**Nettle, Andrews & Bateson: Food insecurity as a driver of obesity in humans: The insurance hypothesis**

**Online Appendix B: Meta-analysis methods and descriptive statistics**

This appendix presents more details of the methods of the meta-analysis reported in section 5 of the main paper. Section B1 gives more details of the aims and scope of the meta-analysis. Section B2 gives the details of the methods used. Section B3 presents the results, including analyses to check for the accuracy of the data coding (section B3.1), the main meta-analytic models (section B3.2), and the analysis of potential publication bias (section B3.3).

## B1. Aims and scope

We sought to review the published empirical evidence relating food insecurity to overweight or obesity. The scope of our dataset was thus papers that reported quantitative data on an association between, as the predictor, a measure of food insecurity, and, as outcome, a variable relating to body weight, in a sample of adults or children. We did not seek to include studies where the predictor was participation in a food stamps programme, unless the study also included a direct measure of food insecurity. A number of studies have found positive associations between food-stamp programme participation and high body weight, and suggested that this might be because programmes where food stamps are issued periodically lead to cycles of food insecurity, but we left this question outside the scope of our review (see DeBono, Ross, & Berrang-Ford, 2012; Dinour, Bergen, & Yeh, 2007). We also did not seek to include studies where the outcome variable was not directly weight-based but indirectly related to weight (for example, diet quality or diabetes).

## B2. Methods

### *B2.1 Search strategy*

Our search strategy was as follows. We first searched the databases Scopus and PubMed (July 2015) for papers with either “obesity” or “overweight”, and either “food security” or “food insecurity” in title, abstract, or keywords (Scopus) or title and abstract (Pubmed). We read the abstracts of all these papers to identify those likely to meet the inclusion criteria (see below). This produced 156 candidate articles (114 identified through both Scopus and Pubmed, 35 through Scopus alone, and 7 through Pubmed alone). We then enriched this sample by adding in any papers not already identified that had been discussed in key previous empirical reviews (Dinour et al., 2007; Franklin et al., 2012; Larson & Story, 2011; Morais, Dutra, Franceschini, & Priore, 2014), and also by reading abstracts of all the papers that had cited those reviews on Scopus. This enrichment produced 17 more candidates, giving a final candidate set of 173. We obtained and read the full text for all articles in the candidate set.

### *B2.2 Inclusion of papers from the candidate set*

Our criteria for inclusion in the final sample from the candidate set were as follows. First, the study had to present empirical data not already published in an earlier paper in the candidate set. Second, food insecurity (FI) must have been measured. This was usually via one of the validated questionnaires (possibly abbreviated or translated), but on occasion a single question or interview theme was used instead. Third, data had to be presented on body weight or some categorisation derived from it. This was generally BMI-based (BMI itself, overweight = BMI≥25, obese = BMI≥30 for adults; weight percentile for age or some categorization derived from this for children). Fourth, data associating FI with body weight had to be presented in a format that could be made comparable to other studies (see next section). Given these criteria, we were able to include 125 of the 173 candidate papers in the final data set.

*B2.3 Estimates of association strength*

The analytic methods used in this literature are varied, and consequently representation of associations in a common format was not straightforward. The most frequently presented result is an odds ratio for a weight outcome (e.g. obese versus non-obese) by a FI comparison (e.g. insecure versus secure), accompanied by its standard error or 95% confidence interval. We converted these to log odds ratios (LORs, zero denotes no association). Where studies did not present odds ratios but did present: 1. numbers of participants falling into the different combinations of weight category and FI category; 2. means and standard deviations of body mass index by category of FI; or 3. correlations/standardized regression coefficients between a continuous FI measure and BMI, we were able to convert these to LORs using the methods described in Borenstein, Hedges, Higgins and Rothstein (2009) and Peterson and Brown (2005). These methods involve assumptions about how categorical distinctions map onto underlying continua, and moreover, in some cases, such as where sampling weights had been applied, conversion involved numerical computations and approximations on our part. We recorded whether the LORs were directly provided in the original paper, or had been converted by us.

Where studies reported prevalence ratios, we took these as if they were odds ratios. Close to the point of null association, prevalence ratios and odds ratios are identical (both equal to 1); as the association becomes stronger, the odds ratio exceeds the prevalence ratio by an amount determined by the prevalence of the predictor and outcome (Zocchetti, Consonni, & Bertazzi, 1997). Thus, taking prevalence ratios as odds ratios is conservative, leading to the underestimation of strong associations. Associations are in any case likely to be weak or moderate in this domain.

*B2.4 Statistical adjustment*

Studies varied in the degree of statistical adjustment made for covariates such as income, education and ethnicity. Where both adjusted and unadjusted estimates were available, we recorded both the unadjusted and (maximally) adjusted ones in the dataset. The main models reported in the paper use only the adjusted associations in cases where both were available. Where only unadjusted estimates were available, we included these but recorded their unadjusted status to include as a moderator in the meta-analysis.

*B2.5 Multiple comparisons*

The final data set included 301 associations from the 125 studies; hence, many studies provided multiple associations. In some cases this was because there were multiple subgroups, such as men and women, or different ethnic groups. Since there was prior evidence of sex differences in association, we preferred separate-by-sex associations to whole sample associations where both of these were available. Since we had no *a priori* interest in differences by ethnicity, we preferred whole sample associations to separate-by-ethnicity associations where both of these were available. However, where only separate-by-ethnicity associations were reported in the original papers, these were all used. Multiple associations from the same study also arose because of multiple categories of predictor (e.g. three levels of FI, with the most secure taken as the reference category) or of outcome (e.g. three levels of body weight, with the lightest taken as the reference category). In general, *j* levels of predictor and *k* levels of outcome produces *j-1 x k-1* associations to report. To account for the non-independence arising from the inclusion of multiple comparisons from the same study in the dataset, we analysed the data using multilevel meta-analytic models (Van den Noortgate, López-López, Marín-Martínez, & Sánchez-Meca, 2012), implemented in R (R Core Development Team, 2015) using the 'metafor' package (Viechtbauer, 2010). These models include two levels of random effect. First, there is a random effect at the level of the association, reflecting the fact that the associations measured within a study are heterogeneous and are a subset of all the possible associations that could have been measured. This is nested within a random effect at the level of the study, reflecting the fact that associations from within each study are non-independent, and each study is drawn from a theoretical population of many other potential studies that could have been done, and about which we wish to generalise.

*B2.6 Moderating variables*

We also recorded, for each association in the dataset, a set of variables describing the methodology, sample and exact nature of the comparison made, to analyse as potential moderators of association strength. These are described below.

*Design*. This variable had two levels, cross-sectional and longitudinal. For associations to count as longitudinal, they not only had to have multiple time points, but had to report statistics in which the predictor was change in FI status and/or the outcome was change in body weight. Note that several longitudinal studies provided cross-sectional associations at baseline as well as any longitudinal associations.

*Association type.* We recorded whether the association was originally given as a (log) odds ratio (or prevalence ratio, see above), or whether the odds ratio had been converted from other kinds of association or descriptive statistics by us. The 'narrow subset' of studies mentioned in the main paper is the set restricted to those where the odds ratio was provided in the original paper.

*Adjustment.* Associations were recorded as adjusted or unadjusted, although the exact set of covariates adjusted for varied from study to study.

*Classification of predictor variable.* Most studies used a dichotomy of food insecure versus food secure. We assigned these predictor type 'All FI versus FS'. Some studies used a three-way classification of FI. We classified the associations from these studies as either 'Moderate FI versus FS' or 'Severe FI versus FS'. (Individual studies differed in their terminology for the more and less severe type of insecurity, but we mapped all of these onto 'moderate' and 'severe' respectively). For four-way classifications where there was a clear hierarchy of severity, we equated the most severe category to the severe FI category from papers using a three-way classification; the next most severe category to the moderate FI category; and assigned the remaining category a new status of 'Marginal FI'. This reflected the papers' own terminology in most cases. For some cases of four-way classification, it was not clear that the three insecure classes formed a hierarchy of severity (specifically, the four-way classification of food security/household insecurity/individual insecurity/child hunger); for these cases, all three insecure categories were combined to make a single dichotomous comparison of 'All FI versus FS'. For studies that used food insecurity score as a continuous quantitative variable, we classified the predictor as continuous.

*Classification of outcome variable.* We recorded whether the outcome in the association was obesity, overweight, or a continuous measure of body mass. Almost all papers in this literature use the same standard definitions of overweight (BMI ≥ 25) and obesity (BMI ≥ 30) for adults. Definitions for children are somewhat more variable but usually involve the 85$^{th}$ and 95$^{th}$ percentiles of weight for age, or weight for height). We did not distinguish associations where the outcome was obesity versus normal weight from those where it was obesity versus non-obesity, nor those where the outcome was 25 ≤ BMI ≤ 30 versus BMI < 25 from those where it was BMI ≥ 25 versus BMI < 25. Any differences between these slightly different classifications are likely to be slight.

*Sex and age group.* We recorded sex of sample (male, female, or mixed), and whether the sample were adults or children. A child sample was defined for these purposes as one in which most participants were under 16 years old. For child samples, we also recorded the mean age or, where this was not given, the central point of the age range.

*Country.* To establish whether there were differences in association between samples from developed and developing countries, we recorded whether the country that was the source of the sample was classified by the World Bank as high-income or middle/low-income (World Bank, 2015).

*B2.7 Analysis strategy*

We fitted a first meta-analytic statistical model with no moderators to examine whether there was an association between food insecurity and high body weight overall (statistical model 1). We subsequently explored moderator variables to attempt to explain the variation in association strength. As the number of moderators was relatively large, we were not able to enter them all simultaneously in one model. We hence fitted a series of statistical models, including non-overlapping sets of moderators respectively to do with the design and statistics (statistical model 2), the outcome and predictor variables (statistical model 3), and the participants included in the study (statistical model 4).

**B3. Results**

*B3.1 Dataset and coding checking*

The final set of papers included is listed in Online Appendix C, whilst the raw data are provided as Online Appendix D. The R script for the analysis is also available via the Open Science Framework at https://osf.io/zarn6/. Table B1 gives descriptive statistics for the associations included in the dataset.

To verify that our coding of the data was accurate and that our conversion of different types of associations to the common format of LORs had not led to any anomalies, we classified associations according to whether the authors of the original paper had stated the association to be positive and statistically significant, or not. For 58 associations, no explicit statement was made either way in the original papers. For the remainder, we calculated Cohen's Kappa measure of inter-rater agreement between statistical significance as stated by the original authors, and the lower 95% confidence limit for the LOR being greater than 0 in our dataset. The Kappa was 0.96, indicating a very high level of agreement. Figure B1 plots the lower 95% confidence limit in our dataset by the authors' original claim of significance, separated our by each of the major types of pre-conversion association measure: odds ratios, prevalence ratios, correlations or standardized beta coefficients, frequencies of individuals in each combination of FI and obesity, or means and standard deviations of BMI for different FI groups. As the figure shows, for every association type, the significant associations as claimed by the original authors have lower 95% confidence limits greater than 0, whilst the non-significant associations have 95% confidence limits less than 0. We thus infer that our encoding and conversion of the literature has faithfully preserved the key features of the original analyses.

Table B1. Descriptive statistics for the final meta-analysis data set.

| **Variable** | **Level** | **Number of associations** | **Number of distinct studies** |
|---|---|---|---|
| Design | Cross-sectional | 287 | 123 |
| | Longitudinal | 14 | 7 |
| Association type | Given as odds ratio | 185 | 64 |
| | Converted | 116 | 62 |
| Adjustment | Adjusted | 172 | 65 |
| | Unadjusted | 129 | 64 |
| Predictor variable | All FI versus FS | 137 | 83 |
| | Marginal FI versus FS | 23 | 13 |
| | Moderate FI versus FS | 66 | 36 |
| | Severe FI versus FS | 67 | 37 |
| | Continuous | 8 | 7 |
| Outcome variable | Obesity | 121 | 60 |
| | Overweight | 129 | 64 |
| | Continuous BMI | 42 | 25 |
| | Other for longitudinal designs | 9 | 3 |
| Sex | Female | 117 | 53 |
| | Male | 41 | 20 |
| | Mixed | 143 | 74 |
| Age group | Adults | 189 | 79 |
| | Children | 112 | 52 |
| Country | High income | 209 [178 from USA] | 91 [77 from USA] |
| | Low or middle income | 92 | 36 |

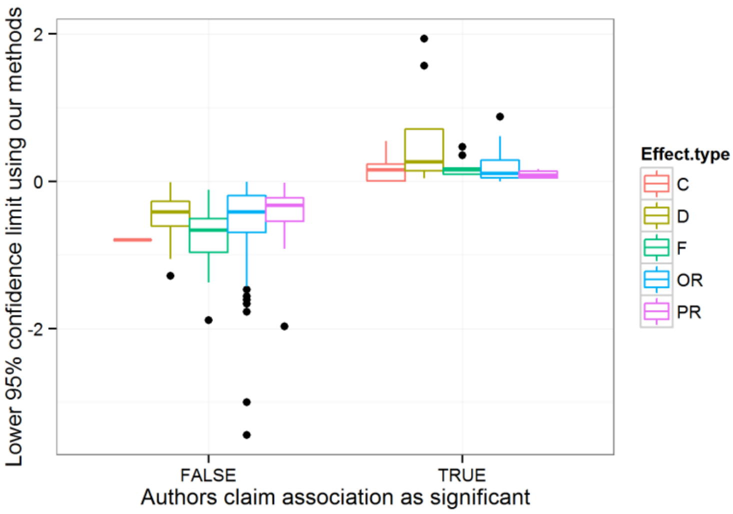


Figure B1. Lower 95% confidence limit of the log odds ratio for each association in our data set, by whether the authors stated the association to be positive and statistically significant in the original paper, and by the original format of the association. C: Correlation coefficient or standardized beta; D: Group means and standard deviations; F: Frequencies of individuals in each FI/Obesity combination; OR: Odds ratio or log odds ratio; PR: Prevalence ratio.

*B3.2 Main statistical analyses*

Table B2 gives the full summaries of the statistical models. Statistical model 1 tested whether there was a significantly positive association between food insecurity and high body weight overall. There was (LOR = 0.19, 95% CI 0.13 – 0.25, z = 6.30, $p < 0.01$). There was however significant heterogeneity in the associations above and beyond that expected due to sampling variation ($Q_{300}$ = 1261.63, $p < 0.01$). Of the observed variability, 70.39% was between studies, whilst the remaining 29.61% was among associations reported within the same study. To satisfy ourselves that the pattern was not an artefact of our conversion of non-odds ratio associations into odds ratios, we reran statistical model 1 using the narrower subset of 154 comparisons that were stated in the form of odds ratios in the original papers. The results were extremely similar to those from the full dataset (LOR = 0.20, 95% CI 0.14 – 0.27, z = 6.11, $p < 0.01$). In light of this, all subsequent results use the full dataset.

Statistical model 2 examined the effects of methodological and statistical factors, by including the design of the study (longitudinal versus cross-sectional), and whether or not the results were adjusted for possibly confounding factors like socioeconomic position and ethnicity. The moderators did not explain a significant portion of the heterogeneity in association ($Q_2$ = 0.86, p = 0.65). Although unadjusted estimates tended to be slightly higher than adjusted ones, this difference was not significant (B = 0.05, 95% CI -0.07 – 0.16, z = 0.81, p = 0.42). This conclusion was supported by a paired t-test directly comparing the adjusted and unadjusted LORs for the 49 cases where the original authors provided both for exactly the same comparison in their data (mean unadjusted 0.28; mean adjusted 0.23; $t_{48}$ = -0.82, p = 0.42). There was no significant difference in association strength between longitudinal and cross-sectional study designs (B = 0.04, 95% CI -0.15 – 0.23, z = 0.41, p = 0.68).

Table B2. Full model output for the four main meta-analysis statistical models.

| Model | Fixed effects | Parameter (95% CI) | Residual variances | | Q-statistics | |
|---|---|---|---|---|---|---|
| Model 1 | Intercept | 0.19 (0.13 – 0.25)* | Study | 0.067 | Residual | $Q_{300}$ = 1261.63, p < 0.01 |
| | | | Association | 0.028 | | |
| Model 2 | Intercept | 0.17 (0.09 – 0.25)* | Study | 0.067 | Moderators | $Q_{2}$ = 0.86, p = 0.65 |
| | Design cross-sectional | Reference category | Association | 0.029 | Residual | $Q_{298}$ = 1246.66, p < 0.01 |
| | Design longitudinal | 0.04 (-0.15 – 0.23) | | | | |
| | Adjusted | Reference category | | | | |
| | Unadjusted | 0.05 (-0.07 – 0.16) | | | | |
| Model 3 | Intercept | 0.27 (0.17 – 0.36)* | Study | 0.059 | Moderators | $Q_{6}$ = 19.41, p < 0.01 |
| | Outcome obesity | Reference category | Association | 0.027 | Residual | $Q_{280}$ = 1087.25, p < 0.01 |
| | Outcome overweight | -0.16 (-0.25 – - 0.07)* | | | | |
| | Outcome continuous | 0.02 (-0.17 – 0.20) | | | | |
| | Predictor all FI versus FS | Reference category | | | | |
| | Predictor marginal FI versus FS | 0.01 (-0.14 – 0.16) | | | | |
| | Predictor moderate FI versus FS | -0.07 (-0.20 – 0.05) | | | | |
| | Predictor severe FI versus FS | -0.01 (-0.14 – 0.12) | | | | |
| | Predictor continuous | 0.13 (-0.19 – 0.46) | | | | |
| Model 4 | Intercept | 0.37 (0.29 – 0.46)* | Study | 0.048 | Moderators | $Q_{4}$ = 57.60, p < 0.01 |
| | Sex female | Reference category | Association | 0.019 | Residual | $Q_{296}$ = 965.48, p < 0.01 |
| | Sex male | -0.26 (-0.35 – 0.16)* | | | | |
| | Sex mixed | -0.06 (-0.18 – 0.05) | | | | |
| | Adults | Reference category | | | | |
| | Children | -0.14 (-0.25 –0.03)* | | | | |
| | High income country | Reference category | | | | |
| | Low or middle income country | -0.27 (-0.39 – -0.15)* | | | | |

* 95% confidence interval does not include zero.

Statistical model 3 included moderators to do with the predictor and outcome variables (this model used the data from just the cross-sectional studies, since outcome variables are different in longitudinal designs). The possible outcomes were obesity (usually defined as BMI ≥ 30 or weight for age above 95$^{th}$ percentile, versus its absence), overweight (BMI ≥ 25 or weight for age above 85$^{th}$ percentile, again versus its absence), or a continuous BMI variable. The possible predictors were: dichotomous comparison of food insecurity versus food security; marginal food insecurity versus food security; moderate food insecurity versus food security; severe food insecurity versus food security; and a continuous food security variable. In model 3, the moderators did explain a significant proportion of the heterogeneity in association ($Q_6 = 19.41$, $p < 0.01$), though substantial unexplained heterogeneity remained ($Q_{280} = 1087.25$, $p < 0.01$). Comparisons using overweight as the outcome found weaker associations than those using obesity (B = -0.16, 95% CI -0.25 – 0.07, z = -3.58, $p < 0.01$). There was no significant difference between associations using obesity and those using continuous BMI as the outcome. Thus it appears that stronger associations may be detected by using the more extreme category of high body weight, or else BMI as a continuous variable, than by using the less extreme overweight category. There were no significant differences between the different types of predictor.

Statistical model 4 examined the types of participants of the study as a source of heterogeneity in association. The participants variables were: composition of the sample by sex (male, female, mixed); by age group (adults or children); and whether the study was performed in a World Bank-defined high-income country or not. These moderators accounted for significant heterogeneity ($Q_4 = 57.60$, $p < 0.01$), although again substantial unexplained heterogeneity remained ($Q_{296} = 965.48$, $p < 0.01$). There was a significant effect of participant sex, with male samples showing significantly weaker associations than female ones (B = -0.26, 95% CI -0.35 – -0.16, z = -5.25, $p < 0.01$). Indeed, there was no evidence of a non-zero association in the male samples considered as a subset. Mixed-sex samples did not differ significantly from female ones (B = -0.06, 95% CI -0.18 – 0.05, z = -1.07, p = 0.26). There was also an effect of age group, with children showing significantly weaker associations than adults (B = -0.14, 95% CI -0.25 – -0.03, z = -2.54, $p < 0.01$). We also found an effect of being in a high income country, with studies from low- and middle-income countries finding weaker associations than those from high income countries (B = -0.27, 95% CI -0.39 – -0.15, z = -4.51, $p < 0.01$). Associations from low- and middle-income countries considered separately did not differ significantly from zero, whereas those from high-income countries had a central LOR estimate of 0.26, equivalent to an odds ratio of 1.29.

To investigate the pattern within the child samples, we ran additional statistical models using just the child samples, both in an intercept-only model and including age and sex of the children as moderators (table B3). The association in the intercept-only model did not differ from zero (LOR = 0.06, 95% CI -0.03 – 0.14, z = 1.29, p = 0.20). The only significant moderator in the model with moderators was an interaction between age and sex. Figure B2 illustrates this interaction by dividing the child samples up into those where the modal age was ten years or older, and those where it was younger, and according to whether the sample was male, female, or mixed. In the younger age group, all types of samples have similar estimates of association. In the older age group, the female samples show a significantly stronger association than the male ones, albeit not significantly different from zero. Thus, the sex difference that is so clear in adults seems to be beginning to emerge in adolescents, whereas there is no evidence of it in younger children.

Table B3. Full model output for the two meta-analysis models of the child samples alone.

| **Model** | **Fixed effects** | **Parameter (95% CI)** | **Residual variances** | | **Q-statistics** | |
|---|---|---|---|---|---|---|
| Model C1 | Intercept | 0.05 (-0.03 – 0.14)* | Study | 0.048 | Residual | $Q_{111} = 487.61$, $p < 0.01$ |
| | | | Association | 0.033 | | |
| Model C2 | Intercept | -0.16 (-0.61 – 0.29)* | Study | 0.050 | Moderators | $Q_{5} = 10.71$, $p = 0.06$ |
| | Sex female | Reference category | Association | 0.024 | Residual | $Q_{106} = 347.51$, $p < 0.01$ |
| | Sex male | 0.29 (-0.13 – 0.70) | | | | |
| | Sex mixed | 0.10 (-0.40 – 0.59) | | | | |
| | Age | 0.03 (-0.01 – 0.08) | | | | |
| | Sex male * Age | -0.06 (-0.10 – 0.01)* | | | | |
| | Sex mixed * Age | -0.0 (-0.06 – 0.03) | | | | |

* 95% confidence interval does not include zero.

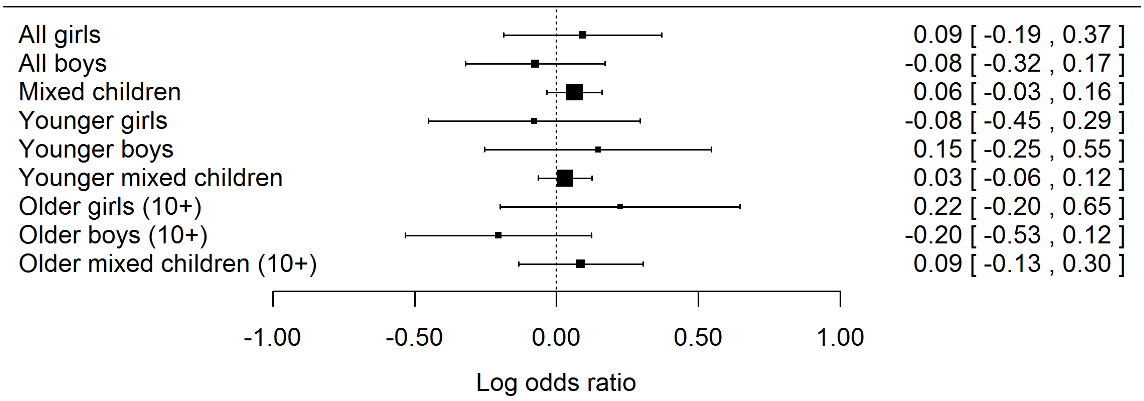


Figure B2. Central estimates (log odds ratios and their 95% confidence intervals) for associations between food insecurity and high body weight in subgroups of the child samples.

*B3.3 Publication bias*

Methods for testing publication bias are not implemented in the ‘metafor’ package for multilevel models. We thus repeated the main model 1 using a simple random-effects model. This yielded very similar results to the multilevel version (central estimate: LOR = 0.18, 95% CI 0.14 – 0.22, z = 8.17, p < 0.01). The funnel plot for this model (figure B3, left panel) fails to show clearly the predicted greater variability of association estimates where the precision is low (i.e. the funnel shape). This may reflect the fact that the associations come from studies that in most instances have high precision, but are heterogeneous in a number of substantive ways.

We performed the random-effects version of the Egger test (Egger, Davey Smith, Schnieder, & Minder, 1997) on this model: the test was significant, suggesting that publication bias might be operative ($z = 2.60$, $p < 0.01$). We then used the trim and fill method (Duval & Tweedie, 2000) to estimate how many unreported null associations might be missing (figure B3, right panel). The estimated number was 26 (standard error 10.98), or just under 10% of the total number of associations. Repeating the equivalent of model 1 with the missing associations imputed via the trim and fill method produced a central LOR estimate of 0.12 (95% CI 0.07 – 0.17, $z = 4.89$, $p < 0.01$). Thus, this analysis suggests that there may be publication bias in operation, but that even imputing 26 null associations to make the funnel plot symmetrical does not abolish the significant association overall between FI and high body weight; the association is attenuated by around one third, but remains significant.

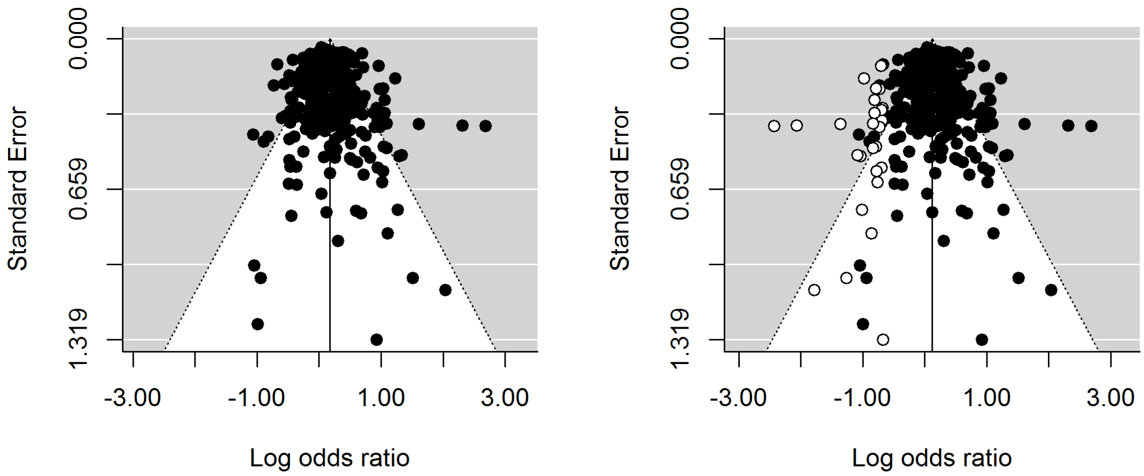


Figure B3. Funnel plots for the data (left panel); and the data (filled points) with 26 associations imputed by the trim and fill method (open points) to make the funnel plot symmetrical (right panel).

It is not possible to retest models 1-4 from table B2 using the dataset with the extra associations imputed via the trim and fill method, since there is no method for imputing the moderator variables for the missing associations. Instead, to examine whether the effects of age, sex and high-income country survived adjustment for publication bias, we divided the data up into a series of relevant subsets, and performed a trim and fill analysis on each subset in turn. We then extracted the central estimate of association strength, and its 95% confidence interval, for each of these trimmed and filled subsets. The results are shown in figure B4. As for the analysis in the main paper, the association is clearly present in high-income countries, but not in low and middle income countries; is present in adult women but not adult men; and is weak (though in this specification, just significantly different from 0) for children. Thus, it seems unlikely that any of the main conclusions of our meta-analysis is a consequence of publication bias.

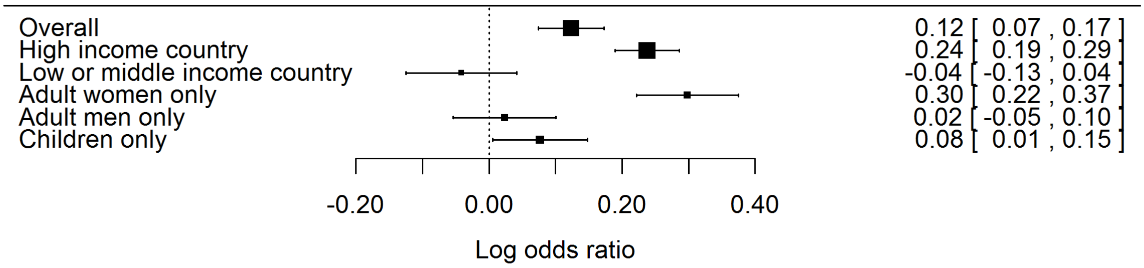


Figure B4. Central estimates of association (log odds ratios and their 95% confidence intervals) overall, and various subsets of the data, with missing associations imputed via the trim and fill method. Note that these estimates employ a standard random-effects model, not a multilevel model.

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