9-2009

Bounding the effects of food insecurity on children's health outcomes

Craig Gundersen
University of Illinois

Brent Kreider
Iowa State University, bkreider@iastate.edu

Bounding the effects of food insecurity on children's health outcomes

Abstract
Previous research has estimated that food insecure children are more likely to suffer from a wide array of negative health outcomes than food secure children, leading many to claim that alleviating food insecurity would lead to better health outcomes. Identifying the causal impacts is problematic, however, given endogenous selection into food security status and potential mismeasurement of true food security status. Using recently developed nonparametric bounding methods and data from the 2001-2006 National Health and Nutritional Examination Survey (NHANES), we assess what can be identified about the effects of food insecurity on child health outcomes in the presence of nonrandom selection and nonclassical measurement error. Under relatively weak monotonicity assumptions, we can identify that food security has a statistically significant positive impact on good general health and being a healthy weight. Our work suggests that previous research has more likely underestimated than overestimated the causal impacts of food insecurity on health.

Keywords
food insecurity, health outcomes, nonclassical measurement error, nonparametric bounds, average treatment effect

Bounding the Effects of Food Insecurity on Children's Health Outcomes*

Craig Gundersen

University of Illinois

cggunder@illinois.edu

Brent Kreider

Iowa State University

bkreider@iastate.edu

June 2009

Abstract. Previous research has estimated that food insecure children are more likely to suffer from a wide array of negative health outcomes than food secure children, leading many to claim that alleviating food insecurity would lead to better health outcomes. Identifying the causal impacts is problematic, however, given endogenous selection into food security status and potential mismeasurement of true food security status. Using recently developed nonparametric bounding methods and data from the 2001-2006 National Health and Nutritional Examination Survey (NHANES), we assess what can be identified about the effects of food insecurity on child health outcomes in the presence of nonrandom selection and nonclassical measurement error. Under relatively weak monotonicity assumptions, we can identify that food security has a statistically significant positive impact on good general health and being a healthy weight. Our work suggests that previous research has more likely underestimated than overestimated the causal impacts of food insecurity on health.

Keywords: food insecurity; health outcomes; nonclassical measurement error; nonparametric bounds; average treatment effect

JEL classification: I32, I12

*This research is funded through a RIDGE grant from the Economic Research Service, U.S. Department of Agriculture and the Harris School, University of Chicago. The views expressed in this paper are solely those of the authors. Previous versions of this paper were presented at the ERS/Harris School RIDGE Workshop, the RIDGE Conference, the Annual Meetings of the Association for Public Policy Analysis and Management, and the University of Illinois. The authors thank attendees at those venues, especially Tom DeLeire, and an anonymous referee for very helpful comments. Brandie Ward provided excellent research assistance.

1 Introduction

Positive associations between food insecurity and poor health outcomes among children have been widely documented. Previous research, spanning numerous academic studies, has found that children in households suffering from food insecurity are more likely to have poor health (Cook et al., 2004; Weinreb et al., 2002; Dunifon and Kowaleski-Jones, 2003), psychosocial problems (Kleinman et al., 1998; Weinreb et al., 2002; Murphy et al., 1998), frequent stomachaches and headaches (Alaimo et al., 2001a), increased odds of being hospitalized (Cook et al., 2004), greater propensities to have seen a psychologist (Alaimo et al., 2001a), behavior problems (Slack and Yoo, 2005; Whitaker et al., 2006), worse developmental outcomes (Jyoti et al., 2005; Rose-Jacobs et al., 2008), more chronic illnesses (Weinreb et al., 2002), impaired functioning (Murphy et al., 1998), impaired mental proficiency (Zaslow et al., 2008), and higher levels of iron deficiency with anemia (Skalicky et al., 2006). Perhaps paradoxically, food insecurity has also been associated with higher propensities to be obese (Casey et al., 2001; Casey et al., 2006; Dubois et al., 2006; Jyoti et al., 2005). These consistently negative health findings emerge from a variety of data sources, employ a variety of statistical techniques, and appear to be robust to different measures of food insecurity.

Based on this evidence, most authors conclude that efforts to reduce food insecurity would lead to improvements in these health outcomes. That is, if children in food insecure households were to become food secure, they would be expected to achieve health outcomes like those in observationally similar food secure households. The central vehicle for helping alleviate food insecurity among children is the Food Stamp Program, now called the Supplemental Nutrition Assistance Program (SNAP) (U.S. Department of Agriculture, Food and Nutrition Service, p.7). This program directly augments a household's resources available for purchasing food. Prior research has suggested that SNAP leads to reductions in food insecurity (e.g., Gundersen and Oliveira, 2001). Other policies, such as the Earned Income Tax Credit (EITC) and educational programs to assist families with food budgeting, may indirectly alleviate food insecurity. More generally, any program that expands a low-income household's budget opportunities may lead to less food insecurity.

Irrespective of how policymakers pursue these improvements, the general conclusion that efforts to reduce food insecurity would lead to improvements in health outcomes is tenuous for two main reasons. First, food insecurity is not randomly distributed among the population. Even after controlling for characteristics that can be observed in the data, there may remain important unobserved factors that lead some children to be simultaneously at higher risk of being food insecure and of being in poor health. Due to these unobserved influences, a policy prescription that would alleviate food insecurity among these children, even if worthwhile on other grounds, might not lead to the predicted improvements in health status.

Second, this literature presumes that food insecurity is accurately measured in household surveys. However, food insecurity status may be mismeasured for a variety of reasons. Food insecurity is partially subjective, and there may be divergences between how experts and various households interpret the survey questions (Gundersen and Ribar, 2004). Even if food insecurity were objectively defined, some parents might misreport being food secure if they feel ashamed about heading a household in which their children are not getting enough food to eat (Hamelin et al., 2002). Alternatively, some households might misreport being food insecure if they believe that reporting otherwise could jeopardize their eligibility for an assistance program – especially one that provides food assistance, like SNAP. More generally, validation studies consistently reveal large degrees of response error in popular surveys, even for variables thought to be relatively objective. In an important survey of the causes and consequences of measurement error, Bound et al. (2001) conclude that response error constitutes a serious problem for applied econometric work across a wide range of topics. Moreover, they find little reason to believe that such errors tend to occur randomly. Instead, they provide evidence that response errors tend to be correlated with the underlying variable of interest and common socioeconomic attributes. Consistent with this concern, Black et al. (2003) find that more than a third of respondents to the U.S. Census reporting a professional degree have no such degree, with widely varying patterns of false positive and false negative reports across demographic groups. *A priori*, there seems to be good reason to consider the consequences of at least some small degree of misclassification in food insecurity responses. Even small degrees of classification error can lead to large degrees of uncertainty for inferences.[1]

In this paper, we reconsider what can be learned about the effects of food security on child health outcomes when formally accounting for the uncertainty created by unobserved counterfactuals and

[1]In a regression setting, Kreider (forthcoming) finds that health insurance misclassification rates of less than 1.3 percent are sufficient to generate double-digit percentage point ranges of uncertainty about the variable's true marginal effect on the probability of using health services in a month.

questions about the reliability of self-reported food insecurity status. In the absence of strong (and untestable) assumptions on counterfactual outcomes and the reporting error process, we cannot fully identify the impact of food security on health. Nevertheless, we can provide informative bounds on these impacts using relatively weak nonparametric assumptions. Our analysis applies and extends recent partial identification bounding methods that allow researchers to consider relatively weak nonparametric assumptions (see, e.g., Manski, 1995; Molinari, 2008 and forthcoming; Kreider and Pepper, 2007; Gundersen and Kreider, 2008; Kreider and Hill, 2009; and Kreider et al., 2009). Using these methods, coupled with data from the 2001-2006 National Health and Nutrition Examination Survey (NHANES), we assess the impact of food insecurity on the health of children. We focus on two key measures studied in previous work: a child's general health status and obesity status.

In the next section, we describe the central variables of interest in this paper – food insecurity, general health outcomes, and obesity – followed by a description of the 2001-2006 NHANES. In Section 3, we highlight the statistical identification problems created by selection issues and the potential unreliability of self-reported food insecurity. We then show how the average treatment effects of interest can be partially identified under various assumptions about the classification error and selection processes. Section 4 presents our empirical results, and Section 5 concludes.

2 Concepts and Data

2.1 Food Insecurity

The extent of food insecurity in the United States has become a well-publicized issue of concern to policymakers and program administrators. In 2007, 11.1% of the U.S. population reported that they suffered from food insecurity at some time during the previous year (Nord et al., 2008). These households were uncertain of having, or unable to acquire, enough food for all their members because they had insufficient money or other resources. For about 4.1% of the population, the degree of food insecurity was severe enough to be recorded as very low food security. For households with children, the reported levels were higher: 15.8% and 4.7%, respectively. As with other determinants of health status (e.g., having health insurance), food insecurity status depends on the ability to afford adequate amounts of food. In 2007, households with incomes below 185% of the poverty line had food insecurity rates over five times higher than those with incomes below this threshold

(Nord et al., 2008; Table 2). Food insecurity is often related to nonpecuniary factors as well, such as financial management skills and nutrition knowledge.

These official food insecurity rates, defined over a 12 month period, are calculated based on households' responses to a series of 18 questions posed in the Core Food Security Module (CFSM) for families with children.[2] Each question is designed to capture some aspect of food insecurity and, for some questions, the frequency with which it manifests itself. Examples include "I worried whether our food would run out before we got money to buy more" (the least severe outcome); "Did you or the other adults in your household ever cut the size of your meals or skip meals because there wasn't enough money for food?" and "Did a child in the household ever not eat for a full day because you couldn't afford enough food?" (the most severe outcome). A complete listing of the food insecurity questions is presented in Table 1.[3] Following official definitions, we classify a household with children as food insecure if it responds affirmatively to three or more questions in the CFSM; otherwise, it classified as food secure. We also consider two other measures of food insecurity, both detailed in the annual report on food insecurity in the United States (Nord et al., 2008). The first classifies a household as food insecure with hunger (called "very low food security" since 2006) if it responds affirmatively to eight or more of the questions. The second classifies a household as marginally food secure (or at risk of food insecurity) if it responds affirmatively to at least one question. Our primary analysis employs the standard food insecurity measure, but we consider the other two thresholds in ancillary sensitivity analysis.

Central to this paper is the possibility that food insecurity is mismeasured in household surveys. Beyond the issues raised above, Gundersen and Kreider (2008) provide evidence that some households do not answer the CFSM questions consistently. They exploit the ordered nature of the food insecurity questions and find at least one inconsistency for 6.1% of the sample.[4] Of course, the presence or absence of such inconsistencies cannot by itself determine the reliability of a household's aggregate food insecurity classification. The presence of inconsistencies is not necessarily pivotal in determining the aggregate classification, and food insecurity can be misclassified even if the house-

[2] For families without children and for one-person households, a subset of 10 questions are posed.

[3] Responses to individual questions from the CFSM are suppressed for confidentiality reasons in the NHANES. To see prevalence rates for a similar sample from the Current Population Survey, see Gundersen and Kreider (2008).

[4] For example, it would be expected that if a household responded affirmatively to "Child skipped meal due to lack of money" (item 16 in Table 1), the respondent should also respond affirmatively to "Child was hungry" (item 14) and to "Child not eating enough" (item 9).

hold always reports consistently. Still, the significant fraction of inconsistencies provides one source of concern even prior to considering the other aforementioned sources of potential measurement error.

2.2 Health Outcomes

2.2.1 Childhood Obesity

Approximately 17.1% of children in the U.S. between the ages of 2 and 19 years are classified as obese, and another 16.5% are overweight (Ogden et al., 2006). This prevalence has increased threefold for children since 1970 (Wang and Zhang, 2006). Childhood obesity is thought to have negative physical, psychological, and social consequences that have current and future implications (e.g., Schwimmer et al., 2003; Carroll et al., 2007; Bender et al., 2007; Nguyen et al., 2007) including reduced life expectancy (Fontaine et al., 2003). As such, childhood obesity is of great interest to policymakers.

The research on the relationship between food insecurity and childhood obesity is mixed. Some have found a positive relationship (Dubois et al., 2006; Casey et al., 2001; Jyoti et al., 2005; Casey et al. 2006), others have found no relationship (Alaimo et al., 2001b; Kaiser et al., 2002; Martin and Ferris, 2007; Gundersen et al., 2008; Bhargava et al., 2008; Gundersen et al., 2009), and others have found a negative relationship (Jimenez-Cruz et al., 2003; Rose and Bodor, 2006; Matheson et al., 2002). This work has used a variety of data sets and methods. In common to these papers is an assumption that reports of food insecurity are classified accurately.

In this paper, we divide childhood weight status into two categories: (1) healthy weight and (2) overweight or obese.[5] A child is in the former category if his or her body mass index (BMI) (kg/m^2) falls below the $85th$ percentile for age and gender and in the latter category otherwise. These percentiles were established by the Centers for Disease Control and Prevention (CDC). In ancillary analyses we compare children who are obese (i.e., at or above the $95th$ percentile for BMI) with children who are overweight (but not obese) or healthy weight.

[5] These are the designations provided by the American Academy of Pediatrics. Other terms for these categories are also used. A small number of children fall in the underweight category with BMIs under the 5th percentile. We include them in the healthy weight category, but our results are robust to whether they are included or omitted from the analyses.

2.2.2 General Health

Our second health outcome is the general health of the child as reported by the mother. This measure has been widely used as a measure of child health (e.g., Case et al., 2002; Currie et al., 2007; Currie and Stabile, 2003; Dowd, 2007; Murasko, 2008). Its use is due, in part, to its correlation with other current and future health outcomes (e.g., Case et al., 2002; Idler and Kasl, 1995; Idler and Bensymini, 1997; Van Doorslaer and Gerdtham, 2003) including some of the outcomes associated with food insecurity in the studies noted above.

Based on parents' responses, a child's health using this measure is categorized as excellent, very good, good, fair, or poor. In this paper, we combine these general health categories into two categories: (1) excellent, very good, or good and (2) fair or poor. The former we call "good health or better". In the ancillary analyses, we consider two different comparisons: excellent health compared with the remaining categories and very good or excellent health compared with the remaining categories.

2.3 Data

Our analysis uses data from the 2001-2006 NHANES. The NHANES, conducted by the National Center for Health Statistics, Centers for Disease Control (NCHS/CDC), is a program of studies designed to assess the health and nutritional status of adults and children in the U.S. through interviews and direct physical examinations. The survey now examines a nationally representative sample of about 5,000 persons each year, about half of whom are children. The interview includes demographic, socioeconomic, dietary, and health-related questions with components consisting of medical and dental examinations, physiological measurements, and laboratory tests. Of particular relevance to this study, food insecurity is calculated using the full set of questions in the CFSM as described above,[6] the child's height and weight were measured with an automated data-collection system by a trained technician in the NHANES mobile examination center, and the child's general health is based on parental reports. Since food insecurity is rare among households above 200% of the poverty line (Nord et al., 2008), we limit our sample to households with incomes below this threshold. Our sample contains $6,056$ children.

[6] For confidentiality reasons, however, the responses to individual questions are suppressed in the NHANES data.

3 Identification

The central goal of this paper is to learn about the effect of food security on (a) whether a child is in good or better health and (b) whether a child is a healthy weight. Our treatment effects approach considers the following thought experiment: To what extent might expected health outcomes differ under a hypothetical treatment that would make food insecure households food secure, without the treatment affecting health status through other avenues? To this end, we consider what can be known about the Average Treatment Effect (ATE),

$$ATE = P[H(FS^* = 1) = 1] - P[H(FS^* = 0) = 1], \tag{1}$$

under various assumptions, where $H = 1$ denotes a "good health" outcome (e.g., the child is a healthy weight), $FS^* = 1$ if a child is truly food secure,[7] and $FS^* = 0$ if a child is truly food insecure. The ATE reveals how the mean health outcome would differ if all low-income children were food secure versus the mean outcome if all low-income children were food insecure. Instead of observing FS^*, we observe a self-reported counterpart FS. A latent variable Z^* indicates whether a report is accurate: $Z^* = 1$ if $FS^* = FS$, with $Z^* = 0$ otherwise. In the absence of measurement error, FS^* can be replaced with FS.[8]

Two forms of uncertainty arise when one assesses the ATE. First, even if FS^* were observed for all children (i.e., there were no conceptual or practical measurement issues), the outcome $H(1)$ is counterfactual for all children who were food insecure. Similarly, the outcome $H(0)$ is counterfactual for all children who were food secure. A statistical "selection" problem arises in that households become food secure or food insecure based in part on factors unobserved to the researcher. Thus, for example, the mean health outcomes of the currently food insecure, should they become food secure, may not reflect the mean health outcomes of the currently food secure. Second, true food insecurity status is not observed. Even if all households respond accurately to survey questions, the state of being food insecure is conceptually difficult to measure. We refer to this issue as the

[7] Food insecurity is defined at the household level but, for simplicity of exposition, we refer to a child being food secure or food insecure.

[8] For ease of notation, we leave implicit any conditioning variables. We focus on bounding treatment effects for the population of low-income households with children as a whole, but it is straightforward to condition on any observed subpopulations of interest. One might loosely interpret $H(FS)$ as a reduced form health production function, though our approach does not require that we condition on other attributes. Note that we are not estimating a regression, and there are no regression orthogonality conditions to be satisfied.

classification error problem.[9] Existing research on the effects of food security on health outcomes has not addressed either of these identification problems. In what follows, we first focus on the selection problem and then assess the additional uncertainty created by potentially misclassified food insecurity status.[10]

3.1 Selection

To illustrate the selection problem, the first component of Equation (1) can be written as:

$$P[H(1)=1]=P[H(1)=1|FS^*=1]P\left(FS^*=1\right)+P[H(1)=1|FS^*=0]P\left(FS^*=0\right) \quad (2)$$

where we denote $H(1)\equiv H(FS^*=1)$ and $H(0)\equiv H(FS^*=0)$. For the moment, assume that reports of food security are known to be accurate such that FS^* is observed. In this case, we can identify $P\left(FS^*=1\right)$ and $P\left(FS^*=0\right)$, the fractions of children who are food secure and food insecure, respectively, and $P[H(1)=1|FS^*=1]$, the probability of a favorable health outcome for food secure children. What is not identified, however, is the counterfactual probability of a favorable health outcome for food insecure children if they were to become food secure, $P[H(1)=1|FS^*=0]$. Absent other information, this value could lie anywhere between 0 and 1. Taking these extreme cases, we can bound Equation (2) as follows:

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

which reduces to

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

[9] Official statistics treat food insecurity as a binary event (e.g., Nord et al., 2008), and virtually the entire literature has treated food insecurity in the manner (exceptions include Gundersen (2008) and Gundersen et al. (2003)). As noted above, responses to individual questions in the CFSM component of the NHANES are not available due to confidentiality concerns. For these reassons, and because our approach does not lend itself to continuous treatments, we follow the vast majority of the food insecurity literature in treating food insecurity status as binary. We do, however, consider alternative indicators of food insecurity as part of the sensitivity analysis.

[10] Using numerical search methods, our results can be generalized to cases where H is also measured with error. In that case, our identified treatment effect bounds would naturally become wider.

using $P[H(FS^* = j) = 1|FS^* = j] = P(H = j|FS^* = j)$ for $j = 1, 0$.

Each of the terms in these bounds is identified by the observed data. We can analogously bound the quantity $P[H(0) = 1]$. Taking the difference between the upper bound on $P[H(1) = 1]$ and the lower bound on $P[H(0) = 1]$ obtains a sharp upper bound on ATE, and analogously a sharp lower bound (Manski, 1995):

$$P(H = 1, FS^* = 1) - P(H = 1, FS^* = 0) - P(FS^* = 1) \tag{3}$$

$$\leq ATE_{Manski} \leq$$

$$P(H = 1, FS^* = 1) - P(H = 1, FS^* = 0) + P(FS^* = 0).$$

These bounds have a width of 1. To obtain these bounds, Manski (1995) presumes that all variables are measured accurately. Confidence intervals around ATE can be computed using methods developed in Imbens and Manski (2004).

The bounds in Equation (3) can be narrowed by making assumptions about the relationship between food security and health outcomes. Under the strong assumption that selection is exogenous, for example, one can point-identify $P[H(FS^* = j) = 1]$ as equal to $P(H = 1|FS^* = j)$ for $j = 1, 0$ (see Equation (2)) since, by exogeneity, $P[H(1) = 1|FS^* = 0] = P[H(1) = 1|FS^* = 1]$. In this case, the average treatment effect is identified as

$$ATE_{Exogenous} = P(H = 1|FS^* = 1) - P(H = 1|FS^* = 0), \tag{4}$$

an observed quantity in the absence of measurement error since, in that case, FS^* is observed.

In lieu of the exogeneity assumption, we consider the identifying power of various combinations of three types of weaker monotonicity assumptions: monotone treatment response (MTR), monotone treatment selection (MTS), and a monotone instrumental variable (MIV) restriction. We discuss each assumption in turn.

3.1.1 Monotone Treatment Response (MTR)

For the parts of our analysis that impose MTR, we assume that becoming food secure would not lead to a reduction in a child's health status. Formally, we assume:

$$H(FS_i^* = 1) \geq H(FS_i^* = 0) \text{ for all } i$$

where i denotes the particular child. Under this assumption, it is readily apparent that ATE is constrained to be nonnegative. Using the law of total probability, it can also be shown that

$$P[H(0) = 1] \leq P(H = 1) \leq P[H(1) = 1].$$

For the general health outcome, the MTR assumption seems relatively innocuous. At least in the short run, it is difficult to imagine how becoming food secure would lead to worsened general children's health. With respect to the healthy weight outcome, the MTR assumption is perhaps more tenuous because potential increases in caloric intake could result in weight gains. Of course, most increases in weight are not associated with obesity, and the previous literature has found that food insecurity can lead to higher probabilities of being overweight due to (1) overconsumption of cheaper, energy-dense foods (Dietz, 1995; Drewnowski and Specter, 2004), (2) overeating when food is more plentiful (Scheier, 2005), (3) metabolic changes to ensure a more efficient use of energy (Alaimo et al., 2001b), and (4) parents protecting their children by giving them more food than needed when food is available (McIntyre et al., 2003). In such instances, becoming food secure decreases the likelihood of childhood obesity. Still, the potential that becoming food secure could lead to increases in a child's weight leaves open the possibility that becoming food secure could lead to weight problems in the short run and poorer general health outcomes in the long run. We impose the MTR assumption in deriving our baseline results, but we make transparent how the results vary when the assumption is discarded.

3.1.2 Monotone Treatment Selection (MTS)

The MTS assumption (Manski and Pepper, 2000) places structure on the selection mechanism through which children become food secure or insecure. The literature on food security suggests that food secure children are advantaged compared with food insecure children across several economic and demographic characteristics (Nord et al., 2008). These characteristics are associated with better health outcomes with respect to both general health (Case et al., 2002; Currie et al., 2007; Currie and Stabile, 2003; Dowd, 2007; Murasko, 2008) and obesity (McKay et al., 2008; Forshee et al., 2004; Van Hook and Stamper Balistreri, 2007). Suppose that children who are food secure under the status quo would be more likely to be healthy, relative to their currently food insecure counterparts, conditional on the food security treatment. In that case, the following MTS restrictions hold:

$$P[H(FS^* = j) = 1|FS^* = 1] \geq P[H(FS^* = j) = 1|FS^* = 0] \text{ for } j = 1, 0.$$

Under the MTS assumption, it can be shown that

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

and

$$P\left[H(0) = 1\right] \geq P(H = 1|FS^* = 0).$$

If FS^* is observed, then the right-hand-side quantities $P(H = 1|FS^* = 1)$ and $P(H = 1|FS^* = 0)$ are known. If instead FS^* is measured with error, then bounds on $P(H = 1|FS^* = 1)$ and $P(H = 1|FS^* = 0)$, derived below, serve as bounds on, respectively, $P\left[H(1) = 1\right]$ and $P\left[H(0) = 1\right]$.

3.1.3 Monotone Instrumental Variables (MIV)

Finally, we consider the identifying power of a monotone instrumental variables (MIV) assumption first analyzed by Manski and Pepper (2000). In our application, we use the CPS-defined "income-to-poverty" ratio as the monotone instrument. This ratio measures a household's income relative to the official poverty line. Under the MIV assumption, we impose the restriction that the probability of being healthy conditional on food security status is weakly larger for children in higher-income households than in lower-income households. Letting v represent the instrument, the MIV assumption implies the following inequalities:[11]

$$\begin{aligned} u_1 &\leq u \leq u_2 \Longrightarrow P[H(FS^* = j) = 1 | v = u_1] \\ &\leq P[H(FS^* = j) = 1 | v = u] \leq P[H(FS^* = j) = 1 | v = u_2] \text{ for } j = 1, 0. \end{aligned} \tag{5}$$

As noted above, the literature on general health outcomes and childhood obesity has demonstrated that people with higher incomes tend to have better health outcomes. This mean monotonicity condition in Equation (5) is weaker than the standard mean independence instrumental variables (IV) assumption. Under mean independence, the inequalities in Equation (5) would be replaced with equalities. It is difficult to find instruments for food insecurity status that would satisfy mean independence, so we impose the weaker MIV assumption that has less identifying power. Unlike the standard IV assumption, the MIV assumption does not imply any exclusion restriction; the mean health outcome is allowed to vary (monotonically) with income though avenues distinct from the impact of income on food security.

Across 12 ordered income categories (about 500 children per group), the estimation procedure enforces a restriction that any derived lower bound on $P[H(FS^* = j) = 1]$ (based on the particular set of other maintained assumptions) for a higher income group must be no smaller than the lower bound derived for a lower income group. Similarly, any derived upper bound on $P[H(FS^* = j) = 1]$ for a lower income group must be no larger than the upper bound derived for a higher income group. Estimation details are provided in Kreider and Pepper (2007) where they derive an estimator that accounts for finite sample bias in Manski and Pepper's (2000) standard MIV estimator.[12] In other applications, the MIV assumption has been effective in substantially narrowing the range of uncertainty about treatment effects (e.g., Kreider and Hill, 2009).

3.2 Bounding the ATE in the Presence of Classification Error

Given the selection problem, the average treatment effect cannot be identified based on the data alone. Even if the relevant variables were known to be measured accurately, the presence of unknown counterfactuals precludes point identification; ATE can only be bounded. When we also allow for

[11] Under the MTS assumption, the treatment FS^* is itself an MIV.

[12] As discussed by Manski and Pepper (2000), their standard estimator is consistent but biased in finite samples.

classification errors in reported food security status, the bounds naturally widen. In this section, we show how to bound ATE under various assumptions about the selection process and about the nature and degree of classification error.

3.2.1 Exogenous selection

We begin with the special case of exogenous selection into food security status using Equation (4). In this case, we are abstracting away from uncertainty about counterfactuals; all identification uncertainty comes from uncertainty about the measurement of FS^*. To assess the impact of classification error in this exogenous selection setting, we draw from the approach in Gundersen and Kreider (2008). Let $\theta_1^+ \equiv P(H = 1, FS = 1, Z^* = 0)$ and $\theta_1^- \equiv P(H = 1, FS = 0, Z^* = 0)$ denote the unobserved fraction of false positive and false negative food security reports, respectively, among healthy children. Let $\theta_0^+ \equiv P(H = 0, FS = 1, Z^* = 0)$ and $\theta_0^- \equiv P(H = 0, FS = 0, Z^* = 0)$ denote the fraction of false positive and false negative food security reports, respectively, among non-healthy children.

Before considering any structure on the pattern of false positives and false negatives, we begin by assessing identification given a limit on the potential degree of misclassification. Following Horowitz and Manski (1995) and much of the subsequent literature, we can study how identification of unknown parameters varies with the confidence in the data. Consider an upper bound, q, on the fraction of inaccurate food security classifications:

$$(i)\ P(Z^* = 0) \equiv \theta_1^+ + \theta_0^+ + \theta_1^- + \theta_0^- \leq q. \tag{6}$$

This assumption incorporates a researcher's beliefs about the potential degree of data corruption. If q equals 0 (as is implicitly assumed in all previous work on relationships between food security and health outcomes), then $P(H = 1|FS^*)$ is point-identified because all food security reports are assumed to be accurate. At the opposite extreme, a researcher unwilling to place any limit on the potential degree of reporting error can set q equal to 1. In that case, there is no hope of learning anything about $P(H = 1|FS^*)$ without constraining the pattern of reporting errors. In any event, the sensitivity of inferences on $P(H = 1|FS^*)$ can be examined by varying the value of

q between 0 and 1. To illustrate identification decay in the presence of even small amounts of food security classification errors, our empirical analysis focuses on values of q between 0 and 0.05.

Regardless of any subsequent assumptions on the pattern of reporting errors, the following constraints must hold:

$$
\begin{aligned}
(ii) \quad & 0 \leq \theta_1^+ \leq P(H=1, FS=1) \equiv p_{11} \\
(iii) \quad & 0 \leq \theta_0^+ \leq P(H=0, FS=1) \equiv p_{01} \\
(iv) \quad & 0 \leq \theta_1^- \leq P(H=1, FS=0) \equiv p_{10} \\
(v) \quad & 0 \leq \theta_0^- \leq P(H=0, FS=0) \equiv p_{00}.
\end{aligned}
$$

For example, the fraction of children experiencing negative health outcomes in households falsely classified as being food secure obviously cannot exceed the fraction of children experiencing negative health outcomes in households classified as being food secure.

Worst-case bounds on $P(H=1|FS^*)$ can be obtained by finding the extrema subject to the restrictions on θ_1^+, θ_0^+, θ_1^-, and θ_0^- provided in constraints (i)-(v). Let $p \equiv P(FS=1)$ be the reported food security rate. In the absence of further assumptions, we obtain the following sharp "corrupt sampling" (arbitrary error) bounds on $P(H=1|FS^*)$ derived by Kreider and Pepper (2007) in another context:[13]

"Corrupt Sampling Bounds With Exogenous Selection" (Kreider-Pepper, 2007, Prop. 1): *Let $P(Z^*=0) \leq q$. Under exogenous selection, the fraction of positive health outcomes if all children were to become food secure is bounded sharply as follows:*

$$\frac{p_{11} - \alpha^+}{p - 2\alpha^+ + q} \leq P(H=1|FS^*=1) \leq \frac{p_{11} + \alpha^-}{p + 2\alpha^- - q}$$

using the values

$$\alpha^+ = \begin{cases} \min\{q, p_{11}\} & \textit{if } p_{11} - p_{01} - q \leq 0 \\ \max\{0, q - p_{00}\} & \textit{otherwise} \end{cases}$$

[13] Corrupt sampling refers to an environment where nothing is known about the pattern of reporting errors.

$$\alpha^- = \begin{cases} \min\{q, p_{10}\} & \textit{if } p_{11} - p_{01} + q \leq 0 \\ \\ \max\{0, q - p_{01}\} & \textit{otherwise.} \end{cases}$$

Analogous bounds for the fraction of positive health outcomes among food insecure children, $P(H = 1|FS^* = 0)$, are obtained by replacing $FS = 1$ with $FS = 0$ and vice versa in each of the relevant quantities. Sharp bounds on $ATE_{Exogenous}$ are obtained by subtracting worst-case lower bounds from worst-case upper bounds on $P(H = 1|FS^* = 1)$ and $P(H = 1|FS^* = 0)$. Intuitively, the bounds converge to $P(H = 1|FS = 1)$ as q goes to 0. Increasing q may widen the bounds over some ranges of q but not others, and the rate of identification decay can be highly nonlinear as q increases (especially for larger values of q).

These corrupt sampling bounds can be narrowed, sometimes dramatically, by imposing restrictions on the patterns of false positives and false negatives. We focus on an "orthogonal errors" assumption that food security classification errors occur independently of whether the household is truly food secure:[14]

$$P(FS^* = 1|Z^* = 1) = P(FS^* = 1|Z^* = 0). \tag{7}$$

In this case, the false positive and false negative classification errors must satisfy the constraint:

$$(vi) \quad \left[1 - p - (\theta_1^- + \theta_0^-)\right] \left[\left(\theta_1^+ + \theta_0^+\right) + (\theta_1^- + \theta_0^-)\right]$$

$$= \left(\theta_1^+ + \theta_0^+\right) \left[1 - \left(\theta_1^+ + \theta_0^+\right) - (\theta_1^- + \theta_0^-)\right].$$

As revealed in our empirical results, this orthogonality assumption has substantial identifying power. While this restriction cannot be tested, it is obviously weaker than the standard assumption in previous work that food insecurity status is reported without error. We cannot obtain closed-form bounds on ATE for this case, but we can obtain sharp bounds by imposing this constraint using numerical methods.[15]

[14] Many studies have assumed that classification errors arise independently of the variable's true value (see Molinari (2008) for a discussion). Bollinger (1996), for example, discusses the possibility that a worker's true union status has no influence on whether union status is misreported in the data. Kreider and Pepper (2008) consider the identifying assumption that, among certain types of respondents, misreported disability status does not depend on true disability status. Gundersen and Kreider (2008) and Kreider et al. (2009) consider a "no false positives" identifying assumption that respondents may fail to report receiving food stamps but not falsely claim to receive food stamps.

[15] Our Gauss program is available upon request.

3.2.2 Endogenous selection

When selection into food security status is endogenous, the average treatment effect is no longer constrained by the bounds in Equation (4). To derive corrupt sampling bounds for this case in the presence of classification error, we begin by writing

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

We can set $P[H(1)=1|FS^*=0]$ equal to 0 for the lower bound and equal to 1 for the upper bound since this quantity is unrestricted. Then we can write

$$P(H=1, FS=1) + \theta_1^- - \theta_1^+ \leq P[H(1)=1] \leq P(H=1, FS=1) + P(FS=0) + \theta_0^+ - \theta_0^-.$$

To obtain the worst-case lower bound, we must set $\theta_1^- = 0$ and $\theta_1^+ = \min\{q, P(H=1, FS=1)\}$. For the worst-case upper bound, we must set $\theta_0^- = 0$ and $\theta_0^+ = \min\{q, P(H=0, FS=1)\}$. Thus, the corrupt sampling bounds are given by:

"Corrupt Sampling Bounds With Endogenous Selection": *Let $P(Z^*=0) \leq q$. Under arbitrary endogenous selection, the fraction of positive health outcomes if all children were to become food secure is bounded sharply as follows:*

$$\mathrm{LB}_{\mathrm{corrupt}}^{H(1)} = P\left(H=1, FS=1\right) - \min\left\{q, P(H=1, FS=1)\right\}$$

$$\leq P[H(1)=1] \leq$$

$$\mathrm{UB}_{\mathrm{corrupt}}^{H(1)} = P\left(H=1, FS=1\right) + P(FS=0) + \min\left\{q, P(H=0, FS=1)\right\}.$$

Analogous bounds on $P[H(0)=1]$ are obtained by replacing $FS=1$ with $FS=0$ and vice versa in each of the relevant quantities. Sharp bounds on ATE are obtained by subtracting worst-case lower bounds from worst-case upper bounds on $P[H(1)=1]$ and $P[H(0)=1]$. Intuitively, the

ATE bounds with endogenous selection converge to the Manski (1995) bounds in Equation (3) as q goes to 0.

As above, these bounds can be narrowed by imposing restrictions on the patterns of food insecurity classification errors. Using numerical methods to impose constraint (vi), our empirical analysis considers the case where classification errors arise independently of true food insecurity status (i.e., under the assumption of orthogonal errors). In presenting our results, we consider the additional identifying power of the MTR, MTS, and MIV assumptions.

4 Empirical results

We now turn to our empirical results. Figures 1-4, and their accompanying tables, illustrate what can be known about the average treatment effect as a function of q under various assumptions about the selection process and food security misclassification patterns. One set of results focuses on the impact of food security on general health status. A parallel set of results focus on the impact of food security on being a healthy weight.

We begin with the case of exogenous selection into food security status. Figure 1A displays sharp bounds on $ATE_{Exogenous} = P(H = 1|FS^* = 1) - P(H = 1|FS^* = 0)$ for the "good health or better" versus "fair or poor health" outcome over the range $q = 0$ to $q = 0.05$. When $q = 0.05$, for example, up to 5% of the FS^* classifications may be in error. When $q = 0$, $ATE_{Exogenous}$ is point-identified as $0.953 - 0.892 = 0.061$. That is, children in food secure households are 6.1 percentage points more likely to be in good health compared with children in food insecure households. As shown in the accompanying table, the 90% confidence interval is $[0.044, 0.079]$. Since this confidence interval does not include 0, we can identify the sign of $ATE_{Exogenous}$ as positive even after accounting for sampling variability.

As revealed in the figure, however, even tiny degrees of uncertainty about true food insecurity status are sufficient to overturn the conclusion that food secure children are more likely to be in good health. Under corrupt sampling, we can no longer identify the sign of $ATE_{Exogenous}$ (even prior to considering standard errors) if we allow for the possibility that even 1.5% of the food insecurity status classifications are in error. Imposing the orthogonal errors assumption makes little difference. Under this restriction on the pattern of errors, we still cannot identify whether food secure children are more likely to be healthy if up to 2.1% of the classifications may be in error.

Starting at $q = 0$, a one percentage point increase in the degree of uncertainty about the reliability of food insecurity classifications (increase in q), given orthogonal errors, is associated with an additional 8.2 percentage point increase in uncertainty about $ATE_{Exogenous}$. By the time we allow for the possibility of a 5% error rate, we find that children in food secure households may be up to 14.2 percentage points more likely to be in good health than their food insecure counterparts under orthogonal errors – or they may be up to 9.0 percentage points less likely to be in good health. This 23.2 percentage point range of uncertainty about the ATE is striking, especially since it abstracts away from additional uncertainty associated with sampling variability, the selection mechanism, and the possibility that health status might also be mismeasured. Very small degrees of food security classification errors can result in severe degrees of uncertainty about the relationships between food security and health.

Figure 1B presents parallel results for the healthy weight outcome. In the absence of classification error ($q = 0$), we can identify that food secure children are 4.6 percentage points more likely to have a healthy weight ($0.683 - 0.636 = 0.046$). Critical values for q are similar to those identified for the general health case above. If food insecurity status might be arbitrarily misclassified up to 1.5% of the time, then we can no longer identify whether food secure or food insecure children are more likely to have a healthy weight. Under the orthogonal errors assumptions, the critical value rises only slightly to 1.9%.

Figures 2A and 2B make clear how little can be known about the average treatment effect when we impose no restrictions on the nature of the selection process into food secure status. Even if we presume perfectly accurate measurement of the data, we are confronted with a 100 percentage point range of uncertainty about the average treatment effect (see Equation (3) and discussion): ATE could lie anywhere within $[-0.329, 0.671]$ for the general health outcome and anywhere within $[-0.424, 0.576]$ for the healthy weight outcome.

Similarly, little can be known about the fraction of households that would be healthy if all children became food secure, $P[H(1) = 1]$, without making assumptions about the food security selection process. Ignoring measurement error, 93% of the households in our sample are classified as being in good or better health. If all children were to become food secure, the proportion of children in good or better health could lie anywhere between 63.4% and 96.9% (not shown). Likewise, little can be known about the fraction of respondents that would have a healthy weight. In the data, 67% are classified as being a healthy weight; if all children were to become food secure, this outcome could range from 45.5% to 78.9%.

To make tighter inferences about $P[H(1) = 1]$ and ATE, stronger assumptions must be imposed. As seen in Figure 3, the bounds on ATE narrow dramatically after imposing the MTR and MTS monotonicity assumptions. When $q = 0$, the fraction of households that would be healthy if all children were food secure, $P[H(1) = 1]$, is confined to lie within the narrow range $[0.933, 0.953]$ (not shown). As seen in Figure 3A, the range of ATE narrows to $[0, 0.061]$. For healthy weight, $P[H(1) = 1]$ is confined to the narrow range $[0.667, 0.683]$ (not shown). As seen in Figure 3B, ATE lies within the range $[0, 0.046]$. That is, children would be up to 6.1 percentage points more likely to be healthy if all children were food secure versus if all children were food insecure. Similarly, children would be up to 4.6 percentage points more likely to have a healthy weight if children were to become food secure.

After allowing for possible classification errors in food security status, the potential for strong positive effects of food security on health rises substantially. For example, Figure 3A shows that the upper bound on ATE for good health rises to 14.2 percentage points under orthogonal errors, and 19.4 points under arbitrary errors, if even 5% of the food insecurity classifications may be inaccurate. Thus, our results reveal that efforts to limit uncertainty about the reliability of food insecurity data can have important consequences for limiting uncertainty about the effects of food security on health status. If we impose the MTS assumption but discard the MTR assumption, the upper bounds in Figure 3 would remain the same but the lower bounds would fall to the Figure 2 lower bounds.

We now turn to the case when we combine the MTR-MTS assumptions with the MIV assumption. In this case, the average treatment effects are identified to be strictly positive. Recall that the MIV assumption imposes the restriction that, on average, health status does not decline with a family's income-to-poverty ratio. The "no MIV LB" and "no MIV UB" bounds depicted in Figure 4 reproduce the Figure 3 bounds. The MIV bounds tighten these inferences. As seen in Figure 4A, the joint MTR-MTS-MIV assumption allows us to nearly point-identify the general health ATE if the food security classifications are known to be fully reliable. Specifically, ATE is bounded to lie in the narrow range $[0.014, 0.035]$ when $q = 0$. For the healthy weight outcome, ATE is bounded to lie within the range $[0.007, 0.039]$. In both cases, policies that promote food security are identified to promote better health outcomes. When q increases from 0 to 0.05, the upper bound on the average treatment effect for good general health status rises from 0.035 to 0.109, while the lower bound remains constant at 0.014. For healthy weight, the upper bound rises from 0.039 to 0.174 while the lower bound remains constant at 0.007. If we drop the MTR assumption for the general health outcome, the lower bound ranges from -0.307 when $q = 0$ to -0.358 when $q = 0.05$ (not shown). If we drop this assumption for the healthy weight outcome, the lower bound ranges from -0.424 when $q = 0$ to -0.474 when $q = 0.05$.

In Appendix Tables 1 and 2, we assess the robustness of our primary results to alternative constructions of the health indicators (different rows) and food insecurity indicators (different columns). For the general health outcome, we replace the threshold "at least good health" with the alternatives "at least very good health" and "excellent health." For the healthy weight outcome, we replace the threshold "BMI $\leq 85th$ percentile" (representing not overweight or obese) with the alternative "BMI $\leq 95th$ percentile" (not obese). Recall from Section 2.1 that the standard food insecurity indicator classifies a household as food insecure if the household answers affirmatively to three or more questions in the 18-item CFSM. In the sensitivity analysis, we consider an indicator of "food insecure or at risk" (also termed "marginal food insecurity" in the literature) and an indicator of "food insecurity with hunger" (since 2006 called "very low food security"). A household with children is classified as food insecure or at risk if it answers affirmatively to at least one of the 18 questions. A household is classified as food insecure with hunger if it responds affirmatively to eight or more of the 18 questions.

As seen in Appendix Table 1, the main conclusions from Figure 1 are robust to these alternative measures. While the estimated values of Δ are naturally sensitive to the particular definitions (baseline cases in bold), the table reveals that identification of this parameter decays rapidly with q in all cases. Critical values for q in which the sign of Δ is just identified vary between 0.003 and 0.075. Thus, under any set of definitions, the sign of Δ cannot be identified if more than 7.5 percent of the food insecurity classifications may be in error.

Appendix Table 2 displays our sensitivity analysis for the average treatment effect bounds illustrated in Figure 4. The main conclusion from this table is that we can continue to identify

ATE as strictly positive in most cases under the joint MTR-MTS-MIV assumption, at least for small degrees of food insecurity classification error. As an exception, we cannot identify ATE as strictly positive if the threshold is excellent general health. Also, we cannot identify a strictly positive effect for the baseline healthy weight outcome (BMI $\leq 85th$ percentile) under the food insecurity with hunger criterion. As before, the lower bound impacts of food security on health outcomes are relatively uninformative if the MTR assumption is discarded.

Our results demonstrate that uncertainty about the reliability of FS^* does not necessarily translate into symmetric uncertainty for policymakers regarding the efficacy of improving food insecurity in promoting good health. Once we allow for the possibility of data errors in FS^* ($q > 0$), we find that the true impacts of food security on health outcomes may be considerably larger than would be estimated under the assumption of perfectly accurate data ($q = 0$). Conversely, our baseline results suggest that there is relatively little risk that researchers have overestimated the magnitudes of these health impacts.

This conclusion for policymakers is qualitatively consistent with the well-known attenuation bias result associated with classical measurement error in an explanatory variable.[16] In the context of the classical model, random mismeasurement of FS^* in a regression setting would result in a downward-biased estimate of food security on health due to negative correlation between reported food security status and the stochastic regression disturbance. In that case, the attenuation result would be driven by the strong "nondifferential errors" independence assumption embedded in the classical model that, conditional on FS^*, any measurement error in FS must be independent of health status, other conditioning variables of interest, and the regression disturbance. We obtain a similar attenuation result without imposing any of the parametric or distributional assumptions associated with the classical measurement error regression model.

5 Conclusion

Policymakers have long been concerned about the well-being of millions of children who grow up in food insecure households. Much of this concern arises from well-documented links between food insecurity and unfavorable health outcomes. In response, numerous efforts (e.g., SNAP) have

[16] See, e.g., Wooldridge (2002, chapter 4).

been pursued with the goal of ensuring that all children live in food secure homes. While there is little debate that food secure children tend to have more favorable health outcomes, identifying the causal impacts of food security on health is problematic. Food insecurity is obviously not randomly assigned. Many household characteristics, including those unobserved in the data, might lead some children to be simultaneously at higher risk of being food insecure and of having poor health outcomes. Moreover, the potential for conceptual and practical errors in the measurement of food insecurity exacerbates a policymaker's uncertainty about the efficacy of food assistance programs in fostering better health outcomes. Previous analyses of the role of food security for healthy outcomes have not addressed either of these important identification issues.

In this paper, we used nonparametric bounding methods to reconsider what can be identified about causal effects of food security on children's health outcomes. We formally accounted for the uncertainty created by unobserved counterfactuals and potentially mismeasured food insecurity status. Even under the strong and implausible assumption of exogenous selection, we illustrate how the presence of very small degrees of classification error in food security status can be sufficient to lose identification of the sign of the average treatment effect. Under relatively weak monotonicity assumptions, however, we can identify that food security has a statistically significant positive impact on children's general health status, even with endogenous food security status.

We show that uncertainty about the reliability of the food security data need not translate into symmetric uncertainty for policymakers regarding the impact of food security on health outcomes. Under the monotonicity assumptions, we find that allowing for the possibility of food security classification errors opens up the possibility that the true impacts of food security on health outcomes may be considerably larger than estimated under the standard assumption of no errors. Conversely, there appears to be relatively little risk that researchers have systematically overestimated the magnitudes of these health impacts. A qualitatively similar attenuation bias result could be derived using classical measurement error assumptions. Unlike the classical model, however, our methods do not presume that measurement error is exogenous. Instead, we allow for the possibility that classification errors are endogenously related to the true value of the potentially mismeasured food security variable or the health outcomes.

We suggest several areas for future research. First, the bounds in this analysis might be narrowed by imposing additional identifying assumptions. As one possibility, researchers might be willing to assume that at least some subset of the food security classifications are known to be accurate. For example, one might be willing to "verify" that a household is truly food secure if it responds negatively to all 18 of the relevant food security questions in the CFSM. Similarly, a household might be verified to be food insecure if responding affirmatively to a large number of questions. Second, future research on the mechanisms through which food security affects health outcomes is warranted. Of particular import is disentangling the short- and long-run effects of becoming food secure. Third, our analysis has presumed that health outcomes are accurately reported. While the height and weight status of children in the NHANES are objectively measured by trained personnel, the general health outcome relies on more subjective interpretations. The bounds in this analysis naturally widen if we allow for the possibility that both food security and health status are misclassified.

Finally, we emphasize that our analysis is intended to isolate the impact of food security on health, not the impact of program participation on health. Therefore, our analysis cannot directly identify the health consequences of programs designed to alleviate food insecurity, like SNAP. Not everyone who enrolls in a program like SNAP becomes food secure, and any program that provides transfers (or manipulates prices) has the potential to impact health status through avenues distinct from the program's effect on food security. SNAP benefits, for example, free up some of a household's resources that might have been spent on food. If some of these freed resources are spent on medical services, then the program can also impact health status through the consumption of more health care – thus reinforcing the positive impact on health. Further research is required on a program-by-program basis to identify the health consequences of particular policies.

References

[1] Alaimo, K., Olson, C., Frongillo, E., Briefel, R., 2001a. Food insufficiency, family income, and health in US preschool and school-aged children. American Journal of Public Health 91, 781-786.

[2] Alaimo, K., Olson, C. , Frongillo, E., 2001b.. Low family income and food insufficiency in relation to overweight in US children: is there a paradox? Archives of Pediatrics and Adolescent Medicine 155, 1161-1167.

[3] Adams, E., Grummer-Strawn, L., Chavez, G., 2003. Food insecurity is associated with increased risk of obesity in California women. Journal of Nutrition 133, 1070-1074.

[4] Barron, J.,Black, D., and Berger M., 1997. Employer search, training, and vacancy duration. Economic Inquiry 35(1), 167-92.

[5] Bender, B., Fuhlbrigge, A., Walders, N., Zhang, L., 2007. Overweight, race, and psychological distress in the children asthma management program. Pediatrics 120(4), 805–813.

[6] Bhargava, A., Jolliffe, D., Howard, L., 2008. Socioeconomic, behavioral and environmental factors predicted body weights and household food insecurity scores in the Early Childhood Longitudinal Study: kindergarten. British Journal of Nutrition 100(2), 438–444.

[7] Black, D., Sanders, S., Taylor, L.,. 2003. Measurement of higher education in the Census and CPS. Journal of the American Statistical Association 98(463), 545–54.

[8] Bollinger, C., 1996. Bounding mean regressions when a binary variable is mismeasured. Journal of Econometrics, 73(2), 387-99.

[9] Bound, J., Brown, C., Mathiowetz, N., 2001. Measurement error in survey data. In Handbook of Econometrics, V. 5, eds. E. E. Leamer and J. J. Heckman, 3705-3843.

[10] Carroll, C., Stoltz, P., Raykov, N., Smith, S., Zucker, A., 2007. Children overweight increases hospital admission rates for asthma. Pediatrics 120(4), 734–740.

[11] Case, A., Lubotsky, D., Paxson, C., 2002. Economic status and health in childhood: The origins of the gradient. American Economic Review 92(5), 1308-1334.

[12] Casey, P., Simpson, P., Gossett, J., Bogle, M., Champagne, C., Connell, C., Harsha, D., McCabe-Sellers, B., Robbins, J., et al., 2006. The association of child and household food insecurity with childhood overweight status. Pediatrics 118, 1406-1413.

[13] Casey, P., Szeto, K., Lensing, S., Bogle, M., Weber, J. 2001. Children in food-insufficient, low-income families: Prevalence, health and nutrition status. Archives of Pediatrics & Adolescent Medicine 155, 508-514.

[14] Cook, J., Frank, D., Berkowitz, C., Black, M., Casey, P., Cutts, D., Meyers, A., Zaldivar, N., Skalicky, A., Lenenson, S., Heeren, T., Nord, M., 2004. Food insecurity is associated with adverse health outcomes among human infants and toddlers. Journal of Nutrition 134, 1432-1348.

[15] Currie, A., Shields, M., Wheatley, S., 2007. The child health/family income gradient: Evidence from England. Journal of Health Economics 26, 213-232.

[16] Currie, J. Stabile, M., 2003. Socioeconomic status and child health: Why is the relationship stronger for older children? American Economic Review 93, 1813-1823.

[17] Dietz W., 1995. Does hunger cause obesity? Pediatrics 95, 766–7.

[18] Dowd, J., 2007. Early childhood origins of the income/health gradient: The role of maternal health behaviors. Social Science and Medicine 65, 1202-1213.

[19] Drewnowski, A., Specter, S., 2004. Poverty and obesity: The role of energy density and energy costs. American Journal of Clinical Nutrition 79, 6–16.

[20] Dubois L., Farmer, A., Girard, M., Porcherie, M., 2006. Family food insufficiency is related to overweight among preschoolers. Social Science and Medicine 63, 1503-1516.

[21] Dunifon, R., Kowaleski-Jones, L,.2003. The influences of participation in the National School Lunch Program and food insecurity on child well-being. Social Service Review 77, 72-92.

[22] Fontaine, K., Redden, D., Wang, C., Westfall, A., Allison, D., 2003. Years of life lost due to obesity. Journal of the American Medical Association 289(2), 187–193.

[23] Forshee, R., Anderson, P., Storey, M., 2004. The role of beverage consumption, physical activity, sedentary behavior, and demographics on body mass index of adolescents. International Journal of Food Sciences and Nutrition 55(6), 463-478.

[24] Gundersen, C. 2008. Measuring the extent, depth, and severity of food insecurity: An application to American Indians in the United States. Journal of Population Economics, 21(1), 191-215.

[25] Gundersen, C., Kreider, B., 2008. Food stamps and food insecurity: What can be learned in the presence of nonclassical measurement error. Journal of Human Resources 43(2), 352-382.

[26] Gundersen, C., Ribar, D., 2005. "Food insecurity and insufficiency at low levels of food expenditures. Institute for the Study of Labor (IZA) Working Paper No. 1594.

[27] Gundersen, C., Garasky, S., Lohman, B., 2009. Food insecurity is not associated with childhood obesity as assessed using multiple measures of obesity. Journal of Nutrition, 139, 1173-1178.

[28] Gundersen, C., Weinreb, L., Wehler, C., Hosmer, D., 2003. Homelessness and food insecurity. Journal of Housing Economics, 12(3), 250-272.

[29] Gundersen, C., Lohman, B., Eisenmann, J., Garasky, S., Stewart, S., 2008. Child-specific food insecurity and overweight are not associated in a sample of 10- to 15-year-old low-income youth. Journal of Nutrition 138(2), 371–378.

[30] Hamelin, A., Beaudry, M., Habicht, J., 2002. Characterization of household food insecurity in Quebec: Food and feelings. Social Science and Medicine 54, 119-132.

[31] Horowitz, J.,Manski, C. 1995. Identification and robustness with contaminated and corrupted data. Econometrica 63(2), 281-02.

[32] Idler, E., Benysmini, Y., 1997. Self-reported health and mortality: A review of twenty-seven community studies. Journal of Health and Social Behavior 38, 21-37.

[33] Idler, E., Kasl, S., 1995. Self-ratings of health: Do they also predict change in functional ability? Journal of Gerontology: Social Sciences 50(6), S344-S353.

[34] Imbens, G., Manski, C., 2004. Confidence intervals for partially identified parameters. Econometrica 72, 1845-1857.

[35] Jimenez-Cruz A., Bacardi-Gascon, M., Spindler, A., 2003. Obesity and hunger among Mexican-Indian migrant children on the US-Mexico border. International Journal of Obesity 27, 740-747.

[36] Jyoti, D., Frongillo, E., Jones, S., 2005. Food insecurity affects school children's academic performance, weight gain, and social skills. Journal of Nutrition. 135, 2831-9.

[37] Kaiser L., Melgar-Quiñonez, H., Lamp, C., Johns, M., Sutherlin, J., Harwood, J., 2002. Food security and nutritional outcomes of preschool-age Mexican-American children. Journal of the American Dietetic Association 102, 924-929.

[38] Kleinman R., Murphy, J., Little, M., Pagano, M., Wehler, C., Regal, K., Jellinek, M., 1998. Hunger in children in the United States: Potential behavioral and emotional correlates Pediatrics 101, e3.

[39] Kreider, B., Forthcoming. Regression coefficient identification decay in the presence of classification errors. Review of Economics and Statistics.

[40] Kreider, B. Hill, S., 2009. Partially identifying treatment effects with an application to covering the uninsured. Journal of Human Resources 44(2), 409-449.

[41] Kreider, B., Pepper, J., 2007. Disability and employment: Reevaluating the evidence in light of reporting errors. Journal of the American Statistical Association 102(478), 432-441.

[42] Kreider, B., Pepper, J., 2008. Inferring disability status from corrupt data. Journal of Applied Econometrics 23(3), 329-49.

[43] Kreider, B., Pepper, J., Gundersen, C., Jolliffe, D., 2009. Identifying the effects of food stamps on children's health outcomes when participation is endogenous and misreported. Working Paper.

[44] Manski, C., 1995. Identification problems in the social sciences. Cambridge, MA: Harvard University Press.

[45] Manski, C., Pepper, J., 2000. Monotone instrumental variables: With an application to the returns to schooling. Econometrica 68(4), 997-1010.

[46] Martin K., Ferris, A., 2007. Food insecurity and gender are risk factors for obesity. Journal of Nutrition Education and Behavior 39, 31-6.

[47] Matheson, D., Varady, J., Varady, A., Killen, J., 2002. Household food security and nutritional status of Hispanic children in the fifth grade. American Journal of Clinical Nutrition 76, 210-217.

[48] McKay, C., Bell-Ellison, B., Wallace, K., Ferron, J., 2007. A multilevel study of the associations between economic and social context, stage of adolescence, and physical activity and body mass index. Pediatrics 119(suppl 1), S84–S91.

[49] McIntyre, L., Glanville, N., Raine, K., Dayle, J., Anderson, B., Battaglia, N., 2003. Do low-income lone mothers compromise their nutrition to feed their children? Canadian Medical Association Journal 168, 686–91.

[50] Molinari, F., Forthcoming. Missing treatments. Journal of Business and Economic Statistics.

[51] Molinari, F., 2008. Partial identification of probability distributions with misclassified data. Journal of Econometrics 144, 81-117.

[52] Murasko, J., 2008. An evaluation of the age-profile in the relationship between household income and the health of children in the United States. Journal of Health Economics 27,1489-1502 .

[53] Murphy, J., Wehler, C., Pagano, M., Little, M., Kleinman, R., Jellinek, M., 1998. Relationship between hunger and psychosocial functioning in low-income American children. Journal of the American Academy of Child and Adolescent Psychiatry 37(2), 163-170.

[54] Nguyen, S., McCulloch, C., Brakeman, P., Portale, A., Hsu, C., 2008. Being overweight modifies the association between cardiovascular risk factors and microalbuminuria in adolescents. Pediatrics 121(1), 37–45.

[55] Nord, M., Andrews, M., Carlson, S., 2008. Household food security in the United States, 2007. Washington, DC: U.S. Department of Agriculture; 2008. Economic Research Report No. 66.

[56] Ogden, C., Carroll, M., Curtin, L., McDowell, M., Tabak, C., Flegal, K., 2006. Prevalence of overweight and obesity in the United States, 1999–2004. Journal of the American Medical Association 295(13), 1549–1555.

[57] Pepper, J., 2000. The intergenerational transmission of welfare receipt: A nonparametric bounds analysis. Review of Economics and Statistics 82(3), 472–88.

[58] Rose D., Bodor, J., 2006. Household food insecurity and overweight status in young school children: Results from the Early Childhood Longitudinal Study. Pediatrics 117, 464-73.

[59] Rose-Jacobs, R., Black, M., Casey, P., Cook, J., Cutts, D., Chilton, M., et al., 2008. Household food insecurity: Associations with at-risk infant and toddler development. Pediatrics 121(1), 65-72.

[60] Scheier, L., 2005. What is the hunger-obesity paradox? Journal of the American Dietetic Association 105, 883–6.

[61] Schwimmer, J., Burwinkle, T., Varni, J., 2003. Health-related quality of life of severely obese children and adolescents. Journal of the American Medical Association 289(14), 1813–1819.

[62] Skalicky, A., Meyers, A., Adams, W., Yang, Z., Cook, J., Frank, D., 2006. Child food insecurity and iron deficiency anemia in low-income infants and toddlers in the United States. Maternal and Child Health Journal, 10(2), 177-185.

[63] Slack, K., Yoo, J., 2005. Food hardship and child behavior problems among low-income children. Social Service Review 79(3), 511–536.

[64] U.S. Department of Agriculture, Food and Nutrition Service. Annual Historical Review: Fiscal Year 1997. 1999.

[65] Van Doorslaer, E., Gerdtham, U., 2003. Does inequality in self-assessed health predict inequality in survival by income? Evidence from Swedish data. Social Science and Medicine 57, 1621-1629.

[66] Van Hook, J., Stamper Balistreri, K., 2007. Immigrant generation, socioeconomic status, and economic development of countries of origin: A longitudinal study of body mass index among children. Social Science and Medicine 65, 976-989.

[67] Wang, Y., Zhang, Q., 2006. Are American children and adolescents of low socioeconomic status at increased risk of obesity? Changes in the association between overweight and family income between 1971 and 2002. American Journal of Clinical Nutrition 84(4), 707–716.

[68] Weinreb, L., Wehler, C., Perloff, J., Scott, R., Hosmer, D., Sagor, L., Gundersen, C., 2002. Hunger: Its impact on children's health and mental health. Pediatrics 110, e41.

[69] Whitaker, R., Phillips, S., Orzol, S., 2006. Food insecurity and the risks of depression and anxiety in mothers and behavior problems in their preschool-aged children. Pediatrics. 118(3), e859-e868.

[70] Wooldridge, J., 2002. Econometric Analysis of Cross Section and Panel Data. Cambridge, MA: The MIT Press.

[71] Zaslow, M., Bronte-Tinkew, J., Capps, R., Horowitz, A., Moore, K., Weinstein, D., Forthcoming. Food security during infancy: Implications for attachment and mental proficiency in toddlerhood. Maternal and Child Health Journal.

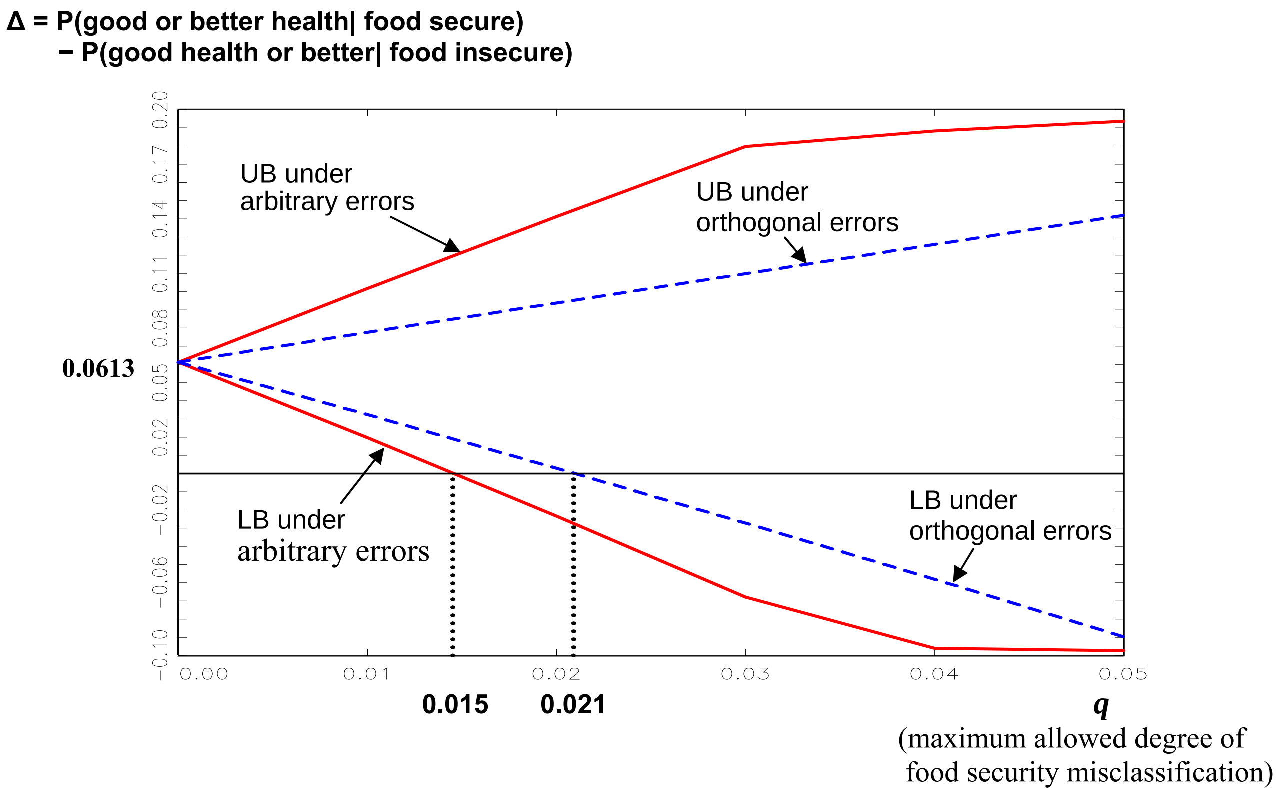
Table 1.
Food Insecurity Questions in the Core Food Security Module

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?
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)

Notes: Responses in bold indicate an affirmative response.

Figure 1A

Sharp Bounds on the Difference in the Probability of Being in Good or Better Health Between Food Secure and Food Insecure Children under Exogenous Selection



	Arbitrary Errors	Orthogonal Errors
$q = 0$	[0.061, 0.061]†	[0.061, 0.061]
	[0.044 0.079]‡	[0.044 0.079]
$q = 0.01$	[0.020, 0.102]	[0.032, 0.077]
	[0.006 0.115]	[0.019 0.091]
$q = 0.05$	[-0.097, 0.194]	[-0.090, 0.142]
	[-0.104 0.207]	[-0.101 0.156]

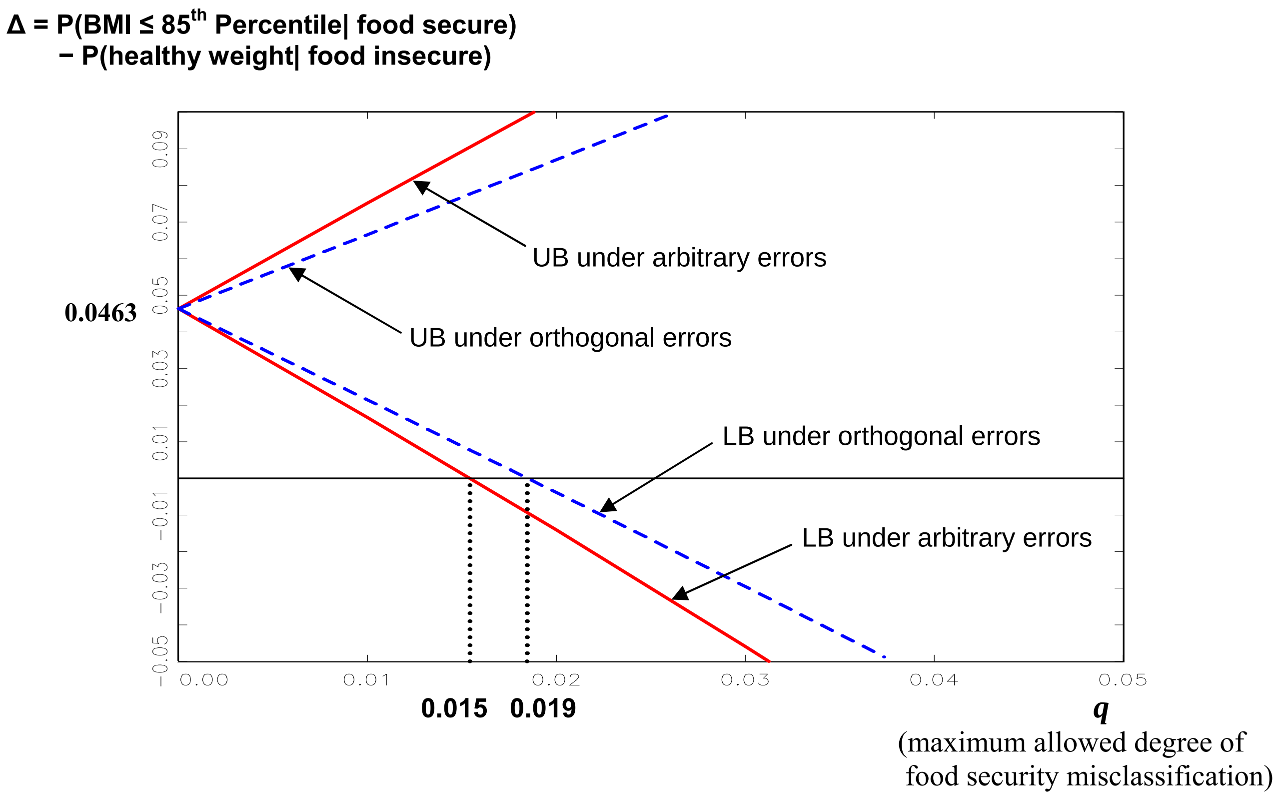
---

† Point estimates of the population bounds

‡ Imbens-Manski (2004) 5th and 95th percentile bounds (1,000 pseudosamples)

Figure 1B

Sharp Bounds on the Difference in the Probability of BMI ≤ 85th Percentile Between
Food Secure and Food Insecure Children under Exogenous Selection



	Arbitrary Errors	Orthogonal Errors
$q = 0$	[0.046, 0.046]†	[0.046, 0.046]
	[0.016 0.077]‡	[0.016 0.077]
$q = 0.01$	[0.017, 0.075]	[0.021, 0.067]
	[-0.008 0.099]	[-0.002 0.091]
$q = 0.05$	[-0.113, 0.185]	[-0.082, 0.149]
	[-0.140 0.207]	[-0.107 0.174]

---

a. "Healthy weight" is defined as having a body mass index below the 85th BMI percentile.

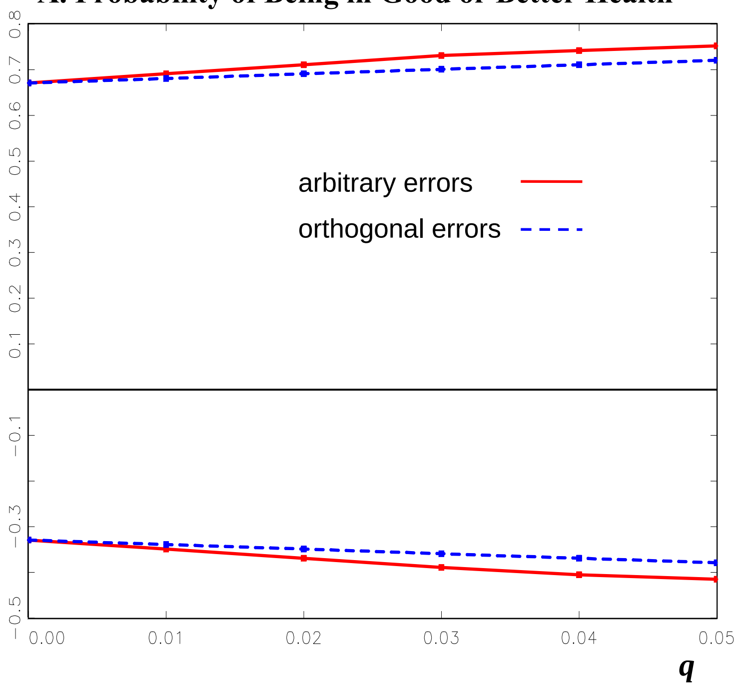
† Point estimates of the population bounds

‡ Imbens-Manski (2004) 5th and 95th percentile bounds (1,000 pseudosamples)

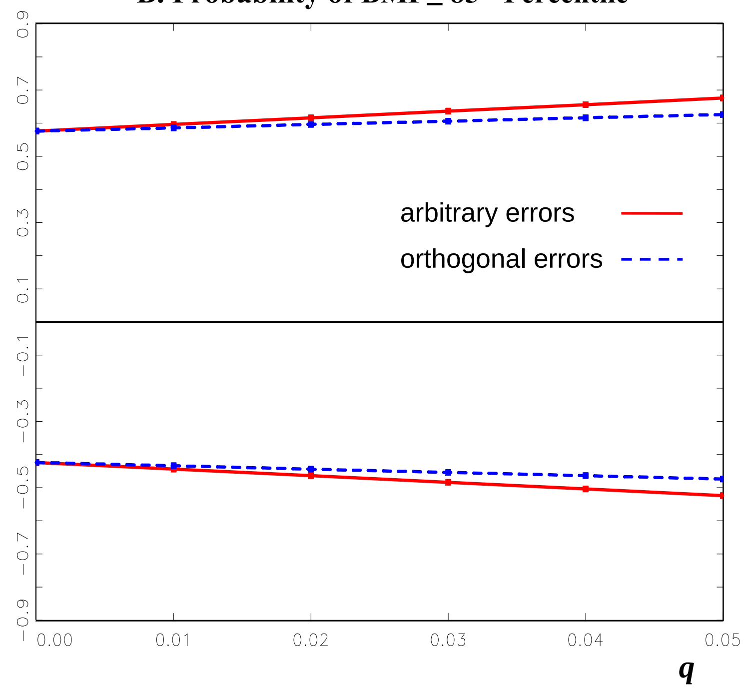
Figure 2

Sharp Bounds on $ATE = P[H(1)=1] - P[H(0)=1]$ with No Monotonicity Assumptions

A. Probability of Being in Good or Better Health



B. Probability of BMI ≤ 85th Percentile



A. Probability of Being in Good or Better Health

	Arbitrary Errors	Orthogonal Errors
$q = 0$	[-0.329, 0.671]†	[-0.329, 0.671]
	[-0.340 0.681]‡	[-0.340 0.681]
$q = 0.01$	[-0.349, 0.691]	[-0.339, 0.681]
	[-0.360 0.701]	[-0.349 0.691]
$q = 0.05$	[-0.415, 0.752]	[-0.379, 0.721]
	[-0.426 0.762]	[-0.390 0.731]

B. Probability of BMI ≤ 85th Percentile

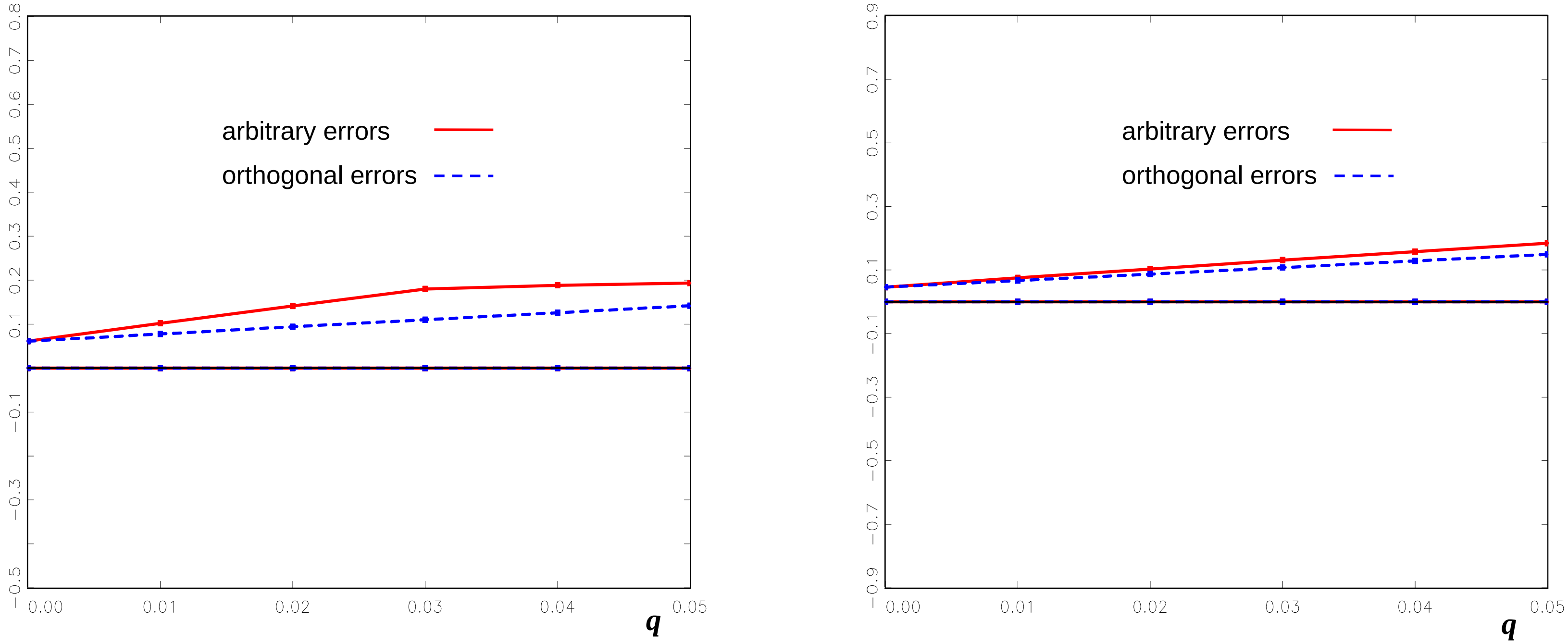
	Arbitrary Errors	Orthogonal Errors
$q = 0$	[-0.424, 0.576]	[-0.424, 0.576]
	[-0.436 0.588]	[-0.446 0.586]
$q = 0.01$	[-0.444, 0.596]	[-0.434, 0.586]
	[-0.456 0.608]	[-0.446 0.598]
$q = 0.05$	[-0.524, 0.676]	[-0.474, 0.626]
	[-0.536 0.688]	[-0.486 0.638]

† Point estimates of the population bounds; ‡ Imbens-Manski (2004) 5th and 95th percentile bounds (1,000 pseudosamples)

Figure 3

Sharp Bounds on $ATE = P[H(1)=1] - P[H(0)=1]$ with MTR and MTS Assumptions

A. Probability of Being in Good or Better Health | **B. Probability of BMI ≤ 85th Percentile**



	Arbitrary Errors	Orthogonal Errors
$q = 0$	[0.000, 0.061]†	[0.000, 0.061]
	[0.000 0.075]‡	[0.000 0.075]
$q = 0.01$	[0.000, 0.102]	[0.000, 0.078]
	[0.000 0.115]	[0.000 0.091]
$q = 0.05$	[0.000, 0.194]	[0.000, 0.142]
	[0.000 0.207]	[0.000 0.156]

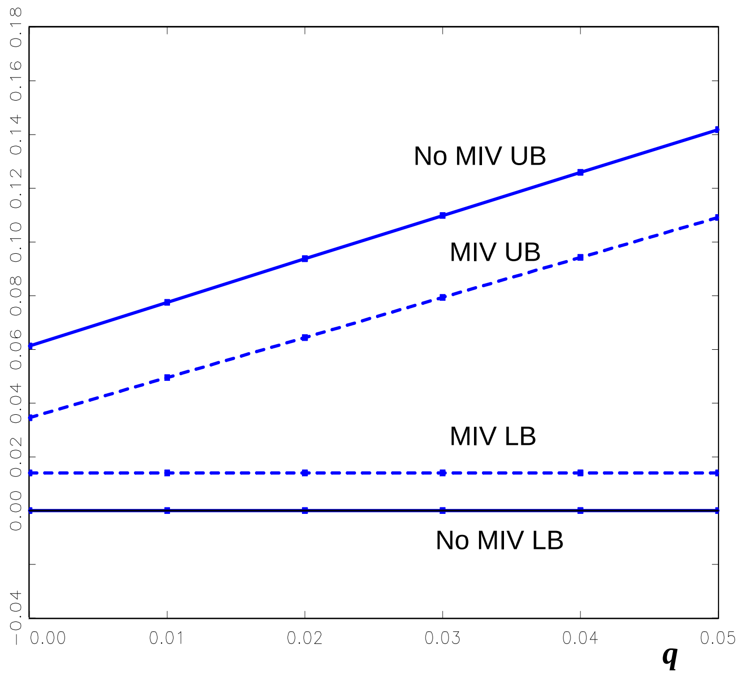
	Arbitrary Errors	Orthogonal Errors
$q = 0$	[0.000, 0.046]	[0.000, 0.046]
	[0.000 0.070]	[0.000 0.070]
$q = 0.01$	[0.000, 0.075]	[0.000, 0.067]
	[0.000 0.099]	[0.000 0.090]
$q = 0.05$	[0.000, 0.185]	[0.000, 0.149]
	[0.000 0.207]	[0.000 0.174]

† Point estimates of the population bounds; ‡ Imbens-Manski (2004) 5th and 95th percentile bounds (1,000 pseudosamples)

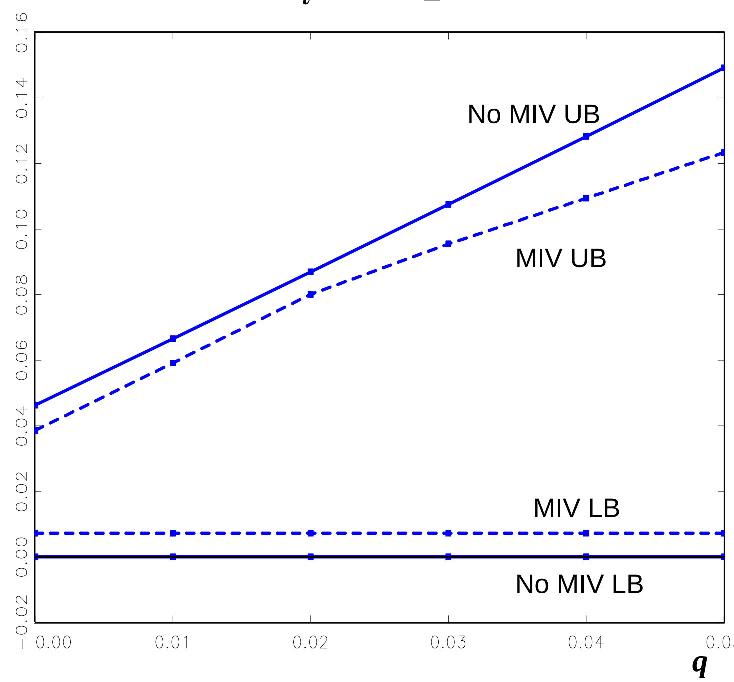
Figure 4

Sharp Bounds on *ATE* = *P*[*H*(1)=1] − *P*[*H*(0)=1] with MTR and MTS:
Comparison of No MIV and MIV Cases under Orthogonal Errors

A. Probability of Being in Good or Better Health



B. Probability of BMI ≤ 85th Percentile



	No MIV	MIV[a]
$q = 0$	[0.000, 0.061]†	[0.014, 0.035]
	[0.000 0.075]‡	[0.000 0.075]
$q = 0.01$	[0.000, 0.078]	[0.014, 0.050]
	[0.000 0.091]	[0.000 0.091]
$q = 0.05$	[0.000, 0.142]	[0.014, 0.109]
	[0.000 0.156]	[0.000 0.154]

	No MIV	MIV
$q = 0$	[0.000, 0.046]	[0.007, 0.039]
	[0.000 0.070]	[0.000 0.070]
$q = 0.01$	[0.000, 0.067]	[0.007, 0.059]
	[0.000 0.090]	[0.000 0.090]
$q = 0.05$	[0.000, 0.149]	[0.007, 0.123]
	[0.000 0.174]	[0.000 0.174]

a. The monotone instrumental variable (MIV) is "Income-to-Poverty Ratio"
† Point estimates of the population bounds; ‡ Imbens-Manski (2004) 5th and 95th percentile bounds (1,000 pseudosamples)

Appendix Table 1. Sensitivity Analysis for Figure 1

Value of Δ at q = 0 and Critical Value q_c for when the Sign of Δ is Identified[†]

	Food Insecure:[a]		At Risk of Being Food Insecure:[b]		Food Insecure With Hunger:[c]	
	$\Delta_{q=0}$	$q^c_{\text{arbitrary}}, q^c_{\text{orthogonal}}$	$\Delta_{q=0}$	$q^c_{\text{arbitrary}}, q^c_{\text{orthogonal}}$	$\Delta_{q=0}$	$q^c_{\text{arbitrary}}, q^c_{\text{orthogonal}}$
At Least Good Health:	**0.061**[‡]	**0.014, 0.021**	0.053	0.014, 0.025	0.067	0.007, 0.008
At Least Very Good Health:	0.152	0.049, 0.059	0.151	0.054, 0.073	0.108	0.016, 0.017
Excellent Health:	0.131	0.051, 0.062	0.150	0.065, 0.075	0.116	0.021, 0.027
BMI ≤ 85th Percentile:	**0.046**	**0.015, 0.018**	0.041	0.015, 0.020	0.019	0.003, 0.003
BMI ≤ 95th Percentile:	0.047	0.012, 0.017	0.040	0.012, 0.019	0.040	0.005, 0.005

[†] The sign of Δ is not identified under arbitrary errors when $q > q^c_{\text{arbitrary}}$ and is not identified when $q > q^c_{\text{orthogonal}}$ under orthogonal errors.

[‡] Baseline estimates presented in bold.

[a] At least three affirmative responses to questions in the 18-item Core Food Security Module (CFSM).

[b] At least one affirmative response to questions in the 18-item CFSM.

[c] At least eight affirmative responses to questions in the 18-item CFSM.

Appendix Table 2. Sensitivity Analysis for Figure 4

Sharp Bounds on $ATE = P[H(1)=1] - P[H(0)=1]$ with MTS and MIV Under Orthogonal Errors

	Food Insecure[a]		Food Insecure or At Risk[b]		Food Insecure With Hunger[c]	
	With MTR	No MTR	With MTR	No MTR	With MTR	No MTR
At Least Good Health:						
$q = 0$	**[0.014, 0.035]**[†]	[-0.307, 0.035]	[0.014, 0.023]	[-0.429, 0.023]	[0.014, 0.035]	[-0.145, 0.035]
$q = 0.01$	**[0.014, 0.050]**	[-0.317, 0.050]	[0.014, 0.039]	[-0.439, 0.039]	[0.014, 0.049]	[-0.156, 0.049]
$q = 0.05$	**[0.014, 0.109]**	[-0.358, 0.109]	[0.014, 0.113]	[-0.479, 0.113]	[0.014, 0.050]	[-0.163, 0.050]
At Least Very Good Health:						
$q = 0$	[0.023, 0.090]	[-0.361, 0.090]	[0.023, 0.109]	[-0.405, 0.109]	[0.023, 0.101]	[-0.325, 0.101]
$q = 0.01$	[0.023, 0.109]	[-0.370, 0.109]	[0.023, 0.126]	[-0.415, 0.126]	[0.023, 0.129]	[-0.335, 0.129]
$q = 0.05$	[0.023, 0.185]	[-0.409, 0.185]	[0.023, 0.188]	[-0.453, 0.188]	[0.023, 0.231]	[-0.374, 0.231]
Excellent Health:						
$q = 0$	[0.000, 0.094]	[-0.455, 0.094]	[0.000, 0.105]	[-0.429, 0.105]	[0.000, 0.083]	[-0.515, 0.083]
$q = 0.01$	[0.000, 0.116]	[-0.465, 0.116]	[0.000, 0.121]	[-0.439, 0.121]	[0.000, 0.136]	[-0.525, 0.136]
$q = 0.05$	[0.000, 0.196]	[-0.505, 0.196]	[0.000, 0.182]	[-0.480, 0.182]	[0.000, 0.415]	[-0.565, 0.415]
	With MTR	No MTR	With MTR	No MTR	With MTR	No MTR
BMI $\leq$ 85[th] Percentile:						
$q = 0$	**[0.007, 0.039]**	[-0.424, 0.039]	[0.007, 0.032]	[-0.469, 0.032]	[0.000, 0.015]	[-0.368, 0.015]
$q = 0.01$	**[0.007, 0.059]**	[-0.434, 0.059]	[0.007, 0.051]	[-0.479, 0.051]	[0.000, 0.054]	[-0.378, 0.054]
$q = 0.05$	**[0.007, 0.123]**	[-0.474, 0.123]	[0.007, 0.123]	[-0.519, 0.123]	[0.000, 0.177]	[-0.413, 0.177]
BMI $\leq$ 95[th] Percentile:						
$q = 0$	[0.011, 0.035]	[-0.372, 0.035]	[0.011, 0.027]	[-0.459, 0.027]	[0.011, 0.019]	[-0.245, 0.019]
$q = 0.01$	[0.011, 0.052]	[-0.382, 0.052]	[0.011, 0.046]	[-0.469, 0.046]	[0.011, 0.042]	[-0.255, 0.042]
$q = 0.05$	[0.011, 0.123]	[-0.422, 0.123]	[0.011, 0.112]	[-0.509, 0.112]	[0.011, 0.180]	[-0.272, 0.180]

[†] Baseline estimates presented in bold.

[a] At least three affirmative responses to questions in the 18-item Core Food Security Module (CFSM).

[b] At least one affirmative response to questions in the 18-item CFSM.

[c] At least eight affirmative responses to questions in the 18-item CFSM.