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ABSTRACT

USDA operates several food assistance programs aimed at alleviating food insecurity. We study whether participation in both SNAP and WIC alleviates food insecurity compared with participation in SNAP alone. We bound underlying causal effects by applying nonparametric treatment effect methods that allow for endogenous selection and underrepresented program participation when validation data are available for one program (treatment) but not the other. We estimate average treatment effects using data from the National Household Food Acquisition and Purchase Survey (FoodAPS). FoodAPS includes administrative data to validate SNAP participation. Information on local food prices allows us to construct a food expenditure-based monotone instrumental variable that does not require a typical IV exclusion restriction. Under relatively weak monotonicity assumptions, we identify that the impact of participating in both programs relative to SNAP alone is strictly positive, suggesting that the programs are nonredundant. This evidence can support improved design and targeting of food programs.

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1. Introduction

A household is food secure if it has access to enough food for an active, healthy life of all of its members; it is food insecure otherwise (NRC 2006). Substantial prevalence of food insecurity in the low-income U.S. population is a matter of public concern, since food insecurity can be detrimental to the health and well-being of adults and children (for a literature review, see Gundersen, Kreider, and Pepper 2011). In fact, among households with income below 130% of the federal poverty threshold in 2016, 35.7% experienced food insecurity (Coleman-Jensen et al. 2017a, 2017b).[1]

The U.S. Department of Agriculture (USDA) administers 15 domestic food assistance programs designed to alleviate food insecurity (Oliveira 2017). Many low-income households are eligible for and participate in more than one program. The largest and third largest programs by expenditures are, respectively, the Supplemental Nutrition Assistance Program (SNAP) ($68.1 billion spent in the fiscal year 2017, 42.2 million participants on average per month) and Special Supplemental Nutrition Program for Women, Infants, and Children (WIC) ($5.7 billion, 7.3 million participants).[2] These two programs are the focus of our paper.

While both SNAP and WIC are means-tested and aim to provide resources to low-income households for the acquisition of food, they differ in several respects (Hoynes and Schanzenbach 2015; U.S. GAO 2010). SNAP offers vouchers to eligible low-income households for the purchase of most food items. In contrast, WIC provides benefits to qualifying individuals in low-income households for the purchase of a restricted set of foods identified to meet the specific nutritional needs of pregnant, post-partum, and lactating women; infants; and children less than 5 years old. WIC also provides nutrition counseling and referrals for health services. Differences in the program design may lead to synergies between SNAP and WIC.[3] For example, WIC expands acquisition of specific foods and may lead to increased awareness of healthy food selection and food purchases that better meet household nutritional needs. In turn, SNAP provides a wider choice over foods. Investigating whether either program has a positive marginal effect on food security given participation in the other is informative about potential programmatic redundancies and contributes to a better understanding of the overall efficacy of the food safety net in the United States.

In practice, the rate of food insecurity among food program recipients is substantial. In particular, 51.2% of households on SNAP and 40.6% on WIC were food insecure in 2016. Moreover, the rate of food insecurity among SNAP (WIC) recipients was twice (1.4 times) that among potentially eligible, low-income nonrecipients (Coleman-Jensen et al. 2017a). These seemingly counterintuitive associations (especially in view of the programs' shared objective to reduce food insecurity) provide an additional motivation for studying SNAP and WIC effects.

Identifying causal, rather than associative, effects of any food program is challenging because of (*i*) endogenous self-selection of households into the program and (*ii*) pervasive underreporting of food assistance in national surveys. In particular, unobserved personal characteristics (e.g., expected future health status) are thought to be related to both food security and program participation. This simultaneity precludes the use of simple regression techniques (e.g., Ordinary Least Squares) to estimate causal effects (see Gundersen and Oliveira 2001; Jensen 2002; Fox, Hamilton, and Lin 2004; Wilde 2007; Nord and Golla 2009). Furthermore, households are thought to systematically underreport the receipt of food assistance (e.g., Bollinger and David 1997; Meyer, Mok, and Sullivan 2015a; 2015b), and the propensity to underreport may vary across households based on their observed and unobserved characteristics. For example, Meyer et al. (2015a) find that less than 60% of SNAP benefits are recorded in recent waves of the Current Population Survey (CPS). Bitler, Currie, and Scholz (2003) find evidence of "severe" underreporting of WIC benefits. Under such circumstances, all of the classical measurement error assumptions are violated, and it becomes particularly important to locate and use any available validation information as a means to mitigate the measurement error problem. In turn, analyzing not just one, but two programs adds an extra layer of complexity.[4]

In this paper, we quantify how participation in both SNAP and WIC affects a household's probability of being food secure compared with participation in SNAP alone. To estimate causal treatment effects, we apply nonparametric bounding methods developed by Jensen, Kreider, and Zhylyevskyy (2018; hereafter JKZ) to address joint program participation. The application of JKZ's methods to available data on household food security and partially validated food program participation status in USDA's National Household Food Acquisition and Purchase Survey (FoodAPS) (see below for details) is the present paper's contribution to the literature.

These methods allow us to place bounds on the causal treatment effects and account for the dual identification problems of endogenous selection and potentially misreported program participation status when auxiliary information is available to validate self-reported participation in one program (e.g., SNAP) but not the other (e.g., WIC). The dual identification problems pose an obstacle to applying standard instrumental variable (IV) techniques to quantify treatment effects, since such techniques are known to produce inconsistent estimates when an endogenous binary treatment variable (e.g., program participation vs. nonparticipation) is mismeasured (e.g., Black et al. 2000; Frazis and Loewenstein 2003; Nguimkeu et al. 2017).[5] If the self-reported indicator of participation is measured with error, it is likely that a valid instrument for receipt is correlated with the measurement error as well. Even in the absence of measurement error, it may still be difficult in practice to find IVs that are both valid and strong. For example, variation in policy instruments across states that affect food assistance participation rates may be endogenously related to food insecurity.[6] For academic studies, the nonparametric bounding methods may often be useful to examine whether point estimates obtained under relatively strong assumptions (e.g., using the IV approach) at least lie within bounds calculated under weaker assumptions. From a program evaluation standpoint, if small point estimates suggest abolishing a program, it would be reassuring to also calculate bounds and show that they rule out effect sizes that would make the program important.

The approach in JKZ generalizes methods in Kreider and Hill (2009) and Kreider et al. (2012), which accommodate binary treatments (e.g., SNAP vs. no SNAP), to handle the case of partially ordered multiple treatments. JKZ derive sharp bounds on average treatment effects (ATEs) that are logically consistent with the observed data, available validation information, and imposed statistical and behavioral assumptions on the data-generating process. This methodology differs from the multiple-programs approaches of Fraker and Moffitt (1988), Keane and Moffitt (1998), and Brien and Swann (2001) who model participation decisions and program effects jointly using simultaneous equations in parametric settings. While these papers also allow for the endogeneity of program participation status, they ignore the possibility of misreported participation and, thus, cannot address implications of such misreporting for the estimation of true program effects. Moreover, these papers impose strong parametric assumptions (e.g., the joint normality of regression disturbance terms) that are relaxed in JKZ's approach.

We apply our previously developed methods to data from FoodAPS. Among existing nationally representative datasets, FoodAPS is particularly well suited for the analysis as it provides self-reported household participation in SNAP and WIC and, furthermore, contains auxiliary administrative data to validate self-reported SNAP participation.[7] We focus only on those households that would be eligible to participate in SNAP and WIC concurrently. Given the eligibility restrictions associated with each of the two programs, we analyze households with income below 130% of the poverty threshold and containing a pregnant woman, or a child aged less than five years.[8] The analytical sample contains 460 households, 37% of whom report being on both programs.

Our empirical analysis starts by estimating the bounds on the ATE of participating in SNAP and WIC jointly vs. in SNAP alone under minimal assumptions. These worst-case bounds are wide and do not allow us to sign the ATE. We then investigate how several middle ground assumptions can narrow the worst-case bounds by restricting relationships between the latent food security outcomes, program participation, and observed covariates. For example, we study the identifying power of an assumption that, on average, the probability of a favorable food security outcome weakly rises with more household expenditures on food at home relative to expenditures consistent with the Thrifty Food Plan (TFP) (Carlson et al. 2007). Unlike standard instrumental variables (IVs), such monotone instrumental variables (MIVs) require no independence assumption / exclusion restriction. The trade-off is that we are only able to bound and not point-identify causal effects. Still, when combined with the FoodAPS data, our assumptions are strong enough to identify substantial beneficial effects of participating in multiple food assistance programs.

The remainder of this paper is organized as follows. Section 2 describes the data and characteristics of our analytical sample. Section 3 lays out the methodological framework, formally defines the identification problems, and employs several new sets of closed-form analytical formulas derived in JKZ to bound ATEs given a potentially mismeasured, partially ordered, and partially verified treatment. Our empirical results highlight the identifying power of successively stronger nonparametric assumptions. Section 4 concludes.

2. Data

FoodAPS

Our main data source, FoodAPS, is a recent, nationally representative survey to collect comprehensive information about household food purchases and acquisitions. It was co-sponsored by ERS and FNS and conducted in the field by Mathematica Policy Research. The survey was administered on a stratified sample of 4,826 households drawn from three population groups: SNAP households, low-income households not participating in SNAP, and higher income households. Households participated in FoodAPS for one seven-day week between April 2012 and January 2013.

FoodAPS captures detailed information about purchases and acquisitions of food items intended for consumption at home and away from home, including items acquired through

USDA's food assistance programs, as well as the amount and source of payment for food. The survey also collects information about household and personal attributes, including demographic and socioeconomic characteristics, income, receipt of SNAP benefits, confirmation of SNAP receipt through an administrative match, and self-reported WIC receipt along with information to determine WIC eligibility.

Among other data reported, households filled out a 10-item food security questionnaire (referenced to the last 30 days), which is the basis for calculating raw food security scores and assigning households to categories of food security. Using the USDA's 30-day adult food security scale, "food insecure" households are those with the raw score of 3 or more.[9] Those with scores of 0, 1, or 2 are labeled as "food secure."

Through its Geography Component (FoodAPS-GC), the survey provides information about the local food environment, including the location of food retailers, measures of access to these retailers, food prices, and food-related public policies.[10] We employ FoodAPS-GC to construct variables that can be used as MIVs. In particular, we use local food price data to construct measures of the cost of TFP consistent with each household's size and composition. The TFP measures vary with respect to the geographic level of price aggregation: county vs. stores located within 20 miles of the household. We then construct a food expenditure MIV by dividing reported household expenditures on food at home by the TFP cost.[11]

ANALYTICAL SAMPLE

We focus on FoodAPS households that would be eligible to participate in SNAP and WIC concurrently. Our analytical sample is comprised of 460 households with income below 130% of the poverty threshold and containing a pregnant woman, or a child aged less than five years. All sample statistics and estimates incorporate FoodAPS household weights. It should be noted that SNAP participation is relatively infrequent among households with higher incomes. For example, among FoodAPS households with income between 130% and 200% of the poverty threshold (995 cases in the FoodAPS sample), only 11.1% are confirmed participants as implied by the FoodAPS variable *SNAPNOWADMIN*. In addition, we calculate that among all FoodAPS households, 3.2% are confirmed participants and report income greater than 130% of poverty. Also, among SNAP-eligible FoodAPS households, as estimated by Mathematica Policy Research using different models, the fraction of confirmed participants reporting income greater than 130% of poverty does not exceed 4.6%.

Table 1 provides the joint distribution of our analytical sample by self-reported, current household participation in SNAP and WIC.[12] The table shows that joint participation in the two programs is empirically relevant: 36.7% of the households report being on both SNAP and WIC. Also, 16.6% are reportedly on WIC but not SNAP, and 31.4% are on SNAP but not WIC. The remaining 15.3% indicate no participation in either program.

To ascertain SNAP participation, FoodAPS households were asked to provide consent to be matched to SNAP administrative records (no attempt was made to validate WIC participation). Most households consented; in fact, in our analytical sample only 2.3% of the households withheld consent. SNAP administrative records are drawn from two distinct sources: state SNAP caseload files and the Anti-Fraud Locator EBT Retailer Transactions (ALERT) database. Caseload files include data on the identity of program participants, benefit amounts, and dates of disbursement. FoodAPS households were matched to caseload records probabilistically, using names, addresses, and phone numbers. A household was deemed to be a true current participant if a benefits disbursement date fell on a 32-day window before the survey date. Unfortunately, not all states covered in FoodAPS provided usable caseload data.

The ALERT database records transactions made using SNAP EBT cards (SNAP participants must use such cards to access program benefits). FoodAPS households reporting SNAP usage during the survey week were probabilistically matched to ALERT by purchase amount and store ID. The matched card’s transaction history was examined for increases in the amount of available benefits between adjacent transactions. An increase indicates a disbursement on a date between corresponding transaction dates. Using ALERT, a household is considered to be a true current SNAP participant if the matching procedure indicated a disbursement during a 36-day window before the survey date.

Courtemanche et al. (2018), among other researchers, point out limitations of SNAP administrative records employed in FoodAPS, including missing data and varying degree of data quality across states. Also, the two administrative data sources sometimes disagree, perhaps in part due to underlying timing discrepancies. Probabilistic matching may lead to error as well.

Since studying the quality of the data linkage is not our research objective, we do not make a determination as to which of the two administrative sources is more accurate or whether and how one should combine them. Instead, similar to Kang and Moffitt (2018) we rely on the ERS's judgment and use as an indicator of the "true" current SNAP participation the FoodAPS variable *SNAPNOWHH*. This variable was constructed by the ERS by combining all available information, including administrative matches and self-reported data. Notably, when one administrative source "confirms" participation but the other "confirms" nonparticipation, *SNAPNOWHH* records SNAP status to be true participation. Also, when neither a caseload-, nor an ALERT-based match is available, *SNAPNOWHH* resorts to using self-reported SNAP status. In our analytical sample, the SNAP status of 60.2% (weighted) of the households comes from administrative data. In the remaining 39.8% of the cases ("non-matches"), it is based on self-reported participation. While *SNAPNOWHH* may still contain some measurement error, we believe it is quite small.

Table 2 is similar to Table 1, except that the SNAP participation indicator is now based on *SNAPNOWHH*. WIC participation is still self-reported (and unverified). Compared to the distribution in Table 1, the incorporation of administrative data about SNAP receipt leads to an increase in the overall prevalence of SNAP participation by 5.2 percentage points. More specifically, the prevalence of households on SNAP but not on WIC increases by 2.2 percentage points (from 31.4% to 33.6%), while the prevalence of households on both SNAP and WIC rises by 3 percentage points (from 36.7% to 39.7%).

Table 3 provides the prevalence of food security in each of four subsamples defined according to self-reported household participation in SNAP and WIC. The rate of food security exceeds 50% throughout, but somewhat varies across the subsamples. (The rate of food security in the analytical sample overall is 55.0%.) Given no WIC receipt, self-reported SNAP participation is associated with a decrease in the prevalence of food security from 53.2% to 52.2%, which is in line with a negative association between food security and SNAP found in the literature (see Gundersen et al. 2011). When WIC is in place, however, SNAP is associated with an increase in the food security rate from 54.5% to 58.5%. Perhaps the process of selecting into SNAP differs depending on whether the household participates in WIC, or perhaps there are synergies between the two programs in promoting food security. Also, the table shows that WIC participation is always associated with more food security given a self-reported SNAP status.

Table 4, which replaces the self-reported SNAP participation indicator with the administratively matched one, likewise shows food security rates in excess of 50% and varying a bit across the four subsamples. With one exception, the table indicates similar associations between the participation indicators and food security to those implied by Table 3. The only exception is that given no SNAP receipt, self-reported WIC participation is now associated with less (rather than more) food security.

Table 5 provides descriptive statistics for selected characteristics of the sample. On average, the households contain 4.5 members (of all ages), 2.3 children (aged < 18 years), and 1.6 young children (aged 0–6 years). Average monthly household income is about $1,600, income-to-poverty ratio is 0.75, and weekly expenditures on food at home are about $113. Twenty-one percent of the households live in rural areas, 78% rent their residence, and 11% have used a food pantry in the past 30 days. Primary respondents in these households are predominantly female (88%) and just under 34 years old on average. Thirty-three percent are Hispanic, 55% are White, 29% are Black or African American. In the sample, 32% have no high school degree and 35% have some college education or have received a bachelor’s degree. Also, 44% are single and 29% are married; 43% are employed, 17% are looking for work, and 40% are not working.

ANALYSIS OF PROGRAM PARTICIPATION CHOICES

While determinants of program participation are not the focus of this paper, we perform additional analyses to better understand why some households pick only one program when eligible for both and why some choose SNAP only while others select WIC only. We summarize the findings below and relegate tables with numerical results to Appendix A.

First, we partition the analytical sample into four subsamples according to participation in SNAP and WIC and calculate subsample descriptive statistics (Table A1). Qualitatively, households in the WIC-only subsample tend to be larger and have higher income-to-poverty ratios, whereas households in the SNAP-only subsample are smaller and poorer. Also, WIC-only (SNAP-only) primary respondents are more (less) likely to be Hispanic, less (more) likely to be Black or African American, and more (less) likely to be married. The subsamples also differ somewhat with respect to the educational attainment and labor force participation of the primary respondent. However, notable differences overall are few and far between.

Second, to investigate the extent to which socioeconomic characteristics can help explain program participation patterns, we estimate several probit models (Tables A2A and A2B). (Explanatory variables correspond to characteristics in Tables 5 and A1.) Since not every variable is exogenous, the results need not reflect causal relationships.

The estimates suggest that households with higher income-to-poverty and those containing a primary respondent with a GED are relatively more likely to pick one program (either SNAP only, or WIC only) over both programs jointly. SNAP only is relatively more likely to be selected over WIC only when the primary respondent is older, has some college education, and is looking for work; and less likely to be chosen when the household has a lower income-to-poverty ratio, includes more adults, and contains a primary respondent who is married, Hispanic, of other race, and has an associate’s degree. When considering participation in a particular program at a time vs. one of three alternative participation patterns (see Tables A2A and A2B), we find that SNAP only is relatively more likely to be picked when the primary respondent has a GED or some college education and is older and single. In turn, WIC only is relatively more likely to be selected by households with higher income to poverty ratio and those with a younger, Hispanic, and married primary respondent. However, most of these findings are statistically significant only at the 10% level.

Overall, given the paucity of statistically strong estimates and limited explanatory power of the probit models in general (pseudo-R^2 values are modest), program participation patterns in the analytical sample seem to be driven largely by factors other than the included socioeconomic variables.

3. Methodology and results

GENERAL FRAMEWORK

Applying the methods developed in JKZ, let the outcome $Y = 1$ indicate that a household is food secure, with $Y = 0$ otherwise. Let S^* be an unobserved indicator of true program participation where $S^* = 0$ denotes no participation in SNAP or WIC, $S^* = 1$ denotes participation in SNAP alone, $S^* = 2$ denotes participation in WIC alone, and $S^* = 3$ denotes participation in both SNAP and WIC. This treatment variable is partially ordered: $S^* = 1$ or 2 denotes some participation in food assistance programs, while $S^* = 0$ does not, and $S^* = 3$ involves more participation. (Since $S^* = 1$ and $S^* = 2$ represent different programs, these two treatments are not ordered.)

Instead of observing S^* in the data, we observe its counterpart, S, which is comprised of the household's true SNAP participation status (based on the variable *SNAPNOWHH*) and self-reported WIC participation. Even though SNAP participation status has been verified, the value of S cannot tell us the exact value of S^*. In particular, when $S = 0$ or $S = 2$, we can only conclude that $S^* \in \{0, 2\}$; and when $S = 1$ or $S = 3$, $S^* \in \{1, 3\}$.

Using a potential outcomes framework, ATEs associated with participating in both food assistance programs versus a single program, or compared with no participation are defined as follows:

$$ATE_{jk} = P[Y(S^* = j) = 1 \mid X] - P[Y(S^* = k) = 1 \mid X] \text{ for } j,k \in \{0,1,2,3\},\ j \neq k \qquad (1)$$

where $Y(S^*)$ indicates the (latent) potential food security outcome under treatment S^*, X denotes any covariates of interest, and P denotes the probability of an outcome. Because there are no regression orthogonality conditions to be satisfied in this framework, there is no need to include covariates as a means of avoiding omitted variable bias. Instead, covariates here serve to define the subpopulation of interest.[13] Later, we also show how one could use some covariates as MIVs to tighten the ATE bounds. To simplify notation, we suppress the conditioning on X and write $P[Y(S^* = j) = 1]$ more compactly as $P[Y(j) = 1]$.

In this application, we are interested in the case of $j = 3$ vs. $k = 1$. Specifically, $ATE_{31} = P[Y(3) = 1] - P[Y(1) = 1]$ measures how the prevalence of food security would change if all eligible households participated in both SNAP and WIC rather than in SNAP alone.[14] One cannot identify ATE_{31} without additional assumptions, even if S is accurately reported, because the potential outcome $Y(S^* = 3)$ is observed only for households that chose to participate in both SNAP and WIC, while $Y(S^* = 1)$ is observed only for households that chose to participate in SNAP alone. The decomposition $P[Y(3) = 1] = P[Y(3) = 1 \mid S^* = 3]P(S^* = 3)$ $+ P[Y(3) = 1 \mid S^* \neq 3]P(S^* \neq 3)$ highlights the selection problem: the term $P[Y(3) = 1 \mid S^* \neq 3]$ represents an unobserved counterfactual outcome, namely, the likelihood of food security when participating in SNAP and WIC jointly among households that actually chose not to be on both programs.

As a further identification problem, households are thought to systematically underreport program participation in national surveys, and such underreporting may be related to personal characteristics (including the food security outcome itself). Allowing S to deviate from S^*, let

$\theta_i^{j,k} \equiv P(Y=i, S=j, S^*=k)$ for $j,k=\{0,1,2,3\}$ denote the fraction of households with food security status *i* reporting participation status *j* when true participation status is *k*. Using the law of total probability, the first term in ATE_{31} becomes $P[Y(3)=1]=P(Y=1,S=3)+\theta_1^{-3,3}-\theta_1^{3,-3}$ $+P[Y(3)=1\,|\,S^*\neq 3]\left\{P(S\neq 3)+\sum_{j\neq 3}(\theta_1^{-j,j}+\theta_0^{-j,j}-\theta_1^{j,-j}-\theta_0^{j,-j})\right\}$, where $\theta_i^{-j,k} \equiv P(Y=i, S\neq j, S^*=k)$ and $\theta_i^{j,-k} \equiv P(Y=i, S=j, S^*\neq k)$. An analogous expression can be derived for $P[Y(1)=1]$.

Without further assumptions, propositions in JKZ can be used to show that the marginal impact on food security associated with participating in both SNAP and WIC, compared with participating in SNAP alone, is bounded as follows:

$$\begin{aligned} &-1+P(Y=1,S=3)+P(Y=0,S=1)+\Theta_{3,1}^{LB} \\ &\leq ATE_{3,1} \leq \\ &1-P(Y=0,S=3)-P(Y=1,S=1)+\Theta_{3,1}^{UB} \end{aligned} \qquad (2)$$

where $\Theta_{3,1}^{LB} \equiv \theta_1^{-3,3}-\theta_1^{3,-3}+\theta_0^{-1,1}-\theta_0^{1,-1}$ and $\Theta_{3,1}^{UB} \equiv -\theta_0^{-3,3}+\theta_0^{3,-3}-\theta_1^{-1,1}+\theta_1^{1,-1}$ could each be positive or negative. Terms like $P(Y=1,S=3)$ are observed from the data, but the $\{\theta\}$ components are unobserved. Thus, the ATE bounds in Equation (2) are not yet operational.

In our FoodAPS sample, we have $P(Y=1,S=3)=0.238$, $P(Y=0,S=1)=0.159$, $P(Y=0,S=3)=0.165$, and $P(Y=1,S=1)=0.172$. Thus, in our application, the bounds in Equation (2) become

$$-0.603+\Theta_{3,1}^{LB} \quad \leq ATE_{3,1} \leq \quad 0.663+\Theta_{3,1}^{UB}.$$

If participation in SNAP and WIC were accurately measured in the first place or if we could validate participation in both programs so that the true joint program participation status would be known to us, then setting $\Theta_{3,1}^{LB}$ and $\Theta_{3,1}^{UB}$ equal to zero would reduce the bounds in Equation (2) to Manski's (1995) classic worst-case ATE bounds: $[-0.603, 0.663]$.[15] While obviously very wide, it is instructive to recognize that the data alone (if accurately measured) constrain the possible range of $ATE_{3,1}$ to improve on the range [-1,1]. Since $P(Y=1, S=3)$ in Equation (2) is greater than zero, we know that not all households participating in both SNAP and WIC are food insecure. Also, since $P(Y=0, S=1)$ is greater than zero, we know that participating in both programs does not cause all households to *become* food secure; some were already food secure while participating in SNAP alone. These positive probabilities raise the lower bound above -1. Similar logic ensures that the upper bound is less than 1 (again, when SNAP and WIC participation are accurately measured).

In the context of food assistance programs, however, participation is thought to be underreported. Still, the error rates $\Theta_{3,1}^{LB}$ and $\Theta_{3,1}^{UB}$ are logically bounded. For example, $\theta_1^{-1,1}$ cannot exceed $P(Y=1, S\neq 1)=0.378$, another quantity directly observed in the data. Without knowledge about the nature and degree of reporting errors, however, nothing prevents the worst case bounds in Equation (2) from expanding to $[-1, 1]$, in which case they are completely uninformative. For the upper bound, for example, $\theta_0^{3,-3}$ could be as large as $P(Y=0, S=3)$ $=0.165$, while $\theta_1^{1,-1}$ could be as large as $P(Y=1, S=1)=0.172$. Since $\theta_0^{-3,3}$ and $\theta_1^{-1,1}$ could both be 0, the upper bound in Equation (2) attains 1. Analogously, the lower bound attains -1.

PARTIAL VALIDATION DATA IN FoodAPS

Partial validation data in FoodAPS allow us to place informative restrictions on the magnitudes of $\Theta_{3,1}^{LB}$ and $\Theta_{3,1}^{UB}$. Knowledge of whether or not a household truly participates in SNAP is not enough to pinpoint the value of S^*, which represents the true *joint* participation status. In particular, confirmation of participation in SNAP merely identifies that $S^* \in \{1,3\}$; that is, the household might be participating in SNAP alone or in both SNAP and WIC. Similarly, confirmation of nonparticipation in SNAP merely identifies that $S^* \in \{0,2\}$; the household may have been participating in neither program or in WIC alone.

Still, confirmation of SNAP participation status – and modifying the observed treatment indicator *S* accordingly to align with known values – allows us to eliminate many of the error components of $\Theta_{3,1}^{LB}$ and $\Theta_{3,1}^{UB}$. Specifically, $\Theta_{3,1}^{LB} \equiv (\theta_1^{0,3} + \theta_1^{1,3} + \theta_1^{2,3}) - (\theta_1^{3,0} + \theta_1^{3,1} + \theta_1^{3,2}) + (\theta_0^{0,1} + \theta_0^{2,1} + \theta_0^{3,1}) - (\theta_0^{1,0} + \theta_0^{1,2} + \theta_0^{1,3})$ reduces to $\Theta_{3,1}^{LB} = \theta_1^{1,3} - \theta_1^{3,1} + \theta_0^{3,1} - \theta_0^{1,3}$ because $\theta_1^{0,3} = \theta_1^{2,3} = \theta_1^{3,0} = \theta_1^{3,2} = \theta_0^{0,1} = \theta_0^{2,1} = \theta_0^{1,0} = \theta_0^{1,2} = 0$. These eight (out of the 12) error components vanish using the FoodAPS validation information. For example, $\theta_1^{0,3} \equiv P(Y=1, S=0, S^*=3) = 0$ since SNAP validation rules out cases in which a household ends up falsely classified as participating in neither program since we have documentation that the household participated at least in SNAP. Similarly, $\Theta_{3,1}^{UB} \equiv -(\theta_0^{0,3} + \theta_0^{1,3} + \theta_0^{2,3}) + (\theta_0^{3,0} + \theta_0^{3,1} + \theta_0^{3,2}) - (\theta_1^{0,1} + \theta_1^{2,1} + \theta_1^{3,1}) + (\theta_1^{1,0} + \theta_1^{1,2} + \theta_1^{1,3})$ reduces to $\Theta_{3,1}^{UB} = -\theta_0^{1,3} + \theta_0^{3,1} - \theta_1^{3,1} + \theta_1^{1,3}$ since $\theta_0^{0,3} = \theta_0^{2,3} = \theta_0^{3,0} = \theta_0^{3,2} = \theta_1^{0,1} = \theta_1^{2,1} = \theta_1^{1,0} = \theta_1^{1,2} = 0$. [16]

Using the FoodAPS validation data, the average treatment effect bounds in Equation (2) are thus narrowed as follows:

$$\begin{aligned} &-1 + P(Y=1, S=3) + P(Y=0, S=1) + \theta_1^{1,3} - \theta_1^{3,1} + \theta_0^{3,1} - \theta_0^{1,3} \\ &\leq ATE_{3,1} \leq \\ &1 - P(Y=0, S=3) - P(Y=1, S=1) + \theta_1^{1,3} - \theta_1^{3,1} + \theta_0^{3,1} - \theta_0^{1,3}. \end{aligned} \tag{3}$$

Note that the error components $\theta_1^{1,3} - \theta_1^{3,1} + \theta_0^{3,1} - \theta_0^{1,3}$ shift the lower and upper bound by the same unknown constant. In our application,

$$-0.603 + \theta_1^{1,3} - \theta_1^{3,1} + \theta_0^{3,1} - \theta_0^{1,3} \quad \leq ATE_{3,1} \leq \quad 0.663 + \theta_1^{1,3} - \theta_1^{3,1} + \theta_0^{3,1} - \theta_0^{1,3}.$$

Despite eliminating eight of the 12 error components in $\Theta_{3,1}^{LB}$ and $\Theta_{3,1}^{UB}$, the bounds in Equation (3) are still uninformative: the ATE may still lie anywhere between -1 and 1. Thus, on its own, the validation of SNAP participation does not produce informative bounds here. To see this more clearly, it is instructive to closely examine the bounds in Equation (3). Under no classification error, the lower bound is elevated above -1 because some fraction of households $P(Y=1, S=3)=0.238$ are known to be food secure while participating in both SNAP and WIC, while another fraction $P(Y=0, S=1)=0.159$ are known to be food insecure while participating in SNAP alone. The presence of these groups reveals that, at least sometimes, participation in both programs is not harmful relative to participation in SNAP alone. Similarly, the upper bound cannot attain 1 when some fraction of households $P(Y=0, S=3)=0.165$ are known to be food insecure despite participating in both programs, and some from fraction $P(Y=1, S=1)=0.172$ are food secure despite participating only in SNAP. Thus, at least sometimes, participation in both programs is not beneficial compared with participation in SNAP alone.

In the presence of classification error, the difficulty is that $\theta_1^{3,1}=P(Y=1, S=3, S^*=1)$ in the lower bound could be as large as $P(Y=1, S=3)=0.238$ while $\theta_0^{1,3}=P(Y=0, S=1, S^*=3)$ could be as large as $P(Y=0, S=1)=0.159$. Without further assumptions to constrain the patterns or degrees of misclassification, logically we cannot rule out the possibility that food secure households claiming to participate in both programs were actually participating only in SNAP. We also cannot rule out the possibility that food insecure households claiming to participate in SNAP alone were actually participating in both programs. Setting the other error components to zero as a worst case, the lower bound falls to -1, becoming uninformative. Similarly, the upper bound rises to 1. While these scenarios are extreme, they help crystalize how data must be combined with assumptions before we can make logical, informative inferences.

FoodAPS currently does not contain information that can be used to validate WIC participation status.[17] Thus, we cannot further constrain the four remaining error components in $\Theta_{3,1}^{LB}$ and $\Theta_{3,1}^{UB}$ using data alone. To learn anything about $ATE_{3,1}$, we need to impose additional assumptions, such as those about the magnitudes or patterns of reporting errors. We aim to strike a balance between making assumptions that are weak enough to be credible but strong enough to be informative.

NO FALSE POSITIVES

We can make further progress in bounding $ATE_{3,1}$ by imposing a "no false positives" assumption on self-reported WIC participation (recall that the administratively "corrected" SNAP participation measure is already presumed to be accurate). Such an assumption is common in the food assistance literature (e.g., Almada et al. 2016; Kreider, Pepper, Gundersen, and Joliffe 2012, referenced below as KPGJ) and presumes that households reporting program participation are, in fact, true participants. In other words, we assume that *P*(true non-participation | reported participation) = 0. Validation data from previous studies find only rare instances of these errors of commission (e.g., Bollinger and David 1997; Marquis and Moore 1990). Recent papers using FoodAPS disagree somewhat as to the magnitude of the false positive rate in the case of self-reported SNAP participation. According to Courtemanche et al. (2018, Tables 4 and 5), the false positive rate ranges from 4.53% to 12.17%, depending on the sample and the approach to combining the two administrative data sources. In contrast, estimates presented by Kang and Moffitt (2018) imply a false positive rate of less than 1%, and Meyer and Mittag (2018, Table 1) report a rate of 1.2%. In turn, we calculate that among FoodAPS households with administratively confirmed SNAP participation or confirmed non-participation, only 1.8% of those reporting SNAP benefits are found not to be currently receiving them. The no false positives assumption, as specified, implies that no household simultaneously reports participation in a program and does not actually participate in it, which allows us to set $\theta_0^{3,1} = \theta_1^{3,1} = 0$ in Equation (3), and also that all misreporting of program participation comes in the form of underreporting.[18]

Thus, under the no false positives assumption, the ATE bounds in Equation (3) shrink further and become informative:

$$
\begin{aligned}
-1 + P(Y=1, S=3) + P(Y=0, S=1) + \theta_1^{1,3} - \theta_0^{1,3} \\
\le ATE_{3,1} \le \\
1 - P(Y=0, S=3) - P(Y=1, S=1) + \theta_1^{1,3} - \theta_0^{1,3}.
\end{aligned}
\tag{4}
$$

Note that the error components $\theta_1^{1,3} - \theta_0^{1,3}$ shift the lower and upper bound by the same unknown constant. Taking worst cases across $\theta_1^{1,3}$ and $\theta_0^{1,3}$ in Equation (4), JKZ show that $ATE_{3,1}$ is sharply bounded as

$$
-1 + P(Y=1, S=3) \le ATE_{3,1}^{WC} \le 1 - P(Y=0, S=3). \tag{5}
$$

These worst-case bounds are presented in Panel A (*no additional assumptions*) of Table 6. The bounds are very wide, with the width of $2 - P(Y=0, S=3) - P(Y=1, S=3)$. In our sample, $ATE_{3,1}^{WC}$ may lie anywhere in the range $[-0.762, 0.835]$ with a width of 1.60. We have made important progress, however, in moving away from the [-1, 1] uninformative bounds. Specifically, a fraction of households $P(Y=1, S=3) = 0.238$ are food secure while claiming to participate in both programs, thus raising the lower bound away from -1. We trust their participation responses under the no false positives assumption. Similarly, a fraction of households $P(Y=0, S=3) = 0.165$ are food insecure despite participating in both programs, lowering the upper bound away from 1. While it may not be immediately obvious, we should note that households who report no program participation (S = 0) or participation in WIC only (S = 2) are relevant for the identification of the worst-case bounds. The probability terms in Equation (4) are defined with respect to the population of households reporting any of the four possible program participation patterns (S = 0, 1, 2, or 3). If we had excluded households reporting S = 0 and S = 2 from the analytical sample, we would only be able to identify conditional probabilities of the form $P(\cdot|S = 1 \text{ or } 3)$, rather than the probabilities that we need. A similar argument applies to all other bounds discussed in this paper.

To gain an understanding of how underreporting affects uncertainty about $ATE_{3,1}^{WC}$ beyond uncertainty due to unknown counterfactuals, we trace out the bounds in Equation (4) as a function of $P(S^*=3\,|\,Y=0,S=1)$ and $P(S^*=3\,|\,Y=1,S=1)$ in Figure 1. The figure utilizes a heat map. The blue surface depicts the lower bound on $ATE_{3,1}^{WC}$, while the yellow surface depicts the upper bound. The planes are parallel in this case given the structure of the worst-case bounds in Equation (4). The small red circles identify the bounds in the reference case of no classification error, with the dashed vertical red line spanning the range of these bounds. The worst-case lower bound in Equation (5) is attained at the bottom right corner of the blue surface, where $P(S^*=3\,|\,Y=0,S=1)=1$ and $P(S^*=3\,|\,Y=1,S=1)=0$. The worst-case upper bound is attained at the top left corner of the yellow surface, where $P(S^*=3\,|\,Y=0,S=1)=0$ and $P(S^*=3\,|\,Y=1,S=1)=1$. We will return to this figure when discussing an additional nondifferential errors assumption and its associated 45° solid blue lines.

One way to narrow the bounds in Panel A is to further restrict the nature of classification errors. Suppose, for example, that underreporting of SNAP or WIC participation arises independently of the household's food security status. This *nondifferential errors assumption* specifies that

$$P(S^*=j\,|\,S=k,Y=1)=P(S^*=j\,|\,S=k,Y=0). \tag{6}$$

Evidence from FoodAPS suggests that food secure and food insecure households are about equally likely to underreport the receipt of food assistance.[19] In this case, we can write $\theta_0^{1,3}=\kappa\theta_1^{1,3}$ in Equation (4), where $\kappa\equiv P(Y=0,S=1)/P(Y=1,S=1)$ is observed in the data:

$$\begin{aligned}&-1+P(Y=1,S=3)+P(Y=0,S=1)+(1-\kappa)\theta_1^{1,3}\\&\le ATE_{3,1}\le\\&1-P(Y=0,S=3)-P(Y=1,S=1)+(1-\kappa)\theta_1^{1,3}.\end{aligned} \tag{7}$$

This assumption has substantial identifying power in our application, especially when κ is close to 1. In fact, when $\kappa=1$, which implies that half of the households reporting participation in

SNAP alone are food secure, with the other half being food insecure, classification error ceases to be an issue. In that case, the worst-case bounds in Equation (7) reduce to Manski's (1995) classic worst-case bounds in Section 3.1. Otherwise, the bounds under the nondifferential errors assumption reduce to the bounds shown in Panel B of Table 6:

$$
\begin{aligned}
-1 + P(Y=1, S=3) + \min\{P(Y=0, S=1), P(Y=1, S=1)\} \\
\leq ATE_{3,1}^{ND} \leq \qquad\qquad (7') \\
1 - P(Y=0, S=3) - \min\{P(Y=0, S=1), P(Y=1, S=1)\}.
\end{aligned}
$$

Notice the similarity between these bounds and Manski's worst-case bounds in Equation (2) under no measurement error ($\Theta_{3,1}^{LB} = \Theta_{3,1}^{UB} = 0$). When $\kappa = 1$, the bounds are identical: SNAP verification combined with no false positives and nondifferential errors is equivalent to no measurement error at all. When $\kappa > 1$ such that more than half of the households reporting participation in SNAP alone are food insecure, the Table 6 Panel B upper bound is identical to Manski's no-errors upper bound. When $\kappa < 1$ such that more than half of the households reporting participation in SNAP alone are food secure, the Panel B lower bound is identical to Manski's no-errors lower bound.

In our sample, $\kappa = 0.92 < 1$ which implies $P(Y=0, S=1) < P(Y=1, S=1)$. Thus, the Panel B bounds become

$$
\begin{aligned}
-1 + P(Y=1, S=3) + P(Y=0, S=1) \\
\leq ATE_{3,1} \leq \qquad\qquad (7'') \\
1 - P(Y=0, S=3) - P(Y=0, S=1).
\end{aligned}
$$

The worst-case bounds narrow from $[-0.762, 0.835]$ to $[-0.603, 0.676]$ with a width of 1.28, a 32 percentage point reduction in the width. The lower bound of -0.603 is identical to Manski's lower bound (which presumes accurate reporting). Returning to Figure 1, the worst-case bounds shrink as they become restricted to lie on the solid blue lines. These 45° lines impose the

Equation (6) constraint that the true fraction of households participating in both SNAP and WIC among those reporting participation in SNAP alone, $P(S^* = 3 \mid S^* = 1)$, does not vary by food security status, Y. In particular, the lowest feasible value of $ATE_{3,1}$ is no longer at the bottom right corner of the blue plane, and the highest feasible value is no longer at the top left corner of the yellow plane.

Another way to restrict the nature of classification errors in an attempt to narrow the bounds is to assume, for example, that among households who actually participate in both programs, those who truthfully report the receipt of SNAP benefits do not underreport WIC participation. We defer a comprehensive exploration of such an assumption to future research.

As a polar case, Panel C of Table 6 and Figure 2A highlight the identifying power of an *exogenous selection* assumption that, on average, potential outcomes do not depend on the realized treatment:

$$P[Y(j)=1] = P[Y(j)=1 \mid S^* = k] \quad \forall j,k. \tag{8}$$

This assumption would make sense if households were randomly assigned to food assistance programs such that there were no systematic differences in household attributes across treatment groups. In this case, the lower and upper bound planes coincide. In the absence of classification error, the bounds collapse to a point, 0.0384, depicted by the small red circle. The closed-form bounds across all values of the error components are provided in Panel C of Table 6. In our application, the worst-case bounds narrow from $[-0.762, 0.835]$ to $[-0.576, 0.713]$ under exogenous selection. Even though the exogeneity assumption eliminates uncertainty associated with unknown counterfactuals, the bounds remain very wide due to potential measurement error in WIC participation status.

Now consider *exogenous selection with nondifferential errors* (Panel D of Table 6). Figure 2B shows how the exogenous selection bounds in our application become further constrained under the additional nondifferential errors assumption reflected by the 45° solid blue line. As above, this constraint imposes the restriction that $P(S^{*}=3 \mid S^{*}=1)$ does not vary with food security status, *Y*. The added horizontal zero plane helps to see that the ATE is strictly positive across all values of the error components. Using the closed-form bounds in Panel D of Table 6, the average treatment effect is isolated to lie in the narrow range $[0.0384, 0.0701]$ with width 0.0316, nearly point-identifying the parameter. This upper bound is computed as $P(Y=1 \mid S=3)-P(Y=1 \mid S=1)$ = 0.0701, the observed difference in food security rates between households reporting participation in both programs vs. those reporting participation in SNAP alone.[20]

MONOTONICITY ASSUMPTIONS

Because households choose to participate in food programs on their own accord, exogenous selection, while an important reference case, is an untenable assumption in our setting. Therefore, we do not impose this independence assumption in the remainder of the analysis. Instead, we study how the Table 6 Panel A and B worst-case bounds can be narrowed under relatively weak monotonicity restrictions such as Monotone Treatment Selection (Manski and Pepper 2000; KPGJ) and Monotone Treatment Response (Manski 1997; KPGJ). The MTS assumption formalizes the notion that unobserved factors related to food insecurity are likely to be positively associated with the decision to take up food assistance. Under the MTR assumption, participating in SNAP and WIC would not harm food security, on average, conditional on treatment. We emphasize that both the MTS and MTR assumptions are not specified at the individual respondent level, but rather at the level of respondent groups defined as described in detail below. Simply put, these assumptions hold only "on average."

Formally, MTS in our partially-ordered treatment framework is specified as:

$$P[Y(j)=1 \mid S^{*}=3] \leq P[Y(j)=1 \mid S^{*}=k] \leq P[Y(j)=1 \mid S^{*}=0] \quad \forall\, j \text{ and } k=1,2. \qquad (9)$$

For each potential treatment *j*, we posit that the latent food security probability is (weakly) less favorable among households that enrolled in both programs ($S^{*}=3$) compared with only one program ($S^* = 1$ or 2), and similarly less favorable among households that enrolled in one program compared with no program ($S^* = 0$). We impose no ordering between households that enroll in only one program versus the other. The MTS assumption does not imply that any households would be better off changing their participation status—only that those who chose to participate in more programs start out relatively disadvantaged, on average, under any potential treatment. We acknowledge that this relatively modest assumption could fail in some circumstances. For example, in the case of respondents with significant mental health problems or the homeless, true non-participation need not indicate unobservables that favor food security. In fact, such unobservables (e.g., inability to manage one's life affairs) may be the cause of nonparticipation and also detrimental to food security. If such cases comprise a substantial fraction of the true non-participant subsample ($S^* = 0$), the second inequality in Equation (9) need not hold. Thus, if conditioning variables (X) were specified so that an analytical sample excluded extremely disadvantaged respondents, the MTS assumption may be easier to justify.

Returning to Table 6, the MTS lower bound is given by (see Panel E)

$$-1 + \frac{P(Y=1, S=3)}{P(S=3) + P(Y=0, S=1)} \leq ATE_{3,1}^{MTS}$$

with the upper bound unchanged compared with the worst-case upper bound provided in Panel A. Using the FoodAPS data, the worst-case bounds shrink from $[-0.762, 0.835]$ to $[-0.576, 0.835]$. The lower bound is improved further by combining MTS with the nondifferential errors assumption as shown in Panel F:

$$-1 + \max\left\{P(Y=1 \mid S=3), \frac{P(Y=1, S=3) + P(Y=1, S=1)}{P(Y=3) + P(Y=1)}\right\} + P(Y=0 \mid S=1)\left[P(S=3) + P(S=1)\right]$$

$$\leq ATE_{3,1}^{MTS}.$$

In our application, the improvement is dramatic. In particular, the Panel E bounds narrow from $[-0.576, 0.835]$ to $[-0.058, 0.676]$ in Panel F. The lower bound is improved 70 percentage points compared with the Frame B worst-case lower bound, and it is improved 54 percentage points compared with Manski's no-errors worst-case lower bound. Figures 3A and 3B reveal how the MTS bounds and the MTS bounds with nondifferential errors, respectively, vary with the values of $P(S^* = 3 | Y = 0, S = 1)$ and $P(S^* = 3 | Y = 1, S = 1)$.

To formally specify the MTR assumption, JKZ modify Manski's (1995, 1997) original approach. For a given realized program participation status, we suppose that potential participation in SNAP alone or WIC alone would not harm a household's food security on average compared with no participation, nor would participation in both programs be detrimental on average compared with participation in either program alone:

$$\begin{aligned} &P[Y(3)=1 | S^*] \geq P[Y(1)=1 | S^*] \geq P[Y(0)=1 | S^*] \\ &P[Y(3)=1 | S^*] \geq P[Y(2)=1 | S^*] \geq P[Y(0)=1 | S^*]. \end{aligned} \quad (10)$$

In isolation, this assumption is uninformative, since it precludes strictly negative effects by construction. It can have useful identifying power, however, when combined with the instrumental variable assumptions described next. In particular, it assures that the effect is nonnegative across all values of the instrument. It is difficult to imagine that participation in more food assistance programs would itself cause more food insecurity, at least on average (Currie, 2003).

We can further narrow the bounds by employing MIVs. Monotone instruments are often easier to motivate than standard IVs because they do not require any orthogonality/exclusion restrictions. In our application, we merely require that the instrument leads to a weakly improved latent food security outcome, on average, conditional on the treatment. As MIVs, we use variables reflective of important aspects of local food environment, as recorded in FoodAPS-GC.[21] In particular, we employ the ratio of actual household expenditures on food at home to food expenditures consistent with the TFP recommendations and local food prices—the food expenditure MIV; for details, see Section 2.1.[22] We also investigate the usefulness of a conventional income-to-poverty MIV based on household income and composition considered in KPGJ. An assumption underlying these monotone instruments is that, broadly speaking, more resources in the household and access to cheaper food cannot harm food security. Unlike a standard IV, there is no exclusion restriction that the monotone instrument can affect food security only through its effect on program participation. The MTS assumption described above is a special case of the MIV assumption in which the treatment S^* itself is the instrument.

Let u represent a monotone instrument. The MIV assumption specifies that higher values of u lead to weakly improved food security outcomes, on average, under each treatment:

$$u_1 \le u \le u_2 \Rightarrow P[Y(j)=1 \mid v=u_1] \le P[Y(j)=1 \mid v=u] \le P[Y(j)=1 \mid v=u_2] \text{ for each } j.$$

It should be noted that the MIV assumption is not specified at the level of an individual or as a comparison of individual respondents. Rather, it pertains to a comparison of incidences of food security across respondent groups defined by the value of v. While the conditional probabilities above are not identified, they can be bounded as described by Manski and Pepper (2000). Bounds on the unconditional latent probability, $P[Y(j)=1]$, can, in turn, be obtained by applying the law of total probability and calculating a weighted average of the bounds on $P[Y(j)=1 \mid v=u]$ over different values of u.[23] When combined with MTS or MTR, those restrictions are assumed to apply at each value of the instrument, v. In general, using some covariates as MIVs may (but is not guaranteed to) tighten the ATE bounds. In a somewhat similar manner, Firpo and Ridder (2008) note that averaging bounds obtained from conditional (on covariates) outcome distributions may produce more informative bounds than those obtained from unconditional outcome distributions. We note that the MIV assumption could fail in principle if, compared to groups with low values of v, groups with higher values have attributes that are detrimental to food security. For instance, households less prone to be food secure may choose to reside in places with low food prices, or neighborhoods with low food prices may have few food stores. The former is unlikely to be the case: a recent analysis by Ver Ploeg and Wilde (2018) suggests no systematic sorting of households by food security outcomes across local food environments. The latter goes against basic economic intuition: low food prices are likely a reflection of an intense competition in the local food retail industry and, thus, also likely to be associated with more food stores.

Table 7 demonstrates the identifying power of combinations of the MTS, MTR, MIV, and nondifferential errors assumptions when SNAP participation status is known (through administrative data) and WIC participation may be underreported. Point estimates of the bounds are provided along with Imbens-Manski (2004) confidence intervals (CI) that cover the true value of the ATE with 95% probability. Strictly positive estimated average treatment effects are highlighted in bold. The key finding is that we can identify the ATE as strictly positive and statistically significant when combining the MTS, MTR, expenditure MIV, and measurement error assumptions. In particular, the lower bound on the effect of SNAP and WIC compared to SNAP alone on the food security rate among households in our analytical sample is estimated to be 24 percentage points (without accounting for sampling variability). Accounting for sampling variability reflected in the confidence interval, food security would rise by at least 1.9 percentage points (see the bottom right cell in Panel A of Table 7).

The large difference between the point estimate of the lower bound and the confidence interval lower bound reflects our relatively small sample size of 460 households. A larger sample size would not necessarily shrink the width of the estimated bounds on the average treatment effect since the point estimates of the bounds are consistently estimated. However, these bounds would be more precisely estimated. In our setting, the availability of carefully constructed SNAP validation data outweighs our concern about a relatively small sample size.

ESTIMATES ON ALTERNATIVE SAMPLES

To assess the degree of sensitivity of our results to potentially mismeasured food program participation eligibility, we constructed two alternative samples and reestimated the ATE bounds on them. Alternative sample 1 (N = 342) drops from our main analytical sample households that reside in broad based categorical eligibility (BBCE) states and have income-to-poverty ratio of 1 or higher. Alternative sample 2 (*N* = 429) drops from our main analytical sample households residing in two states covered by FoodAPS that have been found by Mathematica Policy Research to have high fractions of households that might become ineligible for SNAP if the state stopped using the BBCE rules. Thus, compared to the main analytical sample, these alternative samples impose more restrictions in terms of who is considered potentially eligible for joint program participation.

Tables B1 and B2 in Appendix B provide descriptive statistics for alternative samples 1 and 2, respectively. Expectedly, households in alternative sample 1 are somewhat poorer on average than those in alternative sample 2 as well as those in the main analytical sample (see Table 5). Otherwise, descriptive statistics do not seem to differ by much across the three samples.

Tables 8 and 9 present bounds estimated on alternative samples 1 and 2, respectively (the layout of these tables follows that of Table 7). We find the estimates on the alternative samples to be very similar to those obtained on the main analytical sample. While there are some numerical differences throughout, they tend to be small. For example, when using the income-to-poverty MIV, bounds estimated on alternative sample 1 are wider than those obtained on the other two samples and no estimate is statistically significant, whereas bounds estimated on alternative sample 2 are narrower compared to those on the main analytical sample and some become statistically significant.

When combining the food expenditure MIV assumption with the MTS, MTR, and nondifferential errors assumptions, we find qualitatively the same results across all three samples. In particular, the lower bound on the ATE of interest is estimated to be 28 percentage points on alternative sample 1 and 21 percentage point on alternative sample 2 (for comparison, it is 24 percentage points on the main analytical sample). As before, however, sampling variability matters: the effect could be as little as 5 percentage points on alternative sample 1 and is not statistically significant on alternative sample 2 (at the 95 percent significance level).

4. Conclusion

Low-income households in the United States often receive benefits from more than one food assistance program administered by USDA, which raises the question of whether these programs could have meaningful synergies or might be redundant. We investigate the issue by focusing on two popular programs, SNAP and WIC, and apply a novel nonparametric bounding methodology to simultaneously handle a multinomial partially ordered treatment, endogenous household selection into assistance programs, and misreported program participation. The literature has shown that even small amounts of misreporting in surveys can lead to substantial identification decay of treatment effect parameters of interest (e.g., Kreider 2010; Millimet 2011). This paper traces out how the availability of validation data, even for only one of the potential treatments, has the potential to substantially sharpen what can be known about the causal effects of multiple program participation. Gaining a better understanding of the conditions under which validation data are particularly valuable may help guide decisions regarding which programs to validate in the future.

We draw on a unique aspect of FoodAPS in that it provides auxiliary administrative data on SNAP participation, which allows us to partially validate the treatment variable. Under endogenous household selection into the programs, Manski's (1995) classical treatment effect bounds are wide and contain zero, which makes it impossible to sign the causal effects. The bounds become even wider in our environment of systematically underreported program participation. However, similar to Kreider et al.'s (2012) approach, we are able to substantially narrow the bounds by combining conventional, relatively mild monotonicity assumptions on the selection process and restrictions on the patterns of WIC misclassification. The methods employed in this paper extend their framework to allow for multiple treatments with validation data for one of the treatments. Our objective is to strike a balance between making assumptions that are weak enough to be credible but strong enough to be informative.

The methods showcase what can be learned about treatment effects regarding multiple programs when validation data are available for one program but not the other. Exploiting the administratively validated SNAP data in FoodAPS, our key finding is that we can identify the average treatment effect as strictly positive under relatively weak assumptions on the selection process combined with a food expenditure monotone instrumental variable. Monotone instrumental variables are weaker than standard IVs in that they require no *a priori* exclusion restrictions. Using our sample of potentially eligible households, we estimate a lower bound on the effect of participating in both SNAP and WIC compared with participating in SNAP alone on the food security rate at 24 percentage points (without accounting for sampling variability). While this estimated lower bound is large and statistically significant, it is not precisely estimated. With our relatively small sample size of 460 households, food security might rise by as little as 1.9 percentage points after accounting for sampling variability reflected in the 95 percent confidence interval.

Overall, our results provide evidence that SNAP and WIC are not redundant. These findings have direct policy relevance in that they inform policymakers about the existence of complementarities between SNAP and WIC, which can help contribute to designing a more efficient food safety net in the United States. The degree of the complementarity remains an open question owing in part to the relatively small sample size in our analysis. Moreover, the SNAP administrative data could themselves contain errors (e.g., if the household matching algorithm has imperfections), and we do not have direct evidence about the nature of WIC classification errors. Validation of participation status for WIC and other assistance programs beyond SNAP would allow for narrower and more reliable bounds on the average treatment effects of interest.

References

Almada, L., I. McCarthy, and R. Tchernis. 2016. What Can We Learn About the Effects of Food Stamps on Obesity in the Presence of Misreporting? *American Journal of Agricultural Economics* 98(4):997-1017.

Bitler, M., J. Currie, and J. Scholz. 2003. WIC eligibility and participation. *Journal of Human Resources* 38(5):1139–79.

Black, D., M. Berger, and F. Scott. 2000. Bounding Parameter Estimates with Non-Classical Measurement Error. *Journal of the American Statistical Association* 95(451):739-48.

Bollinger, C., and M. David. 1997. Modeling discrete choice with response error: Food stamp participation. *Journal of the American Statistical Association* 92(439):827–35.

Bonanno, A. and S. J. Goetz. 2012. Food store density, nutrition education, eating habits and obesity. *International Food and Agribusiness Management Review* 15(4):1–26.

Brien, M. J. and C. A. Swann. 2000. *Does Participation in Multiple Welfare Programs Improve Birth Outcomes?* Working Paper, University of North Carolina at Greensboro. Available at: https://www.researchgate.net/publication/23551170 (last accessed on October 30, 2017).

Carlson, A., M. Lino, , W.-Y. Juan, K. Hanson, and P. P. Basiotis. 2007. *Thrifty Food Plan, 2006.* CNPP-19. U.S. Department of Agriculture, Center for Nutrition Policy and Promotion.

Coleman-Jensen, A., M. P. Rabbitt, C. A. Gregory, and A. Singh. 2017a. *Household Food Security in the United States in 2016*. ERR-237. U.S. Department of Agriculture, Economic Research Service.

Coleman-Jensen, A., M. P. Rabbitt, C. A. Gregory, and A. Singh. 2017b. *Statistical Supplement to Household Food Security in the United States in 2016*. AP-077. U.S. Department of Agriculture, Economic Research Service.

Courtemanche, C. J., A. Denteh, and R. Tchernis. 2018. Estimating the associations between SNAP and food insecurity, obesity, and food purchases with imperfect administrative measures of participation. NBER Working Paper No. 24412. http://www.nber.org/papers/w24412 (last accessed on September 28, 2018).

Currie, J. 2003. U.S. Food and Nutrition Programs. In *Means Tested Transfer Programs in the United States*, edited by R. Moffitt. Chicago, IL: University of Chicago Press, pp. 199–289.

Economic Research Service (ERS). 2017a. *National Household Food Acquisition and Purchase Survey (FoodAPS)*. U.S. Department of Agriculture (USDA). Available at: http://www.ers.usda.gov/foodaps (last accessed on November 1, 2017).

Economic Research Service (ERS). 2017b. *SNAP Policy Database*. U.S. Department of Agriculture (USDA). Available at: http://www.ers.usda.gov/data-products/snap-policy-database.aspx (last accessed on October 3, 2017).

Firpo, S. and G. Ridder. 2008. Bounds on functionals of the distribution of treatment effects. *Escola de Economia de Sao Paulo Discussion Paper 201*. https://bibliotecadigital.fgv.br/dspace/handle/10438/6647 (last accessed on November 7, 2018).

Fox, M., W. Hamilton, and Lin, B. 2004. *Effects of Food Assistance and Nutrition and Health: Volume 4, Executive Summary of the Literature Review*. Food Assistance and Nutrition Research Report No. 19-4, U.S. Department of Agriculture, Economic Research Service.

Fraker, T. and R. Moffitt. 1988. The Effect of Food Stamps on Labor Supply: A Bivariate Selection Model. *Journal of Public Economics* 35(1):25–56.

Frazis, H. and M. A. Loewenstein. 2003. Estimating linear regressions with mismeasured, possibly endogenous, binary explanatory variables. *Journal of Econometrics* 117(1): 151–78.

Gregory, C. A. and P. Deb. 2015. Does SNAP Improve Your Health? *Food Policy* 50:11–19.

Gundersen, C., B. Kreider, and J. Pepper. 2011. The Economics of Food Insecurity in the United States. *Applied Economic Perspectives and Policy* 33(3):281–303.

Gundersen, C., B. Kreider, and J. Pepper. 2012. The Impact of the National School Lunch Program on Child Health: A Nonparametric Bounds Analysis. *Journal of Econometrics* 166(1):79–91.

Gundersen, C. and V. Oliveira. 2001. The Food Stamp Program and food insufficiency. *American Journal of Agricultural Economics* 84(3):875–87.

Hoynes, H. W. and D. Schanzenbach. 2015. U.S. Food and Nutrition Programs. NBER Working Paper No. 21057. Available at: http://www.nber.org/papers/w21057 (last accessed on March 8, 2018).

Imbens, G. and C. Manski. 2004. Confidence intervals for partially identified parameters. *Econometrica* 72(6):1845–57.

Jensen, H. H. 2002. Food insecurity and the Food Stamp Program. *American Journal of Agricultural Economics* 84(5):1215–28.

Jensen, H. H., B. Kreider, and O. Zhylyevskyy. 2018. Causal Effects under Joint Program Participation when Participation is Validated for Only One of Two Programs. *Department of Economics Working Paper,* Iowa State University.

Kang, K.M. and R. A. Moffitt. 2018. The effect of SNAP and school food programs on food security, diet quality, and food spending: Sensitivity to program reporting error. *Working paper*, Johns Hopkins University.

Keane, M. and R. Moffitt. 1998. A Structural Model of Multiple Welfare Program Participation and Labor Supply. *International Economic Review* 39(3):553–89.

Kreider, B. 2010. Identification decay of regression coefficients in the presence of infrequent classification errors. *Review of Economics and Statistics* 92(4):1017–23.

Kreider, B. and S. Hill. 2009. Partially Identifying Treatment Effects with an Application to Covering the Uninsured. *Journal of Human Resources* 44(2): 409–49.

Kreider, B., J. Pepper, C. Gundersen, and D. Jolliffe. 2012. Identifying the effects of SNAP (food stamps) on children's health outcomes when participation is endogenous and misreported. *Journal of the American Statistical Association* 107(499): 958–75.

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

Lee, H. 2012. The role of local food availability in explaining obesity risk among young school-aged children. *Social Science and Medicine* 74:1193–1203.

Manski, C. F. 1995. *Identification Problems in the Social Sciences*. Cambridge, MA: Harvard University Press.

Manski, C. F., 1997. Monotone Treatment Response. *Econometrica* 65 (6), 1311–1334.

Manski, C. F. and J. V. Pepper. 2000. Monotone Instrumental Variables: With an Application to the Returns to Schooling. *Econometrica* 68(4):997–1010.

Marquis, K. and J. Moore. 1990. Measurement Errors in SIPP Program Reports, in *Proceedings of the Bureau of the Census Annual Research Conference*, Washington, DC: Bureau of the Census, pp. 721-45.

Meyer, B. D. and N. Mittag. 2018. Misreporting of government transfers: How important are survey design and geography? Working paper, CERGE-EI. http://home.cerge-ei.cz/mittag/papers/FoodAPS.pdf (last accessed on October 1, 2018).

Meyer, B. D., W. K. C. Mok, and J. X. Sullivan. 2015a. Household surveys in crisis. *Journal of Economic Perspectives* 29(4):199–226.

Meyer, B. D., W. K. C. Mok, and J. X. Sullivan. 2015b. *The Under-Reporting of Transfers in Household Surveys: Its Nature and Consequences*. Working Paper, Harris Graduate School of Public Policy Studies, University of Chicago.

Millimet, Daniel L. 2011. The Elephant in the Corner: A Cautionary Tale about Measurement Error in Treatment Effects Models. In Missing Data Methods: Cross-sectional Methods and Applications (*Advances in Econometrics*, Vol. 27), edited by David M. Drukker. Bingley, England: Emerald Group Publishing Limited, pp.1-39.

Moffitt, R. 2005. Remarks on the Analysis of Causal Relationships in Population Research. *Demography* 42(1):91–108.

National Research Council (NRC), 2006. *Food Insecurity and Hunger in the United States: An Assessment of the Measure*. Panel to Review the U.S. Department of Agriculture's Measurement of Food Insecurity and Hunger, edited by G.S. Wunderlich and J.L. Norwood. Washington, DC: National Academies Press.

Nguimkeu, P., A. Denteh, and W. Tchernis. 2017. On the estimation of treatment effects with endogenous misreporting. NBER Working Paper No. 24117. https://www.nber.org/papers/w24117 (last accessed on November 8, 2018).

Nord, M. and A. M. Golla. 2009. *Does SNAP Decrease Food Insecurity? Untangling the Self-Selection Effect*. ERR-85, U.S. Department of Agriculture, Economic Research Service.

Oliveira, V. 2017. *The Food Assistance Landscape: FY 2016 Annual Report*. EIB-169, U.S. Department of Agriculture, Economic Research Service.

Ratcliffe, C., S.-M. McKernan, and S. Zhang. 2011. How Much Does the Supplemental Nutrition Assistance Program Reduce Food Insecurity? *American Journal of Agricultural Economics* 93(4):1082–98.

Rose, D. and R. Richards. 2004. Food store access and household fruit and vegetable use among participants in the US Food Stamp Program. *Public Health and Nutrition* 7(8):1081–88.

Stephens, Jr. and T. Unayama. 2015. Estimating the impacts of program benefits: Using instrumental variables with underreported and imputed data. NBER Working Paper No. 21248. http://www.nber.org/papers/w21248 (last accessed on November 8, 2018).

Thorn, B., C. Tadler, N. Huret, C. Trippe, E. Ayo, M. Mendelson, K. L. Patlan, G. Schwartz, and V. Tran. 2015. *WIC Participant and Program Characteristics 2014*. Prepared by Insight Policy Research under Contract No. AG-3198-C11-0010. Alexandria, VA: USDA, FNS.

U.S. Government Accountability Office (U.S. GAO). 2010. *Domestic Food Assistance: Complex System Benefits Millions, but Additional Efforts Could Address Potential Inefficiency and Overlap among Smaller Programs.* Report to Congressional Requesters, GAO-10-346. Washington, DC. http://www.gao.gov/products/GAO-10-346 (last accessed on October 30, 2017).

Ver Ploeg, M. 2010. Access to affordable, nutritious food is limited in “food deserts.” *Amber Waves* 8(1). U.S. Department of Agriculture, Economic Research Service.

Ver Ploeg, M. and P. E. Wilde, P.E. 2018. How do food retail choices vary within and between food retail environments? *Food Policy* 79(August):300–08.

Wilde, P.E. 2007. Measuring the effect of food stamps on food insecurity and hunger: Research and policy considerations. *Journal of Nutrition* 137:307–10.

Yen, S. T., M. Andrews, Z. Chen, and D. B. Eastwood. 2008. Food Stamp Program participation and food insecurity: An instrumental variables approach. *American Journal of Agricultural Economics* 90(1):117–32.

Zhylyevskyy, O., H. H. Jensen, S. B. Garasky, C. E. Cutrona, and F. X. Gibbons. 2013. Effects of family, friends, and relative prices on fruit and vegetable consumption by African Americans. *Southern Economic Journal* 80(1): 226–51.

Endnotes:

[1] The rate of food insecurity among all U.S. households was 12.3% (Coleman-Jensen et al. 2017a).

[2] The second largest program is the National School Lunch Program (NSLP).

[3] Brien and Swann (2000) find that synergies can reinforce welfare programs' effects.

[4] To avoid further complexity, we abstract away from the issue of potentially mismeasured food security status. To the extent that such misclassification exists, the identified bounds on treatment effects reported in this paper would become wider.

[5] Mismeasurement of a binary variable induces a nonclassical measurement error even if such errors occur randomly, and in our setting errors are systematic in one direction and likely related to household characteristics. Stephens and Unayama (2015) show that the inconsistency of a standard IV estimator also arises when a continuous (rather than binary) endogenous treatment variable (e.g., the amount of received program benefits) is either underreported or imputed.

[6] The policies are not randomly assigned, and policies targeted towards participation (such as eligibility rules or ease of recertification) may be correlated with other state policies that could directly affect food security (e.g. policies that affect the financial well-being of poorer households and therefore their ability to buy food).

[7] No administrative data to validate WIC participation are available in FoodAPS.

[8] The income eligibility cutoffs are 130% and 185% of the poverty threshold in the cases of SNAP and WIC, respectively. Since we study households that are potentially eligible for the two programs concurrently, we impose the income cutoff of min{130%, 185%} = 130% of the poverty threshold when constructing the analytical sample. In the case of WIC, more than 86%

of WIC households had incomes at or below 130% of poverty in 2014 (Thorn et al. 2015, Table III.6, p. 44).

[9] Such households can be further categorized as having “low food security” (score of 3-5) or “very low food security” (6-10).

[10] Many variables pertaining to these public policies come from the SNAP Policy Database (ERS 2017b). They refer to SNAP policies and design features at the state level, including the magnitude of outreach expenditures, length of recertification periods, exemptions from the household asset test, reporting requirements, and fingerprinting of applicants, among others. The literature often uses these variables as IVs for SNAP participation (e.g., Gregory and Deb 2015; Ratcliffe, McKernan, and Zhang 2011; Yen et al. 2008).

[11] Our analysis involves using confidential geographic identifiers and other restricted-access FoodAPS data. We access them through a secure data enclave of the National Opinion Research Center (NORC). For details on publicly available FoodAPS data, see ERS (2017a).

[12] In FoodAPS, questions about SNAP and WIC refer to current participation.

[13] A tradeoff is that we cannot point-identify the ATE.

[14] Note that we are not restricting a treatment effect to be the same across households. As emphasized by Moffitt (2005), the classical linear response model assumption, for example, is difficult to justify in the case of government assistance programs that are thought to have heterogeneous effects.

[15] With a binary treatment, the Manski bounds would have a width equal to 1 (and always include 0). In the present context with multiple treatments, the Manski bounds have a width greater than 1.

[16] Although we formally treat administrative data in FoodAPS as the gold standard for SNAP participation, we recognize that these data may contain some errors themselves (e.g., if the household matching algorithm has imperfections).

[17] For future research, there is information reported on food expenditures funded through WIC vouchers at purchase events that might be used to partially validate participation. Of concern is the potential for lags in the timing of using WIC benefits after no longer being certified as a program participant.

[18] Naturally, the bounds presented below widen to the extent that this assumption does not hold exactly or other variables are measured with error. Similarly, point estimates in other studies may not be robust to departures from the implicit assumption of perfectly accurately measured variables.

[19] The chance of being found to participate in SNAP when claiming otherwise is about 49% among food secure households and 44% among food insecure households. The fractions are also similar to each other for the rare cases of reporting SNAP benefits not actually received.

[20] JKZ show that either the lower or upper bound is given by this difference in conditional means depending on whether κ is less than or greater than 1.

[21] Previous studies have shown that the local food environment is an important contributor to food security and health through differences in access, availability, and cost of food (e.g., Rose and Richards 2004; Ver Ploeg 2010; Bonanno and Goetz 2012; Lee 2012). In particular, the relative cost of food in the area can substantially affect a low-income household's ability to provide an adequate diet to its members. Zhylyevskyy et al. (2013) find that lower relative fruit and vegetable prices positively affect the selection of these foods in a study of African American youths and parents.

[22] We report the results for the MIV based on food prices at food stores located within 20 miles of the household's place of residence.

[23] As noted by Manski and Pepper (2000), the MIV estimator is consistent but biased in finite samples. We employ Kreider and Pepper's (2007) modified MIV estimator that accounts for the finite sample bias using a nonparametric bootstrap correction method.

Table 1. Sample Distribution by Reported Program Participation (Weighted)

		WIC *No*	WIC *Yes*
SNAP	*No*	15.3%	16.6%
SNAP	*Yes*	31.4%	36.7%

Notes: This table provides the joint distribution of the analytical sample (*N* = 460) by self-reported household participation in SNAP and WIC. Observations are weighted using FoodAPS household weights.

Table 2. Sample Distribution by Reported WIC Participation and Administratively Matched SNAP Participation (Weighted)

		WIC	
		No	*Yes*
SNAP	*No*	13.0%	13.6%
	Yes	33.6%	39.7%

Notes: This table provides the joint distribution of the analytical sample (N = 460) by household participation in SNAP and WIC. WIC participation is self-reported. SNAP participation incorporates administrative data. In particular, for households that can be matched to administrative records, SNAP participation status reflects the administrative record. For households that cannot be matched, SNAP participation is self-reported. Observations are weighted using FoodAPS household weights.

Table 3. Prevalence of Food Security in Subsamples by Self-Reported Program Participation (Weighted)

		WIC	
		No	*Yes*
SNAP	*No*	53.2%	54.5%
	Yes	52.2%	58.5%

Notes: This table shows the prevalence of food security (in percent, weighted) in each of the four subsamples defined according to self-reported participation in SNAP and WIC. Observations are weighted using FoodAPS household weights.

Table 4. Prevalence of Food Security in Subsamples by Self-Reported WIC Participation and Administratively Matched SNAP Participation (Weighted)

		WIC	
		No	*Yes*
SNAP	*No*	55.1%	50.5%
	Yes	51.6%	59.5%

Notes: This table shows the prevalence of food security (in percent, weighted) in each of the four subsamples defined according to self-reported participation in WIC and administratively matched participation in SNAP. Observations are weighted using FoodAPS household weights.

Table 5. Selected Characteristics of Analytical Sample (Weighted)

Characteristic	Mean	Std.Dev.	Min	Max
Household characteristics:				
Number of household members	4.48	1.76	1	≥ 10 [a]
Number of children	2.34	1.31	0	≥ 7 [a]
Number of children aged 0–6 years	1.57	0.93	0	≥ 5 [a]
Household monthly income, $	1,606.69	954.32	0	≥ 5,000 [a]
Income-to-poverty ratio	0.75	0.36	0	1.30
Weekly expenditures on food at home, $	112.92	126.00	0	≥ 1,000 [a]
Rural household	0.21	0.41	0	1
Household rents its residence	0.78	0.42	0	1
No household member owns or leases a vehicle	0.26	0.44	0	1
Household has used food pantry (past 30 days)	0.11	0.32	0	1
Primary respondent's characteristics:				
Female	0.88	0.32	0	1
Age, years	33.71	10.75	17	≥ 75 [a]
Hispanic (ethnicity)	0.33	0.47	0	1
White (race)	0.55	0.50	0	1
Black or African American (race)	0.29	0.46	0	1
All other races	0.16	0.36	0	1
Less than high school degree	0.32	0.47	0	1
High school degree	0.24	0.43	0	1
GED	0.08	0.28	0	1
Some college education	0.20	0.40	0	1
Associate's degree	0.08	0.27	0	1
Bachelor's or higher degree	0.07	0.25	0	1
Single (never married)	0.44	0.50	0	1
Married	0.29	0.46	0	1
Divorced	0.17	0.38	0	1
Separated	0.08	0.27	0	1
Widowed	0.02	0.15	0	1
Employed	0.43	0.50	0	1
Looking for work	0.17	0.37	0	1
Not working	0.40	0.49	0	1

Notes: This table shows descriptive statistics for selected characteristics of the analytical sample. Observations are weighted using FoodAPS household weights.

[a] An exact maximum value is suppressed due to confidentiality requirements.

Table 6. Sharp Bounds on $ATE_{3,1}$, the Impact on Food Security Associated with Participating in SNAP + WIC vs. SNAP Alone, Under No False Positives when SNAP but not WIC Status is Validated

Assumptions	Mathematical Expression for Bounds	Estimated Bounds
A. *No additional assumptions*	$-1+P(Y=1,S=3) \le ATE_{3,1}^{WC} \le 1-P(Y=0,S=3)$	$[-0.762, 0.835]$; width: 1.60
B. *Nondifferential errors:* $P(S^*=j \mid S=k,Y=1)=P(S^*=j \mid S=k,Y=0)$	$-1+P(Y=1,S=3)+\min\{P(Y=0,S=1),P(Y=1,S=1)\}$ $\le ATE_{3,1}^{ND} \le$ $1-P(Y=0,S=3)-\min\{P(Y=0,S=1),P(Y=1,S=1)\}$	$[-0.603, 0.676]$; width: 1.28
C. *Exogenous selection:* $P[Y(j)=1]=P[Y(j)=1 \mid S^*=k]$	$-\frac{P(Y=0,S=3)+P(Y=0,S=1)}{P(S=3)+P(Y=0,S=1)}$ $\le ATE_{3,1}^{exog} \le$ $\frac{P(Y=1,S=3)+P(Y=1,S=1)}{P(S=3)+P(Y=1,S=1)}$	$[-0.576, 0.713]$; width: 1.29
D. *Exogenous selection + nondifferential errors*	$\min\left\{P(Y=1 \mid S=3),\frac{P(Y=1,S=3)+P(Y=1,S=1)}{P(S=3)+P(S=1)}\right\}-P(Y=1 \mid S=1)$ $\le ATE_{3,1}^{exog,ND} \le$ $\max\left\{P(Y=1 \mid S=3),\frac{P(Y=1,S=3)+P(Y=1,S=1)}{P(S=3)+P(S=1)}\right\}-P(Y=1 \mid S=1)$	$[0.0384, 0.0701]$; width: 0.0316

Table 6: Continued

Assumptions	Mathematical Expression for Bounds	Estimated Bounds
E. *Monotone Treatment Selection (MTS): k* = 1,2: $P[Y(j)=1 \mid S^{*}=3] \leq$ $P[Y(j)=1 \mid S^{*}=k] \leq$ $P[Y(j)=1 \mid S^{*}=0]$	$-1+\dfrac{P(Y=1,S=3)}{P(S=3)+P(Y=0,S=1)}$ $\leq ATE_{3,1}^{MTS} \leq$ $1-P(Y=0,S=3)$	$[-0.576, 0.835]$; width: 1.41
F. *MTS + nondifferential errors*	$-1+\max\left\{P(Y=1 \mid S=3), \dfrac{P(Y=1,S=3)+P(Y=1,S=1)}{P(Y=3)+P(Y=1)}\right\}$ $+P(Y=0 \mid S=1)\left[P(S=3)+P(S=1)\right]$ $\leq ATE_{3,1}^{MTS,ND} \leq$ $1-P(Y=0,S=3)-\min\left\{P(Y=0,S=1), P(Y=1,S=1)\right\}$	$[-0.058, 0.676]$; width: 0.73

Table 7. ATE Associated with Participating in Both SNAP and WIC vs. Participating in SNAP Alone

(A) Expenditure MIV:

	Differential Errors			Nondifferential Errors		
	Lower bound	Upper bound	Width	Lower bound	Upper bound	Width
	MTS + MIV			MTS + MIV		
Point estimates	[-0.485,	0.634]	1.119	[**0.239,**	**0.634]**	0.394
CI	[-0.685,	0.768]		[**0.006,**	**0.752]**	
	MTR + MIV			MTR + MIV		
Point estimates	[0.000,	0.634]	0.634	[0.000,	0.634]	0.634
CI	[-0.164,	0.768]		[-0.164,	0.768]	
	MTS + MTR + MIV			MTS + MTR + MIV		
Point estimates	[0.000,	0.634]	0.634	[**0.242,**	**0.634]**	0.392
CI	[-0.164,	0.768]		[**0.019,**	**0.752]**	

(B) Income-to-Poverty MIV:

	Differential Errors			Nondifferential Errors		
	Lower bound	Upper bound	Width	Lower bound	Upper bound	Width
	MTS + MIV			MTS + MIV		
Point estimates	[-0.549,	0.657]	1.206	**[0.025,**	**0.657]**	0.632
CI	[-0.694,	0.752]		[-0.143,	0.752]	
	MTR + MIV			MTR + MIV		
Point estimates	[0.000,	0.657]	0.657	[0.000,	0.657]	0.657
CI	[-0.118,	0.752]		[-0.118,	0.752]	
	MTS + MTR + MIV			MTS + MTR + MIV		
Point estimates	[0.000,	0.657]	0.657	**[0.031,**	**0.657]**	0.626
CI	[-0.118,	0.752]		[-0.118,	0.752]	

Table 8. ATE Associated with Participating in Both SNAP and WIC vs. Participating in SNAP Alone, Alternative Sample 1

(A) Expenditure MIV:

	Differential Errors			Nondifferential Errors		
	Lower bound	Upper bound	Width	Lower bound	Upper bound	Width
	MTS + MIV			MTS + MIV		
Point estimates	[-0.401,	0.582]	0.983	[**0.275,**	**0.582]**	0.307
CI	[-0.615,	0.761]		[**0.044,**	**0.762]**	
	MTR + MIV			MTR + MIV		
Point estimates	[0.068,	0.582]	0.514	[0.068,	0.582]	0.514
CI	[-0.143,	0.761]		[-0.143,	0.761]	
	MTS + MTR + MIV			MTS + MTR + MIV		
Point estimates	[0.068,	0.582]	0.514	[**0.276,**	**0.582]**	0.306
CI	[-0.143,	0.761]		[**0.050,**	**0.761]**	

(B) Income-to-Poverty MIV:

	Differential Errors			Nondifferential Errors		
	Lower bound	Upper bound	Width	Lower bound	Upper bound	Width
	MTS + MIV			MTS + MIV		
Point estimates	[-0.566,	0.690]	1.256	[-0.044,	0.690]	0.734
CI	[-0.696,	0.790]		[-0.508,	0.790]	
	MTR + MIV			MTR + MIV		
Point estimates	[0.000,	0.690]	0.690	[0.000,	0.690]	0.690
CI	[-0.116,	0.790]		[-0.116,	0.790]	
	MTS + MTR + MIV			MTS + MTR + MIV		
Point estimates	[0.000,	0.690]	0.690	[0.000,	0.690]	0.690
CI	[-0.116,	0.790]		[-0.116,	0.790]	

Notes: This sample (N = 342) excludes households that reside in BBCE states and have income-to-poverty ratio of one or higher.

Table 9. ATE Associated with Participating in Both SNAP and WIC vs. Participating in SNAP Alone, Alternative Sample 2

(A) Expenditure MIV:

	Differential Errors			Nondifferential Errors		
	Lower bound	Upper bound	Width	Lower bound	Upper bound	Width
	MTS + MIV			MTS + MIV		
Point estimates	[-0.528,	0.584]	1.112	**[0.211,**	**0.584]**	0.373
CI	[-0.688,	0.745]		**[**-0.061,	0.745**]**	
	MTR + MIV			MTR + MIV		
Point estimates	[0.000,	0.584]	0.584	[0.000,	0.584]	0.584
CI	[-0.190,	0.745]		[-0.190,	0.745]	
	MTS + MTR + MIV			MTS + MTR + MIV		
Point estimates	[0.000,	0.584]	0.584	**[0.211,**	**0.584]**	0.373
CI	[-0.190,	0.745]		[-0.061,	0.745]	

(B) Income-to-Poverty MIV:

	Differential Errors			Nondifferential Errors		
	Lower bound	Upper bound	Width	Lower bound	Upper bound	Width
	MTS + MIV			MTS + MIV		
Point estimates	[-0.384,	0.546]	0.930	**[0.029,**	**0.546]**	0.254
CI	[-0.565,	0.710]		**[0.051,**	**0.713]**	
	MTR + MIV			MTR + MIV		
Point estimates	**[0.023,**	**0.546]**	0.522	**[0.023,**	**0.546]**	0.522
CI	[-0.185,	0.710]		[-0.185,	0.710]	
	MTS + MTR + MIV			MTS + MTR + MIV		
Point estimates	**[0.040,**	**0.546]**	0.506	[**0.029,**	**0.546]**	0.254
CI	[-0.185,	0.710]		**[0.051,**	**0.710]**	

Notes: This sample (N = 429) excludes households that reside in two states covered by FoodAPS with high fractions of households at risk of becoming ineligible for SNAP if the state stopped using BBCE rules.

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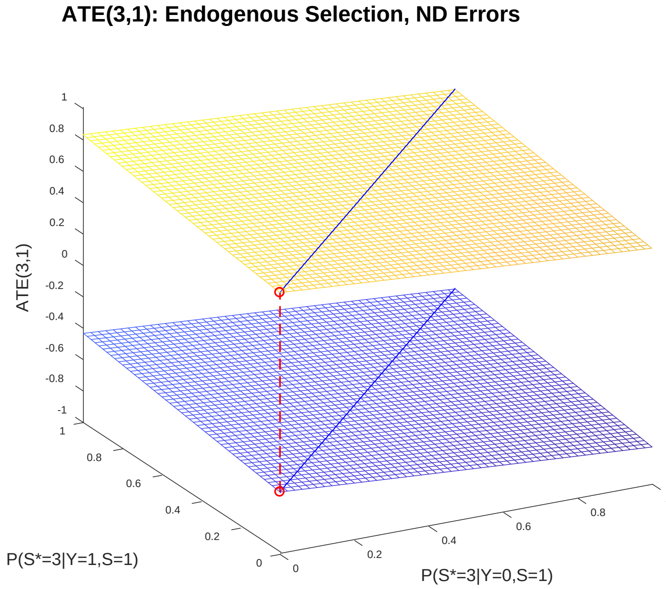

Figure 1. Bounds on ATE_{31} of Participating in SNAP+WIC vs. SNAP Alone Under Endogenous Selection

Notes: The two planes represent the lower and upper bounds for the various combinations of $P(S^* = 3 \mid Y = 0, S = 1)$ and $P(S^* = 3 \mid Y = 1, S = 1)$. The red dashed line represents the identified set in the absence of reporting errors. The solid blue lines depict the bounds under the additional nondifferential errors restriction.

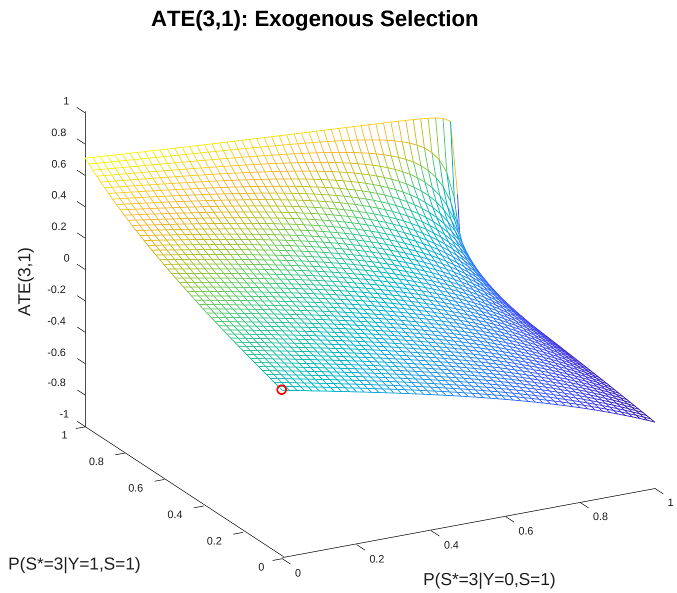

Figure 2A. Bounds on ATE_{31} of Participating in SNAP+WIC vs. SNAP Alone Under Exogenous Selection

Notes: The average treatment effect is point-identified for given values of $P(S^* = 3 \mid Y = 0, S = 1)$ and $P(S^* = 3 \mid Y = 1, S = 1)$. The small red circle represents the identified point in the absence of reporting errors.

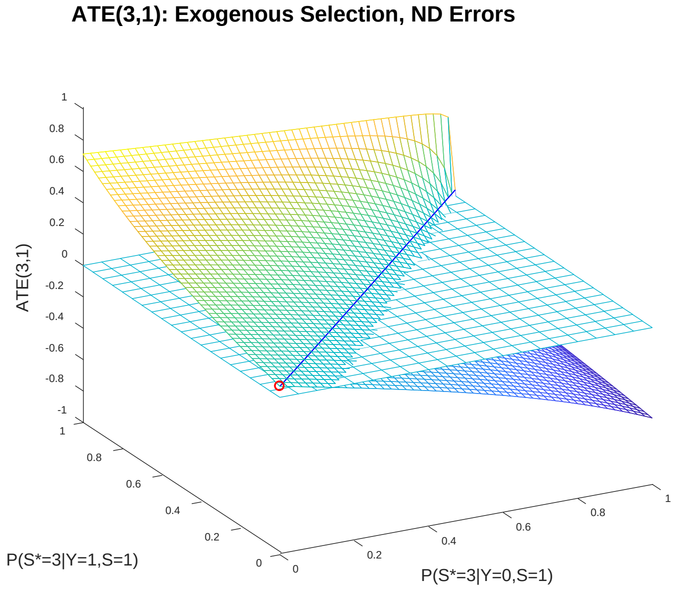

Figure 2B. Bounds on ATE_{31} of Participating in SNAP+WIC vs. SNAP Alone Under Exogenous Selection and Nondifferential Errors

Notes: Identical to Figure 2A, except (i) Figure 2B highlights the zero plane and (ii) the solid blue line depicts the point-identified value under the additional nondifferential errors restriction.

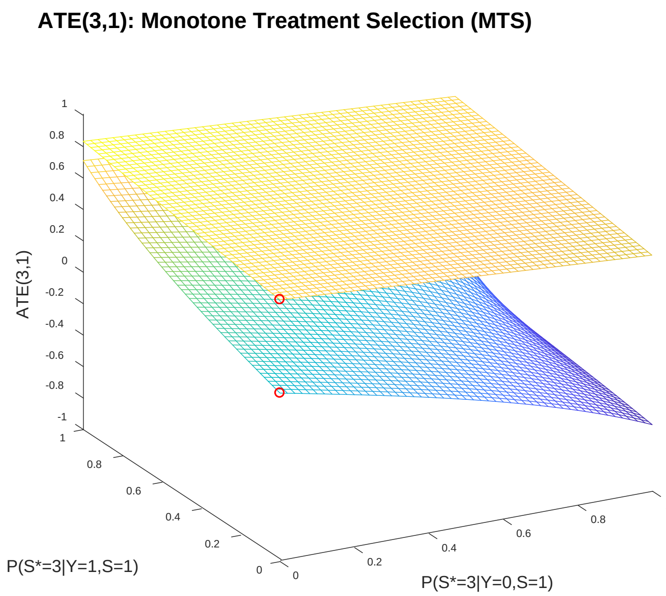

Figure 3A. Bounds on ATE_{31} of Participating in SNAP+WIC vs. SNAP Alone Under Monotone Treatment Selection (MTS)

Notes: The small red circles represent the bounds in the absence of reporting errors.

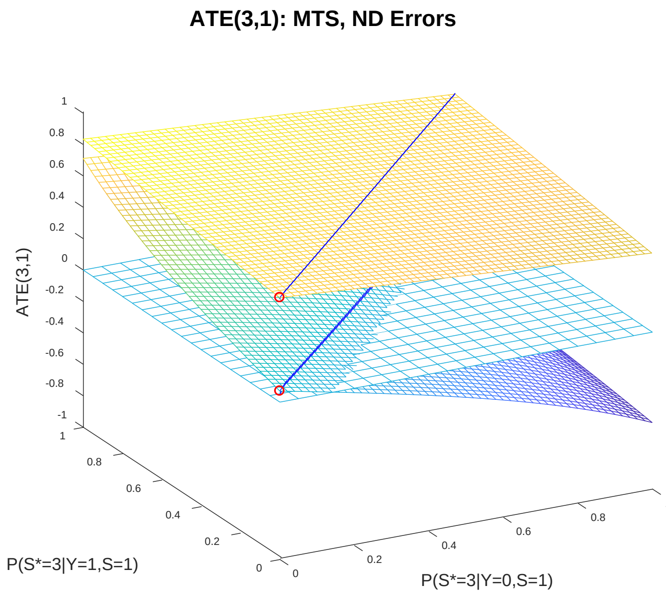

Figure 3B. Bounds on ATE_{31} of Participating in SNAP+WIC vs. SNAP Alone Under MTS and Nondifferential Errors

Notes: Identical to Figure 3A, except (i) Figure 3B highlights the zero plane and (ii) the solid blue lines depict the bounds under the additional nondifferential errors restriction.

Appendix A

Table A1. Selected Characteristics of Subsamples (Weighted)

Subsample:	No program	SNAP only	WIC only	Both programs
Characteristic	Mean (Std. Dev.)	Mean (Std. Dev.)	Mean (Std. Dev.)	Mean (Std. Dev.)
Household characteristics:				
Number of household members	4.41 (1.37)	4.26 (1.85)	5.21 (1.94)	4.44 (1.67)
Number of children	2.18 (1.06)	2.21 (1.33)	2.48 (1.35)	2.46 (1.34)
Number of children aged 0–6 years	1.29 (0.62)	1.43 (0.85)	1.64 (0.88)	1.77 (1.06)
Household monthly income, $	1,974 (820)	1,395 (912)	2,261 (1,038)	1,442 (869)
Income-to-poverty ratio	0.94 (0.32)	0.67 (0.36)	0.94 (0.28)	0.69 (0.36)
Weekly expenditures on food at home, $	91.85 (81.18)	119.37 (134.51)	121.98 (106.71)	111.27 (136.33)
Rural household	0.20 (0.41)	0.19 (0.39)	0.19 (0.40)	0.25 (0.43)
Household rents its residence	0.69 (0.47)	0.85 (0.36)	0.71 (0.46)	0.76 (0.43)
No household member owns or leases a vehicle	0.15 (0.37)	0.30 (0.46)	0.11 (0.31)	0.31 (0.46)
Household has used food pantry (past 30 days)	0.07 (0.26)	0.17 (0.38)	0.09 (0.28)	0.09 (0.28)
Primary respondent's characteristics:				
Female	0.79 (0.41)	0.90 (0.30)	0.86 (0.35)	0.91 (0.29)
Age, years	34.04 (10.75)	34.90 (12.09)	33.73 (9.50)	32.60 (9.90)
Hispanic (ethnicity)	0.35 (0.48)	0.26 (0.44)	0.54 (0.50)	0.31 (0.46)
White (race)	0.50 (0.51)	0.52 (0.50)	0.62 (0.49)	0.57 (0.50)
Black or African American (race)	0.19 (0.39)	0.41 (0.49)	0.14 (0.35)	0.29 (0.45)
All other races	0.31 (0.47)	0.08 (0.27)	0.23 (0.42)	0.15 (0.35)
Less than high school degree	0.33 (0.47)	0.32 (0.47)	0.32 (0.47)	0.32 (0.47)
High school degree	0.19 (0.40)	0.22 (0.42)	0.31 (0.47)	0.24 (0.43)
GED	0.07 (0.25)	0.14 (0.35)	0.08 (0.27)	0.04 (0.20)
Some college education	0.24 (0.43)	0.20 (0.40)	0.09 (0.29)	0.24 (0.43)
Associate's degree	0.09 (0.28)	0.05 (0.21)	0.13 (0.34)	0.09 (0.29)
Bachelor's or higher degree	0.09 (0.29)	0.07 (0.26)	0.08 (0.27)	0.06 (0.24)
Single (never married)	0.29 (0.46)	0.47 (0.50)	0.29 (0.46)	0.50 (0.50)
Married	0.47 (0.50)	0.16 (0.37)	0.58 (0.50)	0.25 (0.43)
Divorced	0.13 (0.34)	0.26 (0.44)	0.09 (0.28)	0.13 (0.34)
Separated	0.08 (0.27)	0.08 (0.27)	0.04 (0.20)	0.09 (0.29)
Widowed	0.02 (0.16)	0.03 (0.16)	0.01 (0.09)	0.03 (0.16)
Employed	0.42 (0.50)	0.39 (0.49)	0.34 (0.48)	0.51 (0.50)
Looking for work	0.18 (0.39)	0.22 (0.42)	0.09 (0.29)	0.14 (0.35)
Not working	0.40 (0.49)	0.38 (0.49)	0.56 (0.50)	0.35 (0.48)
Weighted fraction of analytical sample	13.03%	33.64%	13.59%	39.74%

Notes: This table shows descriptive statistics for selected characteristics of four subsamples that were created by partitioning the analytical sample according to household program participation pattern. SNAP participation measure incorporates administrative data. WIC participation is self-reported. "No program" refers to participation in neither SNAP nor WIC. "Both programs" refers to participation in both SNAP and WIC.

Observations are weighted using FoodAPS household weights.

Table A2A. Probit Models of Program Participation Choice

Model:	One program vs. Both programs	SNAP only vs. WIC only	SNAP only vs. Both programs	WIC only vs. Both programs
Explanatory variable	Estimate (Std. Err.)	Estimate (Std. Err.)	Estimate (Std. Err.)	Estimate (Std. Err.)
# of adults in household	-0.002 (0.064)	-0.209** (0.096)	-0.043 (0.079)	0.126 (0.085)
# of children aged 0–6 years	-0.098 (0.067)	-0.173 (0.137)	-0.098 (0.075)	-0.050 (0.091)
# of children aged 7+ years	0.090 (0.059)	0.104 (0.095)	0.099 (0.065)	0.051 (0.083)
Income-to-poverty ratio	0.519*** (0.197)	-0.858** (0.370)	0.231 (0.219)	1.283*** (0.306)
Rural household	-0.152 (0.171)	-0.173 (0.296)	-0.113 (0.188)	-0.171 (0.252)
Household rents its residence	0.044 (0.163)	0.347 (0.253)	0.164 (0.184)	-0.185 (0.236)
No household member has car	-0.235 (0.162)	-0.049 (0.331)	-0.203 (0.173)	-0.463* (0.280)
Female	-0.313 (0.212)	0.022 (0.326)	-0.263 (0.244)	-0.510 (0.312)
Age, years	0.005 (0.007)	0.029** (0.011)	0.012 (0.008)	-0.008 (0.012)
Hispanic	0.054 (0.163)	-0.521* (0.271)	-0.071 (0.179)	0.387 (0.238)
Black or African American	0.112 (0.178)	0.149 (0.341)	0.128 (0.189)	-0.165 (0.293)
Other race	-0.131 (0.181)	-0.549* (0.334)	-0.210 (0.209)	-0.102 (0.269)
High school degree	0.060 (0.176)	-0.300 (0.317)	0.045 (0.196)	0.099 (0.260)
GED	0.516** (0.250)	0.085 (0.389)	0.571** (0.275)	0.625 (0.400)
Some college education	0.093 (0.200)	0.637* (0.361)	0.229 (0.213)	-0.365 (0.314)
Associate's degree	-0.085 (0.266)	-0.962* (0.530)	-0.149 (0.300)	0.263 (0.359)
Bachelor's or higher degree	0.062 (0.257)	-0.040 (0.380)	0.065 (0.286)	0.117 (0.357)
Married	0.133 (0.168)	-0.949*** (0.306)	-0.130 (0.189)	0.521** (0.226)
Divorced	0.297 (0.215)	-0.496 (0.352)	0.238 (0.229)	0.308 (0.353)
Separated	-0.037 (0.255)	0.729 (0.599)	0.051 (0.263)	-0.513 (0.554)
Widowed	0.275 (0.408)	0.200 (0.775)	0.215 (0.434)	-0.108 (0.619)
Looking for work	0.203 (0.208)	0.716* (0.415)	0.283 (0.224)	-0.372 (0.343)
Not working	0.204 (0.156)	-0.046 (0.265)	0.124 (0.177)	0.281 (0.243)
Constant term	-0.467 (0.428)	1.334* (0.779)	-0.684 (0.473)	-1.539** (0.668)
Sample log-likelihood	-267.86	-88.58	-217.43	-114.65
Pseudo-R^2	0.06	0.30	0.07	0.23

Notes: This table shows coefficient estimates and their robust standard errors for probit models of program participation choice. SNAP participation measure incorporates administrative data. WIC participation is self-reported. "One program" refers to participation either in SNAP only, or in WIC only. "Both programs" refers to participation in both SNAP and WIC.

Statistical significance: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A2B. Additional Probit Models of Program Participation Choice

Model:	SNAP only vs. Not SNAP only	WIC only vs. Not WIC only	SNAP only vs. No program	WIC only vs. No program
Explanatory variable	Estimate (Std. Err.)	Estimate (Std. Err.)	Estimate (Std. Err.)	Estimate (Std. Err.)
# of adults in household	-0.064 (0.063)	0.122 (0.078)	-0.160 (0.105)	0.147 (0.115)
# of children aged 0–6 years	-0.055 (0.068)	0.027 (0.083)	0.353** (0.161)	0.527*** (0.188)
# of children aged 7+ years	0.077 (0.058)	0.010 (0.073)	0.072 (0.102)	-0.044 (0.122)
Income-to-poverty ratio	-0.216 (0.191)	0.927*** (0.257)	-1.360*** (0.370)	0.271 (0.494)
Rural household	-0.070 (0.173)	-0.034 (0.209)	0.032 (0.309)	0.044 (0.428)
Household rents its residence	0.174 (0.163)	-0.255 (0.195)	0.056 (0.274)	-0.215 (0.317)
No household member has car	-0.203 (0.162)	-0.317 (0.238)	-0.340 (0.306)	-0.600 (0.442)
Female	-0.073 (0.206)	-0.254 (0.250)	0.055 (0.334)	-0.306 (0.391)
Age, years	0.015* (0.007)	-0.018* (0.010)	0.020* (0.011)	-0.029* (0.017)
Hispanic	-0.131 (0.167)	0.373* (0.198)	0.022 (0.278)	0.796* (0.441)
Black or African American	0.095 (0.175)	-0.104 (0.254)	-0.100 (0.293)	0.267 (0.461)
Other race	-0.236 (0.188)	0.077 (0.220)	-0.539* (0.327)	-0.102 (0.360)
High school degree	0.042 (0.180)	0.124 (0.220)	-0.163 (0.325)	0.279 (0.390)
GED	0.526** (0.244)	0.193 (0.299)	0.722* (0.407)	0.752 (0.562)
Some college education	0.335* (0.196)	-0.417 (0.256)	0.330 (0.332)	-0.302 (0.523)
Associate's degree	-0.244 (0.271)	0.353 (0.309)	-0.573 (0.454)	0.555 (0.489)
Bachelor's or higher degree	0.042 (0.261)	0.008 (0.290)	-0.268 (0.427)	-0.344 (0.612)
Married	-0.301* (0.171)	0.550*** (0.198)	-0.867*** (0.324)	0.273 (0.373)
Divorced	0.093 (0.205)	0.353 (0.298)	-0.531 (0.348)	0.319 (0.501)
Separated	0.058 (0.250)	-0.495 (0.499)	-0.435 (0.441)	-0.598 (0.804)
Widowed	0.074 (0.411)	0.175 (0.540)	-0.193 (0.683)	0.966 (0.997)
Looking for work	0.173 (0.201)	-0.365 (0.305)	-0.271 (0.343)	-0.479 (0.479)
Not working	0.018 (0.157)	0.239 (0.197)	-0.097 (0.255)	0.414 (0.311)
Constant term	-0.730* (0.422)	-1.621*** (0.554)	1.421* (0.737)	-0.504 (0.939)
Sample log-likelihood	-260.50	-151.34	-87.89	-61.99
Pseudo-R^2	0.07	0.18	0.17	0.19

Notes: This table shows coefficient estimates and their robust standard errors for probit models of program participation choice. SNAP participation measure incorporates administrative data. WIC participation is self-reported. "Not SNAP only" means participation in neither SNAP nor WIC, or in WIC only, or in both SNAP and WIC. "Not WIC only" means participation in neither SNAP nor WIC, or in SNAP only, or in both SNAP and WIC. "No program" means participation in neither SNAP nor WIC.

Statistical significance: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Appendix B

Table B1. Selected Characteristics of Alternative Sample 1 (Weighted)

Characteristic	Mean	Std. Dev.	Min	Max
Household characteristics:				
Number of household members	4.35	1.69	1	$\geq$ 10[a]
Number of children	2.32	1.30	0	$\geq$ 7[a]
Number of children aged 0–6 years	1.52	0.90	0	$\geq$ 5[a]
Household monthly income, $	1,238.01	770.98	0	$\geq$ 4,000[a]
Income-to-poverty ratio	0.59	0.32	0	1.30
Weekly expenditures on food at home, $	109.62	120.26	0	$\geq$ 1,000[a]
Rural household	0.19	0.40	0	1
Household rents its residence	0.79	0.41	0	1
No household member owns or leases a vehicle	0.32	0.47	0	1
Household has used food pantry (past 30 days)	0.14	0.35	0	1
Primary respondent's characteristics:				
Female	0.89	0.31	0	1
Age, years	33.66	11.05	17	$\geq$ 75[a]
Hispanic (ethnicity)	0.34	0.47	0	1
White (race)	0.58	0.49	0	1
Black (race)	0.29	0.45	0	1
All other races	0.13	0.34	0	1
Less than high school degree	0.36	0.48	0	1
High school degree	0.24	0.43	0	1
GED	0.09	0.28	0	1
Some college education	0.16	0.37	0	1
Associate's degree	0.07	0.26	0	1
Bachelor's or higher degree	0.07	0.26	0	1
Single (never married)	0.45	0.50	0	1
Married	0.26	0.44	0	1
Divorced	0.19	0.39	0	1
Separated	0.08	0.27	0	1
Widowed	0.03	0.16	0	1
Employed	0.39	0.48	0	1
Looking for work	0.18	0.39	0	1
Not working	0.43	0.50	0	1

Notes: This table shows descriptive statistics for selected characteristics of the alternative sample 1 (N = 342) that drops households that reside in BBCE states and have income-to-poverty ratio of 1 or higher. Observations are weighted using FoodAPS household weights.

[a] An exact maximum value is suppressed due to confidentiality requirements.

Table B2. Selected Characteristics of Alternative Sample 2 (Weighted)

Characteristic	Mean	Std. Dev.	Min	Max
Household characteristics:				
Number of household members	4.51	1.79	1	$\geq 10^{a}$
Number of children	2.36	1.33	0	$\geq 7^{a}$
Number of children aged 0–6 years	1.57	0.95	0	$\geq 5^{a}$
Household monthly income, $	1,597.34	969.97	0	$\geq 5{,}000^{a}$
Income-to-poverty ratio	0.74	0.37	0	1.30
Weekly expenditures on food at home, $	111.29	118.58	0	$\geq 1{,}000^{a}$
Rural household	0.19	0.40	0	1
Household rents its residence	0.78	0.41	0	1
No household member owns or leases a vehicle	0.27	0.44	0	1
Household has used food pantry (past 30 days)	0.12	0.32	0	1
Primary respondent's characteristics:				
Female	0.88	0.33	0	1
Age, years	33.86	10.92	17	$\geq 75^{a}$
Hispanic (ethnicity)	0.34	0.48	0	1
White (race)	0.53	0.50	0	1
Black (race)	0.31	0.46	0	1
All other races	0.16	0.37	0	1
Less than high school degree	0.34	0.47	0	1
High school degree	0.23	0.42	0	1
GED	0.09	0.28	0	1
Some college education	0.20	0.40	0	1
Associate's degree	0.07	0.26	0	1
Bachelor's or higher degree	0.07	0.26	0	1
Single (never married)	0.43	0.50	0	1
Married	0.30	0.46	0	1
Divorced	0.16	0.37	0	1
Separated	0.08	0.28	0	1
Widowed	0.02	0.16	0	1
Employed	0.42	0.49	0	1
Looking for work	0.17	0.38	0	1
Not working	0.40	0.49	0	1

Notes: This table shows descriptive statistics for selected characteristics of the alternative sample 2 (N = 429) that drops households that reside in two states covered by FoodAPS with high fractions of households that might become ineligible for SNAP if the state stopped using the BBCE rules. Observations are weighted using FoodAPS household weights.

[a] An exact maximum value is suppressed due to confidentiality requirements.