Identifying the Effect of WIC on Infant Health When Participation is Endogenous and Misreported

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Abstract
The existing evaluations of the Special Supplemental Nutrition Program for Women, Infants, and Children (WIC) agree on a beneficial association with birth weight but not necessarily gestation age. Regardless, considerable doubt exists over whether these associations represent a causal relationship. Endogenous selection into WIC, lack of valid exclusion restrictions, and rampant under-reporting of participation are to blame. Here, I utilize the nonparametric bounds method in Kreider et al. (2011) to address both identification problems simultaneously to assess the causal effect of prenatal WIC participation on birth outcomes. In addition, I complement the partial identification approach by reporting instrumental variable estimates following Lewbel (2010) to circumvent the need for a traditional instrument. Using data from the ECLS-B, I show that ignoring misreporting and only accounting for self-selection, WIC improves birth weight and, sometimes, gestation age. However, if only one percent of eligible women misreport their participation, well below the expected level of misreporting, the effect of WIC on birth outcomes cannot be signed.

JEL: C14, C21, I12, I18
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1 Introduction

The Supplemental Nutrition Program for Women, Infants, and Children (WIC) was established as an early intervention program to improve the outcomes of low income pregnant and lactating women, infants, and children under five. The WIC has been the focus of recent and ongoing research. This is partly driven by the growing perception that early life conditions have long term impacts on adult life outcomes (Almond and Currie, 2010). On the other hand, the sheer scope and prominence of the WIC program have spurned this academic and policy interest in its efficacy: there were approximately 9.17 million WIC recipients in the fiscal year (FY) 2010.[2]

There is a third reason for the growing body of research on WIC. Like most transfer programs, evaluation of WIC efficacy is complicated by two distinct identification problems. First, selection into WIC is non-random. Observable (in the data) characteristics and unobservable attributes of the participants may be associated with both program participation and health outcomes. Second, WIC participation is severely under-reported in large scale, nationally representative household surveys like the Survey of Income and Program Participation (SIPP) and the Current Population Survey (CPS). While the existing literature is discussed in greater detail in Section 3, for now I simply note that the existing literature suggests a beneficial causal effect. These estimated effects are, however, plagued by deficiencies such as reliance on potentially invalid instruments or other faulty identification assumptions in the face of both non-random selection and large scale under-reporting of WIC participation.

This study is the first attempt, to the best of my knowledge, to simultaneously address the twin identification problems of endogeneity and measurement error (ME) in identifying the causal effect of prenatal WIC receipt on birth outcomes.

To that effect, I use the nonparametric bounding method proposed in Kreider et al. (2011) accounting for both of these problems in a single unifying framework. This partial identification approach suits the analysis of WIC for a number of reasons. First, existing solutions using classical approaches - instrumental variables (IV) and family-specific fixed effects models - are inconclusive and perhaps rely on faulty assumptions. Second, addressing classification error in binary regressors like the indicator of WIC receipt is complicated; and the classical assumption of ME being independent of the true participation indicator is invalid with large scale systematic under-reporting in case of programs like the WIC and food stamps (Kreider et. al, 2011 and Bollinger, 1996).[3] Third, if the self-reported indicator of WIC receipt is measured with error, it is likely that a valid instrument for WIC receipt is correlated with the ME as well (Black et al., 2000). Family-specific fixed effects models, on the other hand, fail to account for potentially important,

[2] See:http://www.fns.usda.gov/wic/wic-fact-sheet.pdf

[3] Those eligible for food stamps are automatically eligible for WIC.

individual-specific unobservable attributes as well as exacerbate the ME problem (Griliches, 1977).

This method provides sharp bounds on the average treatment effect (ATE) of prenatal WIC participation when the participation indicator is measured with arbitrary error. Moreover, these bounds do not require the assumptions of an IV, classical ME, and the linear response model. These require weaker assumptions with possibly greater consensus in the literature and address *both* ME and selection into WIC. These bounds on the ATE are thus an important step towards identifying the causal effect of the WIC program and reducing the uncertainty in existing evaluations of the causal impact of participation.

In terms of the selection problem, I start with the exogenous case. Then, I discuss what can be learned without making any assumptions concerning the selection mechanism (see Manski, 1995 and Pepper, 2000). Then, I impose several identification assumptions: Monotone Instrumental Variable (MIV) assumption that the latent probability of a good health outcome is nondecreasing in socioeconomic status (SES); the Monotone Treatment Selection (MTS) assumption that infants whose mothers chose to participate in WIC during pregnancy have a lower probability of a good health outcome on average compared to non-participants; and the Monotone Treatment Response (MTR) assumption that prenatal participation in WIC cannot worsen birth outcomes since the program's aim is to provide nutritional supplements and educational counselling to potentially improve birth outcomes. The MIV is a weaker assumption than that required for an IV. The MTS assumption allows for negative selection into WIC, a well established finding in the literature.

In terms of the ME problem, the empirical literature on WIC (as discussed below) suggests that eligible women rarely falsely claim WIC receipt. To define the ME problem, I first assume arbitrary patterns of ME ranging from zero to 10%, and then allow for no false positive errors in consonance with reports of prenatal WIC receipt being more accurate than those of non-receipt.

While the existing literature is plagued by the lack of convincing instruments, the identification problem is exacerbated in the presence of ME. So, to identify the point estimates of the causal effect of WIC, complementing the bounds, I turn to the IV strategy proposed in Lewbel (2010). This approach exploits conditional second moments to circumvent the need for traditional instruments when the latter are absent or suspect. Identification is achieved through the presence of covariates related to the conditional variance of the first-stage errors, but not the conditional covariance between first- and second-stage errors.

I use data on over 4,000 nine month old infants from the Early Childhood Longitudinal Study - Birth cohort of 2001 (ECLS-B). The sample is restricted to households at the WIC eligibility threshold of 185% of the federal poverty level (FPL).[4] I provide informative bounds on the ATE of prenatal WIC participation of

[4] I assume that poverty status (at or below 185% FPL) is unchanged since before the child's birth for the mother to be eligible for WIC prenatally. Since this is the first wave of the survey, there is no way I can verify this assumption.

the mother on binary positive birth outcomes like birth weight of at least 1500 grams, at least 2500 grams, at most 4000 grams, normal birth weight (between 2500 grams and 4000 grams), near-term pregnancy (gestation age of at least 33 weeks), and full term pregnancy (gestation age between 38 and 42 weeks). The timing of the survey is such that the mother reports prenatal WIC receipt when the child is at least nine months old. That is, the lag between actually receiving the WIC benefits and reporting the same is anywhere between 9 months to 18 months.[5] So, along with social stigma, simple recall error introduces another source of ME in self-reported WIC participation.

The results are striking and ought to serve as a note of caution and guide to future evaluations of the WIC program. First, there is selection at least on observables and thus likely also on unobservables such as a family's financial status, expectations about future health outcomes, motivation towards work and family, mother's nutrition knowledge, and the desire to be a good mother which can be simultaneously associated with both program participation and outcomes (Bitler and Currie, 2005 and Currie, 2003). Families may decide to participate only if they expect to be worse off otherwise.

Second, bounds that account for selection only – ignoring the possibility of ME – show that prenatal WIC receipt indeed increases the probability of birth weight of at least 1500 grams, 2500 grams, and the probability of normal birth weight, and lowers the probability of birth weight exceeding 4000 grams. Prenatal WIC participation also leads to an increase in gestation age of the child. Third, bounds accounting for *both* ME and selection fail to sign the ATE for any outcome without imposing additional assumptions beyond those considered here. I am unable to conclude there exists a causal effect (positive or negative) of prenatal WIC receipt on birth outcomes even if as few as one percent of eligible women misreport their participation.

This evidence has strong implications since WIC caters to a very special population of low-income pregnant, postpartum women, and their children. This sub-population is arguably in maximum need of nutritious food, regular health check ups, and counselling. The existing literature acknowledges the serious under-reporting problem, of possibly much greater than one percent, and its potential consequence on evaluating the program's effectiveness. In this first step (of which I am aware) towards quantifying the consequence of ME in reports of prenatal WIC receipt, I show that even one percent of ME is sufficient to render the evidence concerning the causal effect of participation inconclusive. Any greater degrees of ME will only worsen the situation. This study illustrates what can (or cannot) be learned in the presence of ME without additional identifying assumptions that are not likely to be convincing. Accordingly, future work should be cognizant of the consequence of ME and account for *both* these identification problems in isolating the causal effect of participation in WIC. Alternatively, experimental evidence may be necessary

[5] The ECLS-B does not provide information on the duration of WIC receipt.

to obtain credible estimates of the causal effect of the program.

The rest of the paper is organized as follows. I describe the WIC program in Section 2 and summarize the existing literature in Section 3. Section 4 describes the data. In Section 5, I define the empirical questions and present the nonparametric models and the IV strategy proposed in Lewbel (2010). The results are discussed in Section 6, while Section 7 concludes.

2 The WIC Program

The WIC program was established as a pilot program in 1972 by an amendment to the Child Nutrition Act of 1966.[6] It was made permanent in 1974. Like many other programs in the U.S. social safety net, WIC is a federally-funded grant program run by the states.

The principal goal of WIC, since its inception, is to provide nutritious food, directly or through vouchers, and nutritional and health counselling to pregnant and postpartum women, infants, and children less than five years old, at no charge. This is the first categorical eligibility criterion for WIC.

Additionally, in order to be eligible for WIC, the maximum allowable family gross income must not exceed 185% of the FPL. WIC agencies at the state level authorize the local providers to determine eligibility based on family income during the past one year or current family income. Moreover, Supplemental Nutrition Assistance Program (SNAP), Medicaid, and the Temporary Assistance for Needy Families (TANF) recipients automatically ("adjunctively") qualify for WIC. This adjunctive eligibility rule has been criticized since income eligibility expansions in other programs draw higher income women into the ambit of WIC for whom a food package worth $35 may have little effect, thus undermining the effectiveness of the program. Moreover, insufficient funds are allocated to nutritional education with a much greater potential impact (e.g., Besharov and Germanis, 2001 and Besharov and Call, 2009). Since 2000, by federal law, income proofs are required in all states thus quelling some of the controversy related to the number of eligibles being served.

The last criterion for WIC requires recipients to be at nutritional risk, as determined by a physician, nutritionist, or nurse. In practice, all likely recipients satisfy at least one of the nutritional risk criteria (Ver Ploeg and Betson, 2003).[7]

Most WIC state agencies issue vouchers or checks to participants for purchase of specific foods every month. Some states also issue electronic benefit cards instead of paper checks or vouchers. All WIC state agencies will be required to implement electronic benefit transfer (EBT) statewide by October 1, 2020.

[6] See:http://www.ers.usda.gov/publications/fanrr27/fanrr27c.pdf

[7] Brien and Swann (2001) enlist some of the risk criteria followed at the Jefferson WIC Clinic in Charlottesville, VA.

In terms of program participation, WIC has come a long way from 88,000 enrollees in 1974, its first year of operation. Monthly participation reached 1.9 million in 1980 and 7.2 million by 2000. During FY 2010 there were approximately 9.17 million WIC beneficiaries. Children constitute the majority of WIC recipients. Of the 9.17 million WIC recipients each month in FY 2010, about 4.86 million were children, 2.17 million were infants, and 2.14 million were women. In the first 8 months of FY 2011, states reported an average monthly participation of slightly less than 9 million.

WIC stands apart from all major transfer programs in that it is not an entitlement program in the sense that the Congress does not allocate funds separately for WIC to allow every eligible person to participate. Despite that, Ver Ploeg and Betson (2003) suggest that all those who visit WIC clinics are served as showcased by the disappearance of waiting lines. Sometimes, however, the turn out at WIC clinics exceeds the resources available to state agencies, in which case only those on the top of a specific list are served. These invariably include pregnant women (Brien and Swann, 2001). Historically, the Congress appropriated only $20.6 million in 1974 which steadily increased to $2.1 billion in 1990 and $4.0 billion in 2000. In FY 2011, Congress legislated $6.734 billion for WIC.[8]

3 Literature Review

Almond and Currie (2010) discuss a recent report from the Institute of Medicine that finds, for a very special sub-population of women at preterm birth risk, that even randomized trials of several intensive interventions to prevent preterm births fail to find any effect. This casts serious doubt on the existing estimated effects of WIC on birth outcomes.

The existing research on WIC has tried to address this critique using different data sets and methodologies. Most of the research relies on administrative birth certificate data for birth outcomes matched with household survey data for information on participation (Figlio et al., 2009). Since the WIC participation information often comes from survey data, it is possible that it is measured with error. However, the existing evaluations are dominated by empirical strategies to address the non-random selection problem while virtually ignoring the evidence of large scale misreporting of WIC receipt in household surveys. Thus, they fail to isolate the causal effect of WIC in the face of *both* measurement error and endogeneity in WIC participation.

Early works evaluating WIC assume exogenous selection into WIC and ignore ME. For example, Barbara Devaney and her coauthors find that women on WIC bear healthier children compared to non-participants at a lower cost to the state (e.g., Devaney et al., 1992). Currie (2003) review similar early

[8] See:http://www.fns.usda.gov/wic/wic-fact-sheet.pdf. All values are in nominal terms.

contributions on the positive association between prenatal WIC participation and birth outcomes, nutritional intake, and breast-feeding practices, with the largest gains recorded for children of the most disadvantaged mothers.

However, several contributors rule out random selection on observables as well as unobservables. Some contend that more motivated or healthier women with possibly better access to medical care may self-select into WIC thus biasing the estimated effect of WIC upwards (e.g., Germanis and Besharov, 2001; Brien and Swann, 2001; Chatterji et al., 2002; and Kowaleski-Jones and Duncan, 2002). Others like Bitler and Currie (2005) include a long list of unfavorable observables related to education, health, and family relationships to argue that WIC mothers must have other very strong unobservable attributes, systematically correlated with good outcomes, to justify positive selection on unobservables into WIC.

As a result, addressing the selection problem lies at the heart of the recent studies. Several analyses address the selection issue by leveraging observable similarities between participants and non-participants in narrowly defined samples (e.g., Bitler and Currie, 2005; Joyce et al., 2005, 2008; and Figlio et al., 2009). For example, Bitler and Currie (2005) use the Pregnancy Risk Assessment Monitoring System (PRAMS) and selection correction models in a homogeneous sample of Medicaid eligible women to focus only on the observable differences between participants and non-participants. They conclude that "WIC *does* work" by improving birth outcomes, despite negative selection, at least on observables (Bitler and Currie, 2005, p. 88). The impact is larger for the more disadvantaged women.

Figlio et al. (2009), for instance, merge three large administrative data sets on infants from Florida to match the school records of their older siblings to exploit the latter's participation in the National School Lunch Program (NSLP). They label families "marginally ineligible" if they participated in the years adjacent to the birth year, but not in the birth year. Their innovative instrument is a federal policy change in September 1999 that raised the income proof requirements for WIC in Florida, making it harder for WIC applicants to receive benefits. They find that participation in WIC has a beneficial causal effect in compressing the birth weight distribution towards a healthier range, but has no significant impact on gestation age. However, one cannot rule out the possibility of mismatching due to imperfect linking of information across administrative data sets (Kapteyn and Ypma, 2007).

Hoynes et al. (2011) argue that unobservable differences remain between participants and non-participants even in narrowly defined samples such as in Bitler and Currie (2005) and Figlio et al. (2009). They also highlight the drawbacks of using other methodologies to address the selection problem such as unobservable differences between participating and non-participating siblings (e.g., Brien and Swann, 2001; Chatterji et al., 2002; and Kowaleski-Jones and Duncan, 2002) or state variations in program rule and eligibility (e.g., Brien and Swann, 2001 and Chatterji et al., 2002).[9] Additionally, none of these works discuss the potential consequences of ME in reports of WIC receipt in survey data.

Most recently, Hoynes et al. (2011) evaluate the performance of WIC at the time of its establishment as a pilot program in 1972. They address the selection problem by exploiting the plausibly exogenous variation in participation due to the staggered introduction of the program in the 1970s. Employing a difference-in-differences technique and WIC program data, they report that the introduction of WIC has a beneficial causal effect on infant health. The availability of WIC in the county of birth by the third trimester increases the average birth weight in the county by about 2 grams and by 7 grams for infants born to less educated women. However, it is important to note, as Kapteyn and Ypma (2007) point out, that administrative data may not be perfect as well since one cannot rule out the possibility of mismatching due to imperfect linking of information. Moreoever, the authors concede that the number of the treated women (who received WIC benefits during its early years) is only an indirect estimate. So, the estimated treatment effect on the treated may not be unbiased.

Turning now to the evidence on ME in the WIC literature, Bitler et al. (2003) compare the SIPP and the CPS to state level administrative data. They find that the under-reporting problem is the most severe for WIC compared to other transfer programs. The CPS (SIPP) captures only 70% (75%) of the WIC administrative caseload compared to, for example, 85% (90%) of food stamp recipients. The authors hypothesize that this is probably associated with greater stigma for WIC recipients since the purchase of certain types of food is subject to verification by the cashier for WIC eligibility. In the SIPP sample of WIC recipients, the undercount problem is worse for women. However, the undercount problem appears to be random since demographic characteristics of WIC recipients closely resemble the administrative caseloads.

Recently, Meyer et al. (2009) emphasize that the under-reporting problem is synonymous to under-statement and under-recording since it is possibly due to discrepancies on the part of both interviewees and interviewers. They use the CPS, the SIPP, the Panel Study of Income Dynamics (PSID), the American Community Survey (ACS), and the Consumer Expenditure Interview Survey (CE Survey) to analyze the large scale under-reporting phenomenon in several transfer programs. Unobservable, often unverifiable factors like continuity of receipt, the social stigma of being on a "welfare" program, imperfect interviewee recall, sensitivity of income information, and possibly a desire to reduce interview burden potentially drive the under-reporting. This problem is likely even worse in the case of the ECLS-B since women are asked about prenatal WIC participation when the child is at least nine months old.

In summary, the literature on prenatal WIC participation and birth outcomes admits negative selection into WIC as well as severe under-reporting of WIC receipt in household surveys. However, to date, there

[9] The treatment considered in Chatterji et al. (2002) is postpartum participation in WIC by the mother.

has not been any study that addresses both these identification problems simultaneously to isolate the causal effect of WIC on infant health outcomes.

4 Data

The data come from the ECLS-B. It follows a nationally representative cohort of children born in 2001 through first grade. Assembled by the U.S. Department of Education, the ECLS-B focuses on children's early environmental characteristics like health care and in- and out-of-home experiences that play a crucial role in the overall development of children and the first brush with the demands of formal school. The survey has collected information directly from the children's fathers along with the mothers, video-taped parent-child interaction, and assessed child care settings for the sampled children. Actual data collection occurred between Fall 2001 and Fall 2002. The parents of 10,700 children born in 2001 participated in the first wave of the study when the children were approximately nine months old. The ECLS-B is one of the few national U.S. studies that involve fathers through self-reporting driven by the importance of the father's presence in the child's life.[10] The survey includes separate questionnaires for only resident, only non-resident biological, and both resident and non-resident biological fathers.

Since the focus of the study is to analyze the effect of WIC on birth outcomes, only the first wave of the survey is exploited. The focus is on infants from households which are income eligible for WIC, that is, at or below 185% of the FPL. The sample is further restricted to children who are singletons without any missing information on age.[11]

The principal sample has 4,350 nine-month old infants from WIC eligible families. I also study two subsamples based on the race of the child and urban status of the household. The non-white WIC eligible sample consists of 3,150 infants while the urban WIC eligible sample has 3,600 infants. The binary treatment variable, WIC, takes a value of one if the mother reports receiving WIC benefits during pregnancy, and zero otherwise. I focus on the relationship between WIC and binary health outcomes related to birth weight and gestation age. Among the birth weight outcomes, I include an indicator for birth weight of at least 1500 grams, an indicator for birth weight of at least 2500 grams, an indicator for normal birth weight (birth weight between 2500 grams and 4000 grams), and another for birth weight of at most 4000 grams.[12] For gestation age, I include an indicator each for near-term pregnancy (gestation age of at least 33 weeks)

[10] See: The ECLS-B 9-month User's Manual, Chapters 1- 5, p. 64.

[11] 380 observations have missing information on age and are dropped.

[12] More than 7% of the sample are clinically "macrosomic" (birth weight exceeding 4000 grams). Boulet et al.(2004) show that macrosomia is related to fetal injury, perinatal asphyxia, and fetal death, as well as complications for the mother like increasing the probability of caesarean delivery.

and full term pregnancy (gestation age between 38 and 42 weeks). The information on birth weight and gestation age come from the infant's birth certificate. All the outcomes are defined such that an outcome of one (as opposed to zero) is a good thing.

For the IV estimates following Lewbel (2010), I include the following child-specific parental and environmental covariates: child's race (white, black, Asian, and Hispanic), a gender dummy, household socioeconomic status (SES), mother's age, father's age, dummy variables for whether the mother has a high school (HS) degree or less, corresponding indicator for father's education, a marital status indicator for whether the parents are married, region type (Northeast, Midwest, South, and West), and city type (urban cluster, urban area, and rural). Additionally, higher order and interaction terms involving both binary and continuous variables are included in the estimations.

Table A1 in Appendix A provides the summary statistics for the full sample. All analyses are performed using survey weights. The last two columns report the differences in means between the treated (prenatal WIC recipients) and the untreated (income eligible non-participants) along with the p-values.

68.7% of the WIC eligible households report prenatal WIC receipt. In terms of the demographic and socioeconomic characteristics, it is evident that children whose mothers report prenatal WIC receipt are less likely to be white or Asian, and more likely to be black or Hispanic. They are from households with lower SES and fewer family members. These children are more likely to have younger but unmarried parents. The mothers are less likely to report inadequate care (consistent with WIC's focus on nutritional and health care education) and are more likely to be heavier themselves. They are also more likely to have at most a HS degree; and the fathers are less likely to have completed HS. WIC participants are also more likely to reside in less densely populated areas.

In terms of the birth outcomes, the children of prenatal WIC recipients have lower probabilities of near-term and full term pregnancies, compared to those of eligible non-participating mothers. The average birth weight is also lower for children of prenatal WIC participants compared to those of non-participants.

Consistent with the existing research on WIC and birth outcomes, there exists negative selection, at least on observables, into WIC participation.

5 Methodology

For this analysis, I focus on children from WIC eligible families with income at or below 185% of the FPL. My aim is to learn about the ATE of the eligible mother's prenatal WIC receipt on birth outcomes of children. The ATE captures the expected treatment effect if an expectant mother was chosen at random from the WIC eligible population. While there are treatment effect parameters of potential interest, I focus on the ATE for two main reasons. First, Figlio et al. (2009) note that WIC serves half of all pregnant women in the United States. In the ECLS-B data used in this study, 49% of households are income-eligible for WIC and almost 69% of the eligible women report receiving WIC benefits during pregnancy. Second, since I suspect that the treatment in question, self-reported prenatal WIC receipt, is measured with error, the definition of the treated sample will be odd.

With binary outcomes, the ATE is expressed as

$$ATE(1,0) = P\left[H(1) = 1 | X \in \Omega\right] - P\left[H(0) = 1 | X \in \Omega\right] \tag{1}$$

where $H(1)$ denotes a binary measure of health of a child if his or her mother received WIC prenatally, and $H(0)$ denotes the corresponding outcome if the child's eligible mother did not. The probabilities of these health outcomes are conditioned on observed covariates denoted by $X \in \Omega$ with values in the set Ω. In this approach, conditioning on covariates only helps to define subpopulations of interest (Kreider et al., 2011). For notational simplicity, $X \in \Omega$ is dropped in the following derivations.

To assess the effect of prenatal WIC receipt by the mother on a child's health outcome using observational data, two distinct identification problems must be addressed. First, even if true WIC receipt were observed for all eligible households, the potential outcome $H(1)$ is a missing counterfactual for all children whose WIC eligible mothers did not participate. By the Law of Total Probability, it is shown as

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

where $W^* = 1$ represents that the child's mother truly received WIC benefits during her pregnancy and $W^* = 0$, otherwise. If true WIC receipt is observed, the sampling process identifies $P(W^* = 1)$ and $P(W^* = 0)$, the selection and censoring probabilities respectively, and the expected outcome conditional on the outcome being observed $P\left[H(1) = 1 | W^* = 1\right]$. However, it fails to identify the average outcome conditional on censoring, i.e., $P\left[H(1) = 1 | W^* = 0\right]$. Accordingly, both $P\left[H(1) = 1\right]$ and $P\left[H(0) = 1\right]$ are not nonparametrically identified.

The second identification problem arises because true participation status may not be observed for all respondents. The true W^* is not observed; the data has only a self-reported indicator, W, where $W = 1$ if the child's mother reports being a prenatal WIC beneficiary and zero otherwise. This is called the ME or classification error problem. The sampling process fails to provide any useful information on true participation status, W^*, without assumptions on the extent and type of ME. So, all the probabilities on the right hand side of Equation (2) are unknown.

Following Kreider et al. (2011) to focus on the ME problem, let the latent variable Z^* denote whether a report is accurate or not, where $Z^* = 1$ if $W^* = W$ and $Z^* = 0$ otherwise.[13] Using Z^*, Kreider and his coauthors show that $P[H(1) = 1]$ can be decomposed as follows:

$$P[H(1)=1] = [P(H=1,W=1) - \theta_1^+ + \theta_1^-] + P[H=1|W^*=0][P(W=0) + (\theta_1^+ + \theta_0^+) - (\theta_1^- + \theta_0^-)] \quad (3)$$

where H is the actual health outcome, $\theta_j^+ = P(H = j, W = 1, Z^* = 0)$ and $\theta_j^- = P(H = j, W = 0, Z^* = 0)$ represent the proportion of false positive and false negative classifications of WIC beneficiaries, respectively, for children realizing health outcome $j = 1, 0$.

Looking at (3), all of the terms on the right hand side, except $P(H = 1, W = 1)$ and $P(W = 0)$ are unobserved. $P[H = 1|W^* = 0]$ is not identified due to both the selection and ME problems while the θ terms are not identified due to ME.

Given these constraints on identifying the ATE of a binary treatment variable, the bounds on the ATE are derived by combining various selection assumptions with two assumptions about the the nature and extent of ME. I denote UB for upper bound and LB for lower bound of the ATE for each set of assumptions considered. The reader is referred to the technical appendix, Appendix D, for more details.

5.1 Classification Error Assumptions

Bitler et al. (2003, p. 1175) find that the demographic characteristics of WIC recipients in the SIPP and CPS "track the WIC caseload well" so that the undercount problem is approximately random, at least along observable characteristics. Accordingly, I first allow for arbitrary error rates. Then, I tighten the bounds on the ATE by imposing an additional assumption of no false positive errors, i.e., very few women falsely claim WIC receipt. This is true for other programs like food stamps as documented by Kreider and his coauthors, and given that food stamp recipients are income eligible for WIC, this appears to be a reasonable restriction. Moreover, Meyer et al. (2009) acknowledge the growing nature and direction of this problem, and refer to it strictly as an under-reporting problem in lieu of ME. They also verify that false positive reporting is not very high.[14]

Methodologically, I follow Gundersen and Kreider (2008) and impose the following assumptions on classification error:

[13] The formulae and their derivations come from an earlier version of Kreider et al. (2011).

[14] Only Jacknowitz and Tiehen (2010) report a slightly higher prenatal participation rate in the ECLS-B compared to the USDA data for 2001. However, their sample definition is based on prenatal Medicaid receipt by the mother while my sample is based on the WIC income eligibility criterion like Figlio et al.'s (2009) since I suspect non-trivial ME in reports of Medicaid receipt (Kreider and Hill, 2009).

(i) Upper Bound Error Rate Assumption: $P(Z^* = 0) \leq Q$

(ii) No False Positives Assumption: If $W = 1$, then $W^* = 1$.

Here, Q is an upper bound on the degree of data corruption. It takes a value of zero if the researcher is absolutely certain about the accuracy of WIC participation reported by all eligible women. This is the case for existing WIC evaluations. Assumption (ii) states that if the respondents claim WIC receipt, then these reports are presumed to be accurate.

To check the sensitivity of inferences to different assumptions on classification errors, I compare two scenarios: the "arbitrary errors" case imposes only assumption (i) and the "no false positives" model imposes both assumptions (i) and (ii). The above assumptions on classification errors impose reasonable restrictions on the unknown false reporting rates θ_1^-, θ_0^-, θ_1^+, and θ_0^+. Assumption (i) implies

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

and

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

Assumption (ii) implies

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

For both the "arbitrary errors" and the "no false positives errors" models, Q takes values of 0 (no ME), 0.01, 0.02, 0.05, and 0.10. This range is reasonable since Bitler et al. (2003) document under-reporting in the range of 25% to 30% in the SIPP and CPS. So, a maximum Q of 10%, at worst, depicts a less severe situation compared to the existing evidence. Additionally, I assess the degree of ME in the ECLS-B data using the maximum likelihood estimation (MLE) method proposed in Hausman et al. (1998).

Hausman et al.'s (1998) parametric model of asymmetric misclassification applies to the case where the binary dependent variable is measured with error. In the present context, the self-reported indicator of prenatal WIC participation, W, is such a mismeasured variable.

Assuming F is the normal CDF, the probit probabilities of true WIC receipt are given by

$$
\begin{aligned}
\Pr\left[W_i^* = 1 | X_i\right] &= F\left(X_i'\gamma\right) \\
\Pr\left[W_i^* = 0 | X_i\right] &= 1 - \Pr\left[W_i^* = 1 | X_i\right]
\end{aligned}
$$

where X_i represents the covariates.

With misclassification, however, the observed W_i differs from the true W_i^*. Then the misclassification probabilities are

$$\begin{aligned}\alpha_0 &= \Pr[W_i = 1 | W_i^* = 0] \\ \alpha_1 &= \Pr[W_i = 0 | W_i^* = 1].\end{aligned}$$

α_0 represents the proportion of false positive classifications; α_1 represents the fraction of false negative classifications. In this model of misclassification, these probabilities depend on W_i^* but are independent of the X_i. Accounting for misclassification, the probabilities of observed W_i are

$$\begin{aligned}\Pr[W_i = 1 | X_i] &= \Pr[W_i = 1 | W_i^* = 0] \Pr(W_i^* = 0 | X_i) + \Pr[W_i = 1 | W_i^* = 1] \Pr(W_i^* = 1 | X_i) \\ &= \alpha_0 + (1 - \alpha_0 - \alpha_1) F(X_i^{'} \gamma) \\ \Pr[W_i = 0 | X_i] &= 1 - \Pr[W_i = 1 | X_i] \\ &= 1 - \alpha_0 - (1 - \alpha_0 - \alpha_1) F(X_i^{'} \gamma).\end{aligned}$$

The parameters of interest $(\gamma, \alpha_0, \alpha_1)$ are estimated by MLE by maximizing the log likelihood function

$$\begin{aligned}\ln \mathcal{L}(\gamma, \alpha_0, \alpha_1) &= n^{-1} \sum_i \{W_i \ln[\Pr(W_i = 1 | X_i)] + (1 - W_i) \ln[\Pr(W_i = 0 | X_i)]\} \\ &= n^{-1} \sum_i \left\{W_i \ln[\alpha_0 + (1 - \alpha_0 - \alpha_1) F(X_i^{'} \gamma)] + (1 - W_i) \ln[1 - \alpha_0 - (1 - \alpha_0 - \alpha_1) F(X_i^{'} \gamma)]\right\}\end{aligned}$$

over $(\gamma, \alpha_0, \alpha_1)$. The parameters $(\gamma, \alpha_0, \alpha_1)$ are identified by the non-linearity of the normal distribution in addition to a monotonicity assumption: $\alpha_0 + \alpha_1 < 1$.

The estimates of α_0 and α_1 are 0.05 and 0.19, respectively in the ECLS-B data. I also reject the null hypothesis that α_0 and α_1 are jointly equal to zero at the p $<$ 0.01 confidence level. Since $Q = 0.10$ is still less than the sum of the estimated values of α_0 and α_1 in this data, allowing for a maximum of $Q = 0.10$ seems additionally justifiable.[15]

5.2 Exogenous Selection

5.2.1 No Misclassification Errors

While the WIC literature does not believe the existence of exogenous selection into WIC, it is a necessary starting point before the assumption is relaxed to admit certain non-random selection assumptions. The assumption of exogenous selection is expressed as

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

[15] The full set of results is available upon request.

which implies

$$P[H(1)=1,W^*=1]=P[H(1)=1,W^*=0]=P[H(1)=1].$$

Accordingly, using (2) implies

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

So,

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

5.2.2 Allowing for Misclassification Errors

Allowing for misclassification errors, the ATE cannot be identified even under the assumption of exogenous selection as W^* is not observed in (6). To illustrate:

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

can be decomposed as

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

where the sampling process identifies only $P(H=1,W=1)$ and $P(W=1)$. 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 entire eligible population; the term, $(\theta_1^- -\theta_1^+)$, in the numerator, reflects the excess of false negatives relative to the false positives among those children with $H=1$.

Arbitrary Errors Model I assume $P(Z^*=0)\leq Q$. Now, ATE is defined as:

$$ATE=P\left[H(1)=1\right]-P\left[H(0)=1\right]$$

with the corresponding bounds given by

$$\begin{aligned} UB_{ATE} &= UB_{P[H(1)=1]}-LB_{P[H(0)=1]} \\ LB_{ATE} &= LB_{P[H(1)=1]}-UB_{P[H(0)=1]}. \end{aligned}$$

With arbitrary errors, the bounds beome

$$\begin{aligned} UB_{ATE} &= \sup_{a\in(0,\min[Q,P(H=1,\ W=0)])}\left[\frac{P\left[H=1,W=1\right]+a}{P(W=1)+2a-Q}-\frac{P\left[H=1,W=0\right]-a}{P(W=0)-2a+Q}\right] \\ LB_{ATE} &= \inf_{b\in(0,\min[Q,P(H=1,\ W=1)])}\left[\frac{P\left[H=1,W=1\right]-b}{P(W=1)-2b+Q}-\frac{P\left[H=1,W=0\right]+b}{P(W=0)+2b-Q}\right]. \end{aligned}$$

The reader is referred to Propositions 1 and A.1 in Kreider and Pepper (2007) for the proof and derivation.

No False Positives Errors Model Equation (7) implies

$$\frac{P[H=1,W=1]}{P(W=1)+\theta_0^{UB-}} \leq P[H(1)=1] \leq \frac{P[H=1,W=1]+\theta_1^{UB-}}{P(W=1)+\theta_1^{UB-}} \tag{8}$$

and

$$\frac{P[H=1,W=0]-\theta_1^{UB-}}{P(W=0)-\theta_1^{UB-}} \leq P[H(0)=1] \leq \frac{P[H=1,W=0]}{P(W=0)-\theta_0^{UB-}}. \tag{9}$$

Accordingly, the bounds on the ATE become

$$\begin{aligned} UB_{ATE} &= \frac{P[H=1,W=1]+\theta_1^{UB-}}{P(W=1)+\theta_1^{UB-}} - \frac{P[H=1,W=0]-\theta_1^{UB-}}{P(W=0)-\theta_1^{UB-}} \\ LB_{ATE} &= \frac{P[H=1,W=1]}{P(W=1)+\theta_0^{UB-}} - \frac{P[H=1,W=0]}{P(W=0)-\theta_0^{UB-}}. \end{aligned} \tag{10}$$

For derivations, see Appendix D.

5.3 No Selection Assumption

The previous bounds on the ATE assume exogenous selection which is unlikely given the WIC literature and the covariates available in the ECLS-B data. In this section, I consider the effect of prenatal WIC on infant health without assuming any particular selection mechanism following Manski (1995) and Pepper (2000).

5.3.1 No Misclassification Errors

Without ME the true W^* is observed. Additionally, with no assumption on selection, the only available information are that the probabilities $P[H(1)=1|W^*=0]$ and $P[H(0)=1|W^*=1]$ lie between $[0,1]$. Accordingly, the bounds are:

$$P[H=1,W^*=1] \leq P[H(1)=1] \leq P[H=1,W^*=1]+P(W^*=0) \tag{11}$$

and

$$P[H=1,W^*=0] \leq P[H(0)=1] \leq P(W^*=1)+P[H=1,W^*=0]. \tag{12}$$

For derivations, see Appendix D.

The width of the bound on $P[H(1)=1]$ is the censoring probability, $P(W^*=0)$, while the inclusion probability, $P(W^*=1)$, is the width of the bound on $P[H(0)=1]$. Since

$$ATE = P[H(1)=1] - P[H(0)=1],$$

this means that although the bounds on ATE are sharp, the width always equals 1 (see Manski, 1995). So, without identifying restrictions on the selection mechanism, it is impossible to sign the ATE. If true

WIC participation is observed the data is sufficient to identify the effect of WIC participation on birth outcomes.

5.3.2 Allowing for Misclassification Errors

Allowing for ME, the bounds on $P[H(1) = 1]$ and $P[H(0) = 1]$ are:

$$P[H = 1, W = 1] - \theta_1^+ + \theta_1^- \leq P[H(1) = 1] \leq P[H = 1, W = 1] + P(W = 0) + \theta_0^+ - \theta_0^- \tag{13}$$

$$P[H = 1, W = 0] + \theta_1^+ - \theta_1^- \leq P[H(0) = 1] \leq P[H = 1, W = 0] + P(W = 1) - \theta_0^+ + \theta_0^-. \tag{14}$$

Arbitrary Errors Model Imposing Assumption (i) on ME the bounds on ATE are tightened to

$$\begin{aligned} UB_{ATE} &= P[H = 1, W = 1] + P(W = 0) + \min\{Q, \theta_0^{UB+} + \theta_1^{UB-}\} - P[H = 1, W = 0] \\ LB_{ATE} &= P[H = 1, W = 1] - \min\{Q, \theta_1^{UB+} + \theta_0^{UB-}\} - P[H = 1, W = 0] - P(W = 1). \end{aligned} \tag{15}$$

For derivations, refer to Appendix D.

No False Positives Errors Model Imposing Assumptions (i) and (ii) on ME the bounds on ATE are further tightened to

$$\begin{aligned} UB_{ATE} &= P[H = 1, W = 1] + P(W = 0) + \theta_1^{UB-} - P[H = 1, W = 0] \\ LB_{ATE} &= P[H = 1, W = 1] - \theta_0^{UB-} - P[H = 1, W = 0] - P(W = 1). \end{aligned} \tag{16}$$

For derivations, refer to Appendix D.

5.4 Monotonicity Assumptions

To further tighten the estimated bounds on ATE, I exploit the identifying power of three monotonicity assumptions which impose disparate restrictions on the relationships between WIC participation, birth outcomes, and the available data.

5.4.1 Monotone Treatment Selection

The *Monotone Treatment Selection* (MTS) assumption defines the selection mechanism through which mothers become WIC participants (Manski and Pepper, 2000). The literature on prenatal maternal participation in WIC and birth outcomes clearly indicates that among the eligible, those women who choose to participate are more likely to have unfavorable demographic, socioeconomic, and health characteristics to begin with (e.g., Bitler and Currie, 2005). That is, there exists negative selection, at least on observables, into WIC. So, the MTS assumption simply allows for the possibility that infants whose mothers chose to participate in WIC prenatally have a lower probability of a good health outcome on average compared to non-participants. Following Kreider et al. (2011), this assumption translates into:

$$P[H(1) = 1|W^* = 0] \geq P[H(1) = 1|W^* = 1] \tag{17}$$

$$P[H(0) = 1|W^* = 0] \geq P[H(0) = 1|W^* = 1]. \tag{18}$$

Accordingly,

$$\begin{aligned} UB_{ATE} &= P\left[H=1,W=1\right] + P(W=0) + \theta_0^{UB+} - \Big\{P[H=1,W=0] - \theta_1^{UB-}\Big\} \\ LB_{ATE} &= \frac{P\left[H=1,W=1\right] - \theta_1^{UB+}}{P(W=1) - \theta_1^{UB+} + \theta_0^{UB-}} - \left\{\frac{P[H=1,W=0] + \theta_1^{UB+}}{P(W=0) + \theta_1^{UB+} - \theta_0^{UB-}}\right\} \end{aligned} \tag{19}$$

where $\theta_1^{UB+} = \theta_0^{UB-} = \theta_1^{UB-} = \theta_0^{UB+} = 0$ in the absence of ME. See Appendix D for derivations.

Arbitrary Errors Model Imposing Assumption (i) on ME the bounds are tightened such that

$$\begin{aligned} UB_{ATE} &= UB_{ATE} \text{ under the No Selection Assumption Model with Arbitrary Errors} \\ LB_{ATE} &= LB_{ATE} \text{ under the Exogenous Model with Arbitrary Errors.} \end{aligned}$$

So, to get sharp bounds on ATE, the UB_{ATE} under the No Selection Assumption model is used while the LB_{ATE} comes from the exogenous case. See Appendix D for derivations.

No False Positives Errors Model Imposing Assumptions (i) and (ii) on ME the bounds are further tightened such that

$$\begin{aligned} UB_{ATE} &= UB_{ATE} \text{ under the No Selection Assumption Model and the No False Positive Errors Model} \\ LB_{ATE} &= LB_{ATE} \text{ under the Exogenous Model and the No False Positive Errors Model.} \end{aligned}$$

Again, to get sharp bounds on ATE, the UB_{ATE} under the No Selection Assumption model is used while the LB_{ATE} comes from the exogenous case. See Appendix D for derivations.

5.4.2 Monotone Instrumental Variable

To further tighten the bounds, I turn to the *Monotone Instrumental Variable* (MIV) assumption which states that the latent probability of a good health outcome, $P\left[H(t) = 1\right]$, $t = 0, 1$, varies monotonically with observed covariates (Manski and Pepper, 2000). I use household SES as the MIV. Chen et al. (2002) report that child health improves monotonically with SES. The food stamp literature also shows that even among low-income eligible households, those with higher incomes demonstrate a greater probability of better health outcomes in association with food stamps (e.g., Kreider et al., 2011). Since food stamp recipients are automatically eligible for WIC, an equivalent relationship between WIC and SES is additionally justifiable. As in Kreider et al. (2011), the MIV assumption is formalized as follows:

Let ν be the MIV such that for $u_1 < u < u_2$:

$$\begin{aligned} P\left[H\left(1\right)=1|\nu=u_2\right] &\geq P[H(1)=1|\nu=u] \geq P[H(1)=1|\nu=u_1] \\ P\left[H\left(0\right)=1|\nu=u_2\right] &\geq P[H(0)=1|\nu=u] \geq P[H(0)=1|\nu=u_1]. \end{aligned}$$

To bound these latent probabilities, I combine the MIV assumption with the MTS assumption discussed above. If $LB(u)$ and $UB(u)$ are the known lower and upper bounds evaluated at $v = u$ under the MTS assumption, then the MIV assumption implies (Proposition 1 in Manski and Pepper, 2000):

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

To calculate these bounds in practice, the sample is divided into four SES groups.[16] Then, I take the weighted average of the estimators of the MTS LB and UB across the four SES groups to get the joint MTS-MIV bounds on the rates of good health. Such an MIV estimator is biased in finite samples but consistent (Manski and Pepper, 2000). In this light, I use Kreider and Pepper's (2007) nonparametric finite sample bias corrected MIV estimator. See Appendix D for details.

5.4.3 Monotone Treatment Response

In this section, I discuss the *Monotone Treatment Response* (MTR) assumption which states that WIC participation cannot worsen birth outcomes (Manski, 1997). The WIC program exists to assist and guide low-income women to improve their prenatal and neonatal nutrition and health. The focus on pregnant and nursing women and their very young children is to ensure that a healthy mother will enhance the likelihood of a healthy child. The MTR assumptions states that

$$H(1) \geq H(0).$$

To be sure, the MTS assumption states that participants are comparatively more disadvantaged on average than non-participants, so they have worse outcomes on average independent of WIC. The MTR assumption, on the other hand, states that any woman in the population will only participate in WIC if it does not harm her or her child.

[16] Due to the small sample size I run into cell size issues with additional SES groups.

5.5 Instrumental Variable Estimation

The preceding nonparametric bounding approach attempts to partially identify the causal effect of prenatal WIC participation under the explicit reasonable assumptions specified. To complement the bounds analysis, identifying point estimates with an IV strategy would be ideal. Unfortunately, owing to ME in reports of prenatal WIC receipt, typical exclusion restrictions are suspect. Nonclassical ME implies that true WIC participation is negatively correlated with the error, so any valid IV is also likely to be correlated with the ME as well. So, this section presents the alternative IV strategy proposed in Lewbel (2010) that works under certain assumptions. The identification strategy proposed in Lewbel (2010) extends earlier work by Lewbel (1997) and Ebbes et al. (2009).

The outcome model is given by:

$$y_i = X_i\beta + \tau W_i + \varepsilon_i$$

and the first stage equation is:

$$W_i = X_i\beta_1 + \zeta_i$$

where y_i denotes binary health outcome of the ith child; W_i is a binary variable that takes a value of one if the ith child's mother reports prenatal WIC receipt, and zero otherwise; X_i is the set of covariates. ζ_i represents the error term in the first-stage equation, assumed to be correlated with ε_i. The identification problem stems from the fact that W_i is only a self-reported WIC receipt indicator, measured with error, and lacks an exclusion restriction. Lewbel's (2010) strategy shows that the model is identified if ζ_i is heteroskedastic and one can find at least a subset of the elements of X_i which are correlated with the error variances *but* not with the error covariances. Here, W_i, is binary in nature which guarantees that ζ_i is heteroskedastic.

Formally, I choose $z_i \subseteq X_i$ such that

$$E\left[z'\zeta_i^2\right] \neq 0 \tag{14}$$

and

$$E\left[z'\varepsilon\zeta_i\right] = 0. \tag{15}$$

If these assumptions are satisfied, then the valid IV for W_i is $\widetilde{z}_i \equiv \left(z_i - \overline{z}\right)\zeta_i$.

To get the IV estimates, I begin by estimating the first stage equation by OLS to get consistent estimates of ζ_i. Then, to get the subset z_i, I conduct the Breusch-Pagan test for heteroskedasticity and include those that are significantly related to the estimates of ζ_i. Finally, I generate the instruments $\widetilde{z}_i$, and conduct an ordinary two-stage least squares estimation to get the IV estimates.

6 Results

The first part of this section presents the nonparametric bounds on the ATE of prenatal WIC participation on different binary health outcomes. The second part discusses the IV estimates. Since the literature and the ECLS-B data show that prenatal WIC participants are disproportionately non-white, I repeat the above analyses on this subsample and report the results in Appendix B. Also, almost 80% of the WIC eligible pool in the ECLS-B data reside in urban areas. This is an interesting subsample since the proximity to grocery stores and local WIC agencies can potentially worsen social stigma of being recognized as a "welfare" recipient. The results for this subsample are reported in Appendix C.

6.1 Bounds on ATE

The first section focuses on birth weight outcomes. The second discusses the outcomes related to gestation age. It is important to note that these estimated bounds are based on sample probabilities, instead of the population probabilities used to describe this analytical approach in the Methodology section above. To address the additional uncertainty related to sampling variability, I construct the Imbens-Manski (2004) confidence intervals that cover the true value of the ATE with 95% probability (see Kreider et al., 2011).[17]

6.1.1 Birth Weight Outcomes

First, I consider the probability of birth weight of at least 1500 grams. Panel A of Figure 1 compares the sharp bounds on the ATE for the case of exogenous selection to that under no assumption on selection as Q varies from 0 to 0.10. Panel B (Panel C) of Figure 1 shows how the bounds are gradually tightened with the monotonicity assumptions on selection under arbitrary errors (no false positive errors) assumption. Table 1 shows the corresponding ATE bounds for these values of Q.

Panel A in Figure 1 shows that the difference in the sample means between participants and non-participants reported in Table A1 is the consistent estimate of the $ATE(1,0)$ assuming exogenous selection if $Q = 0$, i.e., 0.003. However, when $Q > 0$, I can no longer sign the ATE, even under the assumption of no false positive reporting and exogenous selection. In sharp contrast, without any assumption on the selection mechanism, the ATE of prenatal WIC participation cannot be signed even in the absence of ME.

To narrow the bounds, I apply the assumptions of MTS, joint MTS-MIV, and joint MTS-MTR along with the arbitrary errors model in Panel B. Allowing for negative selection but no misreporting (see column 5, Table 1), the $ATE \in [0.003, 0.684]$ suggesting an ameliorating effect of WIC participation on

[17] These confidence intervals are still being computed, but will only make the bounds wider and not change the qualitative conclusions.

the likelihood of very low birth weight. The bounds are further tightened to $ATE \in [0.005, 0.683]$ under the joint MTS-MIV assumption for $Q = 0$ (see column 7, Table 1). This suggests that WIC increases the probability of birth weight of at least 1500 grams by 0.5 to 68.3 %. However, even if only one percent of eligible women misreport ($Q = 0.01$) I cannot conclude that the ATE of WIC is positive or negative.

In comparison to the case of negative selection with $Q \geq 0.01$, the bounds on the ATE under the MTS-MIV assumption are narrower. Although the evidence continues to be inconclusive, I can rule out a negative effect of WIC of more than 1.8 % on very low birth weight when 10% of women misreport participation ($Q = 0.10$). The joint assumption of MTS-MTR only improves the lower bound of the ATE to 0 for $Q > 0$ suggesting a beneficial effect of WIC (see Figure 1 and column 9, Table 1).

Next, I turn to the more restrictive assumption of no false positive errors along with the monotonicity assumptions to attempt to sign the causal effect of WIC (see Panel C, Figure 1 and columns 6 - 10, Table 1). Although the bounds on the ATE are tighter as expected under stricter assumptions, the results remain the same in spirit: the causal effect of WIC cannot be signed for a meager degree of ME ($Q = 0.01$). Now, I can rule out a negative effect of WIC of more than 1.6% on the likelihood of birth weight of at least 1500 grams.

That is, under the reasonable assumptions about ME and selection mechanism considered here, it takes only one percent of ME to render the evidence concerning the causal effect of participation inconclusive. This is a striking finding since the existing literature documents WIC misreporting rate of at least 25%. Moreover, according to the Hausman et al. (1998) model estimated in Section 5.1 above, the rate of misclassification in the ECLS-B is roughly 24%. This evidence clearly calls for greater attention to the problem of ME in survey data.

Second, I analyze the probability of birth weight of at least 2500 grams. Figure 2 and Table 2 present the results. Accounting for negative selection (MTS alone) without ME, the $ATE \in [0.001, 0.660]$ indicating that WIC improves the prevalence of birth weight exceeding 2500 grams. This positive effect narrows down to $[0.007, 0.661]$ under the joint MTS-MIV assumption with no ME (see Panels B and C, Figure 2 and columns 5 - 8, Table 2). That is, WIC reduces the likelihood of low birth weight by 0.7 to 66.1 % in the absence of ME.

Unfortunately, the ATE cannot be signed as soon as $Q > 0$ regardless of the selection and ME assumptions considered here. Nevertheless, the bounds suggest that the maximum deleterious effect of WIC on the likelihood of low birth weight is 10.9 points when 10% of eligible women misreport participation.

Third, I focus on the probability of normal birth weight. Figure 3 and Table 3 present the results for this outcome. The $ATE \in [0.019, 0.639]$ when $Q = 0$ under the assumption of negative selection (MTS alone). This positive effect narrows down to $[0.026, 0.639]$ under the joint MTS-MIV assumptions and no

ME (see Panels B and C, Figure 3 and columns 5 - 8, Table 3). That is, WIC participation increases the prevalence of normal birth weight by 2.6 to 63.9 points.

Again, the ATE cannot be signed if at least one percent of WIC women misreport. However, the bounds under the joint MTS-MIV assumption rule out any detrimental effect of WIC exceeding 21 points when 10% of women misreport. Of course, more ME will only worsen the situation.

Finally, I turn to the probability of birth weight of at most 4000 grams. The estimated bounds on the ATE are reported in Table 4 and Figure 4. The results are qualitatively the same as the above three indicators of birth weight. The bounds on ATE are gradually tightened from $[0.018, 0.667]$ under MTS to $[0.031, 0.665]$ under the joint MTS-MIV assumption only when $Q = 0$. As before, even if as low as one percent of eligible women misreport their prenatal WIC participation, the sign of the causal effect is indeterminate.

The results for the non-white and urban subsamples are presented in Appendices B and C, respectively. Compared to the full sample, the positive effects of WIC under the joint MTS-MIV assumption without ME are larger for the probabilities of very low and low birth weight in the non-white sample. That is, the estimated LB on the ATE exceed the corresponding LB in the full sample. This conforms to the existing evidence of WIC benefits being larger for the more disadvantaged mothers. In the urban sample, the LB on the ATE under the joint MTS-MIV assumption with no ME exceed the corresponding LB in the full sample for the probabilities of at least 1500 grams, at least 2500 grams, and at most 4000 grams. This is possibly because the benefits of living close to grocery stores accepting WIC vouchers, local WIC agencies, and neighbors who are more likely to be WIC beneficiaries themselves outweigh or even dampen the feeling of social stigma.

With ME in these subsamples, the results are qualitatively similar to the full sample. The only exception is the probability of birth weight of at most 4000 grams in the urban sample. For this outcome, the ATE can be signed to be strictly positive under the joint MTS-MIV assumption if up to one percent of eligible women misreport (see Panels B and C, Figure C4 and columns 5 - 8, Table C4). However, if two percent of women misreport, strong assumptions are required to sign the causal effect and the literature is overlooking this serious problem of ME.

In summary, I find a positive association between birth weight and prenatal WIC participation, only when I ignore ME. This is consistent with the existing literature. In fact, accounting for ME, the results show that it is difficult to sign the ATE under several assumptions about selection and ME. However, it is crucial to account for ME in evaluating WIC when the literature shows that the under-reporting problem is the most severe for WIC relative to other transfer programs.

6.1.2 Gestation Age

First, I consider the probability of near-term pregnancy (gestation age of at least 33 weeks). The results are reported in Figure 5 and Table 5. Panel A of Figure 5 shows that the bounds on the ATE always include zero without any assumption on the selection mechanism even when $Q = 0$. For the baseline case of exogenous selection, the difference in the sample means between participants and non-participants reported in Table A1 is the consistent estimate of the $ATE(1, 0)$ if $Q = 0$, i.e., -0.004. When $Q > 0$, prenatal WIC's effect on the likelihood of near-term pregnancy can only be partially identified. For instance, when only one or two percent of households misreport WIC, the ATE lies in the range $[-0.050, 0.040]$ and $[-0.098, 0.083]$. However, under the additional assumption of no false positive reports, the ATE can be signed as strictly negative, lying in the range $[-0.047, -0.030]$ and $[-0.047, -0.001]$, respectively (see Panel A, Figure 5, and columns 1 and 2, Table 5).

This suggests that the effect of prenatal WIC is negative on the probability of near-term pregnancy, under exogenous selection and allowing up to two percent of eligible women to misreport their participation. This is a surprising result even under the simplest assumption of exogeneity. If more than two percent of women misreport, I cannot sign ATE of prenatal WIC receipt under these assumptions.

Next, allowing for negative selection into WIC I turn to the MTS case in Panels B and C of Figure 5. Table 5 shows that the $ATE \in [-0.004, 0.673]$ even when $Q = 0$. The bounds suggest a slight deleterious effect of 0.4 points. However, the bounds only get wider when more women misreport.

Once again, perhaps the most interesting result emerges when the MTS assumption is combined with the MIV assumption. Columns 7 and 8 of Table 5 show that when there is no ME, the $ATE \in [0.001, 0.673]$. This joint assumption clearly improves upon the solitary assumption of MTS when $Q = 0$ by narrowing the bounds to $[0.001, 0.673]$ from $[-0.004, 0.673]$. Moreover, the joint MTS-MIV bounds indicate that prenatal WIC receipt increases the probability of near-term pregnancy, when there is no ME. However, as soon as even one percent of eligible women misreport their WIC participation, the bounds include negative values and so the ATE can no longer be signed.

Second, I analyze the probability of a full term pregnancy. The results are qualitatively similar to the probability of near-term pregnancy. Table 6 and Figure 6 present the results. Under exogenous selection, the ATE is point identified when $Q = 0$; it suggests a negative association between prenatal WIC receipt and the likelihood of a full term pregnancy without any misreporting. When even one percent of the eligible women misreport, $ATE \in [-0.057, -0.010]$ with the additional assumption of no false positive errors. Any greater rate of misreporting prohibits signing the ATE (see columns 1 and 2, Table 6 and Panel A, Figure 6). Without any assumption on the selection mechanism, I do not find any conclusive relationship between prenatal WIC participation and the probability of a full term pregnancy.

The MTS assumption alone without any ME, i.e., with $Q = 0$ (see columns 5 and 6, Table 6 and Panels B and C, Figure 6) is not strong enough to conclude that participating in WIC leads to a higher or lower probability of a full term pregnancy. However, like before, this assumption increases the lower bound of the ATE compared to that under the worst case scenario for all values of Q. The joint MTS-MTR assumption (see columns 9 and 10, Table 6) improves the lower bound even more to zero.

Again, perhaps the most interesting result pertains to the joint MTS-MIV assumption. The results are reported in columns 7 and 8 of Table 6, and Panels B and C of Figure 6. If WIC receipt is not misreported ($Q = 0$), the $ATE \in [0.001, 0.583]$ suggesting an improvement in gestation age. However, as in the previous cases, for sufficiently small WIC reporting error ($Q \geq 0.01$), I cannot draw any meaningful conclusion regarding the relationship between WIC participation and the probability of a full term pregnancy.

The results for the non-white and urban subsamples are qualitatively similar to the full sample. The only difference is in terms of the probability of full term pregnancy. While the ATE can be signed to be strictly positive under the joint MTS-MIV assumption without ME ($Q = 0$) in the full sample; the bounds on the ATE for this outcome always include zero in both the subsamples. Also, I do not find any conclusive evidence on the effect of WIC on the probability of near-term pregnancy in the urban sample, even under the joint MTS-MIV assumption without ME.

In summary, accounting for negative selection into and misreporting of prenatal WIC participation, I am unable to sign the ATE for gestation age outcomes for as low a degree of ME as one percent. The tightest bounds on ATE are attained under the joint assumption of MIV and MTS in the absence of ME. These bounds show that prenatal WIC participation is beneficial for gestation age for both definitions in the full sample, unlike Figlio and his colleagues (2009) who find no significant effect of WIC on gestation age.

The key result using this nonparametric bounding approach is that identification of ATE deteriorates with ME rapidly, even under the no false positives assumption. In fact, if even one percent of eligible women misreport prenatal WIC participation, there is no conclusive evidence on the causal effect of WIC on a range of birth outcomes. I, therefore, conclude this section with a negative message since there exists ample evidence in the welfare program evaluation literature that misreporting is the most severe in WIC compared to the other programs.

6.2 Instrumental Variables

To learn more about the causal effect of WIC participation, I report IV estimates following the strategy in Lewbel (2010) for three model specifications and the six binary health outcomes. The set of covariates, X_i

includes mother's age, father's age, an indicator for married parents, an indicator for whether the mother has a high school (HS) degree or less, a corresponding indicator for the father, an indicator for whether the child is male, an indicator for whether the child is Black or Hispanic, an indicator for living in a rural area, three regional dummies, and four SES quintile dummies.

Specification (1) includes X_i as is. Specification (2) includes squared age of mother, an interaction term between the mother's age and whether she has a HS degree or less, an interaction term between whether the child is black or Hispanic and whether the mother has at most a HS degree, and an indicator of whether the child is black or Hispanic with married parents. Specification (3) augments Specification (2) with the cubed age of mother and an interaction term between squared mother's age and whether the mother has at most a HS degree. In the non-white sample, the specifications do not include the race indicator or any of its interactions; the urban sample does not include the rural indicator.

The subset of X_i, z_i includes mother's age and four indicators of SES quintiles in all specifications and samples. These were chosen based on the smallest p-values from the Breusch-Pagan test for heteroskedasticity. The results are reported in Tables 7, B7, and C7. Before interpreting the point estimates of WIC identified by this strategy, it is important to note that this strategy seems to work well as indicated by the overidentification and underidentification test results reported in the tables for the respective samples. Also, there is some evidence throughout confirming that WIC is indeed endogenous.

It is also important to note that the IV estimates in this section may not be directly compared to the estimated bounds on the ATE discussed in the previous section. This is because under heterogeneous treatment effects, IV estimates the local average treatment effect or the $LATE$ as opposed to the ATE (Imbens and Angrist, 1994). However, under the assumption of a constant treatment effect, IV estimates the same parameter. Similarly, a direct comparison with existing traditional IV estimates of WIC may be misleading as well. For example, Figlio et al. (2009) focus on a homogeneous sample of prenatal WIC recipients in Florida who have at least one older child enrolled in the NSLP. The authors instrument for WIC participation using changes in the requirements regarding income documentation to prove eligibility. As a result, the set of compliers – those whose treatment status is determined by the instrument – most likely differs from the set of compliers analyzed using the procedure here (which, admittedly, is difficult to conceptualize).

Turning to the results, I start with the probability of birth weight of at least 1500 grams in Panel I of Table 7. The IV estimate is larger and statistically significant at a higher (one percent) level compared to the OLS estimate. This indicates a beneficial causal effect of prenatal WIC receipt on birth weight despite negative selection. Moreover, the estimate of 0.005 (across all the specifications) lies in the estimated bound on the ATE, [0.005, 0.683] under the joint assumption of MIV and MTS ignoring ME. With ME the bounds on the ATE include zero as well as the IV estimate.

A similar result holds for the probability of birth weight of at least 2500 grams (Panel II, Table 7), although the estimates are imprecise. The IV estimates of 0.009 or 0.010 are larger than the OLS estimates of prenatal WIC participation, and lie in the estimated bounds on ATE, [0.007, 0.661] under MTS-MIV with no ME. This suggests a beneficial effect of WIC on yet another measure of birth weight. The bounds on the ATE accounting for ME also include the IV estimate for all the specifications.

In Panel III (Table 7) for the probability of normal birth weight, the IV estimates of 0.030 or 0.031 are larger than their OLS counterparts for all the specifications, are statistically significant at the 10% level, and lie in the estimated bounds on the ATE, [0.026, 0.639] under the joint assumption of MIV and MTS without ME. The wider bounds on the ATE for non-zero ME include the IV estimates for all the specifications. This suggests that WIC has a beneficial causal effect on the prevalence of normal birth weight.

Although the IV estimates of WIC participation on the probability of birth weight of at most 4000 grams do not lie in the estimated bounds, and are statistically insignificant, they still suggest an ameliorating effect of WIC participation. Also, with ME the bounds on the ATE include zero as well as the IV estimate.

Despite the caveat noted above concerning the proper interpretation of the IV estimates here and in the prior literature, the results here suggest that WIC participation has a beneficial causal effect on birth weight by compressing the birth weight distribution, consistent with Figlio et al. (2009). While WIC receipt reduces the likelihood of very low and low birth weight, it also reduces the probability of birth weight exceeding 4000 grams.

Turning to gestation age (Panels V and VI, Table 7), the probability of near-term pregnancy confirms negative selection into WIC by virtue of the IV estimates being larger than the OLS estimates. These are, however, imprecisely estimated. The nonparametric bounds on the ATE under MIV and MTS with ME include the values of the IV estimates.

For the probability of full term pregnancy, the negative IV estimates of prenatal WIC participation do not lie in the estimated bounds when there is no ME. However, when at least two percent of the eligible women misreport participation, the bounds on the ATE include zero as well as the IV estimates. In sum, there is less evidence of a beneficial effect of WIC on gestation age echoing Figlio et el.'s (2009) finding.

The results for both the subsamples are qualitatively similar to the full sample. The only exception is that the IV estimates of prenatal WIC participation are positive (although imprecise) for the probability of near-term pregnancy in both the subsamples unlike the full sample. This is at least consistent with the notion that the largest WIC benefits pertain to the more disadvantaged women and also to those in urban areas with easier access to WIC.

7 Conclusion

The existing evaluations of the WIC program are dominated by empirical strategies focussed on isolating the causal effect by satisfactorily addressing the issue of non-random selection only. Though far from conclusive, the evidence is broadly positive. A distinct identification problem that also clouds the causal interpretation - misreporting prenatal WIC participation - is not accounted for. In this paper, I revisit the impact of prenatal WIC participation on birth outcomes by addressing both these problems in a single partial identification framework proposed in Kreider et al. (2011). This nonparametric approach is especially suitable for this analysis since there remains considerable doubt about the existing estimates from conventional identification approaches using myriad data sets and empirical methods. I also provide point estimates of the causal effect (consistent with the estimated bounds on the ATE for all but one outcome) using the IV strategy proposed in Lewbel (2010) that accounts for both ME and endogeneity under certain assumptions.

Using data from the ECLS-B, I present and explain the various assumptions on the ME and selection problems that help derive sharp bounds on the ATE of WIC on birth outcomes. In the presence of both misreporting of and negative selection into WIC, the sampling process fails to point identify the ATE. So, I impose several weak assumptions on both selection and ME processes to bound the causal impact of prenatal participation in WIC. My basic conclusion is that even if only one percent of the eligible women misreport their prenatal participation in WIC, it is not possible to sign the ATE given the selection and ME assumptions imposed.

With no ME and exogenous selection, I can sign the ATE for all the outcomes considered. I can sign the ATE as strictly negative (under the no false positives assumption) when up to two percent of eligible women misreport participation only for the near-term pregnancy outcome in the full sample. With no assumption on the selection mechanism, it is impossible to sign the ATE. The MTS assumption alone, depicting negative selection, with no ME, almost always portrays prenatal WIC participation in a positive light. This is consistent with the existing literature which accounts for endogeneity but not misreporting. Perhaps the most interesting result, albeit confined to the case of no ME, pertains to that under the joint assumption of MIV and MTS. The evidence suggests a beneficial impact of WIC on all birth weight outcomes in the absence of ME.

Nationally representative household survey data constitute the basis of empirical research aimed at evaluating public policy effectiveness. However, these are plagued by ME about program participation due to a combination of factors like social stigma and recall error. The existing literature on ME suggests that these large scale surveys will be more valuable when coupled with some form of verification about program participation. Although administrative data is potentially the most reliable source of information on program participation, they often lack the breadth of survey data in terms of a broad range of outcomes and missing counterfactuals (Foster et al., 2010).

In sum, this work corroborates the existing literature on WIC: there exists a positive association between WIC and birth outcomes. However, it is impossible to sign the causal effect for several different birth outcomes under the assumptions concerning the selection process considered here when only one percent of women misreport. So, I am unable to conclude there exists a beneficial *causal* impact of WIC using the bounding approach alone. The IV strategy of Lewbel (2010), however, suggests a beneficial causal effect of WIC participation on birth weight. This is the first attempt to quantify the impact of ME in WIC reports and serves as an important caveat for future work on WIC evaluation. Future work could aim for developing alternative methods designed to yield point estimates of the causal effect of WIC in the presence of nonrandom selection and measurement error.

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Figure 1: Sharp Bounds on the ATE of WIC Participation on Birth Weight ≥ 1500 grams When Participation Status May be Misclassified: Various Assumptions about Selection

A. Exogenous Selection or No Assumption on Selection | B. Only MTS or Joint MTS & MIV or MTS & MTR: Arbitrary Errors | C. Only MTS or Joint MTS & MIV or MTS & MTR: No False Positive Errors

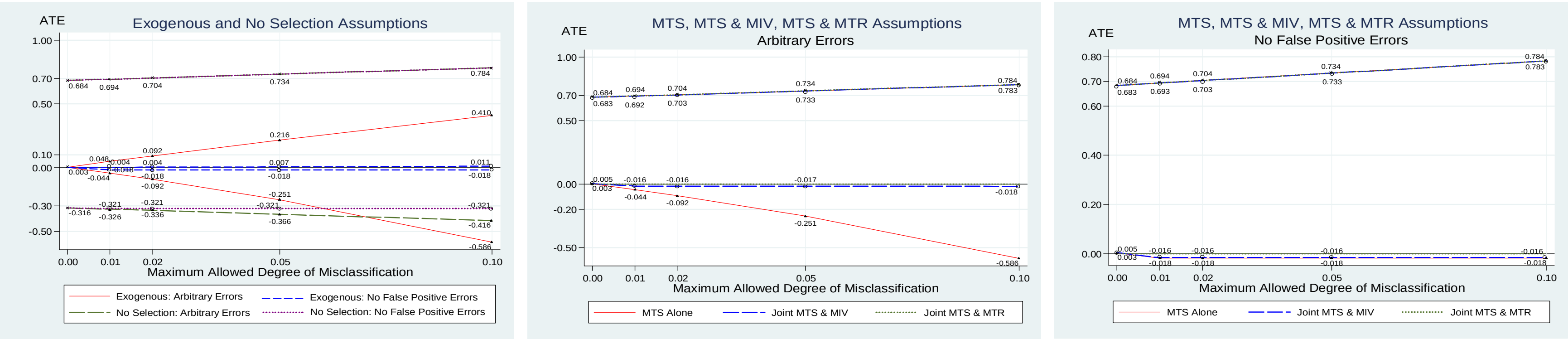

Table 1: Sharp Bounds on the ATE of WIC Participation on Birth Weight ≥ 1500 grams Given Unknown Counterfactuals and Potentially Misclassified Participation Status: Various Assumptions about Selection

Point Estimates of LB and UB and 95% I-M Confidence Intervals (CI) Around the Unknown Parameter ATE

Q_u	Exogenous Selection		No Assumption on Selection		MTS Assumption		MTS and MIV Assumption		MTS and MTR Assumption	
	(1) Arbitrary Errors	(2) No False Positives	(3) Arbitrary Errors	(4) No False Positives	(5) Arbitrary Errors	(6) No False Positives	(7) Arbitrary Errors	(8) No False Positives	(9) Arbitrary Errors	(10) No False Positives
0.00	[0.003, 0.003] p.e.†	[0.003, 0.003] p.e.	[-0.316, 0.684] p.e.	[-0.316, 0.684] p.e.	[0.003, 0.684] p.e.	[0.003, 0.684] p.e.	[0.005, 0.683] p.e.	[0.005, 0.683] p.e.	[0.000, 0.684] p.e.	[0.000, 0.684] p.e.
0.01	[-0.044, 0.048] p.e.	[-0.018, 0.004] p.e.	[-0.326, 0.694] p.e.	[-0.321, 0.694] p.e.	[-0.044, 0.694] p.e.	[-0.018, 0.694] p.e.	[-0.016, 0.692] p.e.	[-0.016, 0.693] p.e.	[0.000, 0.694] p.e.	[0.000, 0.694] p.e.
0.02	[-0.092, 0.092] p.e.	[-0.018, 0.004] p.e.	[-0.336, 0.704] p.e.	[-0.321, 0.704] p.e.	[-0.092, 0.704] p.e.	[-0.018, 0.704] p.e.	[-0.016, 0.703] p.e.	[-0.016, 0.703] p.e.	[0.000, 0.704] p.e.	[0.000, 0.704] p.e.
0.05	[-0.251, 0.216] p.e.	[-0.018, 0.007] p.e.	[-0.366, 0.734] p.e.	[-0.321, 0.734] p.e.	[-0.251, 0.734] p.e.	[-0.018, 0.734] p.e.	[-0.017, 0.733] p.e.	[-0.016, 0.733] p.e.	[0.000, 0.734] p.e.	[0.000, 0.734] p.e.
0.10	[-0.586, 0.410] p.e.	[-0.018, 0.011] p.e.	[-0.416, 0.784] p.e.	[-0.321, 0.784] p.e.	[-0.586, 0.784] p.e.	[-0.018, 0.784] p.e.	[-0.018, 0.783] p.e.	[-0.016, 0.783] p.e.	[0.000, 0.784] p.e.	[0.000, 0.784] p.e.

Notes: † Point estimates (p.e.) and ‡ 95% Confidence Intervals (CI) around ATE are calculated using methods from Imbens-Manski (2004) with 250 pseudosamples. These CI are still being computed. All analyses are weighted using Wave 1 specific sample weights. Number of observations = 4300. Sample sizes are rounded to the nearest 50 by requirement. For other details, refer to Table A1.

Figure 2: Sharp Bounds on the ATE of WIC Participation on Birth Weight $\geq$ 2500 grams When Participation Status May be Misclassified: Various Assumptions about Selection

A. Exogenous Selection or No Assumption on Selection | B. Only MTS or Joint MTS & MIV or MTS & MTR: Arbitrary Errors | C. Only MTS or Joint MTS & MIV or MTS & MTR: No False Positive Errors

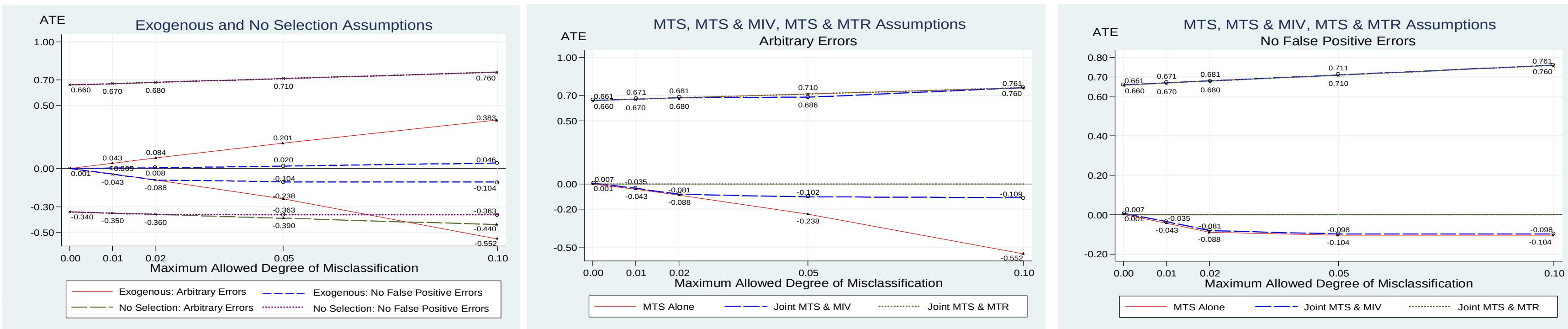

Table 2: Sharp Bounds on the ATE of WIC Participation on Birth Weight ≥ 2500 grams Given Unknown Counterfactuals and Potentially Misclassified Participation Status: Various Assumptions about Selection

Point Estimates of LB and UB and 95% I-M Confidence Intervals (CI) Around the Unknown Parameter ATE

Q_u	Exogenous Selection		No Assumption on Selection		MTS Assumption		MTS and MIV Assumption		MTS and MTR Assumption	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Arbitrary Errors	No False Positives	Arbitrary Errors	No False Positives	Arbitrary Errors	No False Positives	Arbitrary Errors	No False Positives	Arbitrary Errors	No False Positives
0.00	[0.001, 0.001] p.e.†	[0.001, 0.001] p.e.	[-0.340, 0.660] p.e.	[-0.340, 0.660] p.e.	[0.001, 0.660] p.e.	[0.001, 0.660] p.e.	[0.007, 0.661] p.e.	[0.007, 0.661] p.e.	[0.000, 0.660] p.e.	[0.000, 0.660] p.e.
0.01	[-0.043, 0.043] p.e.	[-0.043, 0.005] p.e.	[-0.350, 0.670] p.e.	[-0.350, 0.670] p.e.	[-0.043, 0.670] p.e.	[-0.043, 0.670] p.e.	[-0.035, 0.671] p.e.	[-0.035, 0.671] p.e.	[0.000, 0.670] p.e.	[0.000, 0.670] p.e.
0.02	[-0.088, 0.084] p.e.	[-0.088, 0.008] p.e.	[-0.360, 0.680] p.e.	[-0.360, 0.680] p.e.	[-0.088, 0.680] p.e.	[-0.088, 0.680] p.e.	[-0.081, 0.681] p.e.	[-0.081, 0.681] p.e.	[0.000, 0.680] p.e.	[0.000, 0.680] p.e.
0.05	[-0.238, 0.201] p.e.	[-0.104, 0.020] p.e.	[-0.390, 0.710] p.e.	[-0.363, 0.710] p.e.	[-0.238, 0.710] p.e.	[-0.104, 0.710] p.e.	[-0.102, 0.686] p.e.	[-0.098, 0.711] p.e.	[0.000, 0.710] p.e.	[0.000, 0.710] p.e.
0.10	[-0.551, 0.383] p.e.	[-0.104, 0.046] p.e.	[-0.440, 0.760] p.e.	[-0.363, 0.760] p.e.	[-0.551, 0.760] p.e.	[-0.104, 0.760] p.e.	[-0.109, 0.761] p.e.	[-0.098, 0.761] p.e.	[0.000, 0.760] p.e.	[0.000, 0.760] p.e.

Notes: † Point estimates (p.e.) and ‡ 95% Confidence Intervals (CI) around ATE are calculated using methods from Imbens-Manski (2004) with 250 pseudosamples. All analyses are weighted using Wave 1 specific sample weights. Number of observations = 4300. Sample sizes are rounded to the nearest 50 by requirement. For other details, refer to Table A1.

Figure 3: Sharp Bounds on the ATE of WIC Participation on Birth Weight: 2500 - 4000 grams When Participation Status May be Misclassified: Various Assumptions about Selection

A. Exogenous Selection or No Assumption on Selection | B. Only MTS or Joint MTS & MIV or MTS & MTR: Arbitrary Errors | C. Only MTS or Joint MTS & MIV or MTS & MTR: No False Positive Errors

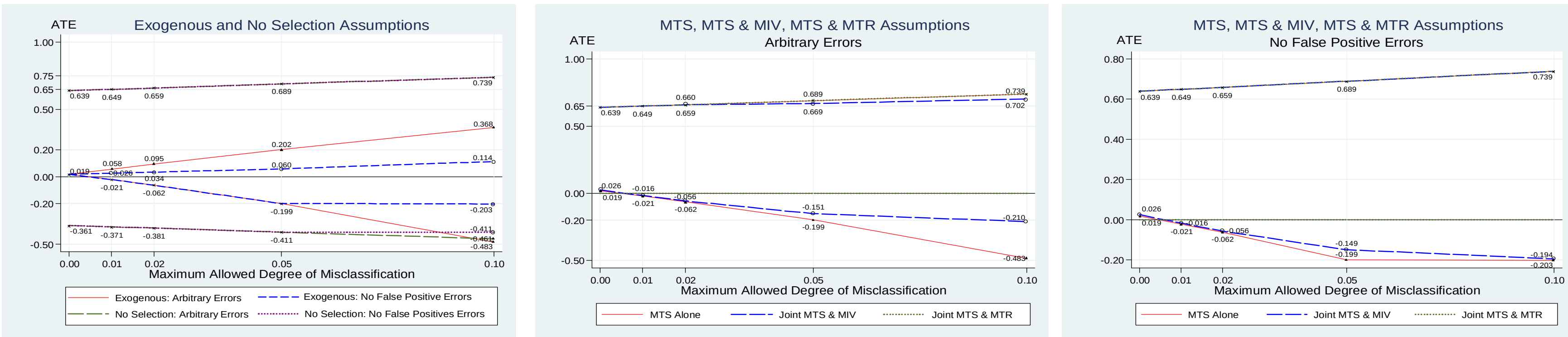

Table 3: Sharp Bounds on the ATE of WIC Participation on Birth Weight: 2500 - 4000 grams Given Unknown Counterfactuals and Potentially Misclassified Participation Status: Various Assumptions about Selection

Point Estimates of LB and UB and 95% I-M Confidence Intervals (CI) Around the Unknown Parameter ATE

Q_u	Exogenous Selection		No Assumption on Selection		MTS Assumption		MTS and MIV Assumption		MTS and MTR Assumption	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Arbitrary Errors	No False Positives	Arbitrary Errors	No False Positives	Arbitrary Errors	No False Positives	Arbitrary Errors	No False Positives	Arbitrary Errors	No False Positives
0.00	[0.019, 0.019] p.e.†	[0.019, 0.019] p.e.	[-0.361, 0.639] p.e.	[-0.361, 0.639] p.e.	[0.019, 0.639] p.e.	[0.019, 0.639] p.e.	[0.026, 0.639] p.e.	[0.026, 0.639] p.e.	[0.000, 0.639] p.e.	[0.000, 0.639] p.e.
0.01	[-0.021, 0.058] p.e.	[-0.021, 0.026] p.e.	[-0.371, 0.649] p.e.	[-0.371, 0.649] p.e.	[-0.021, 0.649] p.e.	[-0.021, 0.649] p.e.	[-0.016, 0.649] p.e.	[-0.016, 0.649] p.e.	[0.000, 0.649] p.e.	[0.000, 0.649] p.e.
0.02	[-0.062, 0.095] p.e.	[-0.062, 0.034] p.e.	[-0.381, 0.659] p.e.	[-0.381, 0.659] p.e.	[-0.062, 0.659] p.e.	[-0.062, 0.659] p.e.	[-0.056, 0.660] p.e.	[-0.056, 0.659] p.e.	[0.000, 0.659] p.e.	[0.000, 0.659] p.e.
0.05	[-0.199, 0.202] p.e.	[-0.199, 0.060] p.e.	[-0.411, 0.689] p.e.	[-0.411, 0.689] p.e.	[-0.199, 0.689] p.e.	[-0.199, 0.689] p.e.	[-0.151, 0.669] p.e.	[-0.149, 0.689] p.e.	[0.000, 0.689] p.e.	[0.000, 0.689] p.e.
0.10	[-0.483, 0.368] p.e.	[-0.203, 0.114] p.e.	[-0.461, 0.739] p.e.	[-0.411, 0.739] p.e.	[-0.483, 0.739] p.e.	[-0.203, 0.739] p.e.	[-0.210, 0.702] p.e.	[-0.194, 0.739] p.e.	[0.000, 0.739] p.e.	[0.000, 0.739] p.e.

Notes: † Point estimates (p.e.) and ‡ 95% Confidence Intervals (CI) around ATE are calculated using methods from Imbens-Manski (2004) with 250 pseudosamples. All analyses are weighted using Wave 1 specific sample weights. Number of observations = 4300. Sample sizes are rounded to the nearest 50 by requirement. For other details, refer to Table A1.

Figure 4: Sharp Bounds on the ATE of WIC Participation on Birth Weight ≤ 4000 grams When Participation Status May be Misclassified: Various Assumptions about Selection

A. Exogenous Selection or No Assumption on Selection | B. Only MTS or Joint MTS & MIV or MTS & MTR: Arbitrary Errors | C. Only MTS or Joint MTS & MIV or MTS & MTR: No False Positive Errors

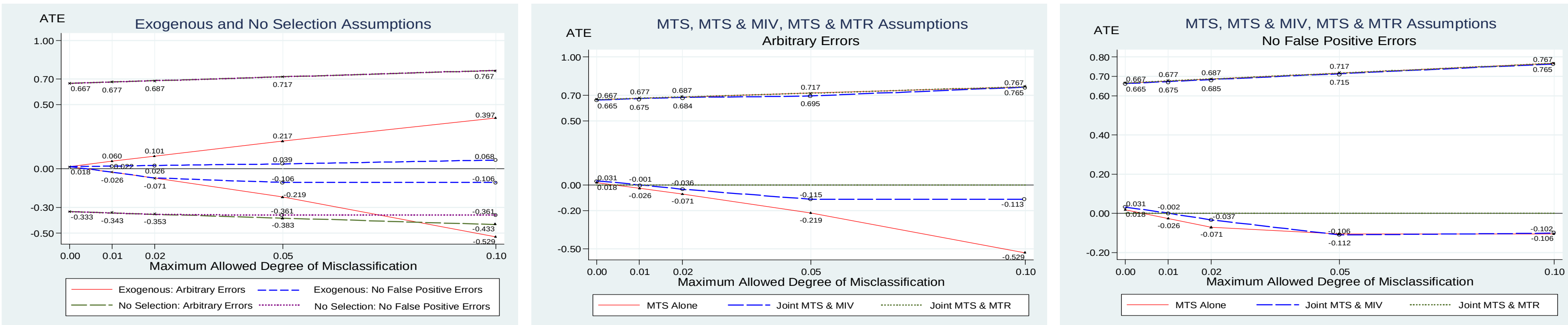

Table 4: Sharp Bounds on the ATE of WIC Participation on Birth Weight ≤ 4000 grams Given Unknown Counterfactuals and Potentially Misclassified Participation Status: Various Assumptions about Selection

Point Estimates of LB and UB and 95% I-M Confidence Intervals (CI) Around the Unknown Parameter ATE

Q_u	Exogenous Selection		No Assumption on Selection		MTS Assumption		MTS and MIV Assumption		MTS and MTR Assumption	
	(1) Arbitrary Errors	(2) No False Positives	(3) Arbitrary Errors	(4) No False Positives	(5) Arbitrary Errors	(6) No False Positives	(7) Arbitrary Errors	(8) No False Positives	(9) Arbitrary Errors	(10) No False Positives
0.00	[0.018, 0.018] p.e.†	[0.018, 0.018] p.e.	[-0.333, 0.667] p.e.	[-0.333, 0.667] p.e.	[0.018, 0.667] p.e.	[0.018, 0.667] p.e.	[0.031, 0.665] p.e.	[0.031, 0.665] p.e.	[0.000, 0.667] p.e.	[0.000, 0.667] p.e.
0.01	[-0.026, 0.060] p.e.	[-0.026, 0.022] p.e.	[-0.343, 0.677] p.e.	[-0.343, 0.677] p.e.	[-0.026, 0.677] p.e.	[-0.026, 0.677] p.e.	[-0.001, 0.675] p.e.	[-0.002, 0.675] p.e.	[0.000, 0.677] p.e.	[0.000, 0.677] p.e.
0.02	[-0.071, 0.101] p.e.	[-0.071, 0.026] p.e.	[-0.353, 0.687] p.e.	[-0.353, 0.687] p.e.	[-0.071, 0.687] p.e.	[-0.071, 0.687] p.e.	[-0.036, 0.684] p.e.	[-0.037, 0.685] p.e.	[0.000, 0.687] p.e.	[0.000, 0.687] p.e.
0.05	[-0.219, 0.217] p.e.	[-0.106, 0.039] p.e.	[-0.383, 0.717] p.e.	[-0.361, 0.717] p.e.	[-0.219, 0.717] p.e.	[-0.106, 0.717] p.e.	[-0.115, 0.695] p.e.	[-0.112, 0.715] p.e.	[0.000, 0.717] p.e.	[0.000, 0.717] p.e.
0.10	[-0.529, 0.397] p.e.	[-0.106, 0.068] p.e.	[-0.433, 0.767] p.e.	[-0.361, 0.767] p.e.	[-0.529, 0.767] p.e.	[-0.106, 0.767] p.e.	[-0.113, 0.765] p.e.	[-0.102, 0.765] p.e.	[0.000, 0.767] p.e.	[0.000, 0.767] p.e.

Notes: † Point estimates (p.e.) and ‡ 95% Confidence Intervals (CI) around ATE are calculated using methods from Imbens-Manski (2004) with 250 pseudosamples. All analyses are weighted using Wave 1 specific sample weights. Number of observations = 4300. Sample sizes are rounded to the nearest 50 by requirement. For other details, refer to Table A1.

Figure 5: Sharp Bounds on the ATE of WIC Participation on Gestation Age ≥ 33 weeks When Participation Status May be Misclassified: Various Assumptions about Selection

A. Exogenous Selection or No Assumption on Selection

B. Only MTS or Joint MTS & MIV or MTS & MTR: Arbitrary Errors

C. Only MTS or Joint MTS & MIV or MTS & MTR: No False Positive Errors

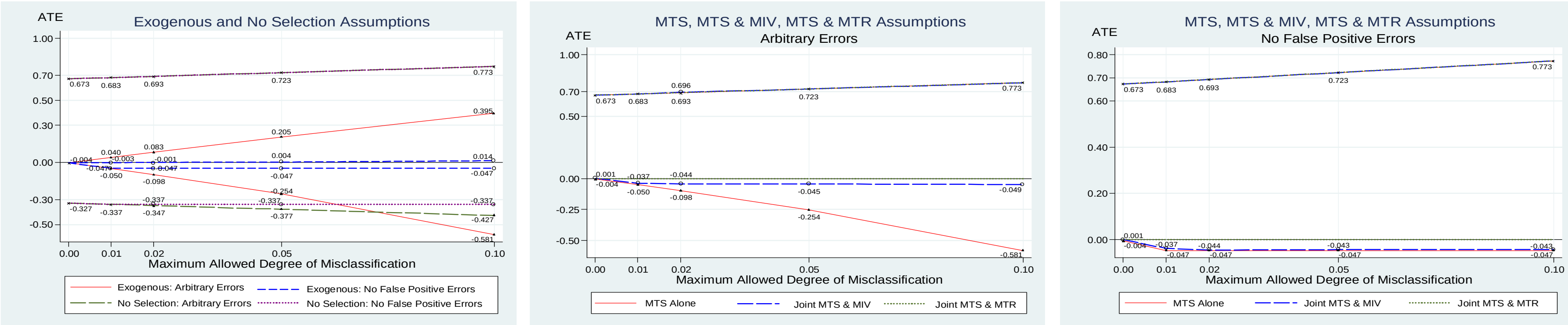

Table 5: Sharp Bounds on the ATE of WIC Participation on Gestation Age ≥ 33 weeks Given Unknown Counterfactuals and Potentially Misclassified Participation Status: Various Assumptions about Selection

Point Estimates of LB and UB and 95% I-M Confidence Intervals (CI) Around the Unknown Parameter ATE

Q_u	Exogenous Selection		No Assumption on Selection		MTS Assumption		MTS and MIV Assumption		MTS and MTR Assumption	
	(1) Arbitrary Errors	(2) No False Positives	(3) Arbitrary Errors	(4) No False Positives	(5) Arbitrary Errors	(6) No False Positives	(7) Arbitrary Errors	(8) No False Positives	(9) Arbitrary Errors	(10) No False Positives
0.00	[-0.004, -0.004] p.e.†	[-0.004, -0.004] p.e.	[-0.327, 0.673] p.e.	[-0.327, 0.673] p.e.	[-0.004, 0.673] p.e.	[-0.004, 0.673] p.e.	[0.001, 0.673] p.e.	[0.001, 0.673] p.e.	[0.000, 0.673] p.e.	[0.000, 0.673] p.e.
0.01	[-0.050, 0.040] p.e.	[-0.047, -0.003] p.e.	[-0.337, 0.683] p.e.	[-0.337, 0.683] p.e.	[-0.050, 0.683] p.e.	[-0.047, 0.683] p.e.	[-0.037, 0.683] p.e.	[-0.037, 0.683] p.e.	[0.000, 0.683] p.e.	[0.000, 0.683] p.e.
0.02	[-0.098, 0.083] p.e.	[-0.047, -0.001] p.e.	[-0.347, 0.693] p.e.	[-0.337, 0.693] p.e.	[-0.098, 0.693] p.e.	[-0.047, 0.693] p.e.	[-0.044, 0.696] p.e.	[-0.044, 0.693] p.e.	[0.000, 0.693] p.e.	[0.000, 0.693] p.e.
0.05	[-0.254, 0.205] p.e.	[-0.047, 0.004] p.e.	[-0.377, 0.723] p.e.	[-0.337, 0.723] p.e.	[-0.254, 0.723] p.e.	[-0.047, 0.723] p.e.	[-0.045, 0.723] p.e.	[-0.043, 0.723] p.e.	[0.000, 0.723] p.e.	[0.000, 0.723] p.e.
0.10	[-0.581, 0.395] p.e.	[-0.047, 0.014] p.e.	[-0.427, 0.773] p.e.	[-0.337, 0.773] p.e.	[-0.581, 0.773] p.e.	[-0.047, 0.773] p.e.	[-0.049, 0.773] p.e.	[-0.043, 0.773] p.e.	[0.000, 0.773] p.e.	[0.000, 0.773] p.e.

Notes: † Point estimates (p.e.) and ‡ 95% Confidence Intervals (CI) around ATE are calculated using methods from Imbens-Manski (2004) with 250 pseudosamples. All analyses are weighted using Wave 1 specific sample weights. Number of observations = 4250. Sample sizes are rounded to the nearest 50 by requirement. For other details, refer to Table A1.

Figure 6: Sharp Bounds on the ATE of WIC Participation on Gestation Age of 38 - 42 weeks When Participation Status May be Misclassified: Various Assumptions about Selection

A. Exogenous Selection or No Assumption on Selection | B. Only MTS or Joint MTS & MIV or MTS & MTR: Arbitrary Errors | C. Only MTS or Joint MTS & MIV or MTS & MTR: No False Positive Errors

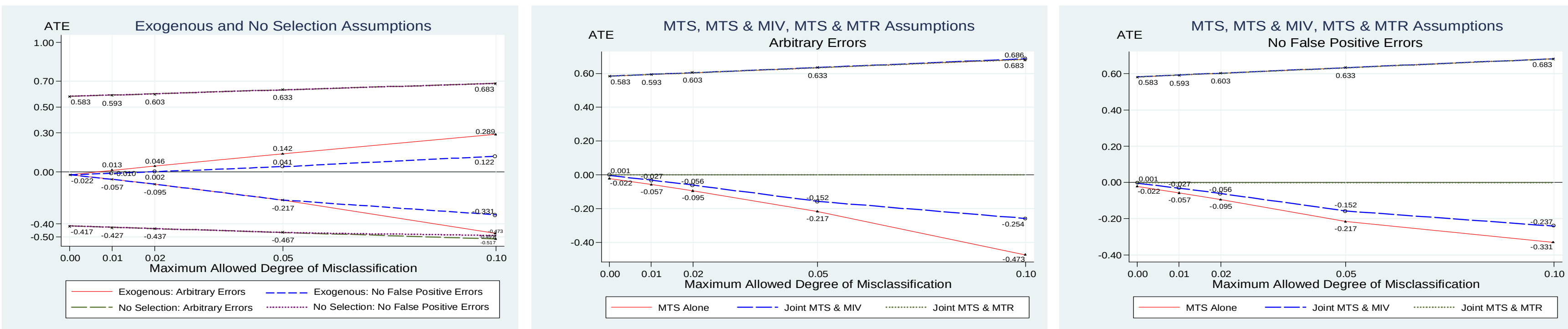

Table 6: Sharp Bounds on the ATE of WIC Participation on Gestation Age of 38 - 42 weeks Given Unknown Counterfactuals and Potentially Misclassified Participation Status: Various Assumptions about Selection

Point Estimates of LB and UB and 95% I-M Confidence Intervals (CI) Around the Unknown Parameter ATE

Q_u	Exogenous Selection		No Assumption on Selection		MTS Assumption		MTS and MIV Assumption		MTS and MTR Assumption	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Arbitrary Errors	No False Positives	Arbitrary Errors	No False Positives	Arbitrary Errors	No False Positives	Arbitrary Errors	No False Positives	Arbitrary Errors	No False Positives
0.00	[-0.022, -0.022] p.e.†	[-0.022, -0.022] p.e.	[-0.417, 0.583] p.e.	[-0.417, 0.583] p.e.	[-0.022, 0.583] p.e.	[-0.022, 0.583] p.e.	[0.001, 0.583] p.e.	[0.001, 0.583] p.e.	[0.000, 0.583] p.e.	[0.000, 0.583] p.e.
0.01	[-0.057, 0.013] p.e.	[-0.057, -0.010] p.e.	[-0.427, 0.593] p.e.	[-0.427, 0.593] p.e.	[-0.057, 0.593] p.e.	[-0.057, 0.593] p.e.	[-0.027, 0.593] p.e.	[-0.027, 0.593] p.e.	[0.000, 0.593] p.e.	[0.000, 0.593] p.e.
0.02	[-0.095, 0.046] p.e.	[-0.095, 0.002] p.e.	[-0.437, 0.603] p.e.	[-0.437, 0.603] p.e.	[-0.095, 0.603] p.e.	[-0.095, 0.603] p.e.	[-0.056, 0.603] p.e.	[-0.056, 0.603] p.e.	[0.000, 0.603] p.e.	[0.000, 0.603] p.e.
0.05	[-0.217, 0.142] p.e.	[-0.217, 0.041] p.e.	[-0.467, 0.633] p.e.	[-0.467, 0.633] p.e.	[-0.217, 0.633] p.e.	[-0.217, 0.633] p.e.	[-0.152, 0.633] p.e.	[-0.152, 0.633] p.e.	[0.000, 0.633] p.e.	[0.000, 0.633] p.e.
0.10	[-0.473, 0.289] p.e.	[-0.331, 0.122] p.e.	[-0.517, 0.683] p.e.	[-0.491, 0.683] p.e.	[-0.473, 0.683] p.e.	[-0.331, 0.683] p.e.	[-0.254, 0.686] p.e.	[-0.237, 0.683] p.e.	[0.000, 0.683] p.e.	[0.000, 0.683] p.e.

Notes: † Point estimates (p.e.) and ‡ 95% Confidence Intervals (CI) around ATE are calculated using methods from Imbens-Manski (2004) with 250 pseudosamples. All analyses are weighted using Wave 1 specific sample weights. Number of observations = 4250. Sample sizes are rounded to the nearest 50 by requirement. For other details, refer to Table A1.

Table 7. IV Estimates of the Effect of Prenatal WIC Participation on Infant Birth Outcomes

	Specification 1		Specification 2		Specification 3	
	OLS	IV	OLS	IV	OLS	IV
I. Probability of Birth Weight ≥ 1500 grams						
WIC	0.004**	0.005***	0.004**	0.005***	0.004**	0.005***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Underid Test		0.000		0.000		0.000
KP F-Stat		1072.789		1052.548		1041.203
Overid Test		0.372		0.304		0.448
Endogeneity		0.116		0.100		0.092
N	4300	4300	4300	4300	4300	4300
II. Probability of Birth Weight ≥ 2500 grams						
WIC	0.008	0.009	0.008	0.010	0.008	0.010
	(0.007)	(0.008)	(0.008)	(0.008)	(0.007)	(0.008)
Underid Test		0.000		0.000		0.000
KP F-Stat		1072.789		1052.548		1041.203
Overid Test		0.803		0.815		0.836
Endogeneity		0.638		0.580		0.568
N	4300	4300	4300	4300	4300	4300
III. Probability of Birth Weight: 2500 - 4000 grams						
WIC	0.021	0.031*	0.022	0.031*	0.022	0.030*
	(0.014)	(0.016)	(0.014)	(0.016)	(0.014)	(0.016)
Underid Test		0.000		0.000		0.000
KP F-Stat		1072.789		1052.548		1041.203
Overid Test		0.568		0.584		0.575
Endogeneity		0.190		0.179		0.215
N	4300	4300	4300	4300	4300	4300
IV. Probability of Birth Weight ≤ 4000 grams						
WIC	0.014	0.021	0.014	0.021	0.014	0.020
	(0.013)	(0.014)	(0.013)	(0.014)	(0.013)	(0.014)
Underid Test		0.000		0.000		0.000
KP F-Stat		1072.789		1052.548		1041.203
Overid Test		0.316		0.368		0.340
Endogeneity		0.257		0.262		0.300
N	4300	4300	4300	4300	4300	4300
V. Probability of Gestation Age ≥ 33 weeks						
WIC	-0.003	-0.002	-0.003	-0.001	-0.002	-0.001
	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
Underid Test		0.000		0.000		0.000
KP F-Stat		1058.825		1037.184		1025.539
Overid Test		0.238		0.255		0.298
Endogeneity		0.912		0.900		0.927
N	4250	4250	4250	4250	4250	4250
VI. Probability of Gestation Age: 38 - 42 weeks						
WIC	-0.025	-0.035*	-0.026	-0.034*	-0.026	-0.034*
	(0.018)	(0.019)	(0.018)	(0.019)	(0.018)	(0.019)
Underid Test		0.000		0.000		0.000
KP F-Stat		1058.825		1037.184		1025.539
Overid Test		0.856		0.868		0.832
Endogeneity		0.180		0.314		0.254
N	4250	4250	4250	4250	4250	4250

NOTES: * p<0.10, ** p<0.05, *** p<0.01. Robust standard errors are in parentheses. All analyses are weighted using Wave 1 specific sample weights. Underid reports the p-value of the Kleibergen-Paap (2006) rk statistic; F-Stat reports the associated F-statistic; Overid reports the p-value of the Hansen J statistic with rejection casting doubt on the instruments' validity; Endogeneity reports the p-value of the endogeneity test of the endogenous regressors. N is the sample size. Sample sizes are rounded to the nearest 50 by requirement. For other details, refer to Table A1.

Appendix A

Table A1: Summary Statistics

Variable	N	Mean	SD	WIC - No WIC Mean	WIC - No WIC p-value
Prenatal WIC Receipt (1 = Yes)	4350	0.687	0.464		
Child's health indicators					
Birth Weight (in grams)	4300	3276.234	574.041	-35.739	0.059
Birth Weight ≥ 2500 grams (1 = Yes)	4300	0.926	0.262	0.001	0.901
Birth Weight ≥ 1500 grams (1 = Yes)	4300	0.988	0.111	0.003	0.400
Birth Weight ≤ 4000 grams (1 = Yes)	4300	0.924	0.264	0.018	0.040
Normal Birth Weight: 2500 grams - 4000 grams (1 = Yes)	4300	0.851	0.357	0.019	0.107
Gestation Age (in weeks)	4250	38.779	2.567	-0.001	0.990
Gestation Age: 38 - 42 weeks (1 = Yes)	4250	0.748	0.434	-0.022	0.131
Gestation Age ≥ 33 weeks (1 = Yes)	4250	0.968	0.177	-0.004	0.491
Gestation Age ≥ 37 weeks (1 = Yes)	4250	0.879	0.327	-0.024	0.025
Controls					
Age (in months)	4350	10.527	2.065	-0.086	0.206
Gender (1 = boy)	4350	0.497	0.500	-0.003	0.875
White (1 = Yes)	4350	0.354	0.478	-0.115	0.000
Black (1 = Yes)	4350	0.205	0.404	0.065	0.000
Hispanic (1 = Yes)	4350	0.367	0.482	0.065	0.000
Asian (1 = Yes)	4350	0.019	0.138	-0.019	0.000
Urbanized Area (1 = Yes)	4350	0.688	0.463	-0.041	0.006
Urbanized Cluster (1 = Yes)	4350	0.142	0.350	0.034	0.003
Northeast (1 = Yes)	4350	0.140	0.347	-0.044	0.000
Midwest (1 = Yes)	4350	0.193	0.395	0.000	0.993
South (1 = Yes)	4350	0.404	0.491	0.005	0.764
West (1 = Yes)	4350	0.262	0.440	0.039	0.006
Household Socioeconomic Status (SES)	4350	-0.665	0.532	-0.287	0.000
Household SES Quintile 1 (1 = Yes)	4350	0.408	0.491	0.173	0.000
Household SES Quintile 2 (1 = Yes)	4350	0.325	0.468	0.047	0.002
Household SES Quintile 3 (1 = Yes)	4350	0.182	0.386	-0.105	0.000
Household SES Quintile 4 (1 = Yes)	4350	0.071	0.257	-0.079	0.000
Household SES Quintile 5 (1 = Yes)	4350	0.015	0.121	-0.036	0.000
Household Size	4350	4.649	1.691	-0.170	0.002
Parents are Married (1 = Yes)	4350	0.470	0.499	-0.151	0.000
Mother's Age	4350	25.877	5.883	-2.229	0.000
Mother's Age (1 = Missing)	4350	0.008	0.090	-0.021	0.000
Kessner Index of Prenatal Care (1 = Adequate)	4350	0.629	0.483	0.028	0.080
Kessner Index of Prenatal Care (1 = Intermediate)	4350	0.232	0.422	0.026	0.063
Kessner Index of Prenatal Care (1 = Inadequate)	4350	0.083	0.277	-0.043	0.000
Kessner Index of Prenatal Care (1 = Unknown)	4350	0.056	0.229	-0.011	0.148
Father's Age	4350	30.355	5.716	-0.923	0.000
Father's Age (1 = Missing)	4350	0.219	0.414	0.088	0.000
Mother's Weight (in kilograms)	4350	72.686	17.833	2.031	0.001
Mother's Weight (1 = Missing)	4350	0.194	0.396	0.001	0.916
Mother's Education = High School (1 = Yes)	4350	0.383	0.486	0.051	0.001
Mother's Education = Some College (1 = Yes)	4350	0.211	0.408	-0.091	0.000
Mother's Education = Bachelor's Degree (1 = Yes)	4350	0.033	0.179	-0.051	0.000
Mother's Education = Advanced College Degree (1 = Yes)	4350	0.011	0.105	-0.023	0.000
Mother's Education (1 = Missing)	4350	0.006	0.079	-0.020	0.000
Father's Education = High School (1 = Yes)	4350	0.364	0.481	-0.006	0.725
Father's Education = Some College (1 = Yes)	4350	0.175	0.380	-0.064	0.000
Father's Education = Bachelor's Degree (1 = Yes)	4350	0.037	0.189	-0.054	0.000
Father's Education = Advanced College Degree (1 = Yes)	4350	0.018	0.134	-0.035	0.000
Father's Education (1 = Missing)	4350	0.045	0.208	0.007	0.286

NOTES: The sample includes only 9-month old children from households with income at or below 185% FPL. All analyses are weighted using Wave 1 specific sample weights. Urban Cluster is defined as less densely populated than an Urbanized Area. Omitted category for race is 'other', area type is 'rural', mother's education is 'less than high school', and father's education is 'less than high school'. Child's number of gestation weeks and birth weight have N < 4350. Sample sizes are rounded to the nearest 50 by requirement.

Appendix B

Figure B1: Sharp Bounds on the ATE of WIC Participation on Birth Weight $\geq$ 1500 grams When Participation Status May be Misclassified: Various Assumptions about Selection

A. Exogenous Selection or No Assumption on Selection | B. Only MTS or Joint MTS & MIV or MTS & MTR: Arbitrary Errors | C. Only MTS or Joint MTS & MIV or MTS & MTR: No False Positive Errors

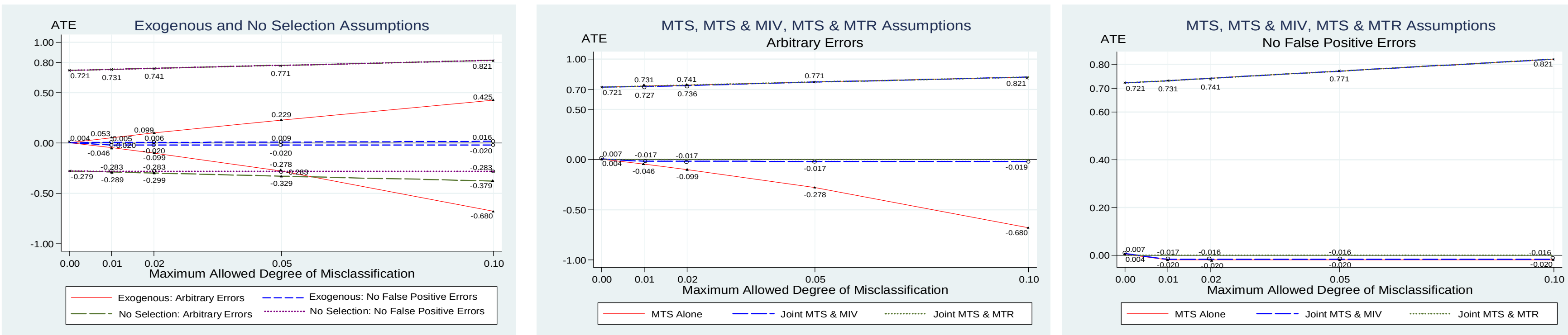

Table B1: Sharp Bounds on the ATE of WIC Participation on Birth Weight $\geq$ 1500 grams Given Unknown Counterfactuals and Potentially Misclassified Participation Status: Various Assumptions about Selection

Point Estimates of LB and UB and 95% I-M Confidence Intervals (CI) Around the Unknown Parameter ATE

Q	Exogenous Selection		No Assumption on Selection		MTS Assumption		MTS and MIV Assumption		MTS and MTR Assumption	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Arbitrary Errors	No False Positives	Arbitrary Errors	No False Positives	Arbitrary Errors	No False Positives	Arbitrary Errors	No False Positives	Arbitrary Errors	No False Positives
0.00	[0.004, 0.004] p.e.†	[0.004, 0.004] p.e.	[-0.279, 0.721] p.e.	[-0.279, 0.721] p.e.	[0.004, 0.721] p.e.	[0.004, 0.721] p.e.	[0.007, 0.721] p.e.	[0.007, 0.721] p.e.	[0.000, 0.721] p.e.	[0.000, 0.721] p.e.
0.01	[-0.046, 0.053] p.e.	[-0.020, 0.005] p.e.	[-0.289, 0.731] p.e.	[-0.283, 0.731] p.e.	[-0.046, 0.731] p.e.	[-0.020, 0.731] p.e.	[-0.017, 0.727] p.e.	[-0.017, 0.731] p.e.	[0.000, 0.731] p.e.	[0.000, 0.731] p.e.
0.02	[-0.099, 0.099] p.e.	[-0.020, 0.006] p.e.	[-0.299, 0.741] p.e.	[-0.283, 0.741] p.e.	[-0.099, 0.741] p.e.	[-0.020, 0.741] p.e.	[-0.017, 0.736] p.e.	[-0.016, 0.741] p.e.	[0.000, 0.741] p.e.	[0.000, 0.741] p.e.
0.05	[-0.278, 0.229] p.e.	[-0.020, 0.009] p.e.	[-0.329, 0.771] p.e.	[-0.283, 0.771] p.e.	[-0.278, 0.771] p.e.	[-0.020, 0.771] p.e.	[-0.017, 0.771] p.e.	[-0.016, 0.771] p.e.	[0.000, 0.771] p.e.	[0.000, 0.771] p.e.
0.10	[-0.680, 0.425] p.e.	[-0.020, 0.016] p.e.	[-0.379, 0.821] p.e.	[-0.283, 0.821] p.e.	[-0.680, 0.821] p.e.	[-0.020, 0.821] p.e.	[-0.019, 0.821] p.e.	[-0.016, 0.821] p.e.	[0.000, 0.821] p.e.	[0.000, 0.821] p.e.

Notes: † Point estimates (p.e.) and ‡ 95% Confidence Intervals (CI) around ATE are calculated using methods from Imbens-Manski (2004) with 250 pseudosamples. The sample includes only 9-month old children from non-white households with income at or below 185% FPL. All analyses are weighted using Wave 1 specific sample weights. Number of observations = 3100. Sample sizes are rounded to the nearest 50 by requirement.

Figure B2: Sharp Bounds on the ATE of WIC Participation on Birth Weight $\geq$ 2500 grams When Participation Status May be Misclassified: Various Assumptions about Selection

A. Exogenous Selection or No Assumption on Selection	B. Only MTS or Joint MTS & MIV or MTS & MTR: Arbitrary Errors	C. Only MTS or Joint MTS & MIV or MTS & MTR: No False Positive Errors

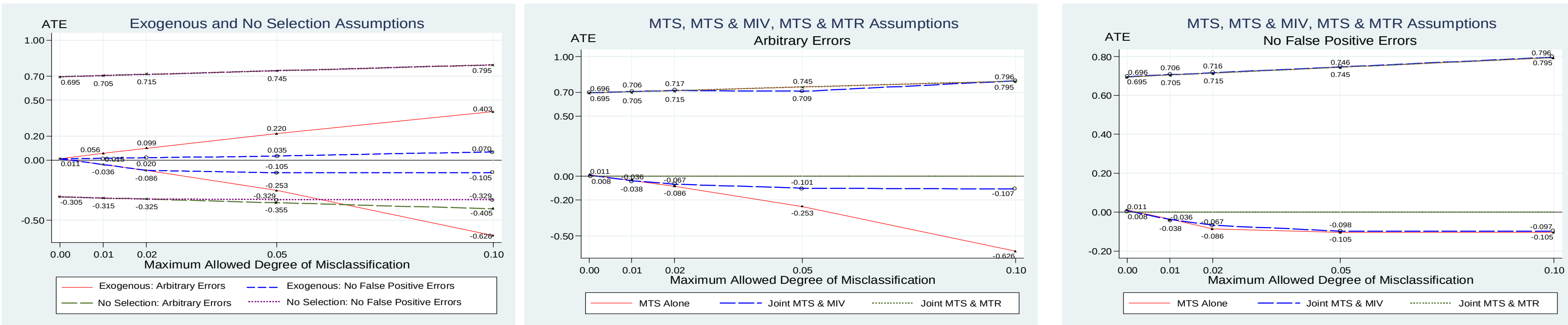

Table B2: Sharp Bounds on the ATE of WIC Participation on Birth Weight ≥ 2500 grams Given Unknown Counterfactuals and Potentially Misclassified Participation Status: Various Assumptions about Selection

Point Estimates of LB and UB and 95% I-M Confidence Intervals (CI) Around the Unknown Parameter ATE

Q	Exogenous Selection		No Assumption on Selection		MTS Assumption		MTS and MIV Assumption		MTS and MTR Assumption	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Arbitrary Errors	No False Positives	Arbitrary Errors	No False Positives	Arbitrary Errors	No False Positives	Arbitrary Errors	No False Positives	Arbitrary Errors	No False Positives
0.00	[0.011, 0.011] p.e.†	[0.011, 0.011] p.e.	[-0.305, 0.695] p.e.	[-0.305, 0.695] p.e.	[0.011, 0.695] p.e.	[0.011, 0.695] p.e.	[0.008, 0.696] p.e.	[0.008, 0.696] p.e.	[0.000, 0.695] p.e.	[0.000, 0.695] p.e.
0.01	[-0.036, 0.056] p.e.	[-0.036, 0.015] p.e.	[-0.315, 0.705] p.e.	[-0.315, 0.705] p.e.	[-0.036, 0.705] p.e.	[-0.036, 0.705] p.e.	[-0.038, 0.706] p.e.	[-0.038, 0.706] p.e.	[0.000, 0.705] p.e.	[0.000, 0.705] p.e.
0.02	[-0.086, 0.099] p.e.	[-0.086, 0.020] p.e.	[-0.325, 0.715] p.e.	[-0.325, 0.715] p.e.	[-0.086, 0.715] p.e.	[-0.086, 0.715] p.e.	[-0.067, 0.717] p.e.	[-0.067, 0.716] p.e.	[0.000, 0.715] p.e.	[0.000, 0.715] p.e.
0.05	[-0.253, 0.220] p.e.	[-0.105, 0.035] p.e.	[-0.355, 0.745] p.e.	[-0.329, 0.745] p.e.	[-0.253, 0.745] p.e.	[-0.105, 0.745] p.e.	[-0.101, 0.709] p.e.	[-0.098, 0.746] p.e.	[0.000, 0.745] p.e.	[0.000, 0.745] p.e.
0.10	[-0.626, 0.403] p.e.	[-0.105, 0.070] p.e.	[-0.405, 0.795] p.e.	[-0.329, 0.795] p.e.	[-0.626, 0.795] p.e.	[-0.105, 0.795] p.e.	[-0.107, 0.796] p.e.	[-0.097, 0.796] p.e.	[0.000, 0.795] p.e.	[0.000, 0.795] p.e.

Notes: † Point estimates (p.e.) and ‡ 95% Confidence Intervals (CI) around ATE are calculated using methods from Imbens-Manski (2004) with 250 pseudosamples. The sample includes only 9-month old children from non-white households with income at or below 185% FPL. All analyses are weighted using Wave 1 specific sample weights. Number of observations = 3100. Sample sizes are rounded to the nearest 50 by requirement.

Figure B3: Sharp Bounds on the ATE of WIC Participation on Birth Weight: 2500 - 4000 grams When Participation Status May be Misclassified: Various Assumptions about Selection

A. Exogenous Selection or No Assumption on Selection | B. Only MTS or Joint MTS & MIV or MTS & MTR: Arbitrary Errors | C. Only MTS or Joint MTS & MIV or MTS & MTR: No False Positive Errors

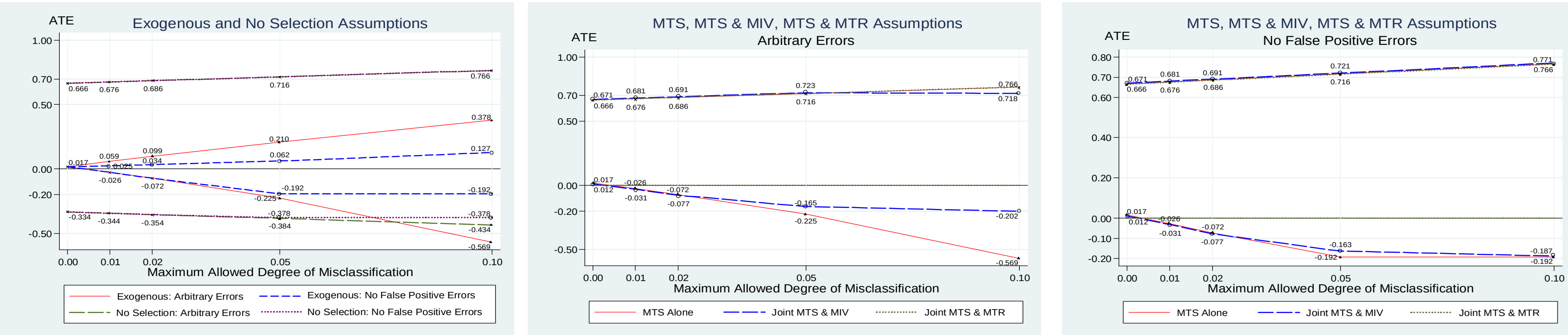

Table B3: Sharp Bounds on the ATE of WIC Participation on Birth Weight: 2500 - 4000 grams Given Unknown Counterfactuals and Potentially Misclassified Participation Status: Various Assumptions about Selection

Point Estimates of LB and UB and 95% I-M Confidence Intervals (CI) Around the Unknown Parameter ATE

Q	Exogenous Selection		No Assumption on Selection		MTS Assumption		MTS and MIV Assumption		MTS and MTR Assumption	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Arbitrary Errors	No False Positives	Arbitrary Errors	No False Positives	Arbitrary Errors	No False Positives	Arbitrary Errors	No False Positives	Arbitrary Errors	No False Positives
0.00	[0.017, 0.017] p.e.[†]	[0.017, 0.017] p.e.	[-0.334, 0.666] p.e.	[-0.334, 0.666] p.e.	[0.017, 0.666] p.e.	[0.017, 0.666] p.e.	[0.012, 0.671] p.e.	[0.012, 0.671] p.e.	[0.000, 0.666] p.e.	[0.000, 0.666] p.e.
0.01	[-0.026, 0.059] p.e.	[-0.026, 0.025] p.e.	[-0.344, 0.676] p.e.	[-0.344, 0.676] p.e.	[-0.026, 0.676] p.e.	[-0.026, 0.676] p.e.	[-0.031, 0.681] p.e.	[-0.031, 0.681] p.e.	[0.000, 0.676] p.e.	[0.000, 0.676] p.e.
0.02	[-0.072, 0.099] p.e.	[-0.072, 0.034] p.e.	[-0.354, 0.686] p.e.	[-0.354, 0.686] p.e.	[-0.072, 0.686] p.e.	[-0.072, 0.686] p.e.	[-0.077, 0.691] p.e.	[-0.077, 0.691] p.e.	[0.000, 0.686] p.e.	[0.000, 0.686] p.e.
0.05	[-0.225, 0.210] p.e.	[-0.192, 0.062] p.e.	[-0.384, 0.716] p.e.	[-0.378, 0.716] p.e.	[-0.225, 0.716] p.e.	[-0.192, 0.716] p.e.	[-0.165, 0.723] p.e.	[-0.163, 0.721] p.e.	[0.000, 0.716] p.e.	[0.000, 0.716] p.e.
0.10	[-0.569, 0.378] p.e.	[-0.192, 0.127] p.e.	[-0.434, 0.766] p.e.	[-0.378, 0.766] p.e.	[-0.569, 0.766] p.e.	[-0.192, 0.766] p.e.	[-0.202, 0.718] p.e.	[-0.187, 0.771] p.e.	[0.000, 0.766] p.e.	[0.000, 0.766] p.e.

Notes: † Point estimates (p.e.) and ‡ 95% Confidence Intervals (CI) around ATE are calculated using methods from Imbens-Manski (2004) with 250 pseudosamples. The sample includes only 9-month old children from non-white households with income at or below 185% FPL. All analyses are weighted using Wave 1 specific sample weights. Number of observations = 3100. Sample sizes are rounded to the nearest 50 by requirement.

Figure B4: Sharp Bounds on the ATE of WIC Participation on Birth Weight ≤ 4000 grams When Participation Status May be Misclassified: Various Assumptions about Selection

A. Exogenous Selection or No Assumption on Selection | B. Only MTS or Joint MTS & MIV or MTS & MTR: Arbitrary Errors | C. Only MTS or Joint MTS & MIV or MTS & MTR: No False Positive Errors

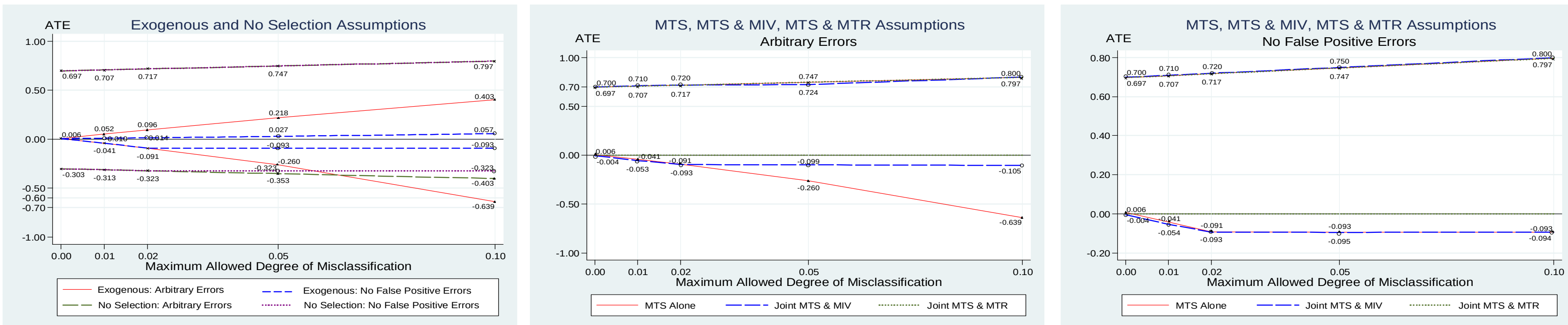

Table B4: Sharp Bounds on the ATE of WIC Participation on Birth Weight ≤ 4000 grams Given Unknown Counterfactuals and Potentially Misclassified Participation Status: Various Assumptions about Selection

Point Estimates of LB and UB and 95% I-M Confidence Intervals (CI) Around the Unknown Parameter ATE

Q	Exogenous Selection		No Assumption on Selection		MTS Assumption		MTS and MIV Assumption		MTS and MTR Assumption	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Arbitrary Errors	No False Positives	Arbitrary Errors	No False Positives	Arbitrary Errors	No False Positives	Arbitrary Errors	No False Positives	Arbitrary Errors	No False Positives
0.00	[0.006, 0.006] p.e.†	[0.006, 0.006] p.e.	[-0.303, 0.697] p.e.	[-0.303, 0.697] p.e.	[0.006, 0.697] p.e.	[0.006, 0.697] p.e.	[-0.004, 0.700] p.e.	[-0.004, 0.700] p.e.	[0.000, 0.697] p.e.	[0.000, 0.697] p.e.
0.01	[-0.041, 0.052] p.e.	[-0.041, 0.010] p.e.	[-0.313, 0.707] p.e.	[-0.313, 0.707] p.e.	[-0.041, 0.707] p.e.	[-0.041, 0.707] p.e.	[-0.053, 0.710] p.e.	[-0.054, 0.710] p.e.	[0.000, 0.707] p.e.	[0.000, 0.707] p.e.
0.02	[-0.091, 0.096] p.e.	[-0.091, 0.014] p.e.	[-0.323, 0.717] p.e.	[-0.323, 0.717] p.e.	[-0.091, 0.717] p.e.	[-0.091, 0.717] p.e.	[-0.093, 0.720] p.e.	[-0.093, 0.720] p.e.	[0.000, 0.717] p.e.	[0.000, 0.717] p.e.
0.05	[-0.260, 0.218] p.e.	[-0.093, 0.027] p.e.	[-0.353, 0.747] p.e.	[-0.323, 0.747] p.e.	[-0.260, 0.747] p.e.	[-0.093, 0.747] p.e.	[-0.099, 0.724] p.e.	[-0.095, 0.750] p.e.	[0.000, 0.747] p.e.	[0.000, 0.747] p.e.
0.10	[-0.639, 0.403] p.e.	[-0.093, 0.057] p.e.	[-0.403, 0.797] p.e.	[-0.323, 0.797] p.e.	[-0.639, 0.797] p.e.	[-0.093, 0.797] p.e.	[-0.105, 0.800] p.e.	[-0.094, 0.800] p.e.	[0.000, 0.797] p.e.	[0.000, 0.797] p.e.

Notes: † Point estimates (p.e.) and ‡ 95% Confidence Intervals (CI) around ATE are calculated using methods from Imbens-Manski (2004) with 250 pseudosamples. The sample includes only 9-month old children from non-white households with income at or below 185% FPL. All analyses are weighted using Wave 1 specific sample weights. Number of observations = 3100. Sample sizes are rounded to the nearest 50 by requirement.

Figure B5: Sharp Bounds on the ATE of WIC Participation on Gestation Age ≥ 33 weeks When Participation Status May be Misclassified: Various Assumptions about Selection

A. Exogenous Selection or No Assumption on Selection

B. Only MTS or Joint MTS & MIV or MTS & MTR: Arbitrary Errors

C. Only MTS or Joint MTS & MIV or MTS & MTR: No False Positive Errors

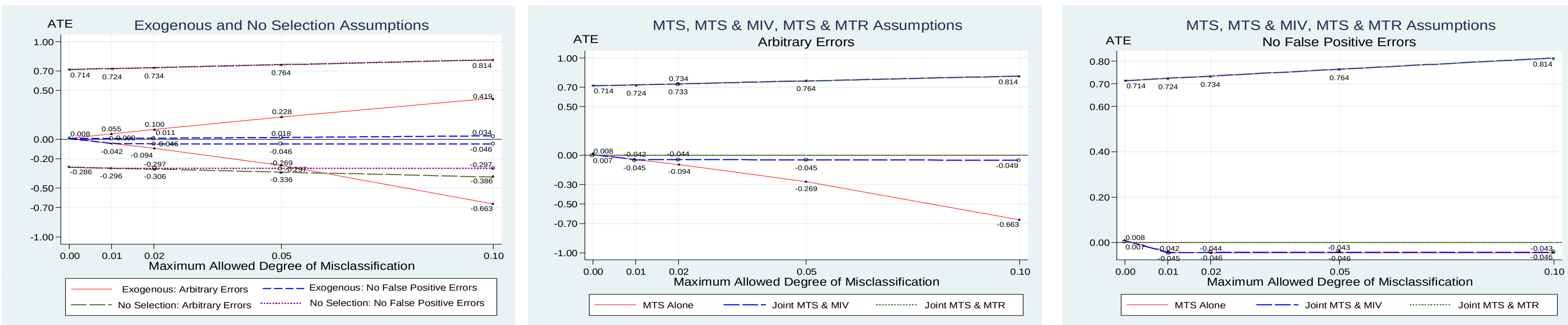

Table B5: Sharp Bounds on the ATE of WIC Participation on Gestation Age ≥ 33 weeks Given Unknown Counterfactuals and Potentially Misclassified Participation Status: Various Assumptions about Selection

Point Estimates of LB and UB and 95% I-M Confidence Intervals (CI) Around the Unknown Parameter ATE

Q	Exogenous Selection		No Assumption on Selection		MTS Assumption		MTS and MIV Assumption		MTS and MTR Assumption	
	(1) Arbitrary Errors	(2) No False Positives	(3) Arbitrary Errors	(4) No False Positives	(5) Arbitrary Errors	(6) No False Positives	(7) Arbitrary Errors	(8) No False Positives	(9) Arbitrary Errors	(10) No False Positives
0.00	[0.008, 0.008] p.e.†	[0.008, 0.008] p.e.	[-0.286, 0.714] p.e.	[-0.286, 0.714] p.e.	[0.008, 0.714] p.e.	[0.008, 0.714] p.e.	[0.007, 0.714] p.e.	[0.007, 0.714] p.e.	[0.000, 0.714] p.e.	[0.000, 0.714] p.e.
0.01	[-0.042, 0.055] p.e.	[-0.042, 0.009] p.e.	[-0.296, 0.724] p.e.	[-0.296, 0.724] p.e.	[-0.042, 0.724] p.e.	[-0.042, 0.724] p.e.	[-0.045, 0.724] p.e.	[-0.045, 0.724] p.e.	[0.000, 0.724] p.e.	[0.000, 0.724] p.e.
0.02	[-0.094, 0.100] p.e.	[-0.046, 0.011] p.e.	[-0.306, 0.734] p.e.	[-0.297, 0.734] p.e.	[-0.094, 0.734] p.e.	[-0.046, 0.734] p.e.	[-0.044, 0.733] p.e.	[-0.044, 0.734] p.e.	[0.000, 0.734] p.e.	[0.000, 0.734] p.e.
0.05	[-0.269, 0.228] p.e.	[-0.046, 0.018] p.e.	[-0.336, 0.764] p.e.	[-0.297, 0.764] p.e.	[-0.269, 0.764] p.e.	[-0.046, 0.764] p.e.	[-0.045, 0.764] p.e.	[-0.043, 0.764] p.e.	[0.000, 0.764] p.e.	[0.000, 0.764] p.e.
0.10	[-0.663, 0.419] p.e.	[-0.046, 0.034] p.e.	[-0.386, 0.814] p.e.	[-0.297, 0.814] p.e.	[-0.663, 0.814] p.e.	[-0.046, 0.814] p.e.	[-0.049, 0.814] p.e.	[-0.043, 0.814] p.e.	[0.000, 0.814] p.e.	[0.000, 0.814] p.e.

Notes: † Point estimates (p.e.) and ‡ 95% Confidence Intervals (CI) around ATE are calculated using methods from Imbens-Manski (2004) with 250 pseudosamples. The sample includes only 9-month old children from non-white households with income at or below 185% FPL. All analyses are weighted using Wave 1 specific sample weights. Number of observations = 3050. Sample sizes are rounded to the nearest 50 by requirement.

Figure B6: Sharp Bounds on the ATE of WIC Participation on Gestation Age of 38 - 42 weeks When Participation Status May be Misclassified: Various Assumptions about Selection

A. Exogenous Selection or No Assumption on Selection | B. Only MTS or Joint MTS & MIV or MTS & MTR: Arbitrary Errors | C. Only MTS or Joint MTS & MIV or MTS & MTR: No False Positive Errors

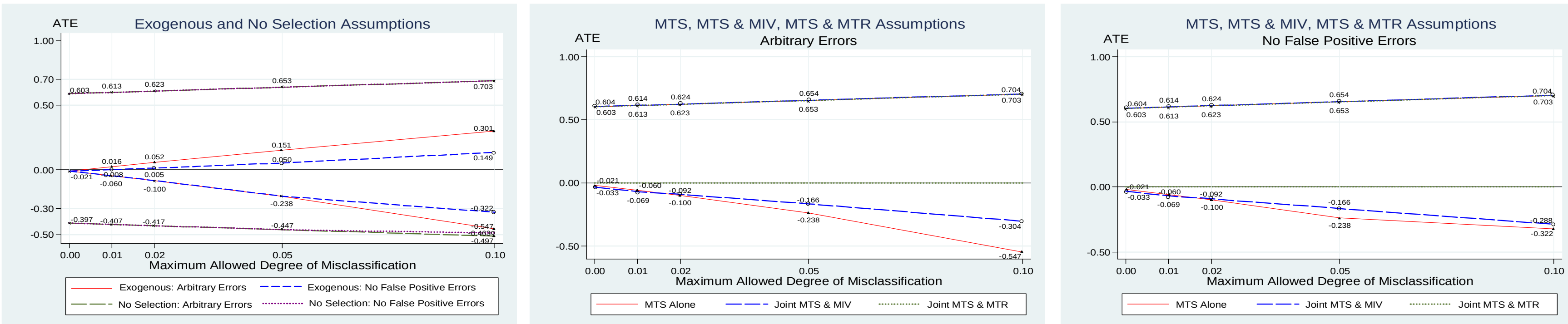

Table B6: Sharp Bounds on the ATE of WIC Participation on Gestation Age of 38 - 42 weeks Given Unknown Counterfactuals and Potentially Misclassified Participation Status: Various Assumptions about Selection

Point Estimates of LB and UB and 95% I-M Confidence Intervals (CI) Around the Unknown Parameter ATE

Q	Exogenous Selection		No Assumption on Selection		MTS Assumption		MTS and MIV Assumption		MTS and MTR Assumption	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Arbitrary Errors	No False Positives	Arbitrary Errors	No False Positives	Arbitrary Errors	No False Positives	Arbitrary Errors	No False Positives	Arbitrary Errors	No False Positives
0.00	[-0.021, -0.021] p.e.†	[-0.021, -0.021] p.e.	[-0.397, 0.603] p.e.	[-0.397, 0.603] p.e.	[-0.021, 0.603] p.e.	[-0.021, 0.603] p.e.	[-0.033, 0.604] p.e.	[-0.033, 0.604] p.e.	[0.000, 0.603] p.e.	[0.000, 0.603] p.e.
0.01	[-0.060, 0.016] p.e.	[-0.060, -0.008] p.e.	[-0.407, 0.613] p.e.	[-0.407, 0.613] p.e.	[-0.060, 0.613] p.e.	[-0.060, 0.613] p.e.	[-0.069, 0.614] p.e.	[-0.069, 0.614] p.e.	[0.000, 0.613] p.e.	[0.000, 0.613] p.e.
0.02	[-0.100, 0.052] p.e.	[-0.100, 0.005] p.e.	[-0.417, 0.623] p.e.	[-0.417, 0.623] p.e.	[-0.100, 0.623] p.e.	[-0.100, 0.623] p.e.	[-0.092, 0.624] p.e.	[-0.092, 0.624] p.e.	[0.000, 0.623] p.e.	[0.000, 0.623] p.e.
0.05	[-0.238, 0.151] p.e.	[-0.238, 0.050] p.e.	[-0.447, 0.653] p.e.	[-0.447, 0.653] p.e.	[-0.238, 0.653] p.e.	[-0.238, 0.653] p.e.	[-0.166, 0.654] p.e.	[-0.166, 0.654] p.e.	[0.000, 0.653] p.e.	[0.000, 0.653] p.e.
0.10	[-0.547, 0.301] p.e.	[-0.322, 0.149] p.e.	[-0.497, 0.703] p.e.	[-0.463, 0.703] p.e.	[-0.547, 0.703] p.e.	[-0.322, 0.703] p.e.	[-0.304, 0.704] p.e.	[-0.288, 0.704] p.e.	[0.000, 0.703] p.e.	[0.000, 0.703] p.e.

Notes: † Point estimates (p.e.) and ‡ 95% Confidence Intervals (CI) around ATE are calculated using methods from Imbens-Manski (2004) with 250 pseudosamples. The sample includes only 9-month old children from non-white households with income at or below 185% FPL. All analyses are weighted using Wave 1 specific sample weights. Number of observations = 3050. Sample sizes are rounded to the nearest 50 by requirement.

Table B7. IV Estimates of the Effect of Prenatal WIC Participation on Infant Birth Outcomes

	Specification 1		Specification 2		Specification 3	
	OLS	IV	OLS	IV	OLS	IV
I. Probability of Birth Weight ≥ 1500 grams						
WIC	0.004	0.005**	0.003	0.005**	0.003	0.005**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Underid Test		0.000		0.000		0.000
KP F-Stat		731.241		734.649		732.446
Overid Test		0.750		0.726		0.718
Endogeneity		0.267		0.246		0.212
N	3100	3100	3100	3100	3100	3100
II. Probability of Birth Weight ≥ 2500 grams						
WIC	0.013	0.015	0.013	0.014	0.013	0.014
	(0.009)	(0.010)	(0.009)	(0.010)	(0.009)	(0.010)
Underid Test		0.000		0.000		0.000
KP F-Stat		731.241		734.649		732.446
Overid Test		0.980		0.983		0.989
Endogeneity		0.671		0.755		0.733
N	3100	3100	3100	3100	3100	3100
III. Probability of Birth Weight: 2500 - 4000 grams						
WIC	0.017	0.026	0.017	0.026	0.017	0.026
	(0.017)	(0.020)	(0.017)	(0.020)	(0.017)	(0.020)
Underid Test		0.000		0.000		0.000
KP F-Stat		731.241		734.649		732.446
Overid Test		0.939		0.931		0.924
Endogeneity		0.316		0.297		0.325
N	3100	3100	3100	3100	3100	3100
IV. Probability of Birth Weight ≤ 4000 grams						
WIC	0.004	0.012	0.004	0.012	0.004	0.012
	(0.015)	(0.017)	(0.015)	(0.017)	(0.015)	(0.017)
Underid Test		0.000		0.000		0.000
KP F-Stat		731.241		734.649		732.446
Overid Test		0.821		0.814		0.820
Endogeneity		0.405		0.356		0.380
N	3100	3100	3100	3100	3100	3100
V. Probability of Gestation Age ≥ 33 weeks						
WIC	0.008	0.011	0.008	0.011	0.008	0.011
	(0.006)	(0.007)	(0.006)	(0.007)	(0.006)	(0.007)
Underid Test		0.000		0.000		0.000
KP F-Stat		719.871		722.622		720.128
Overid Test		0.606		0.596		0.592
Endogeneity		0.122		0.121		0.108
N	3050	3050	3050	3050	3050	3050
VI. Probability of Gestation Age: 38 - 42 weeks						
WIC	-0.021	-0.026	-0.020	-0.025	-0.021	-0.026
	(0.022)	(0.023)	(0.022)	(0.023)	(0.022)	(0.023)
Underid Test		0.000		0.000		0.000
KP F-Stat		719.871		722.622		720.128
Overid Test		0.381		0.382		0.377
Endogeneity		0.674		0.703		0.632
N	3050	3050	3050	3050	3050	3050

NOTES: * p<0.10, ** p<0.05, *** p<0.01. Robust standard errors are in parentheses. The sample includes only 9-month old children from non-white households with income at or below 185% FPL. All analyses are weighted using Wave 1 specific sample weights. Underid reports the p-value of the Kleibergen-Paap (2006) rk statistic; F-Stat reports the associated F-statistic; Overid reports the p-value of the Hansen J statistic with rejection casting doubt on the instruments' validity; Endogeneity reports the p-value of the endogeneity test of the endogenous regressors. N is the sample size. Sample sizes are rounded to the nearest 50 by requirement.

Appendix C

Figure C1: Sharp Bounds on the ATE of WIC Participation on Birth Weight ≥ 1500 grams When Participation Status May be Misclassified: Various Assumptions about Selection

A. Exogenous Selection or No Assumption on Selection — B. Only MTS or Joint MTS & MIV or MTS & MTR: Arbitrary Errors — C. Only MTS or Joint MTS & MIV or MTS & MTR: No False Positive Errors

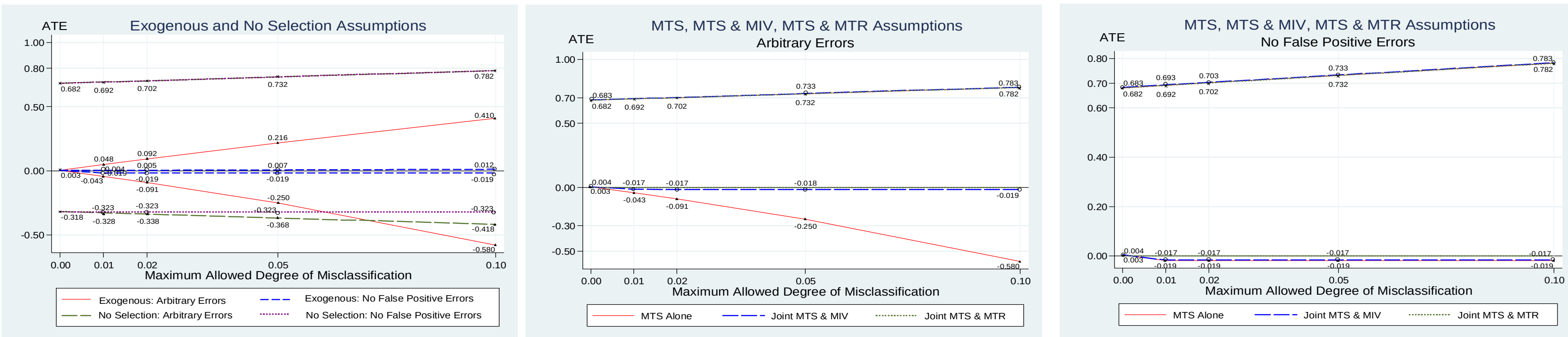

Table C1: Sharp Bounds on the ATE of WIC Participation on Birth Weight ≥ 1500 grams Given Unknown Counterfactuals and Potentially Misclassified Participation Status: Various Assumptions about Selection

Point Estimates of LB and UB and 95% I-M Confidence Intervals (CI) Around the Unknown Parameter ATE

Q	Exogenous Selection		No Assumption on Selection		MTS Assumption		MTS and MIV Assumption		MTS and MTR Assumption	
	(1) Arbitrary Errors	(2) No False Positives	(3) Arbitrary Errors	(4) No False Positives	(5) Arbitrary Errors	(6) No False Positives	(7) Arbitrary Errors	(8) No False Positives	(9) Arbitrary Errors	(10) No False Positives
0.00	[0.003, 0.003] p.e.†	[0.003, 0.003] p.e.	[-0.318, 0.682] p.e.	[-0.318, 0.682] p.e.	[0.003, 0.682] p.e.	[0.003, 0.682] p.e.	[0.004, 0.683] p.e.	[0.004, 0.683] p.e.	[0.000, 0.682] p.e.	[0.000, 0.682] p.e.
0.01	[-0.043, 0.048] p.e.	[-0.019, 0.004] p.e.	[-0.328, 0.692] p.e.	[-0.323, 0.692] p.e.	[-0.043, 0.692] p.e.	[-0.019, 0.692] p.e.	[-0.017, 0.692] p.e.	[-0.017, 0.693] p.e.	[0.000, 0.692] p.e.	[0.000, 0.692] p.e.
0.02	[-0.091, 0.092] p.e.	[-0.019, 0.005] p.e.	[-0.338, 0.702] p.e.	[-0.323, 0.702] p.e.	[-0.091, 0.702] p.e.	[-0.019, 0.702] p.e.	[-0.017, 0.702] p.e.	[-0.017, 0.703] p.e.	[0.000, 0.702] p.e.	[0.000, 0.702] p.e.
0.05	[-0.250, 0.216] p.e.	[-0.019, 0.007] p.e.	[-0.368, 0.732] p.e.	[-0.323, 0.732] p.e.	[-0.250, 0.732] p.e.	[-0.019, 0.732] p.e.	[-0.018, 0.733] p.e.	[-0.017, 0.733] p.e.	[0.000, 0.732] p.e.	[0.000, 0.732] p.e.
0.10	[-0.580, 0.410] p.e.	[-0.019, 0.012] p.e.	[-0.418, 0.782] p.e.	[-0.323, 0.782] p.e.	[-0.580, 0.782] p.e.	[-0.019, 0.782] p.e.	[-0.019, 0.783] p.e.	[-0.017, 0.783] p.e.	[0.000, 0.782] p.e.	[0.000, 0.782] p.e.

Notes: † Point estimates (p.e.) and ‡ 95% Confidence Intervals (CI) around ATE are calculated using methods from Imbens-Manski (2004) with 250 pseudosamples. The sample includes only 9-month old children from urban households with income at or below 185% FPL. All analyses are weighted using Wave 1 specific sample weights. Number of observations = 3550. Sample sizes are rounded to the nearest 50 by requirement.

Figure C2: Sharp Bounds on the ATE of WIC Participation on Birth Weight $\geq$ 2500 grams When Participation Status May be Misclassified: Various Assumptions about Selection

A. Exogenous Selection or No Assumption on Selection | B. Only MTS or Joint MTS & MIV or MTS & MTR: Arbitrary Errors | C. Only MTS or Joint MTS & MIV or MTS & MTR: No False Positive Errors

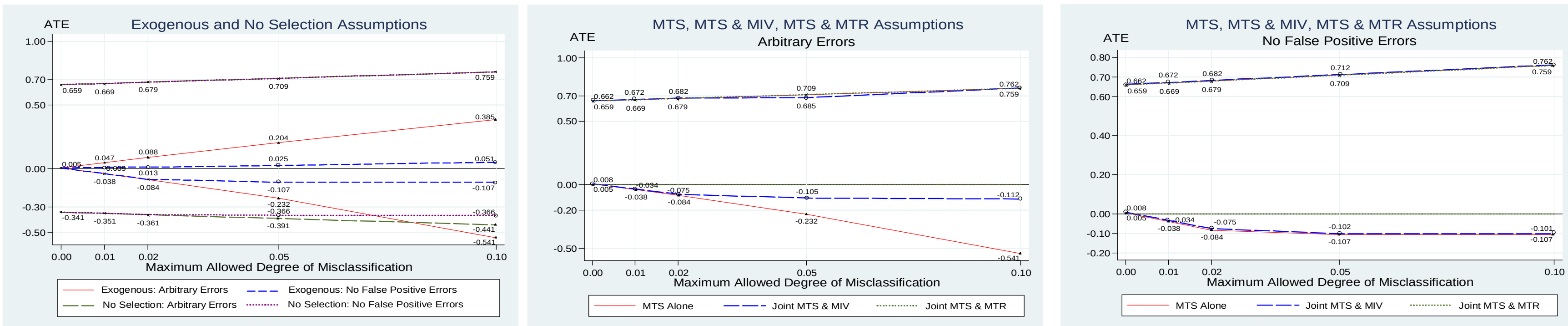

Table C2: Sharp Bounds on the ATE of WIC Participation on Birth Weight $\geq$ 2500 grams Given Unknown Counterfactuals and Potentially Misclassified Participation Status: Various Assumptions about Selection

Point Estimates of LB and UB and 95% I-M Confidence Intervals (CI) Around the Unknown Parameter ATE

Q	Exogenous Selection		No Assumption on Selection		MTS Assumption		MTS and MIV Assumption		MTS and MTR Assumption	
	(1) Arbitrary Errors	(2) No False Positives	(3) Arbitrary Errors	(4) No False Positives	(5) Arbitrary Errors	(6) No False Positives	(7) Arbitrary Errors	(8) No False Positives	(9) Arbitrary Errors	(10) No False Positives
0.00	[0.005, 0.005] p.e.†	[0.005, 0.005] p.e.	[-0.341, 0.659] p.e.	[-0.341, 0.659] p.e.	[0.005, 0.659] p.e.	[0.005, 0.659] p.e.	[0.008, 0.662] p.e.	[0.008, 0.662] p.e.	[0.000, 0.659] p.e.	[0.000, 0.659] p.e.
0.01	[-0.038, 0.047] p.e.	[-0.038, 0.009] p.e.	[-0.351, 0.669] p.e.	[-0.351, 0.669] p.e.	[-0.038, 0.669] p.e.	[-0.038, 0.669] p.e.	[-0.034, 0.672] p.e.	[-0.034, 0.672] p.e.	[0.000, 0.669] p.e.	[0.000, 0.669] p.e.
0.02	[-0.084, 0.088] p.e.	[-0.084, 0.013] p.e.	[-0.361, 0.679] p.e.	[-0.361, 0.679] p.e.	[-0.084, 0.679] p.e.	[-0.084, 0.679] p.e.	[-0.075, 0.682] p.e.	[-0.075, 0.682] p.e.	[0.000, 0.679] p.e.	[0.000, 0.679] p.e.
0.05	[-0.232, 0.204] p.e.	[-0.107, 0.025] p.e.	[-0.391, 0.709] p.e.	[-0.366, 0.709] p.e.	[-0.232, 0.709] p.e.	[-0.107, 0.709] p.e.	[-0.105, 0.685] p.e.	[-0.102, 0.712] p.e.	[0.000, 0.709] p.e.	[0.000, 0.709] p.e.
0.10	[-0.541, 0.385] p.e.	[-0.107, 0.051] p.e.	[-0.441, 0.759] p.e.	[-0.366, 0.759] p.e.	[-0.541, 0.759] p.e.	[-0.107, 0.759] p.e.	[-0.112, 0.762] p.e.	[-0.101, 0.762] p.e.	[0.000, 0.759] p.e.	[0.000, 0.759] p.e.

Notes: † Point estimates (p.e.) and ‡ 95% Confidence Intervals (CI) around ATE are calculated using methods from Imbens-Manski (2004) with 250 pseudosamples. The sample includes only 9-month old children from urban households with income at or below 185% FPL. All analyses are weighted using Wave 1 specific sample weights. Number of observations = 3550. Sample sizes are rounded to the nearest 50 by requirement.

Figure C3: Sharp Bounds on the ATE of WIC Participation on Birth Weight: 2500 - 4000 grams When Participation Status May be Misclassified: Various Assumptions about Selection

A. Exogenous Selection or No Assumption on Selection | B. Only MTS or Joint MTS & MIV or MTS & MTR: Arbitrary Errors | C. Only MTS or Joint MTS & MIV or MTS & MTR: No False Positive Errors

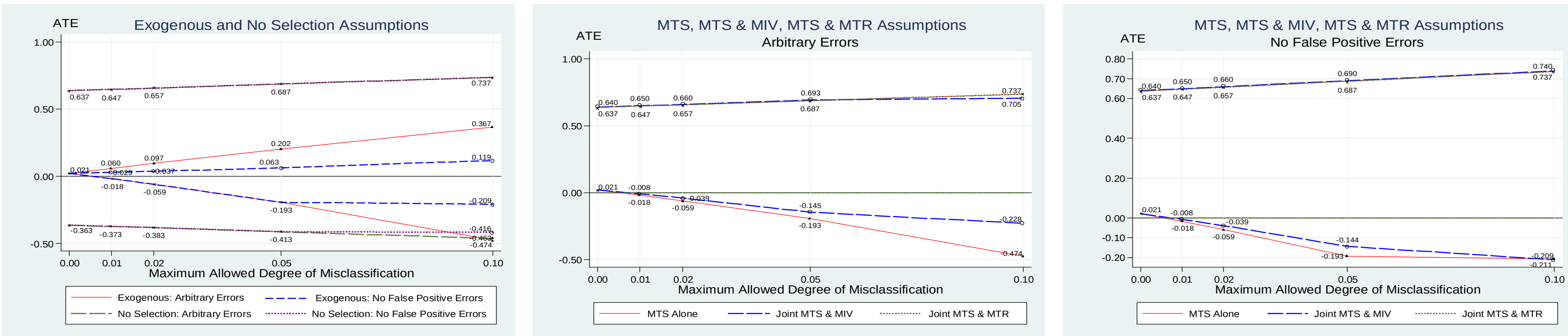

Table C3: Sharp Bounds on the ATE of WIC Participation on Birth Weight: 2500 - 4000 grams Given Unknown Counterfactuals and Potentially Misclassified Participation Status: Various Assumptions about Selection

Point Estimates of LB and UB and 95% I-M Confidence Intervals (CI) Around the Unknown Parameter ATE

Q	Exogenous Selection		No Assumption on Selection		MTS Assumption		MTS and MIV Assumption		MTS and MTR Assumption	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Arbitrary Errors	No False Positives	Arbitrary Errors	No False Positives	Arbitrary Errors	No False Positives	Arbitrary Errors	No False Positives	Arbitrary Errors	No False Positives
0.00	[0.021, 0.021] p.e.†	[0.021, 0.021] p.e.	[-0.363, 0.637] p.e.	[-0.363, 0.637] p.e.	[0.021, 0.637] p.e.	[0.021, 0.637] p.e.	[0.021, 0.640] p.e.	[0.021, 0.640] p.e.	[0.000, 0.637] p.e.	[0.000, 0.637] p.e.
0.01	[-0.018, 0.060] p.e.	[-0.018, 0.029] p.e.	[-0.373, 0.647] p.e.	[-0.373, 0.647] p.e.	[-0.018, 0.647] p.e.	[-0.018, 0.647] p.e.	[-0.008, 0.650] p.e.	[-0.008, 0.650] p.e.	[0.000, 0.647] p.e.	[0.000, 0.647] p.e.
0.02	[-0.059, 0.097] p.e.	[-0.059, 0.037] p.e.	[-0.383, 0.657] p.e.	[-0.383, 0.657] p.e.	[-0.059, 0.657] p.e.	[-0.059, 0.657] p.e.	[-0.039, 0.660] p.e.	[-0.039, 0.660] p.e.	[0.000, 0.657] p.e.	[0.000, 0.657] p.e.
0.05	[-0.193, 0.202] p.e.	[-0.193, 0.063] p.e.	[-0.413, 0.687] p.e.	[-0.413, 0.687] p.e.	[-0.193, 0.687] p.e.	[-0.193, 0.687] p.e.	[-0.145, 0.693] p.e.	[-0.144, 0.690] p.e.	[0.000, 0.687] p.e.	[0.000, 0.687] p.e.
0.10	[-0.474, 0.367] p.e.	[-0.209, 0.119] p.e.	[-0.463, 0.737] p.e.	[-0.416, 0.737] p.e.	[-0.474, 0.737] p.e.	[-0.209, 0.737] p.e.	[-0.228, 0.705] p.e.	[-0.211, 0.740] p.e.	[0.000, 0.737] p.e.	[0.000, 0.737] p.e.

Notes: † Point estimates (p.e.) and ‡ 95% Confidence Intervals (CI) around ATE are calculated using methods from Imbens-Manski (2004) with 250 pseudosamples. The sample includes only 9-month old children from urban households with income at or below 185% FPL. All analyses are weighted using Wave 1 specific sample weights. Number of observations = 3550. Sample sizes are rounded to the nearest 50 by requirement.

Figure C4: Sharp Bounds on the ATE of WIC Participation on Birth Weight ≤ 4000 grams When Participation Status May be Misclassified: Various Assumptions about Selection

A. Exogenous Selection or No Assumption on Selection

B. Only MTS or Joint MTS & MIV or MTS & MTR: Arbitrary Errors

C. Only MTS or Joint MTS & MIV or MTS & MTR: No False Positive Errors

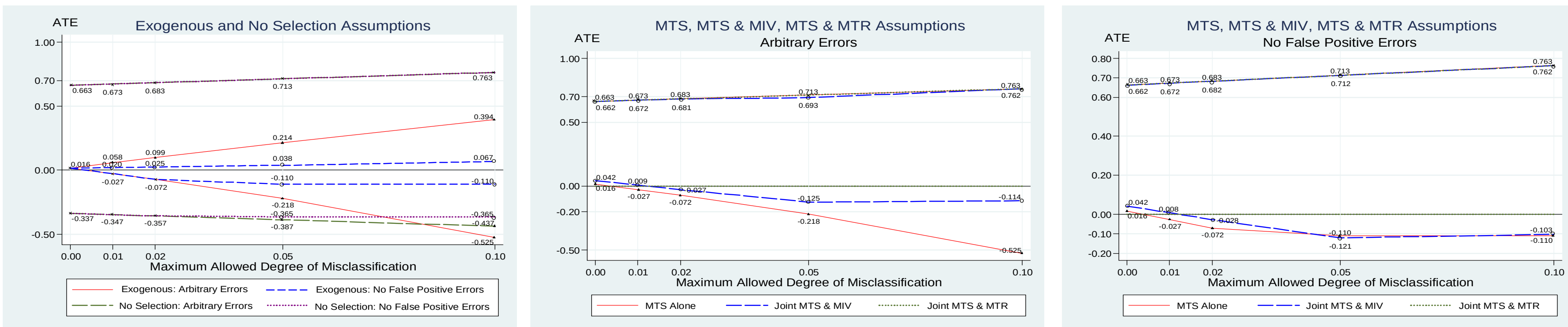

Table C4: Sharp Bounds on the ATE of WIC Participation on Birth Weight ≤ 4000 grams Given Unknown Counterfactuals and Potentially Misclassified Participation Status: Various Assumptions about Selection

Point Estimates of LB and UB and 95% I-M Confidence Intervals (CI) Around the Unknown Parameter ATE

Q	Exogenous Selection		No Assumption on Selection		MTS Assumption		MTS and MIV Assumption		MTS and MTR Assumption	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Arbitrary Errors	No False Positives	Arbitrary Errors	No False Positives	Arbitrary Errors	No False Positives	Arbitrary Errors	No False Positives	Arbitrary Errors	No False Positives
0.00	[0.016, 0.016] p.e.†	[0.016, 0.016] p.e.	[-0.337, 0.663] p.e.	[-0.337, 0.663] p.e.	[0.016, 0.663] p.e.	[0.016, 0.663] p.e.	[0.042, 0.662] p.e.	[0.042, 0.662] p.e.	[0.000, 0.663] p.e.	[0.000, 0.663] p.e.
0.01	[-0.027, 0.058] p.e.	[-0.027, 0.020] p.e.	[-0.347, 0.673] p.e.	[-0.347, 0.673] p.e.	[-0.027, 0.673] p.e.	[-0.027, 0.673] p.e.	[0.009, 0.672] p.e.	[0.008, 0.672] p.e.	[0.000, 0.673] p.e.	[0.000, 0.673] p.e.
0.02	[-0.072, 0.099] p.e.	[-0.072, 0.025] p.e.	[-0.357, 0.683] p.e.	[-0.357, 0.683] p.e.	[-0.072, 0.683] p.e.	[-0.072, 0.683] p.e.	[-0.027, 0.681] p.e.	[-0.028, 0.682] p.e.	[0.000, 0.683] p.e.	[0.000, 0.683] p.e.
0.05	[-0.218, 0.214] p.e.	[-0.110, 0.038] p.e.	[-0.387, 0.713] p.e.	[-0.365, 0.713] p.e.	[-0.218, 0.713] p.e.	[-0.110, 0.713] p.e.	[-0.125, 0.693] p.e.	[-0.121, 0.712] p.e.	[0.000, 0.713] p.e.	[0.000, 0.713] p.e.
0.10	[-0.525, 0.394] p.e.	[-0.110, 0.067] p.e.	[-0.437, 0.763] p.e.	[-0.365, 0.763] p.e.	[-0.525, 0.763] p.e.	[-0.110, 0.763] p.e.	[-0.114, 0.762] p.e.	[-0.103, 0.762] p.e.	[0.000, 0.763] p.e.	[0.000, 0.763] p.e.

Notes: † Point estimates (p.e.) and ‡ 95% Confidence Intervals (CI) around ATE are calculated using methods from Imbens-Manski (2004) with 250 pseudosamples. The sample includes only 9-month old children from urban households with income at or below 185% FPL. All analyses are weighted using Wave 1 specific sample weights. Number of observations = 3550. Sample sizes are rounded to the nearest 50 by requirement.

Figure C5: Sharp Bounds on the ATE of WIC Participation on Gestation Age ≥ 33 weeks When Participation Status May be Misclassified: Various Assumptions about Selection

A. Exogenous Selection or No Assumption on Selection — B. Only MTS or Joint MTS & MIV or MTS & MTR: Arbitrary Errors — C. Only MTS or Joint MTS & MIV or MTS & MTR: No False Positive Errors

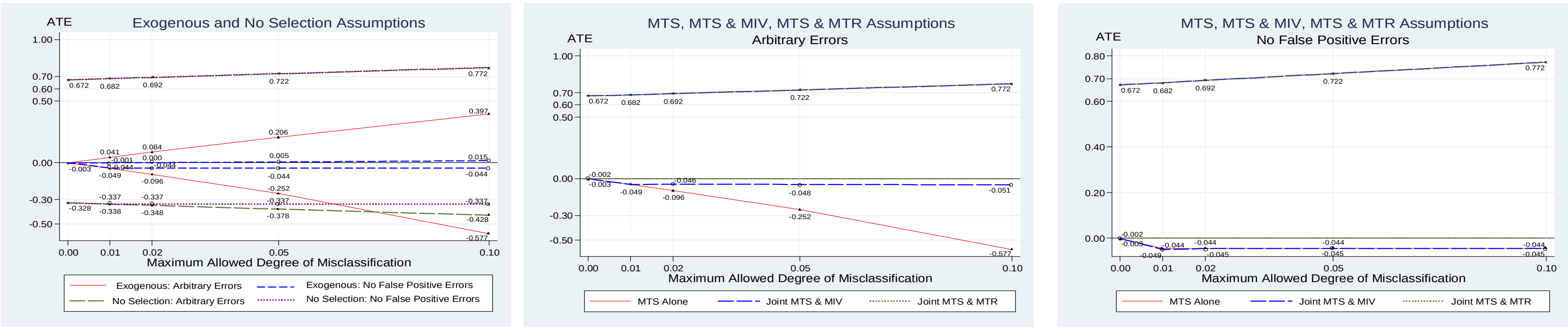

Table C5: Sharp Bounds on the ATE of WIC Participation on Gestation Age ≥ 33 weeks Given Unknown Counterfactuals and Potentially Misclassified Participation Status: Various Assumptions about Selection

Point Estimates of LB and UB and 95% I-M Confidence Intervals (CI) Around the Unknown Parameter ATE

Q	Exogenous Selection		No Assumption on Selection		MTS Assumption		MTS and MIV Assumption		MTS and MTR Assumption	
	(1) Arbitrary Errors	(2) No False Positives	(3) Arbitrary Errors	(4) No False Positives	(5) Arbitrary Errors	(6) No False Positives	(7) Arbitrary Errors	(8) No False Positives	(9) Arbitrary Errors	(10) No False Positives
0.00	[-0.003, -0.003] p.e.†	[-0.003, -0.003] p.e.	[-0.328, 0.672] p.e.	[-0.328, 0.672] p.e.	[-0.003, 0.672] p.e.	[-0.003, 0.672] p.e.	[-0.002, 0.672] p.e.	[-0.002, 0.672] p.e.	[0.000, 0.672] p.e.	[0.000, 0.672] p.e.
0.01	[-0.049, 0.041] p.e.	[-0.044, -0.001] p.e.	[-0.338, 0.682] p.e.	[-0.337, 0.682] p.e.	[-0.049, 0.682] p.e.	[-0.044, 0.682] p.e.	[-0.049, 0.682] p.e.	[-0.049, 0.682] p.e.	[0.000, 0.682] p.e.	[0.000, 0.682] p.e.
0.02	[-0.096, 0.084] p.e.	[-0.044, 0.000] p.e.	[-0.348, 0.692] p.e.	[-0.337, 0.692] p.e.	[-0.096, 0.692] p.e.	[-0.044, 0.692] p.e.	[-0.046, 0.692] p.e.	[-0.045, 0.692] p.e.	[0.000, 0.692] p.e.	[0.000, 0.692] p.e.
0.05	[-0.252, 0.206] p.e.	[-0.044, 0.005] p.e.	[-0.378, 0.722] p.e.	[-0.337, 0.722] p.e.	[-0.252, 0.722] p.e.	[-0.044, 0.722] p.e.	[-0.048, 0.722] p.e.	[-0.045, 0.722] p.e.	[0.000, 0.722] p.e.	[0.000, 0.722] p.e.
0.10	[-0.577, 0.397] p.e.	[-0.044, 0.015] p.e.	[-0.428, 0.772] p.e.	[-0.337, 0.772] p.e.	[-0.577, 0.772] p.e.	[-0.044, 0.772] p.e.	[-0.051, 0.772] p.e.	[-0.045, 0.772] p.e.	[0.000, 0.772] p.e.	[0.000, 0.772] p.e.

Notes: † Point estimates (p.e.) and ‡ 95% Confidence Intervals (CI) around ATE are calculated using methods from Imbens-Manski (2004) with 250 pseudosamples. The sample includes only 9-month old children from urban households with income at or below 185% FPL. All analyses are weighted using Wave 1 specific sample weights. Number of observations = 3500. Sample sizes are rounded to the nearest 50 by requirement.

Figure C6: Sharp Bounds on the ATE of WIC Participation on Gestation Age of 38 - 42 weeks When Participation Status May be Misclassified: Various Assumptions about Selection

A. Exogenous Selection or No Assumption on Selection | B. Only MTS or Joint MTS & MIV or MTS & MTR: Arbitrary Errors | C. Only MTS or Joint MTS & MIV or MTS & MTR: No False Positive Error

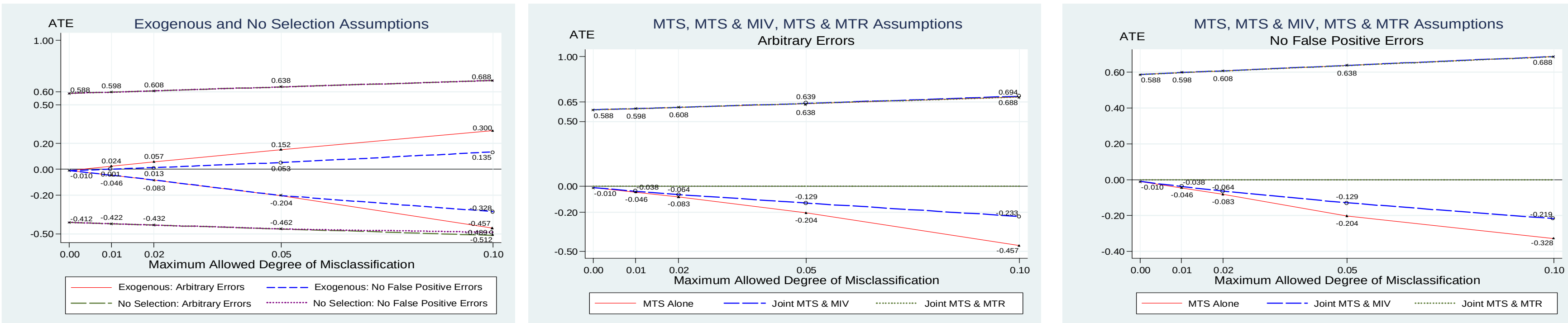

Table C6: Sharp Bounds on the ATE of WIC Participation on Gestation Age of 38 - 42 weeks Given Unknown Counterfactuals and Potentially Misclassified Participation Status: Various Assumptions about Selection

Point Estimates of LB and UB and 95% I-M Confidence Intervals (CI) Around the Unknown Parameter ATE

Q	Exogenous Selection		No Assumption on Selection		MTS Assumption		MTS and MIV Assumption		MTS and MTR Assumption	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Arbitrary Errors	No False Positives	Arbitrary Errors	No False Positives	Arbitrary Errors	No False Positives	Arbitrary Errors	No False Positives	Arbitrary Errors	No False Positives
0.00	[-0.010, -0.010] p.e.†	[-0.010, -0.010] p.e.	[-0.412, 0.588] p.e.	[-0.412, 0.588] p.e.	[-0.010, 0.588] p.e.	[-0.010, 0.588] p.e.	[-0.010, 0.588] p.e.	[-0.010, 0.588] p.e.	[0.000, 0.588] p.e.	[0.000, 0.588] p.e.
0.01	[-0.046, 0.024] p.e.	[-0.046, 0.001] p.e.	[-0.422, 0.598] p.e.	[-0.422, 0.598] p.e.	[-0.046, 0.598] p.e.	[-0.046, 0.598] p.e.	[-0.038, 0.598] p.e.	[-0.038, 0.598] p.e.	[0.000, 0.598] p.e.	[0.000, 0.598] p.e.
0.02	[-0.083, 0.057] p.e.	[-0.083, 0.013] p.e.	[-0.432, 0.608] p.e.	[-0.432, 0.608] p.e.	[-0.083, 0.608] p.e.	[-0.083, 0.608] p.e.	[-0.064, 0.608] p.e.	[-0.064, 0.608] p.e.	[0.000, 0.608] p.e.	[0.000, 0.608] p.e.
0.05	[-0.204, 0.152] p.e.	[-0.204, 0.053] p.e.	[-0.462, 0.638] p.e.	[-0.462, 0.638] p.e.	[-0.204, 0.638] p.e.	[-0.204, 0.638] p.e.	[-0.129, 0.639] p.e.	[-0.129, 0.638] p.e.	[0.000, 0.638] p.e.	[0.000, 0.638] p.e.
0.10	[-0.457, 0.300] p.e.	[-0.328, 0.135] p.e.	[-0.512, 0.688] p.e.	[-0.489, 0.688] p.e.	[-0.457, 0.688] p.e.	[-0.328, 0.688] p.e.	[-0.233, 0.694] p.e.	[-0.219, 0.688] p.e.	[0.000, 0.688] p.e.	[0.000, 0.688] p.e.

Notes: † Point estimates (p.e.) and ‡ 95% Confidence Intervals (CI) around ATE are calculated using methods from Imbens-Manski (2004) with 250 pseudosamples. The sample includes only 9-month old children from urban households with income at or below 185% FPL. All analyses are weighted using Wave 1 specific sample weights. Number of observations = 3500. Sample sizes are rounded to the nearest 50 by requirement.

Table C7. IV Estimates of the Effect of Prenatal WIC Participation on Infant Birth Outcomes

	Specification 1		Specification 2		Specification 3	
	OLS	IV	OLS	IV	OLS	IV
I. Probability of Birth Weight ≥ 1500 grams						
WIC	0.004**	0.005**	0.004**	0.005**	0.004**	0.005***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Underid Test		0.000		0.000		0.000
KP F-Stat		921.711		925.821		917.913
Overid Test		0.360		0.341		0.298
Endogeneity		0.156		0.142		0.143
N	3550	3550	3550	3550	3550	3550
II. Probability of Birth Weight ≥ 2500 grams						
WIC	0.010	0.011	0.011	0.012	0.011	0.012
	(0.008)	(0.009)	(0.008)	(0.009)	(0.008)	(0.009)
Underid Test		0.000		0.000		0.000
KP F-Stat		921.711		925.821		917.913
Overid Test		0.920		0.944		0.942
Endogeneity		0.915		0.769		0.767
N	3550	3550	3550	3550	3550	3550
III. Probability of Birth Weight: 2500 - 4000 grams						
WIC	0.022	0.031*	0.023	0.031*	0.022	0.030*
	(0.016)	(0.018)	(0.016)	(0.017)	(0.016)	(0.017)
Underid Test		0.000		0.000		0.000
KP F-Stat		921.711		925.821		917.913
Overid Test		0.428		0.447		0.438
Endogeneity		0.331		0.290		0.326
N	3550	3550	3550	3550	3550	3550
IV. Probability of Birth Weight ≤ 4000 grams						
WIC	0.012	0.020	0.012	0.019	0.011	0.018
	(0.014)	(0.016)	(0.014)	(0.015)	(0.014)	(0.016)
Underid Test		0.000		0.000		0.000
KP F-Stat		921.711		925.821		917.913
Overid Test		0.152		0.188		0.191
Endogeneity		0.342		0.337		0.374
N	3550	3550	3550	3550	3550	3550
V. Probability of Gestation Age ≥ 33 weeks						
WIC	0.001	0.002	0.002	0.003	0.002	0.003
	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)	(0.005)
Underid Test		0.000		0.000		0.000
KP F-Stat		905.461		908.676		900.847
Overid Test		0.893		0.870		0.797
Endogeneity		0.301		0.294		0.254
N	3500	3500	3500	3500	3500	3500
VI. Probability of Gestation Age: 38 - 42 weeks						
WIC	-0.009	-0.018	-0.008	-0.016	-0.008	-0.017
	(0.020)	(0.021)	(0.020)	(0.021)	(0.020)	(0.021)
Underid Test		0.000		0.000		0.000
KP F-Stat		905.461		908.676		900.847
Overid Test		0.242		0.222		0.264
Endogeneity		0.265		0.452		0.375
N	3500	3500	3500	3500	3500	3500

NOTES: * p<0.10, ** p<0.05, *** p<0.01. Robust standard errors are in parentheses. The sample includes only 9-month old children from urban households with income at or below 185% FPL. All analyses are weighted using Wave 1 specific sample weights. Underid reports the p-value of the Kleibergen-Paap (2006) rk statistic; F-Stat reports the associated F-statistic; Overid reports the p-value of the Hansen J statistic with rejection casting doubt on the instruments' validity; Endogeneity reports the p-value of the endogeneity test of the endogenous regressors. N is the sample size. Sample sizes are rounded to the nearest 50 by requirement.

Appendix D

1 Introduction

This technical Appendix contains detailed derivations of the bounds on the ATE presented in Section 5. This section relies heavily on several earlier works: an earlier version of Kreider et al. (2011), Manski and Pepper (2000), Kreider and Pepper (2007), and Gundersen and Kreider (2008).

Under each assumption about the selection mechanism, I first derive the lower bound (LB) and upper bound (UB) on the components $P[H(1) = 1]$ and $P[H(0) = 1]$ ignoring measurement error (ME). Second, I define the ATE, and define its LB and UB in terms of the components. Then, I introduce ME and derive new bounds on $P[H(1) = 1]$ and $P[H(0) = 1]$. Accordingly, I get the LB and UB on the ATE with ME.

The different assumptions about selection that are considered in this study are:

1. Exogenous Selection
2. No Assumption on Selection
3. Monotone Treatment Selection (MTS) denoting negative selection into the treatment, WIC
4. Monotone Instrumental Variable (MIV) using SES as the MIV
5. Monotone Treatment Response

I consider five scenarios based on selection assumptions. The first three correspond to exogenous selection, no assumption on selection, and MTS. The fourth combines the assumptions of MTS and MIV, and the last combines the MTS and MTR assumptions.

The different assumptions about ME are:

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

The Arbitrary Errors model imposes only the first assumption and the No False Positives model imposes both the assumptions about ME. each of the five selection scenarios are combined with each of the two models of ME to yield ten scenarios in all.

2 Exogenous Selection Bounds

2.1 No Misclassification Errors

With no ME, the true W^* is observed. And, the exogenous selection assumption is given by:

$$
\begin{aligned}
P[H(1) &= 1, W^*] = P[H(1) = 1] \\
&\Longrightarrow P[H(1) = 1, W^* = 1] = P[H(1) = 1, W^* = 0] = P[H(1) = 1] \\
P[H(0) &= 1, W^*] = P[H(0) = 1] \\
&\Longrightarrow P[H(0) = 1, W^* = 1] = P[H(0) = 1, W^* = 0] = P[H(0) = 1].
\end{aligned}
$$

So, Equation (2) becomes:

$$
\begin{aligned}
P\left[H(1) = 1\right] &= P\left[H = 1|W^* = 1\right] P(W^* = 1) + P\left[H(1) = 1|W^* = 0\right] P(W^* = 0) \\
&= P\left[H = 1|W^* = 1\right] P(W^* = 1) + P\left[H = 1|W^* = 1\right] \left[1 - P(W^* = 1)\right] \\
&= P\left[H = 1|W^* = 1\right] \left[P(W^* = 1) - P(W^* = 1)\right] + P\left[H = 1|W^* = 1\right] \\
&\therefore\; P\left[H(1) = 1\right] = P\left[H = 1|W^* = 1\right]
\end{aligned}
$$

$$
\begin{aligned}
P\left[H(0) = 1\right] &= P\left[H(0) = 1|W^* = 1\right] P(W^* = 1) + P\left[H = 1|W^* = 0\right] P(W^* = 0) \\
&= P\left[H = 1|W^* = 0\right] \left[1 - P(W^* = 0)\right] + P\left[H = 1|W^* = 0\right] P(W^* = 0) \\
&= P\left[H = 1|W^* = 0\right] \left[P(W^* = 0) - P(W^* = 0)\right] + P\left[H = 1|W^* = 0\right] \\
&\therefore\; P\left[H(0) = 1\right] = P\left[H = 1|W^* = 0\right].
\end{aligned}
$$

$$
\begin{aligned}
&\therefore\; ATE = P\left[H(1) = 1\right] - P\left[H(0) = 1\right] \\
&= \; P\left[H = 1|W^* = 1\right] - P\left[H = 1|W^* = 0\right].
\end{aligned}
$$

2.2 Allowing for Misclassification Errors

Allowing for ME, the true W^* is not observed. The data only has a self-reported indicator, W. Accordingly, $P\left[H(1) = 1\right]$ and $P\left[H(0) = 1\right]$ cannot be identified without explicit assumptions about ME. To illustrate:

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

This is Equation 7 in Section 5.2.2. Analogously, $P[H(0)=1]$ can be written as

$$\begin{aligned} P[H(0)=1] &= P[H=1|W^*=0] \\ &= \frac{P[H=1,W^*=0]}{P(W^*=0)} \\ P[H(0)=1] &= \frac{[P(H=1,W=0)+\theta_1^+-\theta_1^-]}{[P(W=0)+(\theta_1^++\theta_0^+)-(\theta_1^-+\theta_0^-)]}. \end{aligned}$$

2.2.1 Arbitrary Errors Model

The bounds for this model are derived and proved in Kreider and Pepper (2007): Propositions 1 and A.1.

2.2.2 No False Positives Model

With the additional assumption of no false positive errors, the bounds on $P[H(1)=1]$ in Equation 7 in Section 5.2.2 can be derived as follows:

For the LB I set $\theta_1^+=0$, $\theta_0^- \to \theta_0^{UB-}$, $\theta_1^- \to \theta_1^{LB-}=0$, and $\theta_0^+ \to \theta_0^{LB+}=0$ so that

$$LB=\frac{P[H=1,W=1]}{P(W=1)+\theta_0^{UB-}}.$$

For the UB I set $\theta_1^- \to \theta_1^{UB-}$, $\theta_0^+=0$, $\theta_1^+ \to \theta_1^{LB+}=0$, and $\theta_0^- \to \theta_0^{LB-}=0$ so that

$$UB=\frac{P[H=1,W=1]+\theta_1^{UB-}}{P(W=1)+\theta_1^{UB-}}.$$

Accordingly, $P[H(1)=1]$ is bounded as shown:

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

which is Equation 8 in Section 5.2.2.

Similarly, the bounds on $P[H(0)=1]$ can be derived as follows:

For the LB I set $\theta_1^- \to \theta_1^{UB-}$, $\theta_0^+=0$, $\theta_1^+ \to \theta_1^{LB+}=0$, and $\theta_0^- \to \theta_0^{LB-}=0$ so that

$$LB=\frac{P[H=1,W=0]-\theta_1^{UB-}}{P(W=0)-\theta_1^{UB-}}.$$

For the UB I set $\theta_1^+=0$, $\theta_0^- \to \theta_0^{UB-}$, $\theta_1^- \to \theta_1^{LB-}=0$, and $\theta_0^+ \to \theta_0^{LB+}=0$ so that

$$UB:\frac{P[H=1,W=0]}{P(W=0)-\theta_0^{UB-}}.$$

Accordingly, $P[H(0)=1]$ is bounded as

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

This is Equation 9 in Section 5.2.2.

Since

$$ATE = P\left[H(1)=1\right] - P\left[H(0)=1\right]$$

the bounds on the ATE are given by:

$$\begin{aligned}
UB_{ATE} &= UB_{P[H(1)=1]} - LB_{P[H(0)=1]} \\
&= \frac{P\left[H=1, W=1\right] + \theta_1^{UB-}}{P(W=1) + \theta_1^{UB-}} - \frac{P\left[H=1, W=0\right] - \theta_1^{UB-}}{P(W=0) - \theta_1^{UB-}} \\
LB_{ATE} &= LB_{P[H(1)=1]} - UB_{P[H(0)=1]} \\
&= \frac{P\left[H=1, W=1\right]}{P(W=1) + \theta_0^{UB-}} - \frac{P\left[H=1, W=0\right]}{P(D=0) - \theta_0^{UB-}}.
\end{aligned}$$

These bounds on the ATE are shown in Equation 10 in Section 5.2.2.

3 No Selection Assumption

3.1 No Misclassification Errors

With no ME, the true W^* is observed. By the Law of Total Probability we know:

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

Now, without any assumptions on the nature of selection, all that we know is that the latent probability $P\left[H(1)=1|W^*=0\right] \epsilon [0,1]$.

When $P\left[H(1)=1|W^*=0\right]=0$ the LB is derived as

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

When $P\left[H(1)=1|W^*=0\right]=1$ the UB is attained in the following way:

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

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

This is Equation 11 in Section 5.3.1. Similarly, we know:

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

Again, the latent probability $P\left[H(0)=1|W^*=1\right] \epsilon[0,1]$.

When $P\left[H(0)=1|W^*=1\right]=0$ the LB is:

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

When $P\left[H(0)=1|W^*=1\right]=1$ the UB is:

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

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

This is Equation 12 in Section 5.3.1.

3.2 Allowing for Misclassification Errors

Allowing for ME, the true W^* is not observed. The data only has a self-reported indicator, W. Accordingly, $P\left[H(1)=1\right]$ and $P\left[H(0)=1\right]$ cannot be identified without explicit assumptions about ME.

Accordingly, the bounds on $P\left[H(1)=1\right]$ are derived as follows:

LB: $P\left[H=1, W^*=1\right]=P[H=1, W=1]-\theta_1^+ + \theta_1^-$

UB: $P\left[H=1, W^*=1\right]+P(W^*=0)=P[H=1, W=1]-\theta_1^+ + \theta_1^- + P(W=0)+\theta_1^+ + \theta_0^+ - \theta_1^- - \theta_0^-$
$= P[H=1, W=1]+P(W=0)+\theta_0^+ - \theta_0^-$.

So, $P\left[H(1)=1\right]$ is bounded as

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

This is Equation 13 in Section 5.3.2.

The bounds on $P\left[H(0)=1\right]$ are analogously derived as

LB: $P\left[H=1, W^*=0\right]=P[H=1, W=0]+\theta_1^+ - \theta_1^-$

UB: $P\left[H=1, W^*=0\right]+P(W^*=1)=P[H=1, W=0]+\theta_1^+ - \theta_1^- + P(W=1)-\theta_1^+ - \theta_0^+ + \theta_1^- + \theta_0^-$
$= P[H=1, W=0]+P(W=1)-\theta_0^+ + \theta_0^-$.

So, $P\left[H(0)=1\right]$ is bounded as

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

This is Equation 14 in Section 5.3.2.

3.2.1 Arbitrary Errors Model

Here, I impose only Assumption 1 about ME under the No Selection Assumption case. The bounds on $P\left[H(1)=1\right]$ can be derived in the following way:

For the LB I set $\theta_1^+ \to \theta_1^{UB+}$ and $\theta_1^- \to \theta_1^{LB-} = 0$ so that

$$LB = P[H=1, W=1] - \theta_1^{UB+}.$$

For the UB I set $\theta_0^+ \to \theta_0^{UB+}$ and $\theta_0^- \to \theta_0^{LB-} = 0$ so that

$$UB = P[H=1, W=1] + P(W=0) + \theta_0^{UB+}.$$

Accordingly, $P\left[H(1)=1\right]$ is bounded as:

$$P[H=1, W=1] - \theta_1^{UB+} \leq P[H(1)=1] \leq P[H=1, W=1] + P(W=0) + \theta_0^{UB+}.$$

Similarly, the bounds on $P\left[H(0)=1\right]$ are attained in the following way:

For the LB I set $\theta_1^- \to \theta_1^{UB-}$ and $\theta_1^+ \to \theta_1^{LB+} \Longrightarrow 0$ so that

$$LB = P[H=1, W=0] - \theta_1^{UB-}.$$

For the UB I set $\theta_0^- \to \theta_0^{UB-}$ and $\theta_0^+ \to \theta_0^{LB+} = 0$ so that

$$UB = P[H=1, W=0] + P(W=1) + \theta_0^{UB-}.$$

Accordingly, $P\left[H(0)=1\right]$ is bounded as follows:

$$P[H=1, W=0] - \theta_1^{UB-} \leq P[H(0)=1] \leq P[H=1, W=0] + P(W=1) + \theta_0^{UB-}.$$

Since

$$ATE = P\left[H(1)=1\right] - P\left[H(0)=1\right]$$

the bounds on the ATE are given by:

$$\begin{aligned}
UB_{ATE} &= UB_{P[H(1)=1]} - LB_{P[H(0)=1]} \\
&= P[H=1, W=1] + P(W=0) + \theta_0^{UB+} - \{P[H=1, W=0] - \theta_1^{UB-}\} \\
&= P[H=1, W=1] + P(W=0) + (\theta_0^{UB+} + \theta_1^{UB-}) - P[H=1, W=0] \\
&= P[H=1, W=1] + P(W=0) + Q - P[H=1, W=0].
\end{aligned}$$

$$\begin{aligned}
LB_{ATE} &= LB_{P[H(1)=1]} - UB_{P[H(0)=1]} \\
&= P[H=1, W=1] - \theta_1^{UB+} - \{P[H=1, W=0] + P(W=1) + \theta_0^{UB-}\} \\
&= P[H=1, W=1] - (\theta_1^{UB+} + \theta_0^{UB-}) - P[H=1, W=0] - P(W=1) \\
&= P[H=1, W=1] - Q - P[H=1, W=0] - P(W=1).
\end{aligned}$$

To get the sharp bounds on ATE, the UB of the ATE is maximized subject to Equation 4 in Section 5.1 as follows:

$UB_{ATE} = P[H = 1, W = 1] + P(W = 0) + \min\{Q, \theta_0^{UB+} + \theta_1^{UB-}\} - P[H = 1, W = 0]$.

Similarly, the LB of the ATE is minimized subject to Equation 4 in Section 5.1 as:

$LB_{ATE} = P[H = 1, W = 1] - \min\{Q, \theta_1^{UB+} + \theta_0^{UB-}\} - P[H = 1, W = 0] - P(W = 1)$.

These constitute Equation 15 in Section 5.3.2.

3.2.2 No False Positives Model

With the additional assumption of no false positive errors, the bounds on $P[H(1) = 1]$ are derived as follows:

For the LB I set $\theta_1^+ = 0$ and $\theta_1^- \to \theta_1^{LB-} = 0$ so that

$$LB = P[H = 1, W = 1].$$

For the UB I set $\theta_0^+ = 0$ and $\theta_0^- \to \theta_0^{LB-} = 0$ so that

$$UB = P[H = 1, W = 1] + P(W = 0).$$

Accordingly, $P\left[H(1) = 1\right]$ is bounded as

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

Similarly, the bounds on $P\left[H(0) = 1\right]$ are derived as

For the LB I set $\theta_1^- \to \theta_1^{UB-}$ and $\theta_1^+ \to \theta_1^{LB+} = 0$ so that

$$LB = P[H = 1, W = 0] - \theta_1^{UB-}.$$

For the UB I set $\theta_0^- \to \theta_0^{UB-}$ and $\theta_0^+ \to \theta_0^{LB+} \Longrightarrow 0$ so that

$$UB = P[H = 1, W = 0] + P(W = 1) + \theta_0^{UB-}.$$

Accordingly, $P\left[H(0) = 1\right]$ is bounded as follows:

$$P[H = 1, W = 0] - \theta_1^{UB-} \leq P[H(0) = 1] \leq P[H = 1, W = 0] + P(W = 1) + \theta_0^{UB-}.$$

Since

$$ATE = P\left[H(1) = 1\right] - P\left[H(0) = 1\right]$$

the bounds on the ATE are given by:

$$\begin{aligned} UB_{ATE} &= UB_{P[H(1)=1]} - LB_{P[H(0)=1]} \\ &= P[H=1, W=1] + P(W=0) - \{P[H=1, W=0] - \theta_1^{UB-}\} \\ &= P[H=1, W=1] + P(W=0) + Q_u - P[H=1, W=0] \end{aligned}$$

$$\begin{aligned} LB_{ATE} &= LB_{P[H(1)=1]} - UB_{P[H(0)=1]} \\ &= P[H=1, W=1] - \{P[H=1, W=0] + P(W=1) + \theta_0^{UB-}\} \\ &= P[H=1, W=1] - Q_u - P[H=1, W=0] - P(W=1). \end{aligned}$$

To get the sharp bounds on ATE I maximize the UB of the ATE as follows:

$UB_{ATE} = P[H=1, W=1] + P(W=0) + \theta_1^{UB-} - P[H=1, W=0]$.

Similarly I minimize the LB of the ATE as follows:

$LB_{ATE} = P[H=1, W=1] - \theta_0^{UB-} - P[H=1, W=0] - P(W=1)$.

These constitute Equation 16 in Section 5.3.2.

4 Monotone Treatment Selection

The Monotone Treatment Selection (MTS) assumption denoting negative selection translates into

$$P[H(1)=1|W^*=0] \geq P[H(1)=1|W^*=1]$$

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

So,

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

Now, under MTS:

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

$$\therefore \quad P\left[H(1)=1\right] = P\left[H=1|W^*=1\right] + P(W^*=0)\{term \geq 0\}$$

$$\therefore \quad P\left[H(1)=1\right] \geq P\left[H=1|W^*=1\right].$$

Again:

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

Now, under MTS:

$$P[H(0)=1|W^*=0] \geq P[H(0)=1|W^*=1]$$

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

Now, $P\left[H(1)=1\right]$ can be written as

$$P\left[H(1)=1\right]=P\left[H(1)=1|W^*=1\right]+P(W^*=0)\{P\left[H(1)=1|W^*=0\right]-P\left[H(1)=1|W^*=1\right]\}.$$

Since by MTS: $P\left[H(1)=1|W^*=0\right] \geq P\left[H(1)=1|W^*=1\right]$

The LB is given by:

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

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

The UB is attained by setting $P\left[H(1)=1|W^*=0\right]$ to its maximum value of one as shown below.

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

$P\left[H(1)=1\right]$ is thus bounded as follows:

$$\frac{P\left[H=1,W^*=1\right]}{P(W^*=1)} \leq P\left[H(1)=1\right] \leq P(W^*=0)+P\left[H=1,W^*=1\right].$$

For the bounds on $P\left[H(0)=1\right]$ I begin by writing $P\left[H(0)=1\right]$ as

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

Since by MTS, $P[H(0)=1|W^*=0] \geq P[H(0)=1|W^*=1]$

The LB is given by setting $P[H(0)=1|W^*=1]$ at its minimum value of zero.

So, $P\left[H(0)=1\right] = P\left[H(0)=1|W^*=0\right] P(W^*=0)$ so that

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

And, the UB is attained by setting $P[H=1|W^*=0] = P[H(0)=1|W^*=1]$.

$$\therefore \quad P\left[H(0)=1\right] = P\left[H(0)=1|W^*=1\right]\{1-P(W^*=0)\} + P\left[H=1|W^*=0\right]P(W^*=0)$$

$$\therefore \quad P\left[H(0)=1\right] = P\left[H=1|W^*=0\right]\{1-P(W^*=0)\} + P\left[H=1|W^*=0\right]P(W^*=0)$$

$$\therefore \quad P\left[H(0)=1\right] = P\left[H=1|W^*=0\right]$$

$$\therefore \quad P\left[H(0)=1\right] = \frac{P\left[H=1, W^*=0\right]}{P(W^*=0)}.$$

$P\left[H(0)=1\right]$ is accordingly bounded as follows:

$$P\left[H=1, W^*=0\right] \leq P\left[H(0)=1\right] \leq \frac{P\left[H=1, W^*=0\right]}{P(W^*=0)}.$$

Allowing for ME:

The bounds on $P\left[H(1)=1\right]$ are derived as follows:

The LB given by $\frac{P[H=1,W^*=1]}{P(W^*=1)}$ is now written as

$$LB = \frac{P\left[H=1, W=1\right] + \theta_1^- - \theta_1^+}{\left[P(W=1) - (\theta_1^+ + \theta_0^+) + (\theta_1^- + \theta_0^-)\right]}.$$

Similarly, the UB given by $P(W^*=0) + P\left[H=1, W^*=1\right]$ is written as

$$UB = P(W=0) + \theta_0^+ - \theta_0^- + P\left[H=1, W=1\right].$$

So, with ME $P\left[H(1)=1\right]$ is bounded as follows:

$$\frac{P\left[H=1, W=1\right] + \theta_1^- - \theta_1^+}{\left[P(W=1) - (\theta_1^+ + \theta_0^+) + (\theta_1^- + \theta_0^-)\right]} \leq P\left[H(1)=1\right] \leq P(W=0) + \theta_0^+ - \theta_0^- + P\left[H=1, W=1\right].$$

The bounds on $P\left[H(0)=1\right]$ are derived as follows:

The LB given by $P\left[H=1, W^*=0\right]$ is now given by

$$LB = P[H=1, W=0] + \theta_1^+ - \theta_1^-.$$

The UB given by $\frac{P[H=1,W^*=0]}{P(W^*=0)}$ is now given by

$$UB = \frac{P[H=1, W=0] + \theta_1^+ - \theta_1^-}{\left[P(W=0) + (\theta_1^+ + \theta_0^+) - (\theta_1^- + \theta_0^-)\right]}.$$

With ME, $P\left[H(0)=1\right]$ is bounded as follows:

$$P[H=1, W=0] + \theta_1^+ - \theta_1^- \leq P\left[H(0)=1\right] \leq \frac{P[H=1, W=0] + \theta_1^+ - \theta_1^-}{\left[P(W=0) + (\theta_1^+ + \theta_0^+) - (\theta_1^- + \theta_0^-)\right]}.$$

4.1 Arbitrary Errors Model

Now, I impose only Assumption 1 about ME under the MTS assumption. The bounds on $P[H(1)=1]$ are derived in the following way:

For the LB I set $\theta_1^+ \to \theta_1^{UB+}$, $\theta_0^- \to \theta_0^{UB-}$, $\theta_1^- \to \theta_1^{LB-} = 0$, and $\theta_0^+ \to \theta_0^{LB+} = 0$ so that

$$LB = \frac{P[H=1,W=1] - \theta_1^{UB+}}{[P(W=1) - \theta_1^{UB+} + \theta_0^{UB-}]}.$$

For the UB I set $\theta_0^+ \to \theta_0^{UB+}$ and $\theta_0^- \to \theta_0^{LB-} = 0$ so that

$$UB = P(W=0) + \theta_0^{UB+} + P[H=1,W=1].$$

Accordingly, $P[H(1)=1]$ is bounded as follows:

$$\frac{P[H=1,W=1] - \theta_1^{UB+}}{[P(W=1) - \theta_1^{UB+} + \theta_0^{UB-}]} \leq P[H(1)=1] \leq P[H=1,W=1] + P(W=0) + \theta_0^{UB+}.$$

The bounds on $P[H(0)=1]$ can be derived similarly:

For the LB I set $\theta_1^- \to \theta_1^{UB-}$ and $\theta_1^+ \to \theta_1^{LB+} = 0$ so that

$$LB = P[H=1,W=0] - \theta_1^{UB-}.$$

For the UB I set $\theta_1^+ \to \theta_1^{UB+}$, $\theta_0^- \to \theta_0^{UB-}$, $\theta_1^- \to \theta_1^{LB-} = 0$, and $\theta_0^+ \to \theta_0^{LB+} = 0$ so that

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

Accordingly, $P[H(0)=1]$ is bounded as follows:

$$P[H=1,W=0] - \theta_1^{UB-} \leq P[H(0)=1] \leq \frac{P[H=1,W=0] + \theta_1^{UB+}}{P(W=0) + \theta_1^{UB+} - \theta_0^{UB-}}.$$

Since

$$ATE = P[H(1)=1] - P[H(0)=1]$$

the bounds on the ATE are given by:

$$\begin{aligned}
UB_{ATE} &= UB_{P[H(1)=1]} - LB_{P[H(0)=1]} \\
&= P[H=1,W=1] + P(W=0) + \theta_0^{UB+} - \left\{ P[H=1,W=0] - \theta_1^{UB-} \right\} \\
LB_{ATE} &= LB_{P[H(1)=1]} - UB_{P[H(0)=1]} \\
&= \frac{P[H=1,W=1] - \theta_1^{UB+}}{P(W=1) - \theta_1^{UB+} + \theta_0^{UB-}} - \left\{ \frac{P[H=1,W=0] + \theta_1^{UB+}}{P(W=0) + \theta_1^{UB+} - \theta_0^{UB-}} \right\}.
\end{aligned}$$

This is Equation 19 in Section 5.4.1. This UB_{ATE} is identical to the UB_{ATE} in the No Assumption on Selection scenario under the Arbitrary Errors Model. This LB_{ATE} is identical to the LB_{ATE} in the Exogenous Selection case under the Arbitrary Errors Model.

4.2 No False Positives Model

With the additional assumption of no false positive errors, the bounds on $P\left[H(1)=1\right]$ are derived as follows:

For the LB I set $\theta_1^+ = 0$, $\theta_0^- \to \theta_0^{UB-}$, $\theta_1^- \to \theta_1^{LB-} = 0$, and $\theta_0^+ \to \theta_0^{LB+} = 0$ so that

$$LB = \frac{P\left[H=1, W=1\right]}{\left[P(W=1) + \theta_0^{UB-}\right]}.$$

For the UB I set $\theta_0^+ = 0$ and $\theta_0^- \to \theta_0^{LB-} = 0$ so that

$$UB = P(W=0) + P\left[H=1, W=1\right].$$

Accordingly, $P\left[H(1)=1\right]$ is bounded as follows:

$$\frac{P\left[H=1, W=1\right]}{\left[P(W=1) + \theta_0^{UB-}\right]} \leq P\left[H(1)=1\right] \leq P\left[H=1, W=1\right] + P(W=0).$$

Similarly, the bounds on $P\left[H(0)=1\right]$ can be derived as shown below:

For the LB I set $\theta_1^- \to \theta_1^{UB-}$ and $\theta_1^+ \to \theta_1^{LB+} = 0$ so that

$$LB = P[H=1, W=0] - \theta_1^{UB-}.$$

For the UB I set $\theta_1^+ = 0$, $\theta_0^- \to \theta_0^{UB-}$, $\theta_1^- \to \theta_1^{LB-} = 0$, and $\theta_0^+ \to \theta_0^{LB+} = 0$ so that

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

Accordingly, $P\left[H(0)=1\right]$ is bounded as follows:

$$P[H=1, W=0] - \theta_1^{UB-} \leq P\left[H(0)=1\right] \leq \frac{P[H=1, W=0]}{P(W=0) - \theta_0^{UB-}}.$$

Since

$$ATE = P\left[H(1)=1\right] - P\left[H(0)=1\right]$$

the bounds on the ATE are given by:

$$\begin{aligned}
UB_{ATE} &= UB_{P[H(1)=1]} - LB_{P[H(0)=1]} \\
&= P\left[H=1, W=1\right] + P(W=0) - \left\{P[H=1, W=0] - \theta_1^{UB-}\right\} \\
LB_{ATE} &= LB_{P[H(1)=1]} - UB_{P[H(0)=1]} \\
&= \frac{P\left[H=1, W=1\right]}{P(W=1) + \theta_0^{UB-}} - \left\{\frac{P[H=1, W=0]}{P(W=0) - \theta_0^{UB-}}\right\}.
\end{aligned}$$

This UB_{ATE} is identical to the UB_{ATE} in the No Assumption on Selection scenario under the No False Positives Errors Model. This LB_{ATE} is identical to the LB_{ATE} in the Exogenous Selection case under the No False Positives Errors Model.

5 Joint MTS and MIV

This section is based on Kreider and Pepper's (2007) derivation of MIV bounds, including the finite sample bias corrected MIV bounds. The MIV implies that the latent probability $P[H(1) = 1]$ or $P[H(0) = 1]$ increases with SES.

Let $\nu = MIV = SES$. Since $H(1) = 1$ and $H(0) = 1$ denote good outcomes: $u_1 < u < u_2$ implies

$$P[H(1) = 1|\nu = u_2] \geq P[H(1) = 1|\nu = u] \geq P[H(1) = 1|\nu = u_1]$$

and

$$P[H(0) = 1|\nu = u_2] \geq P[H(0) = 1|\nu = u] \geq P[H(0) = 1|\nu = u_1]$$

We know the MTS assumption implies

$$\begin{aligned} P[H(1) &= 1|W^* = 0] \geq P[H(1) = 1|W^* = 1] \\ P[H(0) &= 1|W^* = 0] \geq P[H(0) = 1|W^* = 1] \end{aligned}$$

such that without ME:

$$\therefore \frac{P\left[H = 1, W^* = 1\right]}{P(W^* = 1)} \leq P\left[H(1) = 1\right] \leq P(W^* = 0) + P\left[H = 1, W^* = 1\right]$$

and

$$P\left[H = 1, W^* = 0\right] \leq P\left[H(0) = 1\right] \leq \frac{P\left[H = 1, W^* = 0\right]}{P(W^* = 0)}.$$

5.1 Deriving MTS-MIV bounds on ATE

1. Divide data into j SES groups, $j = 1, 2, ..., J$.

2. Calculate the MTS LB and UB for each SES group, according to the classification error assumptions. So, for each group, there will be 1 LB-UB pair for Arbitrary Errors model and 1 LB-UB pair for the No False Positives Model.

3. To get the LB_{MIV} for $P\left[H(1) = 1\right]$:

   (a) For each SES group j: I have $LB^j = \frac{P[H=1,W^*=1]}{P(W^*=1)}$. Let P_j denote the fraction of respondents in SES group j. So, the $LB_{MIV} = T_n = \sum_j P_j\{\sup_{j' \leq j} LB^{j'}\}$. This is because $H(1) = 1$ and $H(0) = 1$ imply good outcomes. As SES increases, the probability of a good outcome increases. So, the LB of the j^{th} SES group is greater than the weighted average of the lower bounds of lower SES groups.

(b) To get the finite sample bias-corrected LB_{MIV} : Bootstrap sampling distribution of LB^j.

i. Randomly draw with replacement K independent pseudosamples of the original data.

ii. Get K LB^j-s.

iii. Get $T_n^k = \sum_j P_j\{\sup_{j' \leq j} LB^{j'}\}, k = 1, 2, ..., K$. The expected LB from the bootstrap distribution is:

$$E^*(T_n) = \frac{\sum_{k=1}^{K} T_n^k}{K}.$$

(c) The bias is calculated as follows:

$$\hat{b} = E^*(T_n) - T_n.$$

(d) The bootstrap bias-corrected finite sample LB_{MIV} is given by:

$$LB_{MIV} = T_n^c = T_n - \hat{b} = 2T_n - E^*(T_n).$$

4. To get the UB_{MIV} for $P\left[H(1) = 1\right]$:

(a) For each SES j: I have $UB^j = P(W^* = 0) + P\left[H = 1, W^* = 1\right]$. Let P_j denote the fraction of respondents in SES group j. So, the $UB_{MIV} = U_n = \sum_j P_j\{\inf_{j' \geq j} UB^{j'}\}$.This is because $H(1) = 1$ and $H(0) = 1$ are good outcomes. As SES increases, the probability of a good outcome increases. So, the UB of the j^{th} SES group is smaller than the weighted average of the upper bounds of higher SES groups.

(b) To get the finite sample bias-corrected UB_{MIV} : Bootstrap sampling distribution of UB^j.

i. Randomly draw with replacement K independent pseudosamples of the original data.

ii. Get K UB^j-s.

iii. Get $U_n^k = \sum_j P_j\{\inf_{j' \geq j} UB^{j'}\}, k = 1, 2, ..., K$. The expected UB from the bootstrap distribution is: $E^*(U_n) = \frac{\sum_{k=1}^{K} U_n^k}{K}$.

(c) The bias is calculated as follows:$\hat{b} = E^*(U_n) - U_n$.

(d) The bootstrap bias-corrected finite sample UB_{MIV} is given by:

$$UB_{MIV} = U_n^c = U_n - \hat{b} = 2U_n - E^*(U_n).$$

5. Similarly get the LB_{MIV} and UB_{MIV} for $P\left[H(0) = 1\right]$.

6. Now: $ATE = P[H(1) = 1] - P[H(0) = 1]$. Accordingly,

$$UB_{ATE} = UB_{MIV}^{H(1)} - LB_{MIV}^{H(0)}$$

and

$$LB_{ATE} = LB_{MIV}^{H(1)} - UB_{MIV}^{H(0)}.$$

6 Estimating the Imbens-Manski (2004) CI for partially identified parameters

1. For each assumption model and each value of $Q = 0, 0.01, 0.02, 0.05$, and 0.10. I have UB_{ATE} and LB_{ATE}.

2. Bootstrapping B times will yield B UB_{ATE}, B LB_{ATE}, and $\hat{\sigma}_l$ and $\hat{\sigma}_u$.

3. Define $\Delta = UB_{ATE} - LB_{ATE}$.

4. $$\alpha = \Phi(\overline{C_N} + \sqrt{N}.\frac{\Delta}{\max(\hat{\sigma}_l, \hat{\sigma}_u)}) - \Phi(-\overline{C_N})$$

5. $$CI_{\alpha}^{ATE} = [LB_{ATE} - \overline{C_N}.\frac{\hat{\sigma}_l}{\sqrt{N}}, UB_{ATE} + \overline{C_N}.\frac{\hat{\sigma}_u}{\sqrt{N}}]$$