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# Partial identification of the long-run causal effect of food security on child health

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**Abstract** Food security and obesity represent two of the most significant public health issues. However, little is known about how these issues are intertwined. Here, we assess the causal relationship between food security during early childhood and relatively long-run measures of child health. Identifying this causal relationship is complicated due to endogenous selection and misclassification errors. To overcome these difficulties, we utilize a nonparametric bounds approach along with data from the ECLS-K and ECLS-B. In the absence of misclassification, the analysis suggests a positive (unconditional) association, albeit statistically insignificant, between food insecurity and future child obesity. However, in the absence of strong assumptions concerning the selection and misclassification processes, we are unable to rule out the possibility of no long-run causal relationship between food security and child obesity.

**Keywords** Food insecurity · Health outcomes · Nonclassical measurement error · Nonparametric bounds

## 1 Introduction

The U.S. currently confronts two significant issues related to the health and nutrition of its population. The first is food insecurity. The second is obesity. Food insecurity is a metric of material hardship designed to measure 'hunger' in the U.S.

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(Bhattacharya et al. 2004). For households with children, it is measured using the 18-question Core Food Security Module (CFSM). Households responding in the affirmative to at least one question are categorized as marginally food secure; affirmative responses to at least three (eight) questions are categorized as low (very low) food secure. Obesity, either as a child or adult, is defined as having a body mass index (BMI) above the 95th percentile of the age- and gender-specific reference population. Overweight is defined as above the 85th percentile of the same distribution.

The twin issues of food insecurity and obesity have received significant attention of late. In terms of food insecurity, the most recent figures indicate that 14.9 %, or 17.9 million, households were food insecure in 2011.[1] Of these, 9.2 %, or 11.0 million, households were classified as low food secure; 5.7 %, or 6.8 million, were classified as very low food secure. Among households with children under the age of 18, 10.6 %, or 4.1 million, had one or more food insecure adults (but only food secure children); 10.0 %, or 3.9 million, contained both adults and children classified as food insecure. These figures represent a sizeable increase from 1995, attributable mainly to the Great Recession. See Coleman-Jensen et al. (2012) for further details.

Food insecurity is associated with a host of child health problems (Gundersen 2013; Gundersen et al. 2011; Van den Berg et al. 2011). Some of the health problems associated with food insecurity are: greater cognitive problems (Howard 2011); higher levels of aggression and anxiety (Whitaker et al. 2006); higher probability of being anemic (Eicher-Miller et al. 2009); higher probabilities of being hospitalized (Cook et al. 2006); lower nutrient intakes (Cook et al. 2004); poorer general health (Cook et al. 2006); higher probabilities of dysthymia and other mental health issues (Alaimo et al. 2002); higher probabilities of asthma (Kirkpatrick et al. 2010); higher probabilities of behavioral problems (Huang et al. 2010); and more instances of oral health problems (Muirhead et al. 2009). In fact, one of the primary reasons for the increasing interest in food insecurity is its potential association with nutritional deprivation (Bhattacharya et al. 2004). In sum, Gundersen et al. (2011, p. 282) characterize food insecurity as "one of the most important and high profile nutrition-related public health issues in the United States of America today."

In terms of obesity, and child obesity in particular, the prevalence of obese adolescents has tripled in the last thirty years; it has more than doubled for younger children. Specifically, the rate of child obesity increased from 5 to 10.4 % for 2–5-year-old children, from 4.0 to 19.6 % for 6–11-year-old children, and from 6.1 to 18.1 % for 12–19 year olds between 1971 and 2008 (Ogden and Carroll 2010). While obesity is a concern for children from all demographic groups, its greater prevalence within lower socioeconomic populations is well-established (e.g., Rosin 2008; Liping et al. 2012). In 2010, 2.1 % of preschool children from low-income families were extremely obese while 15.0 % of low-income preschool children were obese (Liping et al. 2012). Brisbois et al. (2012, p. 347) state: "Obesity is considered to be a worldwide epidemic with little evidence that its incidence is declining or that it has even reached a plateau."

As childhood obesity has received greater attention, its consequences have becoming increasingly well documented. Obesity may cause severe physical, economic, and

[1] See http://www.ers.usda.gov/topics/food-nutrition-assistance/food-security-in-the-us/key-statistics-graphics.aspx.

emotional suffering and put children and adolescents at risk for a number of health problems such as those affecting cardiovascular health, the endocrine system, and mental health (Deckelbaum and Williams 2001). Dietz and Gortmaker (2001) noted that 60 % of overweight children aged five to ten years old have at least one associated cardiovascular disease risk factor. Moreover, obesity is persistent; childhood obesity is highly correlated with adolescent and adult obesity (Serdula et al. 1993; Liping et al. 2012). In the USA, the total cost attributable to obesity was over $75 billion in 2000 according to Finkelstein et al. (2004). More recent estimates put the cost over $200 billion (Cawley and Meyerhoefer 2012). Based on a US poll in 2008, obesity tops the list of health problems children face (Cawley 2010). Globally, the World Health Organization ranks obesity among the top ten global public health issues (WHO 1998).

As is evident, food insecurity and obesity represent two significant public health issues in the USA. However, research related to these problems has remained predominantly distinct. This is, perhaps, not surprising given that ‘hunger’ and ‘obesity’ are not usually seen as related. While this may be true in the short-run, the long-run relationship between food insecurity and child BMI is less clear. In this paper, we address this issue by assessing the causal effect of food insecurity on long-run child obesity and overweight status.

The long-run relationship between household food insecurity and child BMI is complex, being potentially affected by a number of factors. First, because food insecurity directly impacts the quantity and quality of food available in the household, nutritional habits may be altered even after a household is elevated to being food secure. For example, households may inadvertently develop unhealthy consumption patterns such as overeating when food is available or consuming energy-dense foods that have no nutritional value (Kuku et al. 2012). Such unhealthy eating patterns may be exacerbated or mitigated over time through participation in nutrition assistance programs such as the School Breakfast Program (SBP), National School Lunch Program (NSLP), and Supplemental Nutrition Assistance Program (SNAP).[2] Second, there is increasing evidence that nutrition *in utero* and during early infancy have long-run consequences on obesity (Dietz 1997; Martorell et al. 2001). Thus, undernutrition due to food insecurity, particularly at critical junctures of fetal, infant, and child development may have long-term effects on future obesity status.

Existing research sheds little light on the long-run causal relationship between food insecurity and child BMI for two reasons. First, the majority of existing studies focus purely on association, not causation. The reported associations run the gamut, finding either no relationship (e.g., Bhattacharya et al. 2004; Martin and Ferris 2007; Bhargava et al. 2008; Gundersen et al. 2008, 2009), a negative relationship (e.g., Matheson et al. 2002; Jimenez-Cruz et al. 2003; Rose and Bodor 2006), or even a positive correlation

[2] In response to concerns about food insecurity, many nutrition assistance programs exist in the USA, with SNAP being the largest (Coleman-Jensen et al. 2012). Gundersen and Kreider (2008) find a beneficial, causal effect of SNAP participation on food security after accounting for non-random selection and measurement error in reports of both SNAP participation and food insecurity. Schanzenbach (2009) and Millimet et al. (2010) find a detrimental, causal effect of NSLP participation on child obesity. Millimet et al. (2010, 2012) obtain a beneficial, causal effect of SBP participation on child obesity. Private food assistance programs administered through the nationwide network of Feeding America are additional sources of food assistance for families (Fiese et al. 2011).

(e.g., Jyoti et al. 2005; Casey et al. 2006; Dubois et al. 2006). Second, the majority of existing studies focus on contemporaneous associations between food insecurity and child outcomes. Moreover, existing studies that do attempt to identify the causal effect of food insecurity on child BMI also focus on contemporaneous effects. As such, Martorell et al. (2001, p. 878S) conclude that "the evidence linking undernutrition to future risk of fatness is limited and contradictory."

As stated above, in this paper, we wish to assess the *causal* effect of food insecurity on future child obesity and overweight status. To do so, two identification issues are to be addressed. First, food insecure households do not constitute a random sample of the population. Observed (in the data) and unobserved attributes of households may be associated both with the propensity to be food insecure and the propensity of its child members to be obese. Second, food insecurity status is often misclassified in household surveys. People may misreport food insecurity status (e.g., Hamelin et al. 2002) or it may be mismeasured (Gundersen and Kreider 2008, 2009). Here, we account for non-random selection and misclassification.

To proceed, we begin by utilizing panel data on over 6,400 children from relatively low socioeconomic status (SES) households during early primary school obtained from the Early Childhood Longitudinal Survey—Kindergarten Class of 1998–1999 (ECLS-K). In particular, we examine the causal effect of household very low food security status in spring kindergarten on child obesity and overweight status in the spring of fifth grade. The analysis contains two stages. In the first stage, we assess the nature of selection into food insecurity status. In the second stage, we use the nonparametric partial identification method proposed in Kreider et al. (2012) to account for both non-random selection and misclassification. We then turn to a younger sample of children obtained from the Early Childhood Longitudinal Study—Birth Cohort (ECLS-B). Here, we examine the causal effect of household very low food security status at nine months of age on child obesity and overweight status at approximately age five.

The nonparametric partial identification method of Kreider et al. (2012) provides sharp bounds on the average treatment effect (ATE) of very low food security when food security is non-random and potentially measured with error. These bounds require weaker assumptions than those typically employed. However, as a consequence, we obtain bounds rather than point estimates. Nonetheless, the bounds reveal exactly what can be learned under different assumptions concerning the nature of the selection process and the extent of misreporting. Tamer (2010, p. 168) summarizes the advantages of this approach: "This partial identification approach favors the principle that inference—and conclusions and actions—based on empirical models with fewer suspect assumptions is more robust, hence more sensible and believable. Stronger assumptions will lead to more information about a parameter, but less credible inferences can be conducted."

In terms of the selection problem, we start with the assumption that selection is exogenous (conditional only on the sample selection criteria). We then discuss what can be learned without making any assumptions concerning the selection mechanism. Finally, we impose two monotonicity assumptions: a monotone instrumental variable (MIV) assumption that the latent probability of child obesity and overweight status is nonincreasing in socioeconomic status (SES); and, a monotone treatment selection (MTS) assumption that children from food insecure households have a higher probability of being obese or overweight compared to food secure children. The MIV assumption is weaker than that required for a typical IV (since the MIV is allowed to have a direct impact on the outcome of interest and may be non-random itself). The MTS assumption posits negative selection into food insecurity, a well-established finding in the literature.

In terms of the misclassification problem, the existing literature on food insecurity asserts that people may either under-report food insecurity due to social stigma (e.g., Hamelin et al. 2002) or over-report food insecurity if they fear losing access to food stamps or other nutrition assistance (Gundersen and Kreider 2008). Thus, we start with the assumption of arbitrary patterns of measurement error ranging from 0 to 10 % of the sample. In comparison with suspected misreporting rates in the empirical literatures on SNAP and the Special Supplemental Nutrition Program for Women, Infants, and Children (WIC) participation, we suspect this range may be conservative.[3] However, allowing for a misclassification rate of 10 % is sufficient to illustrate the impact of an even higher rate on the bounds. Finally, since the empirical literatures on SNAP and WIC suggest that eligible participants rarely falsely claim such receipt (presumably due to stigma), one might wish to extend this logic and assume the absence of false claims of food insecurity. As such, we also investigate the identifying power of the assumption of no false-positive misreporting errors.

The results are interesting. First, in both the ECLS-K and ECLS-B, we obtain predominantly positive associations, albeit mostly statistically insignificant at conventional levels, between very low food security and long-run obesity and overweight status when failing to account for non-random selection on observed or unobserved attributes or misclassification. However, we find strong evidence of non-random selection on observed attributes, suggesting the likelihood of non-random selection on unobserved attributes. Second, if even one percent of households misreport their food security status, then the association between food security and future obesity or overweight status cannot be signed even under exogenous selection.

Third, bounds that account for selection only—ignoring the possibility of measurement error—are strictly negative when examining obesity status in the ECLS-K. However, this result is only suggestive of a long-run, negative causal effect of very low food security on child obesity as the confidence intervals still include zero. Moreover, the ATE cannot be signed when using overweight status as the outcome, or either outcome using the ECLS-B. That said, if we redefine the control group to include only being food secure (as opposed to defining the control as being not very low food secure), we obtain strictly negative bounds when assessing obesity in the ECLS-K and overweight status in both the ECLS-K and ECLS-B. Again, these results are merely suggestive as the confidence intervals include zero and no misclassification is assumed.

Finally, bounds accounting for both misclassification and non-random selection fail to sign the ATE for any outcome in either data set without imposing additional assumptions beyond those considered here. Thus, we are unable to conclude there

[3] For example, Bollinger and David (1997) find self-reported participation in food stamps to be in error in more than 12 % of cases.

exists a long-run causal effect of very low food security on child weight outcomes if even one percent of households misreport their food security status.

The rest of the paper is organized as follows. Section 2 summarizes the existing literature. Section 3 describes the data. Section 4 describes the methodology. Section 5 discusses the results and offers directions for future research. Section 6 concludes.

## 2 Literature review

### 2.1 Food security and child health

As noted in the prior section, a growing number of studies have assessed the contemporaneous association between food insecurity and child obesity. Only a handful of studies investigate the long-run consequences of food insecurity. This research also predominantly focuses on associations.

Metallinos-Katsaras et al. (2012) assess the association between child weight status at two to five years old and household food insecurity measured at infancy for a sample of low-income children participating in the Massachusetts WIC between 2001 and 2006. Using multivariate logistic regression analysis, the authors report that persistent low food insecurity is associated with a 22 % increase in the odds of child obesity compared with those who are persistently food secure. Focusing on a much younger sample of children, Bronte-Tinkew et al. (2007) use data from the 9-month and 24-month waves of the ECLS-B to conclude that experiencing very low food security at nine months of age is associated with a higher probability of being overweight at two years of age. Using structural equation modeling, the authors also note that very low food security is strongly correlated with infant feeding practices, depressive symptoms, and parenting practices which may explain the higher likelihood of being overweight as a toddler.

Dubois et al. (2006) use data from the Longitudinal Study of Child Development in Québec over the period 1998–2002 and multivariate logistic regression analysis to report that family food insufficiency during preschool years is a strong predictor of obesity and overweight status at 4.5 years of age. Moreover, family food insufficiency during preschool years remains a strong predictor of overweight status at 4.5 years of age even if the child was born with a low birthweight.

Several studies utilize the ECLS-K. Jyoti et al. (2005) assess the effect of food insecurity in both kindergarten and third grade on various child development indicators, including BMI, at third grade using multiple linear regression and fixed effects models. The authors find a statistically significant, positive association between kindergarten food insecurity and weight gain for girls, regardless of food security status in the third grade. Bhargava et al. (2008) use the ECLS-K to estimate a dynamic random effects model, in combination with instrumental variables, for child weight. The authors conclude that household food insecurity is unlikely to exacerbate child obesity. Finally, Rose and Bodor (2006) use logistic regression to assess the relationship between food insecurity in kindergarten and overweight status in first grade and weight gain from kindergarten to first grade. The authors conclude that food insecurity is negatively associated with weight gain, but not overweight status. However, their conclusions vary with the definition of food insecurity.

Of the studies assessing the contemporaneous relationship between food insecurity on child BMI, Gundersen and Kreider (2009) merits detailed discussion given the similarity with our analysis. The authors assess the causal effect of food security on child health outcomes while accounting for both non-random selection and measurement error in food security status using pooled cross-sectional data from the 2001–2006 National Health and Nutrition Examination Survey (NHANES) and employing a similar nonparametric bounds approach. The authors obtain bounds that exclude zero under certain monotonicity assumptions and assumptions concerning the misclassification process. Specifically, they find some evidence of a beneficial causal effect of food security on overweight status.

While our study is similar to Gundersen and Kreider (2009), there are important differences. First, we focus on long-run outcomes (i.e., outcomes several years after the measurement of food security). Second, while the age range of children included in their sample is not provided, we examine two specific periods of child development. In particular, the ECLS-B allows us to examine the crucial early postnatal period, while the ECLS-K allows us to examine the crucial period spanning the transition into adolescence (Dietz 1997). Third, although the nonparametric methodology is identical across the two studies and both consider the assumption of arbitrary measurement errors in food security status, we also consider the additional assumption of no false positives in the reporting of food insecurity. Finally, the treatment of primary focus in their study is being marginally food secure or food secure; the control includes being low or very low food secure. In contrast, our baseline analysis defines the treatment as very low food secure and thus the control includes marginally food secure, low food secure, and food secure. We consider their split between the treatment and control in our supplemental analysis.

## 2.2 Non-random selection and measurement error

None of the above longitudinal studies provide evidence on the long-run causal effect of food insecurity and child health since they fail to simultaneously address the selection and measurement error issues. In terms of selection, Coleman-Jensen et al. (2012) report that food insecurity rates were substantially higher than the national average for poor households with children of single parents, black and Hispanic households, and households in large cities and rural areas. Thus, food insecure children are not randomly selected. These characteristics, in turn, are correlated with worse health outcomes such as greater incidence of obesity (e.g., Forshee et al. 2004).

However, food insecurity and poverty are not synonymous. For instance, Gundersen et al. (2011) document that a significant number of poor households are food secure; almost 65 % of households around the poverty line are food secure. Moreover, a substantial number of non-poor households are food insecure; households with an income-to-poverty ratio close to two have a food insecurity rate above 20 %, and households with an income-to-poverty ratio of around three have food insecurity rates of close to 10 %. As such, it is quite likely that unobserved attributes such as nutrition and health knowledge, financial literacy, social networks. may be associated with both food insecurity and obesity and overweight status in adults and children.

Thus, selection into food insecurity depends on more than observed socioeconomic attributes.

Turning to measurement error, Bound et al. (2001) summarize the causes and consequences of measurement error, concluding that response error, while rampant across a wide range of topics, do not tend to occur randomly. Rather, response errors are quite often correlated with the variable of interest and other common socioeconomic characteristics. In the current context, there are several reasons to question the reliability of the self-reported food insecurity status in household surveys. First, a substantial amount of measurement error has been documented in areas similar to food security such as SNAP participation (Kreider et al. 2012), WIC participation (Kreider et al. 2014a, b), NSLP participation (Gundersen et al. 2012), disability status and employment (Kreider and Pepper 2007, 2008), health insurance (Kreider and Hill 2009), and child care subsidy receipt (Johnson and Herbst 2013).

Second, evidence specifically regarding measurement error in food insecurity status abounds. For example, in a sample of SNAP recipients only, Gundersen and Kreider (2008) find that recipients may misreport being food insecure if they fear that reporting otherwise might jeopardize their eligibility. On the other hand, Hamelin et al. (2002) hypothesize that parents may misreport being food secure due to embarrassment. Aside from the direction of the mismeasurement, Gundersen and Kreider (2008) take advantage of the sequential nature of the questions in the food security module to look for inconsistencies across responses. They conclude that over 6 % of the sample exhibits at least one inconsistency. Gundersen and Ribar (2011) also note that measurement error can stem from subjective differences in how questions in the CFSM are perceived.

## 3 Data

Data come from the ECLS-K and ECLS-B, collected by the National Center for Education Statistics. The ECLS-K surveys a nationally representative cohort of children throughout the USA in fall and spring kindergarten, fall and spring first grade, spring third grade, spring fifth grade, and spring eighth grade. The sample includes data on over 20,000 students who entered kindergarten in one of roughly 1,000 schools during the 1998–1999 school year. We retain children for whom we have valid measures of age, gender, height, and weight in fifth grade.[4] The ECLS-B collects information on a nationally representative cohort of roughly 10,700 children born in 2001 at nine months of age, two years, four years, and five years. Both surveys collect detailed family background information, as well as height, weight, and food security. We retain children for whom we have valid measures of age, gender, height, and weight during the final wave. In addition, in both cases we limit the samples by excluding households in highest quintile of SES.[5]

[4] We do not examine eighth grade outcomes due to the high attrition rate of children during the transition to middle school for many children.

[5] The initial sample size of the ECLS-K is 21,260. After cleaning age, weight, and height as described in Millimet and Tchernis (2013, Appendix C), and due to sample attrition, the sample size falls to 9,360 in

From the information on height and weight of the children, we create BMI $z$-scores. We convert $z$-scores to percentiles. Note that $z$-scores and percentiles are based on CDC 2000 growth charts; these are age- and gender-specific and are adjusted for normal growth, and percentiles are based on the underlying reference population.[6] Obesity (overweight) is defined as being above the 95th (85th) percentile.

The official food security rate is defined over the preceding 12 months. In both surveys, it is calculated on the basis of households' responses to a list of 18 questions in the CFSM for families with children.[7] The CFSM is a survey module used by the USDA (Nord et al. 2009). The questions aim to capture certain aspects of food insecurity and vary in terms of the severity of the outcome. For example, "We worried whether our food would run out before we got money to buy more" is the least severe outcome while "Did you or other adults in the household ever cut the size of your meals or skip meals because there was not enough money for food?" is more severe. The most severe food insecurity outcome captured in the CFSM is: "Did any of the children ever not eat for a whole day because there was not enough money for food?" Some of the questions inquire about the frequency with which a certain aspect of food insecurity manifests itself. It is important to note that each of these questions assumes that the condition is due to financial constraints. Table 5 in the appendix presents the CFSM.

The earliest wave of the ECLS-K containing responses to the CFSM is spring kindergarten. The ECLS-B contains responses to the CFSM beginning in the initial wave. Utilizing this information, we obtain three measures of food insecurity following official definitions. First, a household with children is classified as marginally food secure if it affirms at least one question in the CFSM. Second, a household with children is classified as low food secure if it affirms at least three questions in the CFSM. Finally, a household with children is classified as very low food secure if it affirms eight or more questions in the CFSM. We focus primarily on very low food security as this obviously represents the most dire situation. In addition, this category has witnessed relatively greater growth of late with the prevalence rate among households increasing from 3.7

Footnote 5 continued
the fifth grade wave. Restricting the sample to a balanced panel reduces the sample size to approximately 9,160. Excluding children from households in the top quintile of SES in spring kindergarten reduces the sample to 6,470. All samples are rounded to the nearest 10 per NCES restricted data guidelines. In the ECLS-B, the possible sample size is roughly 6,950; the initial sample size in the first wave is about 10,700. Restricting the sample to those with valid data on age, gender, height, and weight reduces the sample size to approximately 5,450. Excluding children from households in the top quintile of SES reduces the sample to 4,100. All sample sizes are rounded to the nearest 50 per NCES restricted data regulations for the ECLS-B. While not reported, we compare the baseline attributes of our final sample to the observations excluded. The samples are generally comparable, although a few differences arise. With the ECLS-K, our sample has slightly higher SES status, is more likely to reside with the biological father, less likely to participate in SNAP, more likely to be white, and less likely to reside in a large city. With the ECLS-B, our sample is modestly more affluent in terms of SES and mother's education; otherwise, included and excluded observations are not qualitatively different.

6 $z$-scores and their percentiles are obtained using the—*zanthro*—command in Stata.

7 Families without children and one-member households face a subset of ten questions.

to 5.7 % from 1998 to 2011; the corresponding change for low food secure households is from 8.1 to 9.2 % (Coleman-Jensen et al. 2012). Put differently, the number of very low food secure households increased by 78 % over this period, whereas the corresponding increase for low food secure households was 32 %.

Tables 6 and 7 in the appendix provide summary statistics. In the ECLS-K, 19.2 % report being marginally food secure, 9.9 % report being low food secure, and 1.9 % report being very low food secure. 43.2 % of children are overweight in the spring of fifth grade; 24.2 % of children are obese. In the ECLS-B, the corresponding figures for food security status are 13.3, 12.8 and 3.4 %. Furthermore, 34.6 % of children are overweight at roughly age five; 17.1 % of children are obese. The unconditional differences in obesity and overweight status in spring fifth grade between food insecure and food secure children in spring kindergarten is positive in the ECLS-K for all three definitions of food insecurity. However, the difference is only statistically significant at at least the $p < 0.10$ level when comparing marginally food secure children to food secure children; marginally food secure children are 4.3 % (3.7 %) more likely to be obese (overweight). In the ECLS-B, the unconditional difference is only statistically significant at the $p < 0.10$ level when examining overweight status and comparing very low food secure children to food secure children; very low food secure children are 6.1 % more likely to be overweight. Since the unconditional *associations* are suggestive of a positive relationship between food insecurity and long-run obesity and overweight status, a negative *causal* effect of food insecurity requires the treatment group to have attributes associated with significantly *lower* BMI percentiles.

In terms of a few observed characteristics, the summary statistics for both samples illustrate that food insecure children, relative to food secure children, are more likely to belong to single-parent households, have more siblings, and have a less educated mother. Since SNAP aims to fight hunger by alleviating food insecurity, it is not surprising that food insecure children are more likely to belong to households participating in SNAP. The observed characteristics thus indicate strong correlations between several observed attributes and food insecurity. To determine the impact of these observed characteristics on the association between food insecurity and child weight status, we estimate several linear probability models (LPM). In the interest of brevity, the results are not shown.[8] However, we find that the coefficients on food insecurity are never statistically significant at conventional levels and are *smaller* than the unconditional differences reported in Tables 6 and 7 in all cases except one. Thus, food insecure children reside, on average, in households possessing observed attributes that are associated with a higher likelihood of being obese or overweight. Consequently, it is possible that salient *unobserved* factors such as inadequate nutrition knowledge, unhealthy food habits, and poor financial management skills also increase the likelihood of bad health as well as being food insecure.

[8] The LPMs include the covariates listed in Tables 6 and 7 and vary the measure of food insecurity. In addition, we include a quadratic term for SES and use robust standard errors. Results are available upon request.

## 4 Methodology

Our objective is to bound the ATE of being food insecure on future weight status. The ATE captures the expected effect of food insecurity (relative to not food insecure) for a random child chosen from the underlying population.[9] With binary outcomes, the ATE is defined as

$$\text{ATE}(1,0) = P\left[H(FI^* = 1) = 1 | X \in \Omega\right] - P\left[H(FI^* = 0) = 1 | X \in \Omega\right] \quad (1)$$

where $P[\cdot]$ denotes the probability of the argument being true, $H$ is a binary indicator defined such that one (zero) denotes a bad (good) health outcome (e.g., obese or overweight), and $FI^*$ is a binary indicator defined such that one (zero) corresponds to *actual* food insecurity (security). The probabilities are conditioned on observed covariates denoted by $X \in \Omega$ with values in the set $\Omega$. In this approach, conditioning on covariates only helps to define subpopulations of interest (Kreider et al. 2012).[10] For notational simplicity, $X \in \Omega$ is dropped in the following derivations. Furthermore, from here on let $H(1) \equiv H(FI^* = 1)$ and $H(0) \equiv H(FI^* = 0)$, where $H(1)$ and $H(0)$ represent *potential* outcomes.

To assess the causal effect of food insecurity on a child's health using observational data, two identification problems must be addressed. The first is the well-known problem of the missing counterfactual. For instance, we do not observe the probability of an adverse health outcome for food insecure children if instead they had been food secure. This is referred to as the *selection* problem. To see this, note that by the Law of Total Probability, we can write

$$\begin{aligned} P\left[H(1) = 1\right] = {} & P\left[H(1) = 1 | FI^* = 1\right] P(FI^* = 1) \\ & + P\left[H(1) = 1 | FI^* = 0\right] P(FI^* = 0). \end{aligned} \quad (2)$$

If actual food insecurity status is observed, the sampling process identifies $P(FI^* = 1)$ and $P(FI^* = 0)$ and the expected potential outcome conditional on the outcome being observed, $P[H(1) = 1|FI^* = 1]$. However, the sampling process fails to identify the average outcome for those not food insecure, $P\left[H(1) = 1|FI^* = 0\right]$. Thus, $P\left[H(1) = 1\right]$ is not nonparametrically identified. A similar result holds for $P\left[H(0) = 1\right]$.

The second identification problem arises if *actual* food insecurity status is not observed for all respondents. Let $FI$ denote the observed, self-reported indicator of food insecurity status, where $FI$ equals one if the household reports being food insecure and zero otherwise. This is referred to as the *measurement* or *misclassification*

[9] In this section, child's weight status implicitly refers to our long-run measures of obesity and overweight status. Food insecurity refers to a measure of household food insecurity (i.e., marginally food secure, low food secure, or very low food secure) obtained in the initial period (spring kindergarten in the ECLS-K and 9 months of age in the ECLS-B). For ease of exposition, we will refer to the child being food insecure (or not) although food security is determined at the household level.

[10] As noted in the prior section, we condition on being below the top quintile in terms of SES during the baseline wave.

*error* problem. With misclassification the sampling process fails to provide any useful information on actual food insecurity status, $FI^*$, absent assumptions on the extent and type of measurement error. In this case, *all* quantities on the right-hand side of Eq. (2) are unknown.

Let the latent variable $Z^*$ denote whether a report is accurate or not; $Z^*$ equals one if $FI^* = FI$ and zero otherwise. Kreider et al. (2012) show that $P[H(1) = 1]$ may be decomposed as follows:

$$\begin{aligned} P[H(1)=1] = & \left[P(H=1, FI=1) - \theta_1^+ + \theta_1^-\right] \\ & + P\left[H=1|FI^*=0\right]\left[P(FI=0)\right. \\ & \left. + \left(\theta_1^+ + \theta_0^+\right) - \left(\theta_1^- + \theta_0^-\right)\right] \end{aligned} \tag{3}$$

where $H$ is the observed (realized) health outcome, $\theta_j^+ \equiv P(H = j, FI = 1, Z^* = 0)$ and $\theta_j^- \equiv P(H = j, FI = 0, Z^* = 0)$ represent the proportion of false-positive and false-negative classifications of food insecure children, respectively, for children realizing health outcome $j = 1, 0$.[11] That is, the first term of Eq. (2) can be broken down into the observed component $P(H = 1, FI = 1)$ plus the unobserved excess of false negatives over false positives among those children with $H = 1$, $\theta_1^- - \theta_1^+$. While the sampling process fails to identify the average outcome for those not food insecure, $P\left[H(1) = 1|FI^* = 0\right]$ in the second term of Eq. (2), the sampling process does identify $P(FI = 0)$. So, the second component can be further broken down into $P(FI = 0)$ and the unobserved excess of false positives over false negatives in the population, $(\theta_1^+ + \theta_0^+) - (\theta_1^- + \theta_0^-)$.

Thus, (3) reveals that all of the terms on the right-hand side except $P(H = 1, FI = 1)$ and $P(FI = 0)$ are unobserved. $P\left[H = 1|FI^* = 0\right]$ is not identified since $FI^*$ is unobserved and the $\theta$ terms are not identified since $Z^*$ is unobserved.

Given the lack of nonparametric identification of the ATE, bounds are derived by combining various assumptions concerning the nature of the selection process along with two assumptions about the nature and extent of measurement error.

## 4.1 Classification error assumptions

When considering measurement error, we allow for two cases. In the first case, we place no structure on the pattern of reporting errors. We refer to this case as *arbitrary errors*. In the second case, we impose some structure by assuming that no households falsely report being food insecure. We refer to this as the case of *no false positives*. Due to social stigma, many households may overstate their level of food security (Hamelin et al. 2002). However, it is also possible that some households falsely report being food insecure if they believe that not doing so may hurt their eligibility for food assistance programs such as SNAP (Gundersen and Kreider 2009). That said, since individuals tend to underreport SNAP and WIC participation in household surveys,

[11] The formulae and their derivations come from an earlier version of Kreider et al. (2012).

the assumption of no false-positive errors appears to be a reasonable restriction (e.g., Kreider et al. 2012, 2014b).[12]

Formally, we follow Gundersen and Kreider (2008) and impose the following assumptions pertaining to classification errors:

(A1) Upper Bound Error Rate Assumption: $P(Z^* = 0) \leq Q$
(A2) No False-Positives Assumption: If $FI = 1$, then $Z^* = FI^* = 1$.

Here, $Q$ is an upper bound on the degree of misclassification. It takes a value of zero if one wishes to rule out the possibility of measurement error in self-reported food security status. The second assumption states that self-reports of food insecurity are presumed to be accurate; no such assumption is made concerning self-reports of food security. The arbitrary errors case imposes only Assumption A1; the no false-positives case imposes both Assumptions A1 and A2. In both cases, we vary values of $Q$, setting $Q = 0, 0.01, 0.02, 0.05$, and $0.10$.

The above assumptions on classification errors impose reasonable restrictions on the unknown misclassification rates $\theta_1^-$, $\theta_0^-$, $\theta_1^+$, and $\theta_0^+$. Assumption A1 implies

$$\begin{aligned}
0 \leq \theta_0^- &\leq \min\{Q, P(H=0, FI=0)\} \equiv \theta_0^{\mathrm{UB}-} \\
0 \leq \theta_1^- &\leq \min\{Q, P(H=1, FI=0)\} \equiv \theta_1^{\mathrm{UB}-} \\
0 \leq \theta_0^+ &\leq \min\{Q, P(H=0, FI=1)\} \equiv \theta_0^{\mathrm{UB}+} \\
0 \leq \theta_1^+ &\leq \min\{Q, P(H=1, FI=1)\} \equiv \theta_1^{\mathrm{UB}+}
\end{aligned}$$

and

$$\theta_1^+ + \theta_1^- + \theta_0^+ + \theta_0^- \leq Q \tag{4}$$

Assumption A2 implies

$$\theta_1^+ = \theta_0^+ = 0. \tag{5}$$

## 4.2 Exogenous selection

### *4.2.1 No misclassification errors*

Since the existing literature on the long-run consequences of food insecurity typically assumes exogenous selection (conditional on observed covariates) into food insecurity, this assumption provides a usual starting point for the analysis. Here, the assumption of exogenous selection is expressed as

$$P[H(1) = 1 | FI^*] = P[H(1) = 1],$$

[12] While the assumption of no false positives may not be convincing to all, the benefit of the bounds approach is to show what can be learned under different sets of assumptions; not all individuals need to agree on the validity of each assumption. Thus, we follow the logic of Manski and Pepper (2011, p. 5) by making “transparent how assumptions shape inferences” and retain the no false positives despite there being some question to its validity.

where the conditioning on $X$ is left implicit as noted above.[13] This implies

$$P[H(1) = 1|FI^* = 1] = P[H(1) = 1|FI^* = 0] = P[H(1) = 1].$$

Accordingly, using (2) implies

$$\begin{aligned} P\left[H(1) = 1\right] &= P\left[H = 1|FI^* = 1\right] \\ P\left[H(0) = 1\right] &= P\left[H = 1|FI^* = 0\right]. \end{aligned}$$

and the ATE is given by

$$\begin{aligned} \text{ATE} &= P\left[H(1) = 1\right] - P\left[H(0) = 1\right] \\ &= P\left[H = 1|FI^* = 1\right] - P\left[H = 1|FI^* = 0\right]. \end{aligned} \tag{6}$$

Under the assumption of no misclassification errors, the ATE is nonparametrically identified.

### *4.2.2 Misclassification errors*

Allowing for misclassification, the ATE is no longer nonparametrically identified even under the assumption of exogenous selection as $FI^*$ is not observed in (6). To illustrate, note that

$$P\left[H(1) = 1\right] = P\left[H = 1|FI^* = 1\right]$$

can be decomposed as[14]

$$P\left[H(1) = 1\right] = \frac{P\left(H = 1, FI = 1\right) + \theta_1^- - \theta_1^+}{P(FI = 1) + \left(\theta_1^- + \theta_0^-\right) - \left(\theta_1^+ + \theta_0^+\right)} \tag{7}$$

where the sampling process identifies only $P(H = 1, FI = 1)$ and $P(FI = 1)$. The term $(\theta_1^- + \theta_0^-) - (\theta_1^+ + \theta_0^+)$, in the denominator, denotes the unobserved excess of false negatives over false positives in the population. The term $(\theta_1^- - \theta_1^+)$, in the numerator, reflects the excess of false negatives over false positives among those children with $H = 1$.

To derive bounds on the ATE under different assumptions concerning the nature and extent of the misclassification errors, recall that ATE is given by

$$\text{ATE} = P\left[H(1) = 1\right] - P\left[H(0) = 1\right]. \tag{8}$$

13 To be clear, our reference to *exogenous selection* may refer to either non-random selection into treatment unconditionally (if $X$ is empty) or conditional on observed covariates (if $X$ is non-empty). In the application, $X$ denotes the various sample selection criteria discussed in Sect. 3, including the exclusion of households in the top quintile in terms of SES.

14 The formulae and their derivations come from an earlier version of Kreider et al. (2012).

Thus, the bounds for the ATE are given by

$$\mathrm{UB}_{\mathrm{ATE}} = \mathrm{UB}_{P[H(1)=1]} - \mathrm{LB}_{P[H(0)=1]} \tag{9}$$

$$\mathrm{LB}_{\mathrm{ATE}} = \mathrm{LB}_{P[H(1)=1]} - \mathrm{UB}_{P[H(0)=1]}, \tag{10}$$

where UB and LB denote the upper and lower bounds, respectively.

With arbitrary errors, Kreider and Pepper (2007) derive the following expressions for the bounds:

$$\mathrm{UB}_{\mathrm{ATE}} = \sup_{a \in (0, \min[Q, P(H=1,\ FI=0)])} \left[ \frac{P[H=1, FI=1] + a}{P(FI=1) + 2a - Q} - \frac{P[H=1, FI=0] - a}{P(FI=0) - 2a + Q} \right] \tag{11}$$

$$\mathrm{LB}_{\mathrm{ATE}} = \inf_{b \in (0, \min[Q, P(H=1,\ FI=1)])} \left[ \frac{P[H=1, FI=1] - b}{P(FI=1) - 2b + Q} - \frac{P[H=1, FI=0] + b}{P(FI=0) + 2b - Q} \right]. \tag{12}$$

Under the assumption of no false positives, the individual components of the ATE, given in (8), are bounded as follows

$$\frac{P[H=1, FI=1]}{P(FI=1) + \theta_0^{\mathrm{UB}-}} \le P[H(1)=1] \le \frac{P[H=1, FI=1] + \theta_1^{\mathrm{UB}-}}{P(FI=1) + \theta_1^{\mathrm{UB}-}}$$

$$\frac{P[H=1, FI=0] - \theta_1^{\mathrm{UB}-}}{P(FI=0) - \theta_1^{\mathrm{UB}-}} \le P[H(0)=1] \le \frac{P[H=1, FI=0]}{P(FI=0) - \theta_0^{\mathrm{UB}-}}.$$

Accordingly, the bounds on the ATE are given by

$$\mathrm{UB}_{\mathrm{ATE}} = \frac{P[H=1, FI=1] + \theta_1^{\mathrm{UB}-}}{P(FI=1) + \theta_1^{\mathrm{UB}-}} - \frac{P[H=1, FI=0] - \theta_1^{\mathrm{UB}-}}{P(FI=0) - \theta_1^{\mathrm{UB}-}} \tag{13}$$

$$\mathrm{LB}_{\mathrm{ATE}} = \frac{P[H=1, FI=1]}{P(FI=1) + \theta_0^{\mathrm{UB}-}} - \frac{P[H=1, FI=0]}{P(FI=0) - \theta_0^{\mathrm{UB}-}}. \tag{14}$$

### 4.3 No selection assumption

The bounds given in (11)–(14) invoke the assumption of exogenous selection which is highly improbable (even if $X$ contains a lengthy vector of observed attributes). Consequently, we next consider what can be learned about the ATE of food insecurity on child health without invoking any assumptions concerning selection into the treatment. This corresponds to the worst-case bounds in Manski (1995).

*4.3.1 No misclassification errors*

In the absence of measurement error, but with no assumptions concerning selection, the only information available concerning the missing counterfactuals are that they lie in the unit interval since they represent probabilities; formally, $P\left[H(1) = 1|FI^* = 0\right]$, $P\left[H(0) = 1|FI^* = 1\right] \in [0, 1]$. Accordingly, the individual components of the ATE are bounded as follows

$$P\left[H = 1, FI^* = 1\right] \leq P\left[H(1) = 1\right] \leq P\left[H = 1, FI^* = 1\right] + P(FI^* = 0)$$
$$P\left[H = 1, FI^* = 0\right] \leq P\left[H(0) = 1\right] \leq P(FI^* = 1) + P\left[H = 1, FI^* = 0\right].$$

Note, the width of the bounds on $P\left[H(1) = 1\right]$ is the censoring probability, $P(FI^* = 0)$, while the width of the bounds on $P\left[H(0) = 1\right]$ is the inclusion probability, $P(FI^* = 1)$. As a result, although the bounds on ATE are sharp, the width always equals unity and includes zero (Manski 1995). Thus, it is impossible to sign the ATE. While the sign is unknown, extreme values are excluded from the bounds, thus providing some potentially useful information.

*4.3.2 Misclassification errors*

Allowing for measurement error, the bounds on individual components of the ATE become

$$\begin{aligned} P[H = 1, FI = 1] - \theta_1^+ + \theta_1^- \leq P\left[H(1) = 1\right] &\leq P[H = 1, FI = 1] \\ &\quad + P(FI = 0) + \theta_0^+ - \theta_0^- \\ P[H = 1, FI = 0] + \theta_1^+ - \theta_1^- \leq P\left[H(0) = 1\right] &\leq P[H = 1, FI = 0] \\ &\quad + P(FI = 1) - \theta_0^+ + \theta_0^-. \end{aligned}$$

With arbitrary errors, the bounds on ATE are given by[15]

$$\begin{aligned} \mathrm{UB}_{\mathrm{ATE}} &= P[H = 1, FI = 1] + P(FI = 0) \\ &\quad + \min\left\{Q, \theta_0^{\mathrm{UB}+} + \theta_1^{\mathrm{UB}-}\right\} - P[H = 1, FI = 0] \end{aligned} \tag{15}$$

$$\begin{aligned} \mathrm{LB}_{\mathrm{ATE}} &= P[H = 1, FI = 1] - \min\left\{Q, \theta_1^{\mathrm{UB}+} + \theta_0^{\mathrm{UB}-}\right\} \\ &\quad - P[H = 1, FI = 0] - P(FI = 1). \end{aligned} \tag{16}$$

Under the more stringent assumption of no false positives, the bounds become potentially tighter and are given by[16]

$$\begin{aligned} \mathrm{UB}_{\mathrm{ATE}} &= P[H = 1, FI = 1] \\ &\quad + P(FI = 0) + \theta_1^{\mathrm{UB}-} - P[H = 1, FI = 0] \end{aligned} \tag{17}$$

[15] The formulae and their derivations come from an earlier version of Kreider et al. (2012).

[16] The bounds under the no false-positive assumption are narrower than under the assumption of arbitrary errors if either $\theta_1^{\mathrm{UB}-}$ or $\theta_0^{\mathrm{UB}-}$ is less than $Q$.

$$\text{LB}_{\text{ATE}} = P[H = 1, FI = 1] \\ -\theta_0^{\text{UB}-} - P[H = 1, FI = 0] - P(FI = 1). \quad (18)$$

## 4.4 Monotonicity assumptions

While the bounds given in (15)–(18) have the advantage of not invoking any assumptions concerning the selection process into actual treatment assignment, they have the disadvantage of never being able to exclude zero from the bounds. To tighten the bounds on ATE, without going so far as to assume exogenous selection, we assess the identifying power of two monotonicity assumptions which impose different restrictions on the relationships between food insecurity, child health outcomes, and the available data.

### *4.4.1 Monotone treatment selection*

The *Monotone Treatment Selection* (MTS) assumption places some structure on the relationship between potential outcomes and treatment assignment (Manski and Pepper 2000). Specifically, the MTS assumption posits that children from food insecure households have worse potential outcomes on average compared to children from food secure households. This assumption is relatively innocuous given the vast literature documenting less favorable demographic, socioeconomic, and health characteristics in food insecure households (e.g., Gundersen and Kreider 2009). Following Kreider et al. (2012), this assumption translates to

$$P[H(1) = 1|FI^* = 1] \geq P[H(1) = 1|FI^* = 0] \quad (19)$$
$$P[H(0) = 1|FI^* = 1] \geq P[H(0) = 1|FI^* = 0] \quad (20)$$

since $H(\cdot) = 1$ represents a worse health outcome (i.e., obese or overweight). Imposing MTS, the bounds on ATE are given by

$$\text{UB}_{\text{ATE}} = \frac{P[H = 1, FI = 1] + \theta_1^{\text{UB}-}}{P(FI = 1) + \theta_1^{\text{UB}-} - \theta_0^{\text{UB}+}} - \frac{P[H = 1, FI = 0] - \theta_1^{\text{UB}-}}{P(FI = 0) + \theta_0^{\text{UB}+} - \theta_1^{\text{UB}-}} \quad (21)$$

$$\text{LB}_{\text{ATE}} = P[H = 1, FI = 1] - \theta_1^{\text{UB}+} \\ -\left\{P[H = 1, FI = 0] + P(FI = 1) + \theta_0^{\text{UB}-}\right\} \quad (22)$$

where $\theta_1^{\text{UB}+} = \theta_0^{\text{UB}-} = \theta_1^{\text{UB}-} = \theta_0^{\text{UB}+} = 0$ in the absence of measurement error.

With arbitrary errors, the upper bound of the ATE is given by the upper bound of the ATE under exogenous selection with arbitrary errors in Eq. (11). The lower bound is given by the lower bound under no selection assumptions with arbitrary errors in Eq. (16). Under the assumption of no false positives, the bounds are obtained from the same models, however, using the corresponding no false-positive assumption [i.e., Eqs. (13) and (18)].

*4.4.2 Monotone instrumental variable*

To further tighten the bounds, we turn to the *Monotone Instrumental Variable* (MIV) assumption which makes use of new information through the introduction of a monotone instrumental variable. A MIV should not be confused with a typical instrumental variable. The only requirement for a MIV is that potential outcomes vary monotonically with the variable (Manski and Pepper 2000). Following Kreider et al. (2012), the MIV assumption imposes

$$P\left[H\left(1\right)=1|\nu=u_2\right]\leq P[H(1)=1|\nu=u]\leq P[H(1)=1|\nu=u_1]$$
$$P\left[H\left(0\right)=1|\nu=u_2\right]\leq P[H(0)=1|\nu=u]\leq P[H(0)=1|\nu=u_1],$$

where $v$ is the MIV and $u_1 < u < u_2$. In other words, lower values of $v$ are associated with worse potential outcomes (again, since $H(\cdot) = 1$ represents a worse health outcome). Here, we use household SES as the MIV. A lengthy literature documents the positive income–health gradient for children (e.g., Case et al. 2002). Moreover, in the linear probability models discussed in Sect. 3, we include a quadratic for SES. We obtain a negative monotonic and statistically significant relationship between SES and the probability of overweight or obese for nearly the entire samples. Specifically, in the ECLS-K, the marginal effect of SES is positive for less than 0.7 % of the sample in all models estimated. In the ECLS-B, the marginal effect is positive for less than 3.7 % of the sample in all models estimated.[17]

To proceed, we combine the MIV and MTS (with and without measurement error) assumptions. Let $\mathrm{UB}(u)$ and $\mathrm{LB}(u)$ denote the upper and lower bounds of the individual components of the ATE obtained under a set of MTS and measurement error assumptions evaluated conditional on $v = u$. As a result, the joint MTS-MIV assumption implies

$$\sup_{u_2\geq u}\mathrm{LB}(u_2)\leq P[H(t)=1|\nu=u]\leq\inf_{u_1\leq u}\mathrm{UB}(u_1),\ t=0,1. \tag{23}$$

See Proposition 1 in Manski and Pepper (2000).

To calculate these bounds in practice, the sample is divided into four SES cells. Weighted averages of the estimates of the UB and LB across the four cells yield joint MTS-MIV bounds on the individual components of the ATE (Corollary 1 of Proposition 1 in Manski and Pepper (2000)). Final bounds for the ATE are then computed using (9) and (10). The MIV estimator is biased in finite samples (Manski and Pepper 2000).[18] In light of this, we follow Kreider et al. (2012) and use Kreider and Pepper's

[17] Moreover, the high mark of 3.7 % occurs when we define the treatment as marginally food secure (or worse), and the control includes only food secure children. This is not the treatment we focus our attention on. When the treatment is defined as low or very low food secure (very low food secure) and the control is defined as food secure, the marginal effect is positive for less than 0.2 % (1.5 %) of the sample.

[18] The asymptotic properties of estimators, such as those based on a MIV, involving nonsmooth functions like sup and inf are a subject of recent debate. Manksi and Pepper (2000, p. 1007) note that "the consistency of the resulting bounds estimates is easy to establish." However, Hirano and Porter (2012, p. 1769) show that in such cases "no locally asymptotically unbiased estimators exist." The distinction may lie in that the

(2007) nonparametric finite sample bias-corrected MIV estimator. However, Hirano and Porter (2012) caution against the use of bias-corrected techniques since such procedures cannot fully eliminate the bias in the case of nonsmooth estimators and may cause substantial increases in variance.[19] As such, we also compute the bounds without using the bias correction.[20]

## 5 Results

### 5.1 Baseline

The baseline set of empirical results are presented in Figs. 1, 2, 3 and 4 and Tables 1, 2, 3 and 4. In all cases, the treatment is very low food security and the control group includes all other children (i.e., children from food secure, marginally food secure, and low food secure households). Figures 1 and 2 and the associated tables utilize data from the ECLS-K; Figs. 3 and 4 and the associated tables utilize data from the ECLS-B. Figures 1 and 3 and the corresponding tables define the outcome as equal to one if the child is obese, zero otherwise; Figs. 2 and 4 and the corresponding tables use overweight status as the outcome. Finally, to address the uncertainty arising from sampling variability, the tables report Imbens and Manski (2004) 95 % confidence intervals (see Kreider et al. 2012).[21]

In each figure, the left panel compares the sharp bounds on the ATE obtained under the assumption that selection is exogenous (conditional only on the sample selection criteria) to those obtained under no assumption on selection as $Q$ varies from 0 to 0.10. The middle (right) panel reports the bounds under different combinations of the monotonicity assumptions concerning selection under the arbitrary errors (no false-

Footnote 18 continued
objects of interest in Manski and Pepper (2000), and here, are the bounds on the ATE. As a result, weighted averages of (23) over $u$ yield a smooth estimator. In any event, obviously the asymptotic properties of such estimators has important implications for conducting proper inference. As this is the subject of ongoing research (e.g., Chernozhukov et al. 2013 and the references therein), our results should be interpreted cautiously.

[19] An alternative to the bias correction procedure utilized in Kreider et al. (2012) and Kreider and Pepper (2008) is the precision-corrected approach recently put forth in Chernozhukov et al. (2013). This procedure adjusts the terms $\mathrm{LB}(u_2)$ and $\mathrm{UB}(u_1)$ in (23) before taking the sup or inf. Thus, the correction is applied during the estimation of the bounds of the conditional probabilities, $P[H(t) = 1|\nu = u]$. In contrast, the approach in Kreider and Pepper (2009) computes the bounds in (23) at each $u$, constructs the weighted averages of the upper and lower bounds across the different values of $u$, and then applies the finite sample correction to the estimated bounds of the unconditional probabilities, $P[H(t) = 1]$. We follow the Kreider and Pepper (2009) approach for two reasons. First, it is computationally simpler. Second, and more importantly, Chernozhukov et al. (2013) discuss only the estimated bounds of the conditional probabilities, $P[H(t) = 1|\nu = u]$, and the associated inference. It is not obvious how this approach should be extended when the focus is on estimation and inferences of the bounds on the ATE.

[20] We re-estimated the MTS-MIV bounds without the bias correction for a few outcomes in Tables 1, 2, 3 and 4. There is no drastic change in the point estimates. The results are available upon request.

[21] As discussed in footnote 18, recent research calls into question the validity of the Imbens-Manski approach for estimators that are nonsmooth. Whether our focus on the bounds of the ATE, which entail weighted averages of nonsmooth functions, introduces sufficient smoothness is not clear. Thus, the results should be interpreted with caution.

**Table 1** Sharp bounds on the ATE of very low food security on child obesity status: ECLS-K

| $Q$ | Exogenous selection | | No assumption on selection | | MTS | | MTS & MIV | |
|---|---|---|---|---|---|---|---|---|
| | (1) AE | (2) No FP | (3) AE | (4) No FP | (5) AE | (6) No FP | (7) AE | (8) No FP |
| 0.00 | [0.031, 0.031] p.e. | [0.031, 0.031] p.e. | [−0.251, 0.749] p.e. | [−0.251, 0.749] p.e. | [−0.251, 0.031] p.e. | [−0.251, 0.031] p.e. | [−0.252, −0.018] p.e. | [−0.252, −0.018] p.e. |
| | [−0.044, 0.120] CI | [−0.044, 0.120] CI | [−0.259, 0.761] CI | [−0.259, 0.761] CI | [−0.259, 0.120] CI | [−0.259, 0.120] CI | [−0.260, 0.064] CI | [−0.260, 0.064] CI |
| 0.01 | [−0.245, 0.325] p.e. | [−0.065, 0.287] p.e. | [−0.261, 0.759] p.e. | [−0.261, 0.759] p.e. | [−0.261, 0.325] p.e. | [−0.261, 0.287] p.e. | [−0.266, 0.221] p.e. | [−0.262, 0.223] p.e. |
| | [−0.254, 0.515] CI | [−0.121, 0.347] CI | [−0.269, 0.771] CI | [−0.269, 0.771] CI | [−0.269, 0.515] CI | [−0.269, 0.347] CI | [−0.275, 0.274] CI | [−0.270, 0.277] CI |
| 0.02 | [−0.248, 1.000] p.e. | [−0.113, 0.417] p.e. | [−0.271, 0.769] p.e. | [−0.271, 0.769] p.e. | [−0.271, 1.000] p.e. | [−0.271, 0.417] p.e. | [−0.277, 0.302] p.e. | [−0.272, 0.299] p.e. |
| | [−0.257, 1.000] CI | [−0.155, 0.460] CI | [−0.279, 0.781] CI | [−0.279, 0.781] CI | [−0.279, 1.000] CI | [−0.279, 0.460] CI | [−0.286, 0.618] CI | [−0.280, 0.390] CI |
| 0.05 | [−0.257, 1.000] p.e. | [−0.178, 0.597] p.e. | [−0.301, 0.799] p.e. | [−0.301, 0.799] p.e. | [−0.301, 1.000] p.e. | [−0.301, 0.597] p.e. | [−0.307, 0.799] p.e. | [−0.302, 0.468] p.e. |
| | [−0.265, 1.000] CI | [−0.206, 0.628] CI | [−0.309, 0.811] CI | [−0.309, 0.811] CI | [−0.309, 1.000] CI | [−0.309, 0.628] CI | [−0.316, 0.815] CI | [−0.310, 0.550] CI |
| 0.10 | [−0.271, 1.000] p.e. | [−0.225, 0.727] p.e. | [−0.351, 0.849] p.e. | [−0.351, 0.849] p.e. | [−0.351, 1.000] p.e. | [−0.351, 0.727] p.e. | [−0.357, 0.844] p.e. | [−0.352, 0.626] p.e. |
| | [−0.280, 1.000] CI | [−0.243, 0.749] CI | [−0.359, 0.861] CI | [−0.359, 0.861] CI | [−0.359, 1.000] CI | [−0.359, 0.749] CI | [−0.366, 0.855] CI | [−0.360, 0.682] CI |

CI around ATE are calculated using methods from Imbens and Manski (2004) with 250 pseudosamples. Number of observations = 6,470 (rounded to nearest 10 per NCES restricted data regulations). See “Appendix” and text for further details

*p.e.* point estimates, *CI* confidence interval, *AE* arbitrary errors, *FP* false positives

**Table 2** Sharp bounds on the ATE of very low food security on child overweight status: ECLS-K

| $Q$ | Exogenous selection | | No assumption on selection | | MTS | | MTS & MIV | |
|---|---|---|---|---|---|---|---|---|
| | (1) AE | (2) No FP | (3) AE | (4) No FP | (5) AE | (6) No FP | (7) AE | (8) No FP |
| 0.00 | [0.041, 0.041] p.e. | [0.041, 0.041] p.e. | [−0.433, 0.567] p.e. | [−0.433, 0.567] p.e. | [−0.433, 0.041] p.e. | [−0.433, 0.041] p.e. | [−0.432, 0.007] p.e. | [−0.432, 0.007] p.e. |
| | [−0.045, 0.129] CI | [−0.045, 0.129] CI | [−0.444, 0.580] CI | [−0.444, 0.580] CI | [−0.444, 0.129] CI | [−0.444, 0.129] CI | [−0.443, 0.097] CI | [−0.443, 0.097] CI |
| 0.01 | [−0.433, 0.553] p.e. | [−0.124, 0.227] p.e. | [−0.443, 0.577] p.e. | [−0.443, 0.577] p.e. | [−0.443, 0.553] p.e. | [−0.443, 0.227] p.e. | [−0.448, 0.292] p.e. | [−0.442, 0.223] p.e. |
| | [−0.445, 0.875] CI | [−0.187, 0.294] CI | [−0.454, 0.590] CI | [−0.454, 0.590] CI | [−0.454, 0.875] CI | [−0.454, 0.294] CI | [−0.459, 0.479] CI | [−0.453, 0.300] CI |
| 0.02 | [−0.439, 1.000] p.e. | [−0.208, 0.322] p.e. | [−0.453, 0.587] p.e. | [−0.453, 0.587] p.e. | [−0.453, 1.000] p.e. | [−0.453, 0.322] p.e. | [−0.460, 0.542] p.e. | [−0.452, 0.276] p.e. |
| | [−0.451, 1.000] CI | [−0.261, 0.378] CI | [−0.464, 0.600] CI | [−0.464, 0.600] CI | [−0.464, 1.000] CI | [−0.464, 0.378] CI | [−0.471, 0.672] CI | [−0.463, 0.358] CI |
| 0.05 | [−0.454, 1.000] p.e. | [−0.323, 0.453] p.e. | [−0.483, 0.617] p.e. | [−0.483, 0.617] p.e. | [−0.483, 1.000] p.e. | [−0.483, 0.453] p.e. | [−0.491, 0.601] p.e. | [−0.482, 0.385] p.e. |
| | [−0.467, 1.000] CI | [−0.358, 0.489] CI | [−0.494, 0.630] CI | [−0.494, 0.630] CI | [−0.494, 1.000] CI | [−0.494, 0.489] CI | [−0.502, 0.611] CI | [−0.493, 0.449] CI |
| 0.10 | [−0.480, 1.000] p.e. | [−0.403, 0.548] p.e. | [−0.533, 0.667] p.e. | [−0.533, 0.667] p.e. | [−0.533, 1.000] p.e. | [−0.533, 0.548] p.e. | [−0.541, 0.635] p.e. | [−0.532, 0.491] p.e. |
| | [−0.493, 1.000] CI | [−0.427, 0.578] CI | [−0.544, 0.680] CI | [−0.544, 0.680] CI | [−0.544, 1.000] CI | [−0.544, 0.578] CI | [−0.552, 0.645] CI | [−0.543, 0.537] CI |

CI around ATE are calculated using methods from Imbens and Manski (2004) with 250 pseudosamples. Number of observations = 6,470 (rounded to nearest 10 per NCES restricted data regulations). See “Appendix” and text for further details

*p.e.* point estimates, *CI* confidence interval, *AE* arbitrary errors, *FP* false positives

**Table 3** Sharp bounds on the ATE of very low food security on child obesity status: ECLS-B

| $Q$ | Exogenous selection | | No assumption on selection | | MTS | | MTS & MIV | |
|---|---|---|---|---|---|---|---|---|
| | (1) AE | (2) No FP | (3) AE | (4) No FP | (5) AE | (6) No FP | (7) AE | (8) No FP |
| 0.00 | [0.061, 0.061] p.e. | [0.061, 0.061] p.e. | [−0.189, 0.811] p.e. | [−0.189, 0.811] p.e. | [−0.189, 0.061] p.e. | [−0.189, 0.061] p.e. | [−0.191, 0.033] p.e. | [−0.191, 0.033] p.e. |
| | [−0.010, 0.170] CI | [−0.010, 0.170] CI | [−0.203, 0.821] CI | [−0.203, 0.821] CI | [−0.203, 0.170] CI | [−0.203, 0.170] CI | [−0.201, 0.119] CI | [−0.201, 0.119] CI |
| 0.01 | [−0.175, 0.245] p.e. | [0.007, 0.245] p.e. | [−0.199, 0.821] p.e. | [−0.199, 0.821] p.e. | [−0.199, 0.245] p.e. | [−0.199, 0.245] p.e. | [−0.208, 0.127] p.e. | [−0.201, 0.127] p.e. |
| | [−0.189, 0.340] CI | [−0.048, 0.338] CI | [−0.213, 0.831] CI | [−0.213, 0.831] CI | [−0.213, 0.340] CI | [−0.213, 0.338] CI | [−0.218, 0.222] CI | [−0.211, 0.222] CI |
| 0.02 | [−0.177, 0.395] p.e. | [−0.028, 0.364] p.e. | [−0.209, 0.831] p.e. | [−0.209, 0.831] p.e. | [−0.209, 0.395] p.e. | [−0.209, 0.364] p.e. | [−0.219, 0.218] p.e. | [−0.211, 0.218] p.e. |
| | [−0.191, 0.822] CI | [−0.076, 0.443] CI | [−0.223, 0.841] CI | [−0.223, 0.841] CI | [−0.223, 0.822] CI | [−0.223, 0.443] CI | [−0.229, 0.312] CI | [−0.221, 0.314] CI |
| 0.05 | [−0.183, 1.000] p.e. | [−0.085, 0.565] p.e. | [−0.239, 0.861] p.e. | [−0.239, 0.861] p.e. | [−0.239, 1.000] p.e. | [−0.239, 0.565] p.e. | [−0.249, 0.686] p.e. | [−0.241, 0.410] p.e. |
| | [−0.198, 1.000] CI | [−0.121, 0.620] CI | [−0.253, 0.871] CI | [−0.253, 0.871] CI | [−0.253, 1.000] CI | [−0.253, 0.620] CI | [−0.259, 1.000] CI | [−0.251, 0.491] CI |
| 0.10 | [−0.194, 1.000] p.e. | [−0.130, 0.732] p.e. | [−0.289, 0.911] p.e. | [−0.289, 0.911] p.e. | [−0.289, 1.000] p.e. | [−0.289, 0.732] p.e. | [−0.299, 0.926] p.e. | [−0.291, 0.603] p.e. |
| | [−0.209, 1.000] CI | [−0.157, 0.774] CI | [−0.303, 0.921] CI | [−0.303, 0.921] CI | [−0.303, 1.000] CI | [−0.303, 0.774] CI | [−0.309, 0.941] CI | [−0.301, 0.667] CI |

CI around ATE are calculated using methods from Imbens and Manski (2004) with 250 pseudosamples. Number of observations = 4,100 (rounded to nearest 50 per NCES restricted data regulations). See "Appendix" and text for further details

*p.e.* point estimates, *CI* confidence interval, *AE* arbitrary errors, *FP* false positives

**Table 4** Sharp bounds on the ATE of very low food security on child overweight status: ECLS-B

| $Q$ | Exogenous selection | | No assumption on selection | | MTS | | MTS & MIV | |
|---|---|---|---|---|---|---|---|---|
| | (1) AE | (2) No FP | (3) AE | (4) No FP | (5) AE | (6) No FP | (7) AE | (8) No FP |
| 0.00 | [0.066, 0.066] p.e. | [0.066, 0.066] p.e. | [−0.352, 0.648] p.e. | [−0.352, 0.648] p.e. | [−0.352, 0.066] p.e. | [−0.352, 0.066] p.e. | [−0.353, 0.032] p.e. | [−0.353, 0.032] p.e. |
| | [−0.001, 0.159] CI | [−0.001, 0.159] CI | [−0.365, 0.663] CI | [−0.365, 0.663] CI | [−0.365, 0.159] CI | [−0.365, 0.159] CI | [−0.365, 0.111] CI | [−0.365, 0.111] CI |
| 0.01 | [−0.186, 0.241] p.e. | [−0.031, 0.207] p.e. | [−0.362, 0.658] p.e. | [−0.362, 0.658] p.e. | [−0.362, 0.241] p.e. | [−0.362, 0.207] p.e. | [−0.371, 0.136] p.e. | [−0.363, 0.138] p.e. |
| | [−0.321, 0.376] CI | [−0.087, 0.285] CI | [−0.375, 0.673] CI | [−0.375, 0.673] CI | [−0.375, 0.376] CI | [−0.375, 0.285] CI | [−0.383, 0.217] CI | [−0.375, 0.208] CI |
| 0.02 | [−0.355, 0.661] p.e. | [−0.093, 0.299] p.e. | [−0.372, 0.668] p.e. | [−0.372, 0.668] p.e. | [−0.372, 0.661] p.e. | [−0.372, 0.299] p.e. | [−0.386, 0.289] p.e. | [−0.373, 0.225] p.e. |
| | [−0.369, 1.000] CI | [−0.145, 0.364] CI | [−0.385, 0.683] CI | [−0.385, 0.683] CI | [−0.385, 1.000] CI | [−0.385, 0.364] CI | [−0.398, 0.420] CI | [−0.385, 0.289] CI |
| 0.05 | [−0.367, 1.000] p.e. | [−0.197, 0.453] p.e. | [−0.402, 0.698] p.e. | [−0.402, 0.698] p.e. | [−0.402, 1.000] p.e. | [−0.402, 0.453] p.e. | [−0.417, 0.698] p.e. | [−0.403, 0.368] p.e. |
| | [−0.380, 1.000] CI | [−0.238, 0.502] CI | [−0.415, 0.713] CI | [−0.415, 0.713] CI | [−0.415, 1.000] CI | [−0.415, 0.502] CI | [−0.431, 0.779] CI | [−0.415, 0.416] CI |
| 0.10 | [−0.387, 1.000] p.e. | [−0.280, 0.582] p.e. | [−0.452, 0.748] p.e. | [−0.452, 0.748] p.e. | [−0.452, 1.000] p.e. | [−0.452, 0.582] p.e. | [−0.467, 0.735] p.e. | [−0.453, 0.505] p.e. |
| | [−0.402, 1.000] CI | [−0.313, 0.620] CI | [−0.465, 0.763] CI | [−0.465, 0.763] CI | [−0.465, 1.000] CI | [−0.465, 0.620] CI | [−0.481, 0.756] CI | [−0.465, 0.551] CI |

CI around ATE are calculated using methods from Imbens and Manski (2004) with 250 pseudosamples. Number of observations = 4,100 (rounded to nearest 50 per NCES restricted data regulations). See “Appendix” and text for further details

*p.e.* point estimates, *CI* confidence interval, *AE* arbitrary errors, *FP* false positives

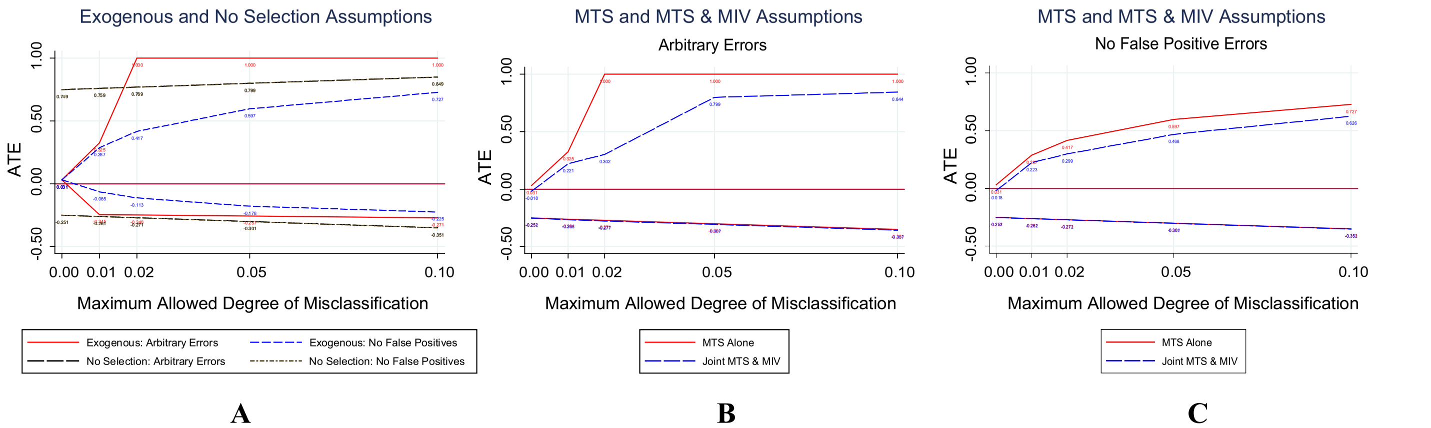


**Fig. 1** Sharp bounds on the ATE of very low food security on child obesity status: ECLS-K. **a** Exogenous selection or no assumption. **b** Only MTS or MTS-MIV: AE. **c** Only MTS or MTS-MIV: no FP. Notes: *AE* arbitrary errors, *FP* false positives

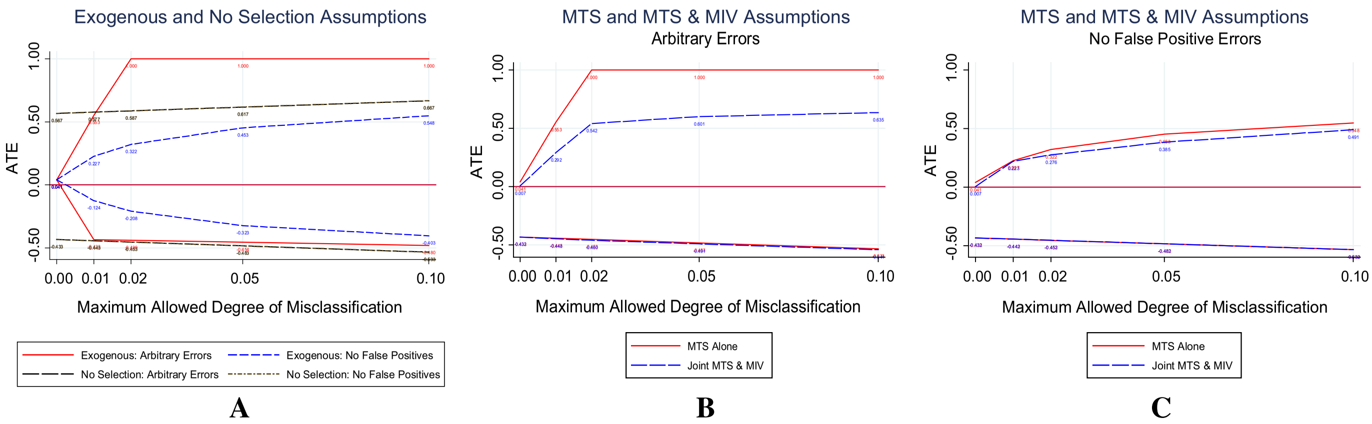


**Fig. 2** Sharp bounds on the ATE of very low food security on child overweight status: ECLS-K. **a** Exogenous selection or no assumption. **b** Only MTS or MTS-MIV: AE. **c** Only MTS or MTS-MIV: no FP. Notes: *AE* arbitrary errors, *FP* false positives

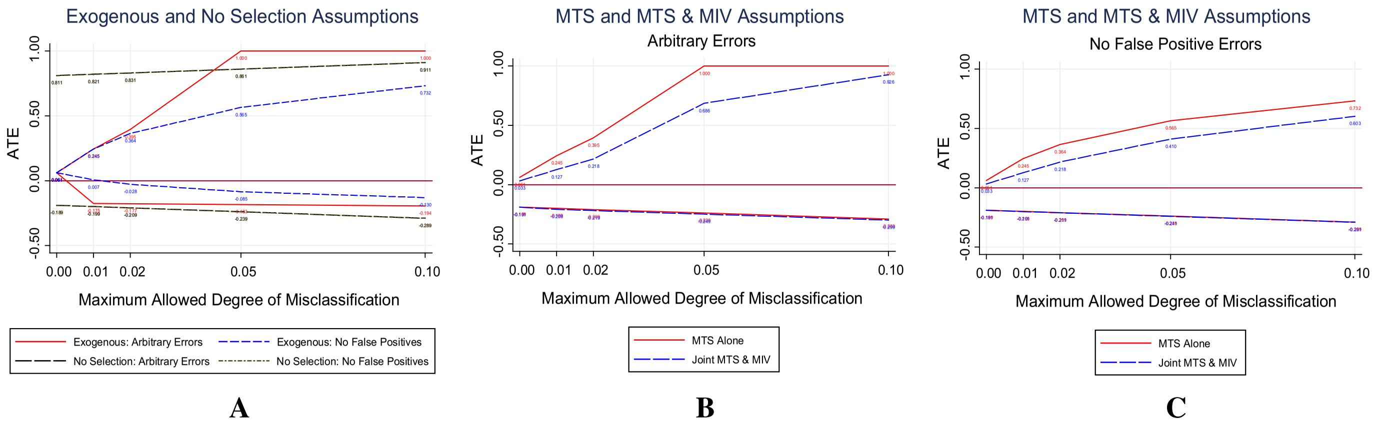


**Fig. 3** Sharp bounds on the ATE of very low food security on child obesity status: ECLS-B. **a** Exogenous selection or no assumption. **b** Only MTS or MTS-MIV: AE. **c** Only MTS or MTS-MIV: no FP. Notes: *AE* arbitrary errors, *FP* false positives

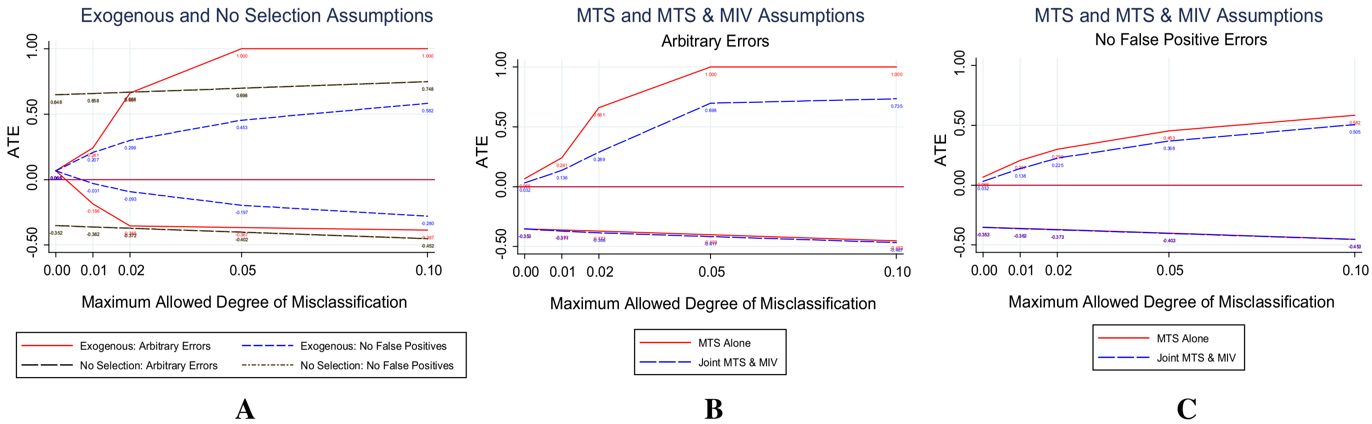


**Fig. 4** Sharp bounds on the ATE of very low food security on child overweight status: ECLS-B. **a** Exogenous selection or no assumption. **b** Only MTS or MTS-MIV: AE. **c** Only MTS or MTS-MIV: no FP. Notes: *AE* arbitrary errors, *FP* false positives

positives) assumption concerning measurement error. The corresponding tables report the actual values along with the confidence intervals.

Turning to the results, several findings stand out. First, in all four tables, the ATE is positive, but not statistically significant, under the assumptions of exogenous selection and no measurement error. The lack of statistical significance is not surprising given the small number of children experiencing very low food security. In the ECLS-K, very low food security during kindergarten is associated with a 3.1 % (4.1 %) increase in the probability of a child being obese (overweight) in fifth grade. In the ECLS-B, very low food security at nine months of age is associated with a 6.1 % (6.6 %) increase in the probability of a child being obese (overweight) at approximately age five. Given the difference in observed characteristics between children in very low food secure households and all other children, this positive association is not surprising.

Second, the impact of misreporting is profound. If even one percent of the sample misreports their food security status, the sign of the ATE cannot be determined even under exogenous selection. Given prior data on misreporting in other contexts (e.g., Bound et al. 2001), combined with the sensitive nature of the food security questionnaire, this is a stark result. Third, without imposing any assumptions concerning the selection process, the bounds are of width one and necessarily include zero as discussed above under the assumption of no measurement error. Nonetheless, the bounds are useful in excluding possible values of the ATE. For instance, Table 1 reveals bounds on the ATE for obesity using the ECLS-K of $[-0.251, 0.749]$. Table 3 reveals bounds of $[-0.189, 0.811]$ using the ECLS-B. Thus, a considerable range of values of the ATE, particularly in the negative domain, is ruled out. These bounds become wider as greater amounts of measurement error are allowed; the corresponding bounds are $[-0.351, 0.849]$ and $[-0.289, 0.911]$ if $Q = 0.10$. However, it is interesting to note that the assumption of no false positives has no identifying power relative to the assumption of arbitrary errors over the range of permissible values of $Q$ utilized.

Fourth, the monotonicity assumptions are quite powerful in terms of tightening the bounds. MTS results in significant shrinkage of the upper bounds; MIV further reduces the upper bounds. In Table 1, the joint MTS-MIV bounds are $[-0.252, -0.018]$; the Imbens and Manski (2004) confidence intervals, however, include zero. If taken at face value, and assuming no measurement error, the estimated bounds are suggestive of a long-run negative effect of very low food security on child obesity, which could have important policy implications. While certainly no one would advocate inducing food insecurity to combat the obesity epidemic, a negative effect would imply the existence of some tension in simultaneously combating hunger and obesity.

Finally, it is worth noting that even upon invoking the various monotonicity assumptions, even small rates of misreporting significantly widen the bounds. However, in combination with the monotonicity assumptions, the assumption of no false positives has significant identifying power. For example, in Tables 1 and 2, the upper bound under MTS alone attains its maximum possible value of unity when $Q = 0.02$ under arbitrary errors; this occurs at $Q = 0.05$ in Tables 3 and 4 under arbitrary errors. However, the upper bound, while still high, never exceeds 0.75 under MTS and the assumption of no false positives.

In summary, we find that very low food security in kindergarten (relative to not very low security) has a negative but statistically insignificant causal effect on obesity in fifth grade under the minimal assumptions of MTS-MIV only if we assume food security is reported without error. However, it is not possible to sign the long-run relationship between very low food security in kindergarten and child overweight status in the fifth grade, nor very low food security at nine months of age on child obesity or overweight status at five years of age, even in the absence of measurement error in self-reported household food security status. Moreover, our results illustrate the difficulty in not only narrowing the range of plausible values for the ATE, but even estimating its sign, in the absence of strong assumptions regarding the selection and misclassification processes. Thus, absent such assumptions, we cannot rule out the possibility of no long-run causal relationship between food security and child obesity and overweight status.

## 5.2 Additional analyses

We undertake several additional analyses to see what can be learned under the set of assumptions considered here when we alter the parameter being bounded. As stated previously, in the baseline analysis, we estimate bounds for the ATE of being very low food secure relative to not being very low food secure. Thus, the control consists of any level of food security in the initial period except very low food secure. As a result, being low food secure or marginally food secure, in addition to food secure, comprise the control. Our first supplemental analysis maintains the same treatment group—children in very low food secure households—but restricts the control to only food secure children. Our second supplemental analysis alters the treatment group as well as the control group. Here, we first define the treatment as being low or very low food secure, retaining marginally food secure and food secure as the control, and second define the treatment as being marginally, low, or very low food secure, retaining only food secure as the control. Our final supplemental analysis defines the treatment as low or very low food secure, but includes only food secure as the control.

### *5.2.1 Alternative control*

Bounds for the ATE of being very low food secure relative to food secure are presented in Figs. 5, 6, 7 and 8 and Tables 8, 9, 10 and 11 in the "Appendix". These figures and tables are analogous to those in Figs. 1, 2, 3 and 4 and Tables 1, 2, 3 and 4. The only difference is that now the control group excludes children in low and marginally food secure households. Because of the greater disparity between the treatment and control groups in terms of the provision of food, one might expect a more stark impact of the treatment.[22]

Turning to the results, many of the findings from the baseline results continue to hold. Thus, in the interest of brevity, we focus on the one main difference. In the

[22] It is important to remember that the causal effect of a treatment is only defined with respect to a specific control. As the control differs from that used in the baseline analysis, the parameter being estimated is different. In the baseline analysis, we are bounding the ATE of being very low food secure relative to being not very low food secure. Here, we are bounding the ATE of being very low food secure relative to being food secure.

baseline case, the MTS-MIV bounds under the assumption of no measurement error exclude zero only when using the ECLS-K to assess obesity status. However, when defining the control as food secure, the point estimates for the bounds exclude zero not only in this case (Fig. 5; Table 8), but also when assessing overweight status in the ECLS-K (Fig. 6; Table 9) and ECLS-B (Fig. 8; Table 11). That said, the Imbens and Manski (2004) confidence intervals include zero in these cases. Moreover, we cannot rule out the possibility of no long-run causal relationship between food security and child obesity and overweight status once the assumption of no misclassification of food security status is relaxed. Thus, the fact that no statistically significant effect is discerned even under this more extreme comparison is perhaps quite telling.

### *5.2.2 Alternative treatment*

Our next analyses assess the causal effect of less extreme forms of food insecurity. First, we bound the ATE of being low or very low food secure relative to being marginally food secure or food secure. These results are presented in Panel I of Tables 12, 13, 14 and 15 in the "Appendix".[23] Second, we bound the ATE of being marginally, low, or very low food secure relative to being food secure. These results are presented in Panel II of Tables 12, 13, 14 and 15.

It continues to be the case that results are very similar to the baseline results. Thus, we focus on only a few salient findings. First, while the associations between the two treatments and weight status continue to be positive when using the ECLS-K assuming that selection is exogenous (conditional only on the sample selection criteria) and the absence of measurement error, the estimates are also statistically significant in Panel II of Tables 12 and 13. The associations between the two treatments and weight status under exogenous and no measurement error are very close to zero when using the ECLS-B and, in fact, become negative for both treatments when assessing overweight status (Table 15). Thus, while perhaps not statistically different, there is some evidence that the long-run association between low and marginal food security is closer to zero during the years prior to kindergarten than during early primary school.

Second, the MTS-MIV bounds exclude zero in many cases when no misreporting is assumed. Specifically, we obtain bounds for the ATE of low or very low food security (relative to marginally food secure or food secure) on obesity status of $[-0.289, -0.013]$ and $[-0.277, -0.011]$ in the ECLS-K (Panel I, Table 12) and ECLS-B (Panel I, Table 14), respectively. The bounds for this treatment also exclude zero when assessing overweight status in the ECLS-B (Panel I, Table 15). Finally, bounds for the ATE of marginally, low, or very low food security (relative to food secure) on obesity and overweight status also exclude zero when assessing either obesity (Panel II, Table 14) or overweight (Panel II, Table 15) status in the ECLS-B. Finally, when assessing overweight status in the ECLS-B, MTS alone, along with the assumption of no measurement error, is sufficient to exclude zero from the bounds for both treatments (Panels I and II, Table 15). That said, the Imbens and Manski (2004) confidence intervals include zero in all cases. As such, we cannot rule out the

[23] To conserve space, we omit the corresponding figures.

possibility of no long-run causal relationship between food security and child obesity and overweight status once misreporting is allowed.

Our final analysis retains the same treatment from Panel I of Tables 12, 13, 14 and 15, namely being either low or very low food secure, but now the control is food secure (rather than marginally food secure or food secure). As in the prior section, this introduces a greater wedge between the treatment and control. The results are presented in Table 16 for the ECLS-K and Table 17 for the ECLS-B. For the ECLS-K, the change in definition of the control affects very little. The point estimates obtained under the exogenous selection assumption and no measurement error are very similar, the MTS-MIV bounds assuming no measurement error exclude zero when assessing obesity status, and the impact of misreporting is of similar magnitude. For the ECLS-B, however, some interesting results emerge. First, under the assumption of no measurement error, MTS-MIV is sufficient to exclude zero from the bounds for both obesity and overweight status. Second, the bounds continue to exclude zero for overweight status even when some measurement error is allowed ($Q = 0.01$) under either arbitrary errors or no false positives. Finally, MTS alone is sufficient to exclude zero when assessing overweight status assuming no measurement error. Again, though, the Imbens and Manski (2004) confidence intervals include zero in all cases, indicating we cannot rule out the possibility of no long-run causal relationship between food security and child obesity and overweight status once misreporting is allowed.

## 5.3 Discussion

Placing restrictions on the nature of the non-random selection into various degrees of food insecurity *and* assuming self-reports of food security status are accurate, the results provide suggestive evidence of a long-run, negative causal effect of food insecurity on child obesity and overweight status as the bounds are sometimes strictly negative (although the confidence intervals include zero). The fact that the point estimates of the bounds are sometimes able to exclude zero highlights what can be learned under minimal monotonicity assumptions. However, the results point to the substantial loss of information from relatively little (and most likely present) measurement error. Researchers in this area (and others) should heed this warning. It is not sufficient to overlook measurement error under the rationale that it is a relatively ‘minor’ problem. With even one percent of the sample misreporting their food security status, the width of the bounds increase markedly, prohibiting one from drawing conclusions regarding the long-run causal effect of food insecurity on childhood obesity.

Returning to the long-run, negative causal effect often suggested by the analysis under the assumption of no measurement error, further discussion is warranted. In particular, it is noteworthy that the study most similar to this by Gundersen and Kreider (2009) obtain bounds providing some evidence that food *security* reduces the probability of children being overweight. As stated previously, there are several differences between their study and ours. First, the definitions of the treatment, control, and outcome in their primary analysis correspond most closely to Panel I of Table 13 in the “Appendix.” Specifically, they bound the ATE of being marginally food secure or food secure relative to being low or very low food secure on contemporaneous overweight status. Second, the age ranges of the samples may differ; it is not reported in their study. Third, and most importantly, the bounds in Gundersen and Kreider (2009) typically exclude zero only when they impose an additional assumption not considered here, monotone treatment response (MTR), in addition to MTS-MIV. As stated in Gundersen and Kreider (2009), the validity of the MTR assumption when analyzing weight outcomes is highly questionable. It is noteworthy that when they impose MTS-MIV only, along with the assumption of no measurement error, they obtain bounds for the ATE of low food security on contemporaneous overweight status of [−0.424, 0.039], whereas our corresponding bounds for the ATE on long-run overweight status are [−0.444, 0.003] and [−0.397, −0.016] in the ECLS-K and ECLS-B, respectively. Moreover, in the ancillary analysis in Gundersen and Kreider (2009), they also estimate bounds for the ATE of very low food security on contemporaneous overweight and obesity status under MTS-MIV alone. Under the assumption of no measurement error, they obtain bounds of [−0.368, 0.015] and [−0.245, 0.019], respectively. Our corresponding bounds for the ATE on long-run overweight and obesity status are [−0.432, 0.007] and [−0.252, −0.018], respectively, in the ECLS-K; [−0.353, 0.032] and [−0.191, 0.033], respectively, in the ECLS-B. Thus, there is little difference between the short- and long-run results and across the various data sets once the MTR assumption is dropped.

## 6 Conclusion

The existing literature on the long-run relationship between food security status and child obesity and overweight status explores only the *association* between these two major public health concerns instead of the *causal* relationship. This is because existing studies do not account for two important identification issues: non-random selection and misreporting in household surveys. Here, we revisit the long-run impact of food security on obesity and overweight status, addressing both identification issues in a single partial identification framework proposed in Kreider et al. (2012). This nonparametric approach is especially suitable for this analysis given that obtaining consistent *point* estimates of an endogenous and mismeasured binary variable is not trivial (Black et al. 2000). Moreover, our study complements prior work on bounding the short-run causal effect of food security on child weight in Gundersen and Kreider (2009).

In the presence of both misreporting of and non-random selection into food insecurity status, the average treatment effect is not nonparametrically identified. To circumvent this, we impose a variety of assumptions concerning both the selection and measurement error processes to bound the long-run causal impact of food security. Using data from the ECLS-K and ECLS-B, we assess the identifying power of these assumptions to determine what can be learned about the average treatment effect. While there are a host of interesting findings, two main results arise. First, only in the absence of measurement error do we find any suggestive evidence that food insecurity has a long-run (negative) causal effect on child obesity and overweight status; even then the results are not statistically significant. Second, measurement error, which is likely to be present, is extremely consequential. If only one percent of the households misreport their food security status, we cannot rule out the possibility of no long-run causal relationship between food security and child obesity and overweight status. Given the public health issues involved, future research is clearly warranted to determine whether there is a causal relationship between food security and child obesity and overweight status.

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## 7 Appendix

See Tables 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17 and Figs. 5, 6, 7, 8.

**Table 5** Core food security module (CFSM)

1. "We worried whether our food would run out before we got money to buy more". Was that **often**, **sometimes** or never true for you in the last 12 months?
2. "The food that we bought just didn't last and we didn't have money to get more". Was that **often**, **sometimes** or never true for you in the last 12 months?
3. "We couldn't afford to eat balanced meals". Was that **often**, **sometimes** or never true for you in the last 12 months?
4. "We relied on only a few kinds of low-cost food to feed our children because we were running out of money to buy food". Was that often, sometimes or never true for you in the last 12 months?
5. In the last 12 months, did you or other adults in the household ever cut the size of your meals or skip meals because there wasn't enough money for food? (**Yes**/No)
6. "We couldn't feed our children a balanced meal, because we couldn't afford that". Was that **often**, **sometimes** or never true for you in the last 12 months?
7. In the last 12 months, did you ever eat less than you felt you should because there wasn't enough money for food? (**Yes**/No)
8. (If yes to Question 5) How often did this happen—**almost every month**, **some months but not every month**, or in only 1 or 2 months?
9. "The children were not eating enough because we just couldn't afford enough food". Was that **often**, **sometimes** or never true for you in the last 12 months?
10. In the last 12 months, were you ever hungry, but didn't eat, because you couldn't afford enough food? (**Yes**/No)
11. In the last 12 months, did you lose weight because you didn't have enough money for food? (**Yes**/No)
12. In the last 12 months, did you ever cut the size of any of the children's meals because there wasn't enough money for food? (**Yes**/No)
13. In the last 12 months did you or other adults in your household ever not eat for a whole day because there wasn't enough money for food? (**Yes**/No)
14. In the last 12 months, were the children ever hungry but you just couldn't afford more food? (**Yes**/No)
15. (If yes to Question 13) How often did this happen—**almost every month**, **some months but not every month**, or in only 1 or 2 months?

**Table 5** continued

| |
|---|
| 16. In the last 12 months, did any of the children ever skip a meal because there wasn't enough money for food? (**Yes**/No) |
| 17. (If yes to Question 16) How often did this happen—**almost every month**, **some months but not every month**, or in only 1 or 2 months? |
| 18. In the last 12 months did any of the children ever not eat for a whole day because there wasn't enough money for food? (**Yes**/No) |

Responses in bold are "affirmative". Table taken from Kuku et al. (2012)

**Table 6** ECLS-K summary statistics

| Variable | *N* | Mean | SD | Marginally food secure (F1–FS) | | Low food security (F1–FS) | | Very low food security (F1–FS) | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | Mean | *p* value | Mean | *p* value | Mean | *p* value |
| Marginally food secure (1 = yes) | 6,470 | 0.192 | 0.394 | | | | | | |
| Low food security (1 = yes) | 6,470 | 0.099 | 0.299 | | | | | | |
| Very low food security (1 = yes) | 6,470 | 0.019 | 0.138 | | | | | | |
| Obese (1 = yes) | 6,470 | 0.242 | 0.428 | 0.043 | 0.006 | 0.021 | 0.301 | 0.049 | 0.277 |
| Overweight (1 = yes) | 6,470 | 0.432 | 0.495 | 0.037 | 0.007 | 0.026 | 0.137 | 0.037 | 0.334 |
| SNAP recipient (1 = yes) | 6,470 | 0.153 | 0.360 | 0.242 | 0.000 | 0.281 | 0.000 | 0.313 | 0.000 |
| Household SES status | 6,470 | −0.251 | 0.549 | −0.371 | 0.000 | −0.456 | 0.000 | −0.514 | 0.000 |
| Household size | 6,470 | 4.583 | 1.431 | 0.473 | 0.000 | 0.660 | 0.000 | 0.732 | 0.000 |
| Two parent household (1 = yes) | 6,470 | 0.781 | 0.414 | −0.141 | 0.000 | −0.136 | 0.000 | −0.168 | 0.000 |
| One parent household (1 = yes) | 6,470 | 0.198 | 0.399 | 0.140 | 0.000 | 0.143 | 0.000 | 0.173 | 0.000 |
| Number of siblings | 6,470 | 1.492 | 1.182 | 0.453 | 0.000 | 0.628 | 0.000 | 0.651 | 0.000 |
| Mother's education | | | | | | | | | |
| Less than high school (1 = yes) | 6,370 | 0.152 | 0.359 | 0.162 | 0.000 | 0.216 | 0.000 | 0.226 | 0.000 |
| High school (1 = yes) | 6,370 | 0.369 | 0.482 | 0.005 | 0.721 | −0.015 | 0.468 | −0.013 | 0.771 |
| Voc. degree/some coll. (1 = yes) | 6,370 | 0.373 | 0.484 | −0.086 | 0.000 | −0.103 | 0.000 | −0.124 | 0.005 |

**Table 6** continued

| Variable | N | Mean | SD | Marginally food secure (F1–FS) Mean | Marginally food secure (F1–FS) p value | Low food security (F1–FS) Mean | Low food security (F1–FS) p value | Very low food security (F1–FS) Mean | Very low food security (F1–FS) p value |
|---|---|---|---|---|---|---|---|---|---|
| Bachelor's degree (1 = yes) | 6,370 | 0.095 | 0.293 | −0.077 | 0.000 | −0.091 | 0.000 | −0.086 | 0.002 |
| Advanced degree (1 = yes) | 6,370 | 0.011 | 0.104 | −0.005 | 0.174 | −0.007 | 0.107 | −0.004 | 0.699 |

Number of observations rounded to the nearest 10 per NCES restricted data requirement. SES = socioeconomic status. Sample excludes households in the highest quintile of SES. Data are from the kindergarten wave except for obese and overweight which are from the spring fifth grade wave. Omitted category for family structure is 'other or missing', and for mother's education is 'missing'. Columns 5, 7, and 9 report the mean difference between food insecure (F1) households (according to the definition indicated) and food secure (FS) households; $p$ values obtained using $t$ test

**Table 7** ECLS-B summary statistics

| Variable | N | Mean | SD | Marginally food secure (F1–FS) Mean | Marginally food secure (F1–FS) p value | Low food security (F1–FS) Mean | Low food security (F1–FS) p value | Very low food security (F1–FS) Mean | Very low food security (F1–FS) p value |
|---|---|---|---|---|---|---|---|---|---|
| Marginally food secure (1 = yes) | 4,100 | 0.133 | 0.339 | | | | | | |
| Low food security (1 = yes) | 4,100 | 0.128 | 0.334 | | | | | | |
| Very low food security (1 = yes) | 4,100 | 0.034 | 0.181 | | | | | | |
| Obese (1 = yes) | 4,100 | 0.171 | 0.377 | 0.000 | 0.992 | −0.028 | 0.221 | 0.067 | 0.105 |
| Overweight (1 = yes) | 4,100 | 0.346 | 0.476 | 0.000 | 0.995 | −0.011 | 0.556 | 0.061 | 0.059 |
| SNAP recipient (1 = yes) | 4,100 | 0.268 | 0.443 | 0.113 | 0.000 | 0.276 | 0.000 | 0.343 | 0.000 |
| Household SES status | 4,100 | −0.376 | 0.584 | −0.247 | 0.000 | −0.446 | 0.000 | −0.461 | 0.000 |
| Household size | 4,100 | 4.561 | 1.561 | 0.158 | 0.028 | 0.184 | 0.011 | 0.179 | 0.176 |
| Two parent household (1 = yes) | 4,100 | 0.748 | 0.434 | −0.048 | 0.017 | −0.115 | 0.000 | −0.224 | 0.000 |
| One parent household (1 = yes) | 4,100 | 0.244 | 0.430 | 0.050 | 0.012 | 0.118 | 0.000 | 0.232 | 0.000 |
| Number of siblings | 4,100 | 1.140 | 1.165 | 0.106 | 0.048 | 0.208 | 0.000 | 0.385 | 0.000 |

**Table 7** continued

| Variable | *N* | Mean | SD | Marginally food secure (F1–FS) | | Low food security (F1–FS) | | Very low food security (F1–FS) | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | Mean | *p* value | Mean | *p* value | Mean | *p* value |
| Mother's education | | | | | | | | | |
| Less than high school (1 = yes) | 4,100 | 0.230 | 0.421 | 0.103 | 0.000 | 0.187 | 0.000 | 0.104 | 0.003 |
| High school (1 = yes) | 4,100 | 0.335 | 0.472 | 0.005 | 0.824 | 0.040 | 0.077 | 0.071 | 0.082 |
| Voc. degree/some coll. (1 = yes) | 4,100 | 0.321 | 0.467 | −0.017 | 0.420 | −0.116 | 0.000 | −0.067 | 0.097 |
| Bachelor's degree (1 = yes) | 4,100 | 0.098 | 0.298 | −0.081 | 0.000 | −0.108 | 0.000 | −0.099 | 0.000 |
| Advanced degree (1 = yes) | 4,100 | 0.015 | 0.121 | −0.009 | 0.120 | −0.003 | 0.593 | −0.009 | 0.396 |

Number of observations rounded to the nearest 50 per NCES restricted data requirement. SES = socioeconomic status. Sample excludes households in the highest quintile of SES. Data are from the 9-month wave except for obese and overweight which are from wave 4 (approximately five years old). Omitted category for family structure is 'other or missing', and for mother's education is 'missing'. Columns 5, 7, and 9 report the mean difference between food insecure (F1) households (according to the definition indicated) and food secure (FS) households; *p* values obtained using *t* test

**Table 8** Sharp bounds on the ATE of very low food security on child obesity status with alternative control group: ECLS-K

| $Q$ | Exogenous selection | | No assumption on selection | | MTS | | MTS & MIV | |
|---|---|---|---|---|---|---|---|---|
| | (1) AE | (2) No FP | (3) AE | (4) No FP | (5) AE | (6) No FP | (7) AE | (8) No FP |
| 0.00 | [0.037, 0.037] p.e. | [0.037, 0.037] p.e. | [−0.246, 0.754] p.e. | [−0.246, 0.754] p.e. | [−0.246, 0.037] p.e. | [−0.246, 0.037] p.e. | [−0.247, −0.022] p.e. | [−0.247, −0.022] p.e. |
| | [−0.022, 0.117] CI | [−0.022, 0.117] CI | [−0.259, 0.765] CI | [−0.259, 0.765] CI | [−0.259, 0.117] CI | [−0.259, 0.117] CI | [−0.261, 0.029] CI | [−0.261, 0.029] CI |
| 0.01 | [−0.241, 0.263] p.e. | [−0.047, 0.263] p.e. | [−0.256, 0.764] p.e. | [−0.256, 0.764] p.e. | [−0.256, 0.263] p.e. | [−0.256, 0.263] p.e. | [−0.261, 0.153] p.e. | [−0.257, 0.153] p.e. |
| | [−0.251, 0.407] CI | [−0.091, 0.327] CI | [−0.269, 0.775] CI | [−0.269, 0.775] CI | [−0.269, 0.407] CI | [−0.269, 0.327] CI | [−0.275, 0.220] CI | [−0.271, 0.222] CI |
| 0.02 | [−0.243, 1.000] p.e. | [−0.093, 0.389] p.e. | [−0.266, 0.774] p.e. | [−0.266, 0.774] p.e. | [−0.266, 1.000] p.e. | [−0.266, 0.389] p.e. | [−0.273, 0.228] p.e. | [−0.267, 0.230] p.e. |
| | [−0.254, 1.000] CI | [−0.130, 0.444] CI | [−0.279, 0.785] CI | [−0.279, 0.785] CI | [−0.279, 1.000] CI | [−0.279, 0.444] CI | [−0.287, 0.294] CI | [−0.281, 0.299] CI |
| 0.05 | [−0.251, 1.000] p.e. | [−0.161, 0.575] p.e. | [−0.296, 0.804] p.e. | [−0.296, 0.804] p.e. | [−0.296, 1.000] p.e. | [−0.296, 0.575] p.e. | [−0.303, 0.883] p.e. | [−0.297, 0.395] p.e. |
| | [−0.263, 1.000] CI | [−0.185, 0.615] CI | [−0.309, 0.815] CI | [−0.309, 0.815] CI | [−0.309, 1.000] CI | [−0.309, 0.615] CI | [−0.317, 0.925] CI | [−0.311, 0.460] CI |
| 0.10 | [−0.265, 1.000] p.e. | [−0.210, 0.715] p.e. | [−0.346, 0.854] p.e. | [−0.346, 0.854] p.e. | [−0.346, 1.000] p.e. | [−0.346, 0.715] p.e. | [−0.353, 0.853] p.e. | [−0.347, 0.563] p.e. |
| | [−0.278, 1.000] CI | [−0.228, 0.745] CI | [−0.359, 0.865] CI | [−0.359, 0.865] CI | [−0.359, 1.000] CI | [−0.359, 0.745] CI | [−0.367, 0.864] CI | [−0.361, 0.618] CI |

Control group includes only food secure households. CI around ATE are calculated using methods from Imbens and Manski (2004) with 250 pseudosamples. Number of observations = 5,350 (rounded to nearest 10 per NCES restricted data regulations)

*p.e.* point estimates, *CI* confidence interval, *AE* arbitrary errors, *FP* false positives

**Table 9** Sharp bounds on the ATE of very low food security on child overweight status with alternative control group: ECLS-K

| Q | Exogenous selection | | No assumption on selection | | MTS | | MTS & MIV | |
|---|---|---|---|---|---|---|---|---|
| | (1) AE | (2) No FP | (3) AE | (4) No FP | (5) AE | (6) No FP | (7) AE | (8) No FP |
| 0.00 | [0.049, 0.049] p.e. | [0.049, 0.049] p.e. | [−0.426, 0.574] p.e. | [−0.426, 0.574] p.e. | [−0.426, 0.049] p.e. | [−0.426, 0.049] p.e. | [−0.427, −0.013] p.e. | [−0.427, −0.013] p.e. |
| | [−0.049, 0.136] CI | [−0.049, 0.136] CI | [−0.439, 0.586] CI | [−0.439, 0.586] CI | [−0.439, 0.136] CI | [−0.439, 0.136] CI | [−0.442, 0.113] CI | [−0.442, 0.113] CI |
| 0.01 | [−0.350, 0.407] p.e. | [−0.097, 0.213] p.e. | [−0.436, 0.584] p.e. | [−0.436, 0.584] p.e. | [−0.436, 0.407] p.e. | [−0.436, 0.213] p.e. | [−0.442, 0.165] p.e. | [−0.437, 0.151] p.e. |
| | [−0.436, 0.633] CI | [−0.163, 0.283] CI | [−0.449, 0.596] CI | [−0.449, 0.596] CI | [−0.449, 0.633] CI | [−0.449, 0.283] CI | [−0.458, 0.362] CI | [−0.452, 0.275] CI |
| 0.02 | [−0.434, 1.000] p.e. | [−0.178, 0.304] p.e. | [−0.446, 0.594] p.e. | [−0.446, 0.594] p.e. | [−0.446, 1.000] p.e. | [−0.446, 0.304] p.e. | [−0.455, 0.279] p.e. | [−0.447, 0.196] p.e. |
| | [−0.445, 1.000] CI | [−0.228, 0.363] CI | [−0.459, 0.606] CI | [−0.459, 0.606] CI | [−0.459, 1.000] CI | [−0.459, 0.363] CI | [−0.471, 0.521] CI | [−0.462, 0.333] CI |
| 0.05 | [−0.448, 1.000] p.e. | [−0.296, 0.440] p.e. | [−0.476, 0.624] p.e. | [−0.476, 0.624] p.e. | [−0.476, 1.000] p.e. | [−0.476, 0.440] p.e. | [−0.488, 0.607] p.e. | [−0.477, 0.313] p.e. |
| | [−0.460, 1.000] CI | [−0.329, 0.479] CI | [−0.489, 0.636] CI | [−0.489, 0.636] CI | [−0.489, 1.000] CI | [−0.489, 0.479] CI | [−0.504, 0.638] CI | [−0.492, 0.408] CI |
| 0.10 | [−0.472, 1.000] p.e. | [−0.382, 0.542] p.e. | [−0.526, 0.674] p.e. | [−0.526, 0.674] p.e. | [−0.526, 1.000] p.e. | [−0.526, 0.542] p.e. | [−0.538, 0.641] p.e. | [−0.527, 0.434] p.e. |
| | [−0.486, 1.000] CI | [−0.407, 0.569] CI | [−0.539, 0.686] CI | [−0.539, 0.686] CI | [−0.539, 1.000] CI | [−0.539, 0.569] CI | [−0.554, 0.651] CI | [−0.542, 0.502] CI |

Control group includes only food secure households. CI around ATE are calculated using methods from Imbens and Manski (2004) with 250 pseudosamples. Number of observations = 5,350 (rounded to nearest 10 per NCES restricted data regulations
*p.e.* point estimates, *CI* confidence interval, *AE* arbitrary errors, *FP* false positives)

**Table 10** Sharp bounds on the ATE of very low food security on child obesity status with alternative control group: ECLS-B

| $Q$ | Exogenous selection | | No assumption on selection | | MTS | | MTS & MIV | |
|---|---|---|---|---|---|---|---|---|
| | (1) AE | (2) No FP | (3) AE | (4) No FP | (5) AE | (6) No FP | (7) AE | (8) No FP |
| 0.00 | [0.060, 0.060] p.e. | [0.060, 0.060] p.e. | [−0.197, 0.803] p.e. | [−0.197, 0.803] p.e. | [−0.197, 0.060] p.e. | [−0.197, 0.060] p.e. | [−0.197, 0.021] p.e. | [−0.197, 0.021] p.e. |
| | [−0.008, 0.138] CI | [−0.008, 0.138] CI | [−0.211, 0.817] CI | [−0.211, 0.817] CI | [−0.211, 0.138] CI | [−0.211, 0.138] CI | [−0.208, 0.112] CI | [−0.208, 0.112] CI |
| 0.01 | [−0.162, 0.207] p.e. | [0.017, 0.207] p.e. | [−0.207, 0.813] p.e. | [−0.207, 0.813] p.e. | [−0.207, 0.207] p.e. | [−0.207, 0.207] p.e. | [−0.213, 0.154] p.e. | [−0.207, 0.154] p.e. |
| | [−0.191, 0.265] CI | [−0.041, 0.265] CI | [−0.221, 0.827] CI | [−0.221, 0.827] CI | [−0.221, 0.265] CI | [−0.221, 0.265] CI | [−0.224, 0.209] CI | [−0.218, 0.209] CI |
| 0.02 | [−0.180, 0.311] p.e. | [−0.013, 0.312] p.e. | [−0.217, 0.823] p.e. | [−0.217, 0.823] p.e. | [−0.217, 0.311] p.e. | [−0.217, 0.312] p.e. | [−0.227, 0.208] p.e. | [−0.217, 0.208] p.e. |
| | [−0.194, 0.363] CI | [−0.066, 0.361] CI | [−0.231, 0.837] CI | [−0.231, 0.837] CI | [−0.231, 0.363] CI | [−0.231, 0.361] CI | [−0.238, 0.278] CI | [−0.228, 0.278] CI |
| 0.05 | [−0.186, 1.000] p.e. | [−0.069, 0.507] p.e. | [−0.247, 0.853] p.e. | [−0.247, 0.853] p.e. | [−0.247, 1.000] p.e. | [−0.247, 0.507] p.e. | [−0.257, 0.335] p.e. | [−0.247, 0.355] p.e. |
| | [−0.200, 1.000] CI | [−0.108, 0.549] CI | [−0.261, 0.867] CI | [−0.261, 0.867] CI | [−0.261, 1.000] CI | [−0.261, 0.549] CI | [−0.269, 0.563] CI | [−0.258, 0.433] CI |
| 0.10 | [−0.197, 1.000] p.e. | [−0.117, 0.685] p.e. | [−0.297, 0.903] p.e. | [−0.297, 0.903] p.e. | [−0.297, 1.000] p.e. | [−0.297, 0.685] p.e. | [−0.307, 0.942] p.e. | [−0.297, 0.533] p.e. |
| | [−0.211, 1.000] CI | [−0.145, 0.719] CI | [−0.311, 0.917] CI | [−0.311, 0.917] CI | [−0.311, 1.000] CI | [−0.311, 0.719] CI | [−0.319, 1.000] CI | [−0.308, 0.607] CI |

Control group includes only food secure households. CI around ATE are calculated using methods from Imbens and Manski (2004) with 250 pseudosamples. Number of observations = 3,050 (rounded to nearest 50 per NCES restricted data regulations)

*p.e.* point estimates, *CI* confidence interval, *AE* arbitrary errors, *FP* false positives

**Table 11** Sharp bounds on the ATE of very low food security on child overweight status with alternative control group: ECLS-B

| $Q$ | Exogenous selection | | No assumption on selection | | MTS | | MTS & MIV | |
|---|---|---|---|---|---|---|---|---|
| | (1) AE | (2) No FP | (3) AE | (4) No FP | (5) AE | (6) No FP | (7) AE | (8) No FP |
| 0.00 | [0.063, 0.063] p.e. | [0.063, 0.063] p.e. | [−0.358, 0.642] p.e. | [−0.358, 0.642] p.e. | [−0.358, 0.063] p.e. | [−0.358, 0.063] p.e. | [−0.361, −0.042] p.e. | [−0.361, −0.042] p.e. |
| | [−0.015, 0.161] CI | [−0.015, 0.161] CI | [−0.375, 0.659] CI | [−0.375, 0.659] CI | [−0.375, 0.161] CI | [−0.375, 0.161] CI | [−0.376, 0.130] CI | [−0.376, 0.130] CI |
| 0.01 | [−0.108, 0.181] p.e. | [−0.014, 0.175] p.e. | [−0.368, 0.652] p.e. | [−0.368, 0.652] p.e. | [−0.368, 0.181] p.e. | [−0.368, 0.175] p.e. | [−0.378, 0.086] p.e. | [−0.371, 0.087] p.e. |
| | [−0.212, 0.299] CI | [−0.073, 0.250] CI | [−0.385, 0.669] CI | [−0.385, 0.669] CI | [−0.385, 0.299] CI | [−0.385, 0.250] CI | [−0.395, 0.212] CI | [−0.386, 0.210] CI |
| 0.02 | [−0.360, 0.387] p.e. | [−0.069, 0.256] p.e. | [−0.378, 0.662] p.e. | [−0.378, 0.662] p.e. | [−0.378, 0.387] p.e. | [−0.378, 0.256] p.e. | [−0.392, 0.193] p.e. | [−0.381, 0.189] p.e. |
| | [−0.374, 0.634] CI | [−0.121, 0.325] CI | [−0.395, 0.679] CI | [−0.395, 0.679] CI | [−0.395, 0.634] CI | [−0.395, 0.325] CI | [−0.409, 0.336] CI | [−0.396, 0.247] CI |
| 0.05 | [−0.372, 1.000] p.e. | [−0.170, 0.407] p.e. | [−0.408, 0.692] p.e. | [−0.408, 0.692] p.e. | [−0.408, 1.000] p.e. | [−0.408, 0.407] p.e. | [−0.429, 0.591] p.e. | [−0.411, 0.342] p.e. |
| | [−0.387, 1.000] CI | [−0.211, 0.462] CI | [−0.425, 0.709] CI | [−0.425, 0.709] CI | [−0.425, 1.000] CI | [−0.425, 0.462] CI | [−0.445, 0.786] CI | [−0.426, 0.381] CI |
| 0.10 | [−0.393, 1.000] p.e. | [−0.259, 0.544] p.e. | [−0.458, 0.742] p.e. | [−0.458, 0.742] p.e. | [−0.458, 1.000] p.e. | [−0.458, 0.544] p.e. | [−0.479, 0.727] p.e. | [−0.461, 0.460] p.e. |
| | [−0.409, 1.000] CI | [−0.287, 0.589] CI | [−0.475, 0.759] CI | [−0.475, 0.759] CI | [−0.475, 1.000] CI | [−0.475, 0.589] CI | [−0.496, 0.750] CI | [−0.476, 0.512] CI |

Control group includes only food secure households. CI around ATE are calculated using methods from Imbens and Manski (2004) with 250 pseudosamples. Number of observations = 3,050 (rounded to nearest 50 per NCES restricted data regulations)

*p.e.* point estimates, *CI* confidence interval, *AE* arbitrary errors, *FP* false positives

**Table 12** Sharp bounds on alternative ATEs on child obesity status: ECLS-K

| *Q* | Exogenous selection | | No assumption on selection | | MTS | | MTS & MIV | |
|---|---|---|---|---|---|---|---|---|
| | (1) AE | (2) No FP | (3) AE | (4) No FP | (5) AE | (6) No FP | (7) AE | (8) No FP |
| *I. ATE of low or very low food secure versus marginally food secure or food secure* | | | | | | | | |
| 0.00 | [0.022, 0.022] p.e. | [0.022, 0.022] p.e. | [−0.289, 0.711] p.e. | [−0.289, 0.711] p.e. | [−0.289, 0.022] p.e. | [−0.289, 0.022] p.e. | [−0.289, −0.013] p.e. | [−0.289, −0.013] p.e. |
| | [−0.010, 0.061] CI | [−0.010, 0.061] CI | [−0.300, 0.721] CI | [−0.300, 0.721] CI | [−0.300, 0.061] CI | [−0.300, 0.061] CI | [−0.300, 0.023] CI | [−0.300, 0.023] CI |
| 0.01 | [−0.069, 0.097] p.e. | [−0.005, 0.098] p.e. | [−0.299, 0.721] p.e. | [−0.299, 0.721] p.e. | [−0.299, 0.097] p.e. | [−0.299, 0.098] p.e. | [−0.308, 0.058] p.e. | [−0.299, 0.058] p.e. |
| | [−0.102, 0.132] CI | [−0.033, 0.132] CI | [−0.310, 0.731] CI | [−0.310, 0.731] CI | [−0.310, 0.132] CI | [−0.310, 0.132] CI | [−0.320, 0.097] CI | [−0.310, 0.097] CI |
| 0.02 | [−0.180, 0.162] p.e. | [−0.028, 0.163] p.e. | [−0.309, 0.731] p.e. | [−0.309, 0.731] p.e. | [−0.309, 0.162] p.e. | [−0.309, 0.163] p.e. | [−0.323, 0.101] p.e. | [−0.309, 0.101] p.e. |
| | [−0.217, 0.196] CI | [−0.054, 0.196] CI | [−0.320, 0.741] CI | [−0.320, 0.741] CI | [−0.320, 0.196] CI | [−0.320, 0.196] CI | [−0.335, 0.144] CI | [−0.320, 0.144] CI |
| 0.05 | [−0.267, 0.314] p.e. | [−0.080, 0.314] p.e. | [−0.339, 0.761] p.e. | [−0.339, 0.761] p.e. | [−0.339, 0.314] p.e. | [−0.339, 0.314] p.e. | [−0.362, 0.196] p.e. | [−0.339, 0.196] p.e. |
| | [−0.279, 0.413] CI | [−0.103, 0.344] CI | [−0.350, 0.771] CI | [−0.350, 0.771] CI | [−0.350, 0.413] CI | [−0.350, 0.344] CI | [−0.375, 0.237] CI | [−0.350, 0.237] CI |
| 0.10 | [−0.283, 1.000] p.e. | [−0.140, 0.487] p.e. | [−0.389, 0.811] p.e. | [−0.389, 0.811] p.e. | [−0.389, 1.000] p.e. | [−0.389, 0.487] p.e. | [−0.414, 0.331] p.e. | [−0.389, 0.337] p.e. |
| | [−0.295, 1.000] CI | [−0.157, 0.513] CI | [−0.400, 0.821] CI | [−0.400, 0.821] CI | [−0.400, 1.000] CI | [−0.400, 0.513] CI | [−0.428, 0.409] CI | [−0.400, 0.376] CI |
| *II. ATE of marginally, low, or very low food secure versus food secure* | | | | | | | | |
| 0.00 | [0.037, 0.037] p.e. | [0.037, 0.037] p.e. | [−0.330, 0.670] p.e. | [−0.330, 0.670] p.e. | [−0.330, 0.037] p.e. | [−0.330, 0.037] p.e. | [−0.330, 0.017] p.e. | [−0.330, 0.017] p.e. |
| | [0.008, 0.067] CI | [0.008, 0.067] CI | [−0.341, 0.683] CI | [−0.341, 0.683] CI | [−0.341, 0.067] CI | [−0.341, 0.067] CI | [−0.340, 0.042] CI | [−0.340, 0.042] CI |

**Table 12** continued

| Q | Exogenous selection | | No assumption on selection | | MTS | | MTS & MIV | |
|---|---|---|---|---|---|---|---|---|
| | (1) AE | (2) No FP | (3) AE | (4) No FP | (5) AE | (6) No FP | (7) AE | (8) No FP |
| 0.01 | [−0.013, 0.082] p.e. | [0.020, 0.082] p.e. | [−0.340, 0.680] p.e. | [−0.340, 0.680] p.e. | [−0.340, 0.082] p.e. | [−0.340, 0.082] p.e. | [−0.350, 0.069] p.e. | [−0.340, 0.069] p.e. |
| | [−0.043, 0.112] CI | [−0.007, 0.113] CI | [−0.351, 0.693] CI | [−0.351, 0.693] CI | [−0.351, 0.112] CI | [−0.351, 0.113] CI | [−0.360, 0.087] CI | [−0.350, 0.087] CI |
| 0.02 | [−0.066, 0.125] p.e. | [0.005, 0.125] p.e. | [−0.350, 0.690] p.e. | [−0.350, 0.690] p.e. | [−0.350, 0.125] p.e. | [−0.350, 0.125] p.e. | [−0.369, 0.102] p.e. | [−0.350, 0.102] p.e. |
| | [−0.099, 0.154] CI | [−0.021, 0.155] CI | [−0.361, 0.703] CI | [−0.361, 0.703] CI | [−0.361, 0.154] CI | [−0.361, 0.155] CI | [−0.380, 0.129] CI | [−0.360, 0.129] CI |
| 0.05 | [−0.264, 0.237] p.e. | [−0.035, 0.237] p.e. | [−0.380, 0.720] p.e. | [−0.380, 0.720] p.e. | [−0.380, 0.237] p.e. | [−0.380, 0.237] p.e. | [−0.417, 0.172] p.e. | [−0.380, 0.172] p.e. |
| | [−0.285, 0.266] CI | [−0.058, 0.266] CI | [−0.391, 0.733] CI | [−0.391, 0.733] CI | [−0.391, 0.266] CI | [−0.391, 0.266] CI | [−0.427, 0.219] CI | [−0.390, 0.219] CI |
| 0.10 | [−0.298, 0.394] p.e. | [−0.089, 0.394] p.e. | [−0.430, 0.770] p.e. | [−0.430, 0.770] p.e. | [−0.430, 0.394] p.e. | [−0.430, 0.394] p.e. | [−0.480, 0.297] p.e. | [−0.430, 0.297] p.e. |
| | [−0.308, 0.434] CI | [−0.110, 0.420] CI | [−0.441, 0.783] CI | [−0.441, 0.783] CI | [−0.441, 0.434] CI | [−0.441, 0.420] CI | [−0.491, 0.335] CI | [−0.440, 0.335] CI |

CI around ATE are calculated using methods from Imbens and Manski (2004) with 250 pseudosamples. Number of observations = 6,470 (rounded to nearest 10 per NCES restricted data regulations

*p.e.* point estimates, *CI* confidence interval, *AE* arbitrary errors, *FP* false positives)

**Table 13** Sharp bounds on alternative ATEs on child overweight status: ECLS-K

| $Q$ | Exogenous selection | | No assumption on selection | | MTS | | MTS & MIV | |
|---|---|---|---|---|---|---|---|---|
| | (1) AE | (2) No FP | (3) AE | (4) No FP | (5) AE | (6) No FP | (7) AE | (8) No FP |
| *I. ATE of low or very low food secure versus marginally food secure or food secure* | | | | | | | | |
| 0.00 | [0.015, 0.015] p.e. | [0.015, 0.015] p.e. | [−0.443, 0.557] p.e. | [−0.443, 0.557] p.e. | [−0.443, 0.015] p.e. | [−0.443, 0.015] p.e. | [−0.444, 0.003] p.e. | [−0.444, 0.003] p.e. |
| | [−0.033, 0.056] CI | [−0.033, 0.056] CI | [−0.455, 0.571] CI | [−0.455, 0.571] CI | [−0.455, 0.056] CI | [−0.455, 0.056] CI | [−0.455, 0.047] CI | [−0.455, 0.047] CI |
| 0.01 | [−0.054, 0.072] p.e. | [−0.031, 0.072] p.e. | [−0.453, 0.567] p.e. | [−0.453, 0.567] p.e. | [−0.453, 0.072] p.e. | [−0.453, 0.072] p.e. | [−0.464, 0.067] p.e. | [−0.454, 0.067] p.e. |
| | [−0.104, 0.116] CI | [−0.075, 0.108] CI | [−0.465, 0.581] CI | [−0.465, 0.581] CI | [−0.465, 0.116] CI | [−0.465, 0.108] CI | [−0.475, 0.097] CI | [−0.465, 0.096] CI |
| 0.02 | [−0.137, 0.136] p.e. | [−0.070, 0.121] p.e. | [−0.463, 0.577] p.e. | [−0.463, 0.577] p.e. | [−0.463, 0.136] p.e. | [−0.463, 0.121] p.e. | [−0.482, 0.082] p.e. | [−0.464, 0.083] p.e. |
| | [−0.192, 0.188] CI | [−0.111, 0.156] CI | [−0.475, 0.591] CI | [−0.475, 0.591] CI | [−0.475, 0.188] CI | [−0.475, 0.156] CI | [−0.493, 0.157] CI | [−0.475, 0.137] CI |
| 0.05 | [−0.457, 0.488] p.e. | [−0.160, 0.234] p.e. | [−0.493, 0.607] p.e. | [−0.493, 0.607] p.e. | [−0.493, 0.488] p.e. | [−0.493, 0.234] p.e. | [−0.526, 0.183] p.e. | [−0.494, 0.154] p.e. |
| | [−0.469, 0.617] CI | [−0.195, 0.267] CI | [−0.505, 0.621] CI | [−0.505, 0.621] CI | [−0.505, 0.617] CI | [−0.505, 0.267] CI | [−0.538, 0.255] CI | [−0.505, 0.206] CI |
| 0.10 | [−0.484, 1.000] p.e. | [−0.262, 0.364] p.e. | [−0.543, 0.657] p.e. | [−0.543, 0.657] p.e. | [−0.543, 1.000] p.e. | [−0.543, 0.364] p.e. | [−0.586, 0.435] p.e. | [−0.544, 0.258] p.e. |
| | [−0.496, 1.000] CI | [−0.292, 0.394] CI | [−0.555, 0.671] CI | [−0.555, 0.671] CI | [−0.555, 1.000] CI | [−0.555, 0.394] CI | [−0.599, 0.535] CI | [−0.555, 0.301] CI |
| *II. ATE of marginally, low, or very low food secure versus food secure* | | | | | | | | |
| 0.00 | [0.043, 0.043] p.e. | [0.043, 0.043] p.e. | [−0.445, 0.555] p.e. | [−0.445, 0.555] p.e. | [−0.445, 0.043] p.e. | [−0.445, 0.043] p.e. | [−0.446, 0.031] p.e. | [−0.446, 0.031] p.e. |
| | [0.017, 0.070] CI | [0.017, 0.070] CI | [−0.456, 0.567] CI | [−0.456, 0.567] CI | [−0.456, 0.070] CI | [−0.456, 0.070] CI | [−0.459, 0.057] CI | [−0.459, 0.057] CI |
| 0.01 | [0.007, 0.077] p.e. | [0.015, 0.077] p.e. | [−0.455, 0.565] p.e. | [−0.455, 0.565] p.e. | [−0.455, 0.077] p.e. | [−0.455, 0.077] p.e. | [−0.466, 0.069] p.e. | [−0.456, 0.070] p.e. |
| | [−0.021, 0.103] CI | [−0.011, 0.103] CI | [−0.466, 0.577] CI | [−0.466, 0.577] CI | [−0.466, 0.103] CI | [−0.466, 0.103] CI | [−0.479, 0.094] CI | [−0.469, 0.093] CI |

**Table 13** continued

| $Q$ | Exogenous selection | | No assumption on selection | | MTS | | MTS & MIV | |
|---|---|---|---|---|---|---|---|---|
| | (1) AE | (2) No FP | (3) AE | (4) No FP | (5) AE | (6) No FP | (7) AE | (8) No FP |
| 0.02 | [−0.032, 0.108] p.e. | [−0.011, 0.108] p.e. | [−0.465, 0.575] p.e. | [−0.465, 0.575] p.e. | [−0.465, 0.108] p.e. | [−0.465, 0.108] p.e. | [−0.486, 0.101] p.e. | [−0.466, 0.101] p.e. |
| | [−0.063, 0.137] CI | [−0.037, 0.134] CI | [−0.476, 0.587] CI | [−0.476, 0.587] CI | [−0.476, 0.137] CI | [−0.476, 0.134] CI | [−0.499, 0.130] CI | [−0.479, 0.127] CI |
| 0.05 | [−0.178, 0.232] p.e. | [−0.081, 0.191] p.e. | [−0.495, 0.605] p.e. | [−0.495, 0.605] p.e. | [−0.495, 0.232] p.e. | [−0.495, 0.191] p.e. | [−0.541, 0.165] p.e. | [−0.496, 0.153] p.e. |
| | [−0.215, 0.267] CI | [−0.105, 0.216] CI | [−0.506, 0.617] CI | [−0.506, 0.617] CI | [−0.506, 0.267] CI | [−0.506, 0.216] CI | [−0.556, 0.225] CI | [−0.509, 0.203] CI |
| 0.10 | [−0.487, 0.595] p.e. | [−0.176, 0.307] p.e. | [−0.545, 0.655] p.e. | [−0.545, 0.655] p.e. | [−0.545, 0.595] p.e. | [−0.545, 0.307] p.e. | [−0.617, 0.302] p.e. | [−0.546, 0.242] p.e. |
| | [−0.499, 0.685] CI | [−0.198, 0.331] CI | [−0.556, 0.667] CI | [−0.556, 0.667] CI | [−0.556, 0.685] CI | [−0.556, 0.331] CI | [−0.631, 0.366] CI | [−0.559, 0.285] CI |

CI around ATE are calculated using methods from Imbens and Manski (2004) with 250 pseudosamples. Number of observations = 6,470 (rounded to nearest 10 per NCES restricted data regulations)

*p.e.* point estimates, *CI* confidence interval, *AE* arbitrary errors, *FP* false positives

**Table 14** Sharp bounds on alternative ATEs on child obesity status: ECLS-B

| *Q* | Exogenous selection | | No assumption on selection | | MTS | | MTS & MIV | |
|---|---|---|---|---|---|---|---|---|
| | (1) AE | (2) No FP | (3) AE | (4) No FP | (5) AE | (6) No FP | (7) AE | (8) No FP |
| *I. ATE of low or very low food secure versus marginally food secure or food secure* | | | | | | | | |
| 0.00 | [0.006, 0.006] p.e. | [0.006, 0.006] p.e. | [−0.276, 0.724] p.e. | [−0.276, 0.724] p.e. | [−0.276, 0.006] p.e. | [−0.276, 0.006] p.e. | [−0.277, −0.011] p.e. | [−0.277, −0.011] p.e. |
| | [−0.024, 0.045] CI | [−0.024, 0.045] CI | [−0.290, 0.738] CI | [−0.290, 0.738] CI | [−0.290, 0.045] CI | [−0.290, 0.045] CI | [−0.291, 0.016] CI | [−0.291, 0.016] CI |
| 0.01 | [−0.057, 0.064] p.e. | [−0.006, 0.064] p.e. | [−0.286, 0.734] p.e. | [−0.286, 0.734] p.e. | [−0.286, 0.064] p.e. | [−0.286, 0.064] p.e. | [−0.296, 0.060] p.e. | [−0.287, 0.060] p.e. |
| | [−0.088, 0.102] CI | [−0.035, 0.103] CI | [−0.300, 0.748] CI | [−0.300, 0.748] CI | [−0.300, 0.102] CI | [−0.300, 0.103] CI | [−0.308, 0.078] CI | [−0.301, 0.078] CI |
| 0.02 | [−0.129, 0.117] p.e. | [−0.017, 0.117] p.e. | [−0.296, 0.744] p.e. | [−0.296, 0.744] p.e. | [−0.296, 0.117] p.e. | [−0.296, 0.117] p.e. | [−0.312, 0.095] p.e. | [−0.297, 0.095] p.e. |
| | [−0.160, 0.155] CI | [−0.045, 0.155] CI | [−0.310, 0.758] CI | [−0.310, 0.758] CI | [−0.310, 0.155] CI | [−0.310, 0.155] CI | [−0.325, 0.122] CI | [−0.311, 0.122] CI |
| 0.05 | [−0.203, 0.253] p.e. | [−0.046, 0.253] p.e. | [−0.326, 0.774] p.e. | [−0.326, 0.774] p.e. | [−0.326, 0.253] p.e. | [−0.326, 0.253] p.e. | [−0.354, 0.182] p.e. | [−0.327, 0.182] p.e. |
| | [−0.216, 0.289] CI | [−0.072, 0.289] CI | [−0.340, 0.788] CI | [−0.340, 0.788] CI | [−0.340, 0.289] CI | [−0.340, 0.289] CI | [−0.366, 0.228] CI | [−0.341, 0.228] CI |
| 0.10 | [−0.215, 0.433] p.e. | [−0.084, 0.433] p.e. | [−0.376, 0.824] p.e. | [−0.376, 0.824] p.e. | [−0.376, 0.433] p.e. | [−0.376, 0.433] p.e. | [−0.405, 0.327] p.e. | [−0.377, 0.327] p.e. |
| | [−0.229, 0.464] CI | [−0.107, 0.464] CI | [−0.390, 0.838] CI | [−0.390, 0.838] CI | [−0.390, 0.464] CI | [−0.390, 0.464] CI | [−0.417, 0.373] CI | [−0.391, 0.373] CI |
| *II. ATE of marginally, low, or very low food secure versus food secure* | | | | | | | | |
| 0.00 | [0.004, 0.004] p.e. | [0.004, 0.004] p.e. | [−0.363, 0.637] p.e. | [−0.363, 0.637] p.e. | [−0.363, 0.004] p.e. | [−0.363, 0.004] p.e. | [−0.364, −0.013] p.e. | [−0.364, −0.013] p.e. |
| | [−0.019, 0.026] CI | [−0.019, 0.026] CI | [−0.375, 0.653] CI | [−0.375, 0.653] CI | [−0.375, 0.026] CI | [−0.375, 0.026] CI | [−0.381, 0.010] CI | [−0.381, 0.010] CI |
| 0.01 | [−0.036, 0.043] p.e. | [−0.004, 0.043] p.e. | [−0.373, 0.647] p.e. | [−0.373, 0.647] p.e. | [−0.373, 0.043] p.e. | [−0.373, 0.043] p.e. | [−0.384, 0.029] p.e. | [−0.374, 0.029] p.e. |
| | [−0.061, 0.065] CI | [−0.027, 0.065] CI | [−0.385, 0.663] CI | [−0.385, 0.663] CI | [−0.385, 0.065] CI | [−0.385, 0.065] CI | [−0.400, 0.053] CI | [−0.391, 0.053] CI |

**Table 14** continued

| Q | Exogenous selection | | No assumption on selection | | MTS | | MTS & MIV | |
|---|---|---|---|---|---|---|---|---|
| | (1) AE | (2) No FP | (3) AE | (4) No FP | (5) AE | (6) No FP | (7) AE | (8) No FP |
| 0.02 | [−0.079, 0.081] p.e. | [−0.012, 0.081] p.e. | [−0.383, 0.657] p.e. | [−0.383, 0.657] p.e. | [−0.383, 0.081] p.e. | [−0.383, 0.081] p.e. | [−0.402, 0.061] p.e. | [−0.384, 0.061] p.e. |
| | [−0.106, 0.102] CI | [−0.035, 0.103] CI | [−0.395, 0.673] CI | [−0.395, 0.673] CI | [−0.395, 0.102] CI | [−0.395, 0.103] CI | [−0.418, 0.091] CI | [−0.401, 0.091] CI |
| 0.05 | [−0.220, 0.187] p.e. | [−0.034, 0.187] p.e. | [−0.413, 0.687] p.e. | [−0.413, 0.687] p.e. | [−0.413, 0.187] p.e. | [−0.413, 0.187] p.e. | [−0.452, 0.159] p.e. | [−0.414, 0.159] p.e. |
| | [−0.233, 0.208] CI | [−0.056, 0.208] CI | [−0.425, 0.703] CI | [−0.425, 0.703] CI | [−0.425, 0.208] CI | [−0.425, 0.208] CI | [−0.468, 0.186] CI | [−0.431, 0.186] CI |
| 0.10 | [−0.242, 0.351] p.e. | [−0.068, 0.351] p.e. | [−0.463, 0.737] p.e. | [−0.463, 0.737] p.e. | [−0.463, 0.351] p.e. | [−0.463, 0.351] p.e. | [−0.515, 0.298] p.e. | [−0.464, 0.299] p.e. |
| | [−0.254, 0.370] CI | [−0.090, 0.370] CI | [−0.475, 0.753] CI | [−0.475, 0.753] CI | [−0.475, 0.370] CI | [−0.475, 0.370] CI | [−0.531, 0.332] CI | [−0.481, 0.332] CI |

CI around ATE are calculated using methods from Imbens and Manski (2004) with 250 pseudosamples. Number of observations = 4,100 (rounded to nearest 50 per NCES restricted data regulations)

*p.e.* point estimates, *CI* confidence interval, *AE* arbitrary errors, *FP* false positives

**Table 15** Sharp bounds on alternative ATEs on child overweight status: ECLS-B

| Q | Exogenous selection | | No assumption on selection | | MTS | | MTS & MIV | |
|---|---|---|---|---|---|---|---|---|
| | (1) AE | (2) No FP | (3) AE | (4) No FP | (5) AE | (6) No FP | (7) AE | (8) No FP |
| *I. ATE of low or very low food secure versus marginally food secure or food secure* | | | | | | | | |
| 0.00 | [−0.006, −0.006] p.e. | [−0.006, −0.006] p.e. | [−0.398, 0.602] p.e. | [−0.398, 0.602] p.e. | [−0.398, −0.006] p.e. | [−0.398, −0.006] p.e. | [−0.397, −0.016] p.e. | [−0.397, −0.016] p.e. |
| | [−0.054, 0.028] CI | [−0.054, 0.028] CI | [−0.417, 0.616] CI | [−0.417, 0.616] CI | [−0.417, 0.028] CI | [−0.417, 0.028] CI | [−0.409, 0.011] CI | [−0.409, 0.011] CI |
| 0.01 | [−0.057, 0.040] p.e. | [−0.030, 0.040] p.e. | [−0.408, 0.612] p.e. | [−0.408, 0.612] p.e. | [−0.408, 0.040] p.e. | [−0.408, 0.040] p.e. | [−0.418, 0.022] p.e. | [−0.407, 0.022] p.e. |
| | [−0.105, 0.074] CI | [−0.075, 0.074] CI | [−0.427, 0.626] CI | [−0.427, 0.626] CI | [−0.427, 0.074] CI | [−0.427, 0.074] CI | [−0.429, 0.069] CI | [−0.419, 0.069] CI |
| 0.02 | [−0.114, 0.082] p.e. | [−0.052, 0.082] p.e. | [−0.418, 0.622] p.e. | [−0.418, 0.622] p.e. | [−0.418, 0.082] p.e. | [−0.418, 0.082] p.e. | [−0.436, 0.058] p.e. | [−0.417, 0.058] p.e. |
| | [−0.165, 0.115] CI | [−0.094, 0.115] CI | [−0.437, 0.636] CI | [−0.437, 0.636] CI | [−0.437, 0.115] CI | [−0.437, 0.115] CI | [−0.450, 0.094] CI | [−0.429, 0.094] CI |
| 0.05 | [−0.337, 0.191] p.e. | [−0.109, 0.191] p.e. | [−0.448, 0.652] p.e. | [−0.448, 0.652] p.e. | [−0.448, 0.191] p.e. | [−0.448, 0.191] p.e. | [−0.484, 0.164] p.e. | [−0.447, 0.164] p.e. |
| | [−0.389, 0.221] CI | [−0.144, 0.221] CI | [−0.467, 0.666] CI | [−0.467, 0.666] CI | [−0.467, 0.221] CI | [−0.467, 0.221] CI | [−0.499, 0.187] CI | [−0.459, 0.188] CI |
| 0.10 | [−0.406, 0.581] p.e. | [−0.183, 0.334] p.e. | [−0.498, 0.702] p.e. | [−0.498, 0.702] p.e. | [−0.498, 0.581] p.e. | [−0.498, 0.334] p.e. | [−0.550, 0.285] p.e. | [−0.497, 0.268] p.e. |
| | [−0.423, 0.770] CI | [−0.213, 0.362] CI | [−0.517, 0.716] CI | [−0.517, 0.716] CI | [−0.517, 0.770] CI | [−0.517, 0.362] CI | [−0.562, 0.380] CI | [−0.509, 0.309] CI |
| *II. ATE of marginally, low, or very low food secure versus food secure* | | | | | | | | |
| 0.00 | [−0.004, −0.004] p.e. | [−0.004, −0.004] p.e. | [−0.438, 0.562] p.e. | [−0.438, 0.562] p.e. | [−0.438, −0.004] p.e. | [−0.438, −0.004] p.e. | [−0.439, −0.024] p.e. | [−0.439, −0.024] p.e. |
| | [−0.034, 0.021] CI | [−0.034, 0.021] CI | [−0.453, 0.575] CI | [−0.453, 0.575] CI | [−0.453, 0.021] CI | [−0.453, 0.021] CI | [−0.453, 0.010] CI | [−0.453, 0.010] CI |
| 0.01 | [−0.036, 0.027] p.e. | [−0.020, 0.027] p.e. | [−0.448, 0.572] p.e. | [−0.448, 0.572] p.e. | [−0.448, 0.027] p.e. | [−0.448, 0.027] p.e. | [−0.459, 0.002] p.e. | [−0.449, 0.002] p.e. |
| | [−0.068, 0.051] CI | [−0.050, 0.051] CI | [−0.463, 0.585] CI | [−0.463, 0.585] CI | [−0.463, 0.051] CI | [−0.463, 0.051] CI | [−0.473, 0.036] CI | [−0.463, 0.036] CI |

**Table 15** continued

| $Q$ | Exogenous selection | | No assumption on selection | | MTS | | MTS & MIV | |
|---|---|---|---|---|---|---|---|---|
| | (1) AE | (2) No FP | (3) AE | (4) No FP | (5) AE | (6) No FP | (7) AE | (8) No FP |
| 0.02 | [−0.070, 0.057] p.e. | [−0.036, 0.057] p.e. | [−0.458, 0.582] p.e. | [−0.458, 0.582] p.e. | [−0.458, 0.057] p.e. | [−0.458, 0.057] p.e. | [−0.479, 0.028] p.e. | [−0.459, 0.028] p.e. |
| | [−0.104, 0.081] CI | [−0.065, 0.081] CI | [−0.473, 0.595] CI | [−0.473, 0.595] CI | [−0.473, 0.081] CI | [−0.473, 0.081] CI | [−0.493, 0.070] CI | [−0.473, 0.070] CI |
| 0.05 | [−0.181, 0.141] p.e. | [−0.080, 0.141] p.e. | [−0.488, 0.612] p.e. | [−0.488, 0.612] p.e. | [−0.488, 0.141] p.e. | [−0.488, 0.141] p.e. | [−0.535, 0.106] p.e. | [−0.489, 0.106] p.e. |
| | [−0.219, 0.164] CI | [−0.107, 0.164] CI | [−0.503, 0.625] CI | [−0.503, 0.625] CI | [−0.503, 0.164] CI | [−0.503, 0.164] CI | [−0.551, 0.141] CI | [−0.503, 0.141] CI |
| 0.10 | [−0.423, 0.270] p.e. | [−0.148, 0.270] p.e. | [−0.538, 0.662] p.e. | [−0.538, 0.662] p.e. | [−0.538, 0.270] p.e. | [−0.538, 0.270] p.e. | [−0.617, 0.230] p.e. | [−0.539, 0.230] p.e. |
| | [−0.438, 0.295] CI | [−0.173, 0.295] CI | [−0.553, 0.675] CI | [−0.553, 0.675] CI | [−0.553, 0.295] CI | [−0.553, 0.295] CI | [−0.631, 0.257] CI | [−0.553, 0.255] CI |

CI around ATE are calculated using methods from Imbens and Manski (2004) with 250 pseudosamples. Number of observations = 4,100 (rounded to nearest 50 per NCES restricted data regulations)

*p.e.* point estimates, *CI* confidence interval, *AE* arbitrary errors, *FP* false positives

**Table 16** Sharp bounds on the ATE of low or very food security with alternative control group: ECLS-K

| Q | Exogenous selection | | No assumption on selection | | MTS | | MTS & MIV | |
|---|---|---|---|---|---|---|---|---|
| | (1) AE | (2) No FP | (3) AE | (4) No FP | (5) AE | (6) No FP | (7) AE | (8) No FP |
| *I. Obesity* | | | | | | | | |
| 0.00 | [0.026, 0.026] p.e. | [0.026, 0.026] p.e. | [−0.290, 0.710] p.e. | [−0.290, 0.710] p.e. | [−0.290, 0.026] p.e. | [−0.290, 0.026] p.e. | [−0.290, −0.004] p.e. | [−0.290, −0.004] p.e. |
| | [−0.007, 0.058] CI | [−0.007, 0.058] CI | [−0.302, 0.723] CI | [−0.302, 0.723] CI | [−0.302, 0.058] CI | [−0.302, 0.058] CI | [−0.305, 0.029] CI | [−0.305, 0.029] CI |
| 0.01 | [−0.056, 0.097] p.e. | [0.002, 0.097] p.e. | [−0.300, 0.720] p.e. | [−0.300, 0.720] p.e. | [−0.300, 0.097] p.e. | [−0.300, 0.097] p.e. | [−0.310, 0.061] p.e. | [−0.300, 0.061] p.e. |
| | [−0.096, 0.128] CI | [−0.029, 0.128] CI | [−0.312, 0.733] CI | [−0.312, 0.733] CI | [−0.312, 0.128] CI | [−0.312, 0.128] CI | [−0.325, 0.081] CI | [−0.315, 0.081] CI |
| 0.02 | [−0.155, 0.158] p.e. | [−0.019, 0.158] p.e. | [−0.310, 0.730] p.e. | [−0.310, 0.730] p.e. | [−0.310, 0.158] p.e. | [−0.310, 0.158] p.e. | [−0.325, 0.085] p.e. | [−0.310, 0.085] p.e. |
| | [−0.202, 0.188] CI | [−0.048, 0.189] CI | [−0.322, 0.743] CI | [−0.322, 0.743] CI | [−0.322, 0.188] CI | [−0.322, 0.189] CI | [−0.342, 0.122] CI | [−0.325, 0.122] CI |
| 0.05 | [−0.265, 0.304] p.e. | [−0.069, 0.304] p.e. | [−0.340, 0.760] p.e. | [−0.340, 0.760] p.e. | [−0.340, 0.304] p.e. | [−0.340, 0.304] p.e. | [−0.364, 0.176] p.e. | [−0.340, 0.176] p.e. |
| | [−0.279, 0.333] CI | [−0.093, 0.333] CI | [−0.352, 0.773] CI | [−0.352, 0.773] CI | [−0.352, 0.333] CI | [−0.352, 0.333] CI | [−0.383, 0.202] CI | [−0.355, 0.202] CI |
| 0.10 | [−0.280, 1.000] p.e. | [−0.128, 0.476] p.e. | [−0.390, 0.810] p.e. | [−0.390, 0.810] p.e. | [−0.390, 1.000] p.e. | [−0.390, 0.476] p.e. | [−0.418, 0.312] p.e. | [−0.390, 0.312] p.e. |
| | [−0.295, 1.000] CI | [−0.148, 0.502] CI | [−0.402, 0.823] CI | [−0.402, 0.823] CI | [−0.402, 1.000] CI | [−0.402, 0.502] CI | [−0.435, 0.333] CI | [−0.405, 0.335] CI |
| *II. Overweight* | | | | | | | | |
| 0.00 | [0.021, 0.021] p.e. | [0.021, 0.021] p.e. | [−0.438, 0.562] p.e. | [−0.438, 0.562] p.e. | [−0.438, 0.021] p.e. | [−0.438, 0.021] p.e. | [−0.438, 0.014] p.e. | [−0.438, 0.014] p.e. |
| | [−0.018, 0.069] CI | [−0.018, 0.069] CI | [−0.450, 0.575] CI | [−0.450, 0.575] CI | [−0.450, 0.069] CI | [−0.450, 0.069] CI | [−0.450, 0.050] CI | [−0.450, 0.050] CI |
| 0.01 | [−0.041, 0.074] p.e. | [−0.021, 0.074] p.e. | [−0.448, 0.572] p.e. | [−0.448, 0.572] p.e. | [−0.448, 0.074] p.e. | [−0.448, 0.074] p.e. | [−0.458, 0.052] p.e. | [−0.448, 0.052] p.e. |
| | [−0.086, 0.122] CI | [−0.060, 0.118] CI | [−0.460, 0.585] CI | [−0.460, 0.585] CI | [−0.460, 0.122] CI | [−0.460, 0.118] CI | [−0.470, 0.095] CI | [−0.460, 0.096] CI |

**Table 16** continued

| Q | Exogenous selection | | No assumption on selection | | MTS | | MTS & MIV | |
|---|---|---|---|---|---|---|---|---|
| | (1) AE | (2) No FP | (3) AE | (4) No FP | (5) AE | (6) No FP | (7) AE | (8) No FP |
| 0.02 | [−0.115, 0.130] p.e. | [−0.057, 0.120] p.e. | [−0.458, 0.582] p.e. | [−0.458, 0.582] p.e. | [−0.458, 0.130] p.e. | [−0.458, 0.120] p.e. | [−0.477, 0.068] p.e. | [−0.458, 0.069] p.e. |
| | [−0.164, 0.186] CI | [−0.095, 0.160] CI | [−0.470, 0.595] CI | [−0.470, 0.595] CI | [−0.470, 0.186] CI | [−0.470, 0.160] CI | [−0.489, 0.137] CI | [−0.470, 0.126] CI |
| 0.05 | [−0.451, 0.418] p.e. | [−0.143, 0.230] p.e. | [−0.488, 0.612] p.e. | [−0.488, 0.612] p.e. | [−0.488, 0.418] p.e. | [−0.488, 0.230] p.e. | [−0.523, 0.148] p.e. | [−0.488, 0.136] p.e. |
| | [−0.463, 0.506] CI | [−0.176, 0.261] CI | [−0.500, 0.625] CI | [−0.500, 0.625] CI | [−0.500, 0.506] CI | [−0.500, 0.261] CI | [−0.535, 0.235] CI | [−0.500, 0.186] CI |
| 0.10 | [−0.478, 1.000] p.e. | [−0.244, 0.359] p.e. | [−0.538, 0.662] p.e. | [−0.538, 0.662] p.e. | [−0.538, 1.000] p.e. | [−0.538, 0.359] p.e. | [−0.583, 0.343] p.e. | [−0.538, 0.238] p.e. |
| | [−0.490, 1.000] CI | [−0.272, 0.386] CI | [−0.550, 0.675] CI | [−0.550, 0.675] CI | [−0.550, 1.000] CI | [−0.550, 0.386] CI | [−0.594, 0.458] CI | [−0.550, 0.286] CI |

Control group includes only food secure households. CI around ATE are calculated using methods from Imbens and Manski (2004) with 250 pseudosamples. Number of observations = 5,870 (rounded to nearest 10 per NCES restricted data regulations)

*p.e.* point estimates, *CI* confidence interval, *AE* arbitrary errors, *FP* false positives

**Table 17** Sharp bounds on the ATE of low or very low food security with alternative control group: ECLS-B

| *Q* | Exogenous selection | | No assumption on selection | | MTS | | MTS & MIV | |
|---|---|---|---|---|---|---|---|---|
| | (1) AE | (2) No FP | (3) AE | (4) No FP | (5) AE | (6) No FP | (7) AE | (8) No FP |
| *I. Obesity* | | | | | | | | |
| 0.00 | [0.007, 0.007] p.e. | [0.007, 0.007] p.e. | [−0.292, 0.708] p.e. | [−0.292, 0.708] p.e. | [−0.292, 0.007] p.e. | [−0.292, 0.007] p.e. | [−0.292, −0.026] p.e. | [−0.292, −0.026] p.e. |
| | [−0.022, 0.033] CI | [−0.022, 0.033] CI | [−0.307, 0.720] CI | [−0.307, 0.720] CI | [−0.307, 0.033] CI | [−0.307, 0.033] CI | [−0.308, 0.014] CI | [−0.308, 0.014] CI |
| 0.01 | [−0.050, 0.059] p.e. | [−0.005, 0.059] p.e. | [−0.302, 0.718] p.e. | [−0.302, 0.718] p.e. | [−0.302, 0.059] p.e. | [−0.302, 0.059] p.e. | [−0.312, 0.015] p.e. | [−0.302, 0.015] p.e. |
| | [−0.081, 0.084] CI | [−0.032, 0.084] CI | [−0.317, 0.730] CI | [−0.317, 0.730] CI | [−0.317, 0.084] CI | [−0.317, 0.084] CI | [−0.327, 0.057] CI | [−0.318, 0.057] CI |
| 0.02 | [−0.112, 0.107] p.e. | [−0.015, 0.107] p.e. | [−0.312, 0.728] p.e. | [−0.312, 0.728] p.e. | [−0.312, 0.107] p.e. | [−0.312, 0.107] p.e. | [−0.328, 0.060] p.e. | [−0.312, 0.060] p.e. |
| | [−0.145, 0.132] CI | [−0.041, 0.132] CI | [−0.327, 0.740] CI | [−0.327, 0.740] CI | [−0.327, 0.132] CI | [−0.327, 0.132] CI | [−0.342, 0.098] CI | [−0.328, 0.098] CI |
| 0.05 | [−0.206, 0.235] p.e. | [−0.042, 0.235] p.e. | [−0.342, 0.758] p.e. | [−0.342, 0.758] p.e. | [−0.342, 0.235] p.e. | [−0.342, 0.235] p.e. | [−0.370, 0.162] p.e. | [−0.342, 0.162] p.e. |
| | [−0.218, 0.258] CI | [−0.066, 0.258] CI | [−0.357, 0.770] CI | [−0.357, 0.770] CI | [−0.357, 0.258] CI | [−0.357, 0.258] CI | [−0.384, 0.185] CI | [−0.358, 0.185] CI |
| 0.10 | [−0.219, 0.410] p.e. | [−0.079, 0.410] p.e. | [−0.392, 0.808] p.e. | [−0.392, 0.808] p.e. | [−0.392, 0.410] p.e. | [−0.392, 0.410] p.e. | [−0.425, 0.299] p.e. | [−0.392, 0.299] p.e. |
| | [−0.232, 0.432] CI | [−0.101, 0.432] CI | [−0.407, 0.820] CI | [−0.407, 0.820] CI | [−0.407, 0.432] CI | [−0.407, 0.432] CI | [−0.441, 0.326] CI | [−0.408, 0.326] CI |
| *II. Overweight* | | | | | | | | |
| 0.00 | [−0.006, −0.006] p.e. | [−0.006, −0.006] p.e. | [−0.405, 0.595] p.e. | [−0.405, 0.595] p.e. | [−0.405, −0.006] p.e. | [−0.405, −0.006] p.e. | [−0.405, −0.056] p.e. | [−0.405, −0.056] p.e. |
| | [−0.044, 0.042] CI | [−0.044, 0.042] CI | [−0.422, 0.611] CI | [−0.422, 0.611] CI | [−0.422, 0.042] CI | [−0.422, 0.042] CI | [−0.422, 0.004] CI | [−0.422, 0.004] CI |
| 0.01 | [−0.051, 0.035] p.e. | [−0.028, 0.035] p.e. | [−0.415, 0.605] p.e. | [−0.415, 0.605] p.e. | [−0.415, 0.035] p.e. | [−0.415, 0.035] p.e. | [−0.425, −0.020] p.e. | [−0.415, −0.020] p.e. |
| | [−0.090, 0.082] CI | [−0.062, 0.082] CI | [−0.432, 0.621] CI | [−0.432, 0.621] CI | [−0.432, 0.082] CI | [−0.432, 0.082] CI | [−0.441, 0.046] CI | [−0.432, 0.046] CI |

**Table 17** continued

| Q | Exogenous selection | | No assumption on selection | | MTS | | MTS & MIV | |
|---|---|---|---|---|---|---|---|---|
| | (1) AE | (2) No FP | (3) AE | (4) No FP | (5) AE | (6) No FP | (7) AE | (8) No FP |
| 0.02 | [−0.101, 0.074] p.e. | [−0.048, 0.074] p.e. | [−0.425, 0.615] p.e. | [−0.425, 0.615] p.e. | [−0.425, 0.074] p.e. | [−0.425, 0.074] p.e. | [−0.444, 0.016] p.e. | [−0.425, 0.016] p.e. |
| | [−0.143, 0.120] CI | [−0.082, 0.120] CI | [−0.442, 0.631] CI | [−0.442, 0.631] CI | [−0.442, 0.120] CI | [−0.442, 0.120] CI | [−0.460, 0.071] CI | [−0.442, 0.071] CI |
| 0.05 | [−0.285, 0.176] p.e. | [−0.101, 0.176] p.e. | [−0.455, 0.645] p.e. | [−0.455, 0.645] p.e. | [−0.455, 0.176] p.e. | [−0.455, 0.176] p.e. | [−0.491, 0.115] p.e. | [−0.455, 0.115] p.e. |
| | [−0.345, 0.219] CI | [−0.133, 0.219] CI | [−0.472, 0.661] CI | [−0.472, 0.661] CI | [−0.472, 0.219] CI | [−0.472, 0.219] CI | [−0.506, 0.166] CI | [−0.472, 0.166] CI |
| 0.10 | [−0.410, 0.425] p.e. | [−0.174, 0.315] p.e. | [−0.505, 0.695] p.e. | [−0.505, 0.695] p.e. | [−0.505, 0.425] p.e. | [−0.505, 0.315] p.e. | [−0.561, 0.241] p.e. | [−0.505, 0.246] p.e. |
| | [−0.428, 0.574] CI | [−0.206, 0.353] CI | [−0.522, 0.711] CI | [−0.522, 0.711] CI | [−0.522, 0.574] CI | [−0.522, 0.353] CI | [−0.574, 0.323] CI | [−0.522, 0.287] CI |

Control group includes only food secure households. CI around ATE are calculated using methods from Imbens and Manski (2004) with 250 pseudosamples. Number of observations = 3,550 (rounded to nearest 50 per NCES restricted data regulations)

*p.e.* point estimates, *CI* confidence interval, *AE* arbitrary errors, *FP* false positives

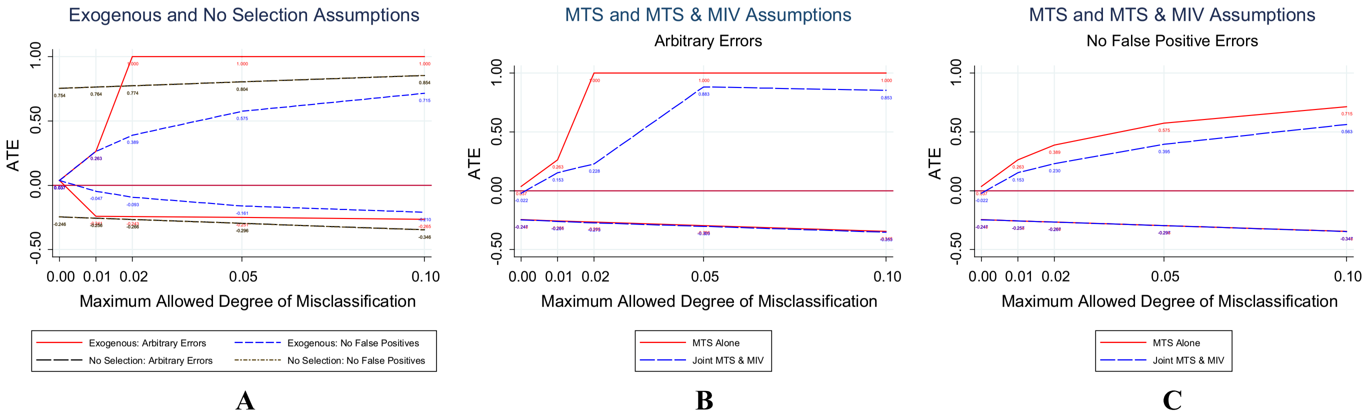


**Fig. 5** Sharp bounds on the ATE of very low food security on child obesity status with alternative control group: ECLS-K. **a** Exogenous selection or no assumption. **b** Only MTS or MTS-MIV: AE. **c** Only MTS or MTS-MIV: no FP. Notes: *AE* arbitrary errors; *FP* false positives

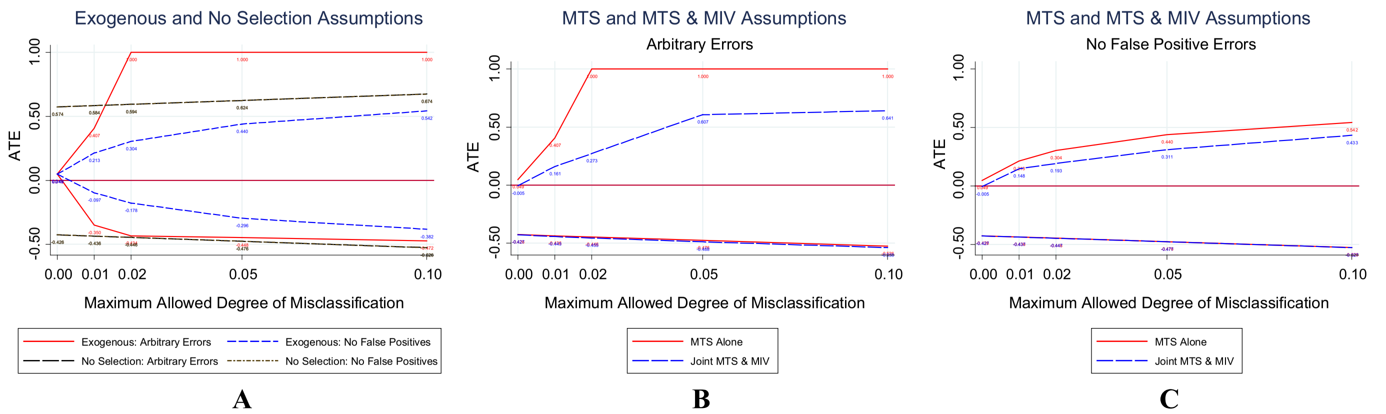


**Fig. 6** Sharp bounds on the ATE of very low food security on child overweight status with alternative control group: ECLS-K. **a** Exogenous selection or no assumption. **b** Only MTS or MTS-MIV: AE. **c** Only MTS or MTS-MIV: no FP. Notes: *AE* arbitrary errors, *FP* false positives

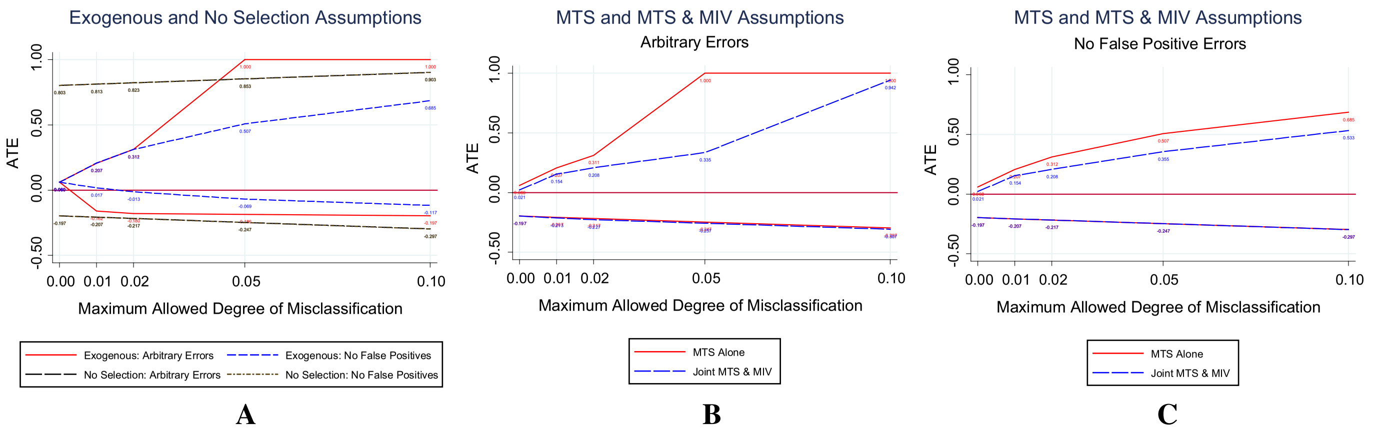


**Fig. 7** Sharp bounds on the ATE of very low food security on child obesity status with alternative control group: ECLS-B. **a** Exogenous selection or no assumption. **b** Only MTS or MTS-MIV: AE. **c** Only MTS or MTS-MIV: no FP. Notes: *AE* arbitrary errors, *FP* false positives

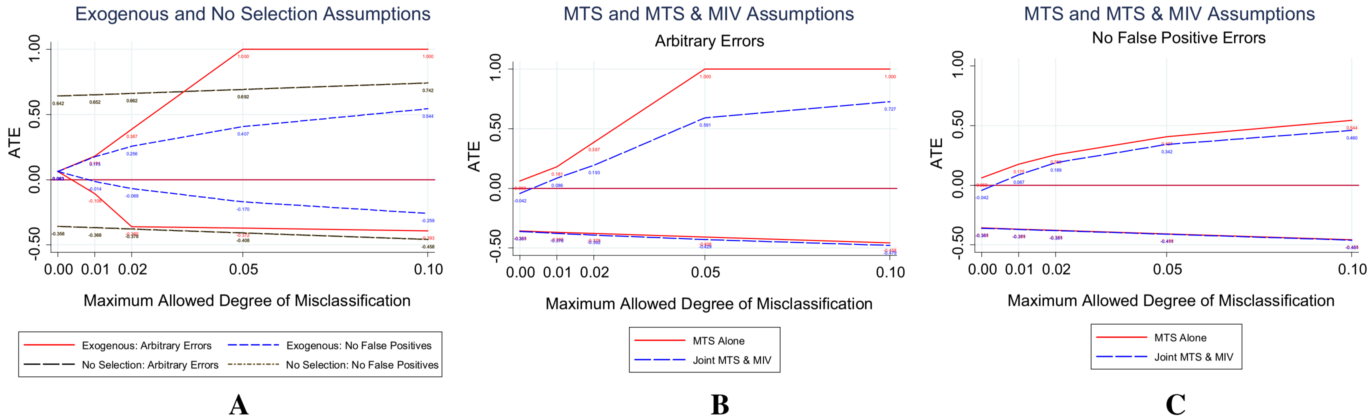


**Fig. 8** Sharp bounds on the ATE of very low food security on child overweight status with alternative control group: ECLS-B. **a** Exogenous selection or no assumption. **b** Only MTS or MTS-MIV: AE. **c** Only MTS or MTS-MIV: no FP. Notes: *AE* arbitrary errors, *FP* false positives

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