experience the following feelings during A LOT OF THE DAY yesterday? How about enjoyment?*

The negative affect questions are:

1. *Did you experience the following feelings during A LOT OF THE DAY yesterday? How about worry?*
2. *How about sadness?*
3. *How about anger?*

All five affect questions were dummy coded as 1 for a "Yes" answer and as 0 for "No," "Don't know" or "Refused" answer. The dummy-coded items were summed to obtain the overall positive and negative experiences index.

We want to estimate the effect on these two SWB measures of a simple but potent food access question: "Have there been times in the past 12 months when you did not have enough money for food?"with Yes = 1, and No/Don't Know/No Response = 0. Food insecure households are however likely to exhibit a variety of other features that make them prone to lower SWB. They are likely to be poorer, but also to have a diminished ability to cover other human needs or have access to relational goods. An increasingly exhaustive set of covariates is used in order to control for these confounding influences. The first basic control is annual per capita household income, transformed for international comparability into international dollars adjusted for purchasing power parity. The resulting income variable was then log transformed to account for the marginal diminishing returns of income on SWB measures (e.g. Sacks, Stevenson & Wolfers, 2010).

Then universal needs are considered, as operationalized by Tay & Diener (2011), whom in turn examined needs derived from Maslow (1954), Deci and Ryan (2000), Ryff and Keyes (1995), De Charms (1968) and Csikszentmihalyi (1988). We exclude the “basic needs”, which include the food security item of interest in the current study. The final list of needs include:

1. Safety and security:
    - Felt safe walking alone
    - Did not have money and/or property stolen during the past 12 months
    - Were not assaulted during the past 12 months
2. Social support and love[2]
    - Have others they can count on for help in an emergency
3. Feeling respected[3]
    - Felt they were treated with respect
4. Mastery[4]
    - Had the experience of learning something
5. Self-direction and autonomy[5]
    - Experienced freedom in life

All itemsare answered on a dichotomous yes/no scale. For the purposes of model estimation, needs were dummy coded, with yes = 1, and No/Don’t Know/No Response = 0. Items available for the human needs approach represent a relatively low threshold, meaning that any one needwill be covered for most people. For this reason a second theoretical framework based on well-being domain satisfaction is considered to account for confounding variables. We use the five essential elements identified by Gallup (Rath, Harter & Harter, 2010), including the following itemsfrom the Gallup-Healthways Well-Being Index (GHWI)[6]:

1. Purpose WB
    a. Like What You Do Each Day
    b. Learn or Do Something Interesting
2. Social
    a. Someone Encourages Your Health
    b. Friends/Family Give You Positive Energy
3. Financial WB
    a. Have Enough Money
    b. Worried About Money

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[2]Tay & Diener (2011) also include in their “Social support and love” needs the item “Experienced love yesterday”, which is not available for this study’s reference period.
[3]Tay & Diener (2011) also include in their “Feeling respected and pride in activities” needs the item “Were proud of something yesterday”, which is not available for this study’s reference period.
[4]Tay & Diener (2011) also include in their “Mastery” needs the item “Did what she or he does best at work”. This item is excluded from the current study, as its inclusion would effectively eliminate from the sample those outside the employed population.
[5]Tay & Diener (2011) also include in their “Self-direction and autonomu” needs the item “Choose how their time was spent”, which is not available for this study’s reference period.
[6]http://www.gallup.com/poll/175694/country-varies-greatly-worldwide.aspx

   c. Feelings About Household Income[7]
4. Physical
   a. Felt Active and Productive
   b. Physical Health Near Perfect
5. Community
   a. City or Area is a Perfect Place
   b. Recognition for Improving City or Area

After eliminating cases with missing data on any of the analysis variables, the final sample includes 126 countries in 10 broad regions of the world, with a total of 120,582 individual respondents. To estimate an unbiased impact coefficient of food insecurity on SWB we follow recommendations from Ferrer-i-Carbonell & Frijters (2004) and Kristoffersen (2010), and estimate LE and AB using an OLS regression approach:

$$SWB = \beta_0 + \alpha D + \beta F + \varepsilon \quad (1)$$

Where β_0 is a constant term, D is a vector of control variables with unknown coefficients α, F is our food insecurity variablewith unknown coefficient β and ε is the unexplained part of the model. To provide a robustness check on the OLS estimates, we also estimate the effects on SWB using Propensity Score Matching (PSM), which does not require strong linearity assumptions (Rosenbaum &Rubin, 1983). We use nearest neighbor matching based on logit distance in propensity scores using R MatchIt package (Ho et al., 2004). Propensity scores are the true probability of unit i being food insecure, given covariates Di, calculated via logistic regression, where Y is a dichotomous variable which is defined as:

$$Y = \begin{cases} 1 & \textit{for those without money for food} \\ 0 & \textit{for those with money for food} \end{cases}$$

And the probability of $Y = 1$ is given by:

$$Pr = \frac{1}{1 + exp[-(\beta_0 + \beta_i D_i)]} \qquad (2)$$

Where β_0 is a constant term, and D_i is a vector of covariates with unknown coefficients β_i. Using one-to-one nearest neighbor matching without replacement, the individual the food insecure group is chosen as a matching partner for an individual in the food secure group that has the closest propensity score. All impact estimations take into account the multi-stage clustered nature of the sample, including the effect of sampling design in all variance estimations using SPSS Complex Samples 18.0 with linearization via Taylor series.

Finally, this study explores heterogeneity of impacts across a typical set of demographic factors, including, gender, region, urban or rural setting, educational attainment, age, and religion. In order to

[7]Not part of the GHWI ítems, but included for its high explanatory power, see Diego-Rosell, Tortora & Bird (submitted).

account for the nested nature of the data, we turn to a multi-level modelling framework. In the interest of brevity we refer to the matrix notation suggested by Albright & Marinova (2010),

$$SWB = X\beta + Zu + \varepsilon \qquad (3)$$

where X is an nxp matrix containing fixed effects regressors, $\beta$is a vector of fixed-effects parameters, Z is an nxpmatrix of random effects regressors, u is a vector of random effects, and ε is avector of errors (p.10). All multilevel models were estimated using the xtmixed program in Stata 12.0.

3. Results

Table 1 presents the survey-weighted coefficients for "Lack of Money for Food" under a series of increasingly stringent models, starting with a bivariate regression coefficient with no controls, which is equal for all models presented, continuing with a model including log of income as a control variable, and then showing the effect of adding needs and WB domains. The PSM approach was only partially successful in eliminating differences in covariates between the food insecure and the matched food insecure group, as seen in figure 1. Differences in income remain after matching on the full set of 19 covariates (Cohen's $d = 0.56$), as do smaller differences in other covariates. For this reason we include a third, further stringent estimation approach that uses the propensity score matched sample, and applies the same regression controls as in the OLS model (shown as PSM +OLS on Table 1).

In spite of these highly restrictive conditions, the effect of food insecurity on SWB remains significantly different from zero at the 95% confidence level across all specifications, going in the expected direction for all three SWB outcomes. However the size of the effect varies considerably depending on the SWB outcome and model specification. The simple bivariate model with no control variables shows that being food insecure lowers life evaluation scores in a 0-10 scale by 1.43 points ($t = -26.16$, $p<.00$). This effect is reduced to -0.82 points ($t = -16.84$, $p<.00$) after controlling for income in an OLS regression, and further down to -0.75 points ($t = -14.68$, $p<.00$) in the OLS+PSM model. The most stringent specification, controlling for income, needs and WB domains in an OLS+PSM model leaves the effect at -0.33 points ($t = -6.80$, $p<.00$).

We can calculate the income compensating differentials of food insecurity, considering that the coefficient for the log of income in this same OLS+PSM model is .643 ($t = -17.31$, $p<.00$). the ratio of coefficients shows that eliminating food insecurity would have an impact equivalent to more than a half-point increase in the log of income (0.33/.643=0.52), which would be equivalent to more than a trebling of income (10**0.52=3.3). Since the average per capita income in international dollars for the food insecure was $2,680 in 2015, the effect on LE of eliminating food insecurity would be equivalent to a cash transfer of $2,680*2.3 = $6,164 to each food insecure individual, a sum that is arguably much larger than the cost of actually eliminating food insecurity in practice.

The impact of food insecurity on experienced well-being is lower than for LE. Excluding the unrealistic model with no statistical controls, effects range from a high of $t = -11.25$ ($p<.00$) to $t = -2.18$ ($p<.05$) for positive experiences. Food insecurity has a larger effect on negative experiences than on positive experiences, ranging from $t = 17.07$ ($p<.00$) to $t = 8.36$ ($p<.05$).

Let us turn now to the exploration of heterogeneity of impacts from a multilevel perspective. We are interested in identifying differences in impacts across regions, with a further analysis of urban/rural, age, education and gender differences in impacts within regions. For this nested modelling approach an empty, intercepts-only respondent-level model is estimated as the starting point,

$$SWB_{ij} = \beta_0 + U_{0j} + e_{ij} \qquad (4)$$

where SWB outcomes for respondent i in region j are equal to thetotal population mean β_0, plus a region-specific effect Uf or each region j, plus an individual-level error e_{ij}. The region effects U_{0j} are assumed to follow a normal distribution and center around 0, with a variance σ^2_{u0}. Individual errors follow the same assumptions and are denoted by σ^2_e.

The overall mean β_0 (across regions) is estimated as 5.52 for life evaluation, 1.40 for Positive affect and 0.80 for negative affect. The between-region variance in LEis estimated as σ^2_{u0}= 0.80, and the within-region between-individual variance is estimated as σ^2_e= 4.85, for a total variance of 0.80 + 4.85 = 5.65. The intraclass correlation coefficient (ICC) is 0.8/5.65 = 0.14, indicating that 14% of the variance in LEcan be attributed to differences between regions.Following the same calculations, ICC for positive affect is 0.05, and 0.02 for negative affect. Given the relatively low ICC for the two experienced affect variables, this study focuses on LE for the rest of the multi-level modelling exercise.

Region-level effects U_{0j} for LE and their standard errors are presented on figure 2, showing that Sub-Saharan Africa and South Asia are significantly below the overall average in Life Evaluation scores, whereas the EU+ region and the US+Canada+ Australia+New Zealand region are significantly above the overall average. In order to explore regional level variation of food security coefficients we add to equation (4)fixed effects for food security and all the individual-level covariates in the prior models, represented by two new terms, $\beta_1 F_{ij}$ and $\beta_i X_{ij}$,

$$SWB_{ij} = \beta_0 + \beta_1 F_{ij} + \beta_i X_{ij} + U_{0j} + e_{ij} \qquad (5)$$

where$\beta_1 F_{ij}$ represents a fixed coefficient for food security, and $\beta_i X_{ij}$ represents a vector of fixed coefficients β_i on covariates X_{ij} (income, needs, WB domains). We want to test the hypothesis of random food security coefficients across regions, so we add the term $U_{1j} F_{ij}$ to equation (5)

$$SWB_{ij} = \beta_0 + \beta_1 F_{ij} + \beta_i X_{ij} + U_{1j} F_{ij} + U_{0j} + e_{ij} \qquad (6)$$

where $U_{1j} F_{ij}$ represents a vector of random coefficients U_{1j} for the food security indicator F_{ij}. We can use a likelihood ratio test to test whether the food security effect varies across regions. The log-likelihood value for model (5) was -250381.64, and for model (6) was -250296.64 so the likelihood ratio test statistic is LR = 2*(-250296.64 --250381.64) = 170 with 1 degree of freedom (because there is only one parameter difference between the models), which is greater than 3.841, the 5% point of a chi-squared distribution with 1 DF[8].

The food security effect $\beta_1 F_{ij}$ for region j is estimated as -.415, and $U_{1j} F_{ij}$, the between-region variance in these slopesis estimated as .028. For the 'average' region we estimate that food insecurity has an impact of -.415 points in LE, with a 95% confidence interval of -.415 ± 1.96*0.08 = -0.5718 to -0.2582. The negative covariance estimate of -.010 means that regions with a high

[8] http://sites.stat.psu.edu/~mga/401/tables/Chi-square-table.pdf

intercept (above-average LE for the food secure) tend to have a lower-than-average effect. Similarly, regions with a low intercept (below-average LE for the food secure) tend to have a more marked increase in LE with food security.

Finally we want to explore whether the impact of food security varies depending on individual-level demographic factors. We continue with our model nested within regions, and add another level of nesting for country, location (urban vs. rural), gender (female vs. male), age (15-29 vs. 30+) and educational attainment (primary or less vs. higher). In order to test the need for a three-level model start with the intercept-only model

$$LE_{ijk} = \beta_{00} + U_{0j} + W_{0jk} + e_{ijk} \qquad (7)$$

where LEfor respondent i in region $j$and country $k$is equal to the total population mean β_{00}, plus a region-specific effect U for each region j, plus a country-specific effect W within each region j, plus an individual-level error e_{ijk}. ICC for country as a third-level nesting variable is 0.21, indicating that 21% of the variation in LE can be attributed to the nesting of countries within regions, with a marginal ICC of 0.10 that is exclusively attributable to the country level, above and beyond the regional effect. Marginal ICCs are also sizeable for educational attainment (0.07), but much lower for the remaining nesting variables we tested, including location (0.03), age (0.02), and gender (0.00). We thus focus on the effect of country and education for the rest of the three-level modelling exercise. We add linear fixed effects for food security and all the individual-level covariates in the prior models, so we add two new fixed terms, $\beta_1 F_{ijk}$ and$\beta_i X_{ijk}$ to equation 7, plus the term$U_{1j} F_{ij}$ for random slopes within regions.

$$LE_{ijk} = \beta_{00} + \beta_1 F_{ijk} + \beta_i X_{ijk} + U_{0j} + W_{0jk} + U_{1j} F_{ij} + e_{ijk} \qquad (8)$$

Equation (8) is equivalent to (6), which showed the significance of region-varying food security effects, but this time with the addition of country/educational effect W_{0jk}. We are interested in the hypothesis of random food security coefficients across countries within regions and across educational levels, so we add the term $U_{1jk} F_{ijk}$ to test for random slopes within countries and education levels

$$LE_{ijk} = \beta_{00} + \beta_1 F_{ijk} + \beta_i X_{ijk} + U_{0j} + W_{0jk} + U_{1j} F_{ij} + U_{1jk} F_{ijk} + e_{ijk} \qquad (9)$$

The LR test for the two equations is significant for random slopes by country (LR=167.14, p<.00, 1*df*), and by education level (LR=28.36, p<.00, 1 *df*).

4. Discussion

The impact estimates we find for food insecurity are significant across all model specifications and sizeable, particularly when considering the income compensating differentials. Our findings are consistent with prior literature, showing that the effect of food insecurity is larger than income equivalent(Guardiola & Rojas, 2016). From the perspective of SWB components, we find that food insecurity has a largest effect on life evaluations, followed by negative affect, and a relatively small effect on positive affect. This is consistent with Tay & Diener (2011), who found a similar pattern for a "Basic Needs" component including food and shelter insecurity indicators.

Our multilevel modelling results show that the impact of food security varies significantly by region, with poorer regions having a more marked increase in LE than richer regions when individuals move from being food insecure to food secure. This finding is surprising considering that our models control for income expressed in international dollars.

A potential hypothesis to explain this finding is that respondents interpret “having enough money for food” differently in different regions. As Figure 3 shows, the average income for food insecure households is, at the global level, almost 4 times lower than that of food secure households. This ratio is lower at the regional level because food insecure households are very unevenly distributed, with Sub-Saharan Africa and South Asia accounting for more than half of all food insecure households. The income ratio between food secure and food insecure households at a regional level is between 1.4 and 2.1, with the ratio increasing with the level of development of each region.

Based on a literal interpretation of our food insecurity question, we would expect that the cut-off point in income where households turn from “having enough money for food” to “not having enough money for food” would be the same in all regions, since income is adjusted for purchasing power differences across countries, and so the same level of income should be needed in all countries to achieve basic food requirements, yet individuals in richer regions have a higher income threshold for reporting food insecurity than those in poorer regions.Taking the East Asia region as an example of a rich region, average annual per capita income among those with “enough money for food” is $18,835 at PPP, compared to $9,065 for those with “Not enough money for food”. In Subsaharan Africa, average income among those with “enough money for food” is $1,791 at PPP, compared to $885 for those with “Not enough money for food”.

While the income gap between the food secure and the food insecure is consistent across all regions, it seems that “not having enough money for food” is interpreted more literally in the poorer regions, whereas it may be just an indicator of general economic hardship in richer regions. These potential measurement equivalence issues highlight the importance of valid and reliable scales of food insecurity such as the Food Insecurity Experience Scale (FIES) developed by FAO (Ballard, Kepple, & Caffier, 2013).

Our current study is not without limitations. Data availability constraints mean that some big countries had to be excluded from the sample, most notably China. Other large countries had a small number of cases (e.g. USA, n=104). Finally, while we strived to adjust our standard errors to account for the stratified clustered sample design of the GWP, the xtmixed program in Stata 12.0 does not allow for survey design adjustments, which probably results in an underestimate of standard errors for the multilevel models. Future studies should try to further explain the multilevel structure identified in our exploratory analysis, particularly variance of impacts of food security at the regional and country levels, which show the largest ICC of all the nesting variables explored.

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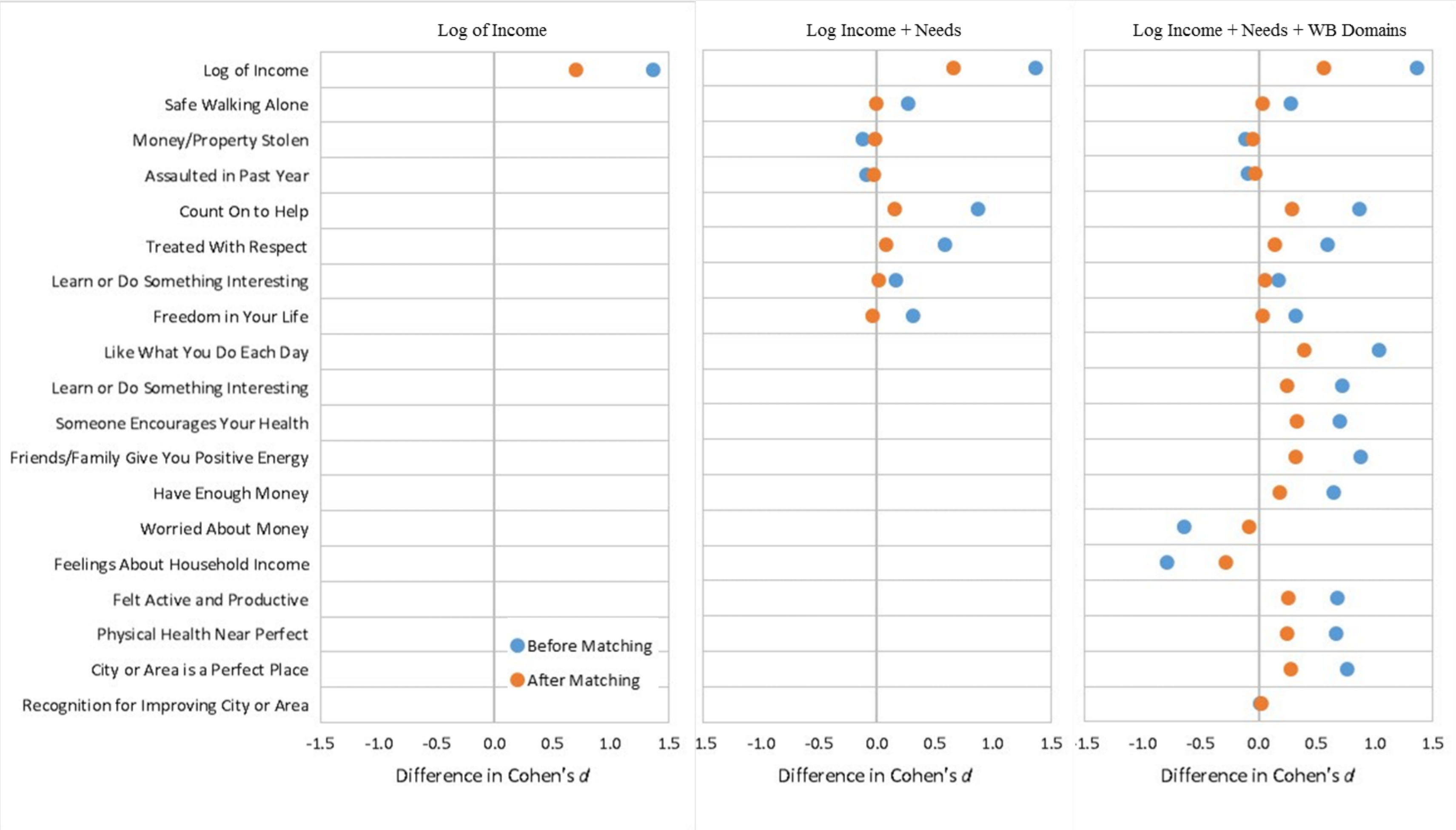

Figure 1: *Dotplot of standardized mean differences for covariates before and after propensity score matching*

Table 1: *OLS, PSM and PSM+OLS coefficients for "Lack of money for food"*

	OLS				PSM				PSM+OLS			
Model	**Coef.**	**St.Err**	**t**	**p**	**Coef.**	**St.Err**	**t**	**p**	**Coef.**		**t**	**p**
Life Evaluation												
No controls	-1.43	0.05	-26.16	.00**	-1.43	0.05	-26.16	.00**	-1.43	0.05	-26.16	.00**
Log Income	-0.82	0.05	-16.84	.00**	-0.82	0.05	-14.91	.00**	-0.75	0.05	-14.68	.00**
Log Income+Needs	-0.68	0.05	-14.48	.00**	-0.76	0.05	-14.10	.00**	-0.65	0.05	-13.35	.00**
Log Income+Needs+WB Domains	-0.35	0.05	-7.22	.00**	-0.68	0.06	-11.72	.00**	-0.33	0.05	-6.80	.00**
Positive Experiences												
No controls	-0.26	0.02	-14.51	.00**	-0.26	0.02	-14.51	.00**	-0.26	0.02	-14.51	.00**
Log Income	-0.21	0.02	-11.25	.00**	-0.22	0.02	-11.73	.00**	-0.22	0.02	-11.27	.00**
Log Income+Needs	-0.12	0.02	-7.92	.00**	-0.17	0.02	-8.97	.00**	-0.13	0.02	-8.21	.00**
Log Income+Needs+WB Domains	-0.04	0.02	-2.43	.02*	-0.13	0.02	-5.86	.00**	-0.04	0.02	-2.18	.03*
Negative Experiences												
No controls	0.53	0.03	21.03	.00**	0.53	0.03	21.03	.00**	0.53	0.03	21.03	.00**
Log Income	0.48	0.03	17.07	.00**	0.47	0.03	17.60	.00**	0.46	0.03	16.93	.00**
Log Income+Needs	0.41	0.03	15.73	.00**	0.43	0.03	16.31	.00**	0.40	0.03	15.80	.00**
Log Income+Needs+WB Domains	0.24	0.03	9.16	.00**	0.33	0.03	11.37	.00**	0.23	0.03	8.36	.00**

*p<.05 **p<.01

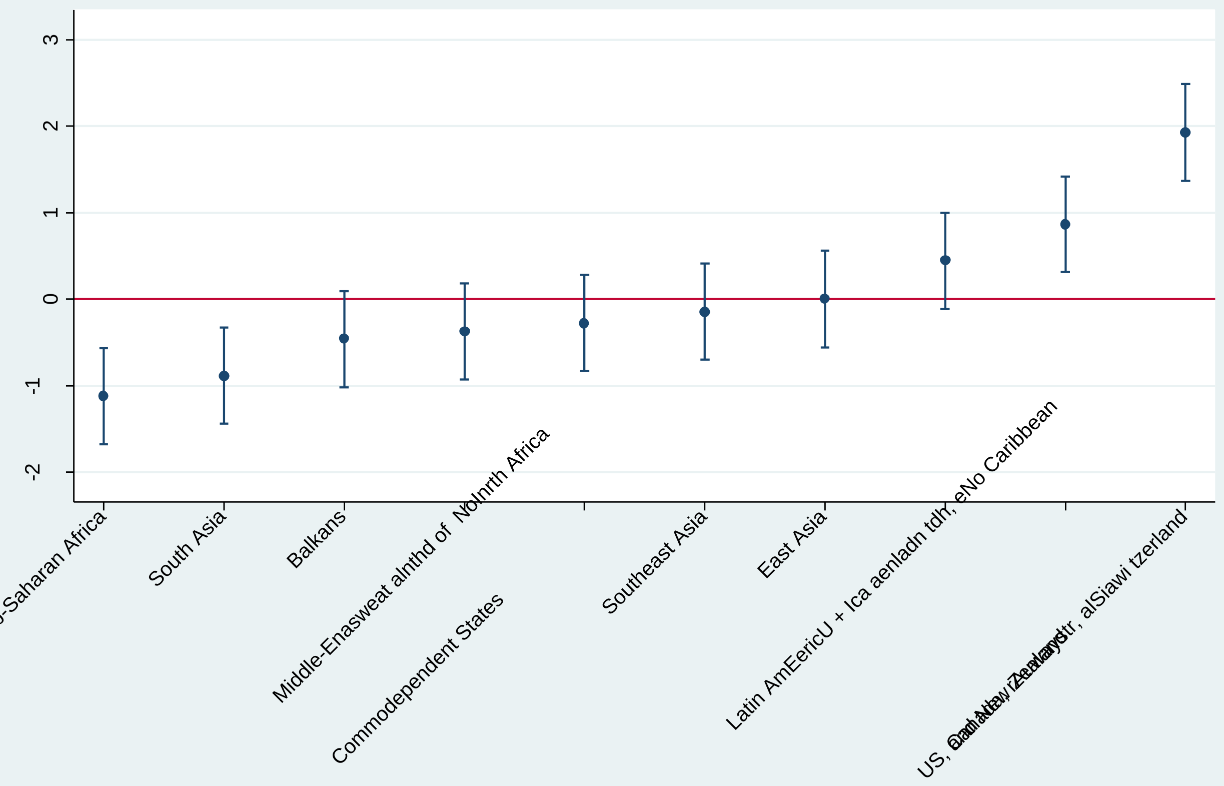

Figure 2: *Region residuals and standard errors for Life Evaluation*

Table 2: *Two-level models of LE with random effects by region and food insecurity*

	Model 1		Model 2†		Model 3†	
	Coef.	**St.Err**	**Coef.**	**St.Err**	**Coef.**	**St.Err**
Fixed Effects						
Intercept β_0	5.52**	0.28	3.20**	0.16	3.24**	0.16
Food Insecurity $\beta_1 F_{ij}$			-0.33**	0.01	-0.41**	0.06
Random Effects						
Intercept U_{0j}	0.80*	0.38	0.23*	0.11	0.24*	0.11
Food Insecurity $U_{1j}F_{ij}$					0.03*	0.01
Model Fit Statistics						
Log Likelihood	-266,349		-250,382		-250,297	
AIC	532,705		500,895		500,729	
BIC	532,734		501,536		501,389	

*p<.05 **p<.01

†Includes controls for needs and WB domains (coefficients omitted)

Table 3: *Intercept-only three-level models of LE by region and country, location, gender, age and education*

	Country		Urban vs. Rural		Gender		Age		Education	
	Coef.	**St.Err**	**Coef.**	**St.Err**	**Coef.**	**St.Err**	**Coef.**	**St.Err**	**Coef.**	**St.Err**
Fixed Effects										
Intercept β_0	5.50**	0.27	5.42**	0.30	5.52**	0.28	5.61**	0.28	5.37**	0.26
Random Effects (Level 1)										
Intercept U_{0j}	0.66	0.35	0.83	0.43	0.79*	0.35	0.75*	0.38	0.49*	0.34
Random Effects (Level 2)										
Intercept W_{0jk}	0.54**	0.07	0.17*	0.08	0.01	0.00	0.12*	0.05	0.40*	0.18
Model Fit Statistics										
Log Likelihood	-260,508		-265,795		-266,333		-265,423		-264,429	
AIC	521,025		531,597		532,673		530,853		528,866	
BIC	521,063		531,636		532,712		530,892		528,905	

*p<.05 **p<.01

Figure 3:*Average per capita income by food security status and region*