Causal Effects of Multiple Food Assistance Program Participation on Child Food Insecurity

Helen H. Jensen, *Iowa State University*Brent Kreider, *Iowa State University*Oleksandr Zhylyevskyy, *Iowa State University*

MEA Annual Meeting

Cincinnati, OH April 1, 2017

Motivation

Food insecurity harms child's physical, intellectual, social development and health (Gundersen et al., 2011)

Prevalence of food insecurity in low-income population is high. Among households with children and income below 130% poverty (Coleman-Jensen et al., 2016):

- 29% had low food security
 12% had very low food security
 3.2M food-insecure households
- Also, 20% (1.5M households) had food-insecure children

Food programs—e.g., SNAP, NSLP, WIC—aim at reducing food insecurity. Most papers focus on one program. Few study multiple programs (e.g., Keane & Moffitt, 1998)

Many assistance recipients participate in multiple programs. How do various programs interact in creating a **food safety net**?

Methodological Challenge

Identifying causal effect is difficult even for a single program:

- Nonrandom selection: unobservables simultaneously affect food security and program participation
 - > Simple regression methods produce **inconsistent** estimates of causal effects
- Nonclassical measurement error: households systematically underreport benefits, misreporting varies across households with different attributes
 - Standard IV methods produce inconsistent estimates

Allowing for **multiple** programs adds another layer of complexity:

- Participation can no longer be modeled using a binary variable
- Dimensionality of measurement error problem increases

Our approach and methodological contribution:

- Introduce a multinomial, partially-ordered treatment variable to model participation
- Extend partial identification methods of Kreider & Hill (2009), Kreider et al. (2012),
 which account for selection and measurement error in a single framework

Research Focus and Relevance

We develop methodology to study two programs jointly

In application, we focus on:

- SNAP: Supplemental Nutrition Assistance Program (food stamps)
- NSLP: National School Lunch Program (school lunches)

Both are large programs. In 2015 (Oliveira, 2016):

- 46M people participated in SNAP on average per month
- 22M children received free/reduced-price school lunches on average per day
- Annual federal expenditures on SNAP: \$74B, NSLP: \$13B

Receipt of benefits is underreported in surveys (Meyer et al., 2015):

40% of SNAP benefits are not reported in CPS; 45% underreporting for NSLP

Our goal is to account for selection and misreporting and quantify:

- To what extent participation in SNAP+NSLP improves food security compared to no participation
- To what extent participation in both programs augments effect of either one alone

Data Sources

Main source: Food Security Supplement of CPS

FSS is administered in December; we pool years 2002–2010

FSS/CPS provides info on food security, food program participation, food expenditures, socioeconomic characteristics

Analytical sample: households with school-age children and income below 130% of poverty line, N = 10,390

Additional sources (data on IVs and MIVs):

- Quarterly Food-at-Home Price Database (QFAHPD) provides prices for 50+ food groups across 35 geographic areas
- SNAP Policy Database provides state-level info on policies regarding eligibility, reporting requirements, use of biometrics

Child Food Security Measure

FSS has 18-item Household Food Security Survey Module

8 items are child specific (answered by adult proxy)

Examples of questions (referenced to past month):

- Did any of the children ever skip a meal because there wasn't enough money for food? Yes/No
- Did any of the children ever not eat for a whole day because there wasn't enough money for food? Yes/No

Responses are scored (0-1) and summed. Summary score is used to construct categories of child food security:

```
food secure (1) high: score = 0 (79.5%) (88.3%) (2) marginal: score = 1 (8.8%) food insecure (3) low: 2 \le \text{score} \le 4 (10.2%) (4) very low: score \ge 5 (1.5%)
```

Reported Program Participation

Weighted sample distribution by program participation, N = 10,390:

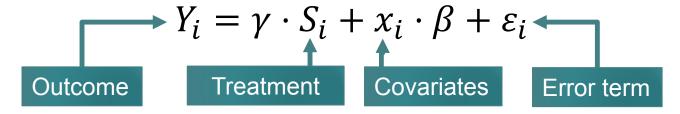
_		_	_
C	NI	Λ	
•	IV	\boldsymbol{H}	г

		yes	no
NSLP	yes	34.9%	35.6%
	no	5.0%	24.6%

- Reference period for food assistance program participation: past month
- Sample: households with 1+ school-age child, income below 130% poverty

Motivation for Our Methodology

Simple parametric approach:



Treatment S_i is **binary**. E.g., $S_i = 1$ if i is on SNAP, 0 if not

If same unobservables affect S_i and Y_i , then $cov(S_i, \varepsilon_i) \neq 0$ and OLS is inconsistent due to **endogeneity**

Measurement error in S_i is **nonclassical** \rightarrow standard IV estimation is inconsistent too

Our **nonparametric bounding** methodology handles endogeneity, misreporting, and multiple treatments (not just *binary* S_i). Also, it allows for heterogeneous response to treatment across i

8

Our Approach: Basics

S*: **true** program participation; $S^* = 0$: none, $S^* = 1$: SNAP only, $S^* = 2$: NSLP only, $S^* = 3$: SNAP+NSLP; S^* is *partially ordered*

S: reported participation; S need not equal S^*

Potential outcomes framework:

 $Y(S^*)$: potential outcome under treatment S^* ; Y = 1 if FS, 0 otherwise

X: covariates (some used as instruments)

We focus on average treatment effects (ATEs):

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

E.g., ATE_{31} measures how likelihood of FS would change if household were to participate in SNAP+NSLP vs. in SNAP only

There are no regression orthogonality conditions to satisfy

Covariates are only used to specify subpopulations

Decomposition Strategy

ATE cannot be point-identified without assumptions even if $S = S^*$

We decompose every formula into what is identified and what isn't

Let's simplify notation: $ATE_{31} = P[Y(3) = 1] - P[Y(1) = 1]$

Consider decomposition:

$$P[Y(3) = 1] = P[Y(3) = 1 | S^* = 3]P(S^* = 3) + P[Y(3) = 1 | S^* \neq 3]P(S^* \neq 3)$$
identified identified not identified identified

Data cannot identify $P[Y(3) = 1 | S^* \neq 3]$ because it refers to unobserved **counterfactual**. We only know $P[Y(3) = 1 | S^* \neq 3] \in [0,1]$

However, using methods of Manski (1995), we can still find worst-case bounds for P[Y(3) = 1], P[Y(1) = 1], and ATE_{31}

Addressing Misreporting

When *S* may deviate from S^* , define: $\theta_i^{j,k} \equiv P(Y = i, S = j, S^* = k)$ P[Y(3) = 1] becomes:

$$P[Y(3) = 1] = P(Y = 1, S = 3) + \theta_1^{-3,3} - \theta_1^{3,-3} + P[Y(3) = 1 | S^* \neq 3] \left\{ P(S \neq 3) + \sum_{j \neq 3} (\theta_1^{-j,j} + \theta_0^{-j,j} - \theta_1^{j,-j} - \theta_0^{j,-j}) \right\}$$

 ATE_{31} is "bounded" as:

$$-P(Y=0,S\neq 1)-P(Y=1,S\neq 3)+\Theta_{3,1}^{LB}$$

$$\leq ATE_{3,1}\leq \qquad \text{unobserved}$$

$$P(Y=0,S\neq 3)+P(Y=1,S\neq 1)+\Theta_{3,1}^{UB}$$

$$\Theta_{3,1}^{LB} \equiv \theta_1^{-3,3} - \theta_1^{3,-3} + \theta_0^{-1,1} - \theta_0^{1,-1}, \ \Theta_{3,1}^{UB} \equiv -\theta_0^{-3,3} + \theta_0^{3,-3} - \theta_1^{-1,1} + \theta_1^{1,-1}$$

Tightening Bounds

Without assumptions, ATE bounds are wide and contain zero

To **tighten** them, we can:

• Use logical constraints on probabilities and auxiliary data to restrict θ 's. Say:

$$\theta_1^{-1,1} \le \min\{P(Y=1, S \ne 1), P(S^*=1)\}$$

- Restrict prevalence of misreporting. Say, constrain value of $\Delta_j \equiv P_j^* P_j$
- Restrict pattern of misreporting. Say, impose "no-stigma verification" assumption: Household with $S \neq 0$ is presumed to provide accurate participation response for both SNAP and NSLP. This assumption zeroes out several θ 's
- Restrict selection process by imposing exogenous selection, monotone treatment selection (MTS), monotone treatment response (MTR), monotone instrumental variables (MIVs), instrumental variables (IVs)

By layering progressively stronger assumptions we demonstrate how they shape inference

Example of Analytical Results

Proposition 2(ii)(B)

Under "no-stigma verification" with endogenous selection, bounds on $ATE_{3,1}$ are as follows:

Lower bound:

$$ATE_{3,1}^{LB} = -P(Y = 1, S \neq 3) - P(Y = 0, S \neq 1) + \max\{0, \Delta_3 - P_{000}\} + \max\{0, \Delta_1 - P_{100}\}$$

Upper bound:

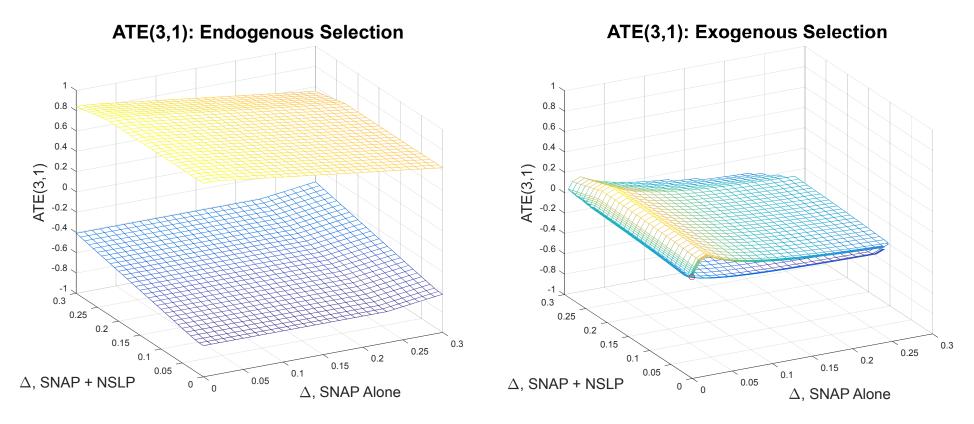
$$ATE_{3,1}^{UB} = P(Y = 0, S \neq 3) + P(Y = 1, S \neq 1)$$
$$-\max\{0, \Delta_3 - P_{100}\} - \max\{0, \Delta_1 - P_{000}\}$$

$$\Delta_1 \equiv P_1^* - P_1, \ \Delta_3 \equiv P_3^* - P_3, \ P_{000} \equiv P(Y = 0, S = 0, V = 0),$$

$$P_{100} \equiv P(Y = 1, S = 0, V = 0)$$

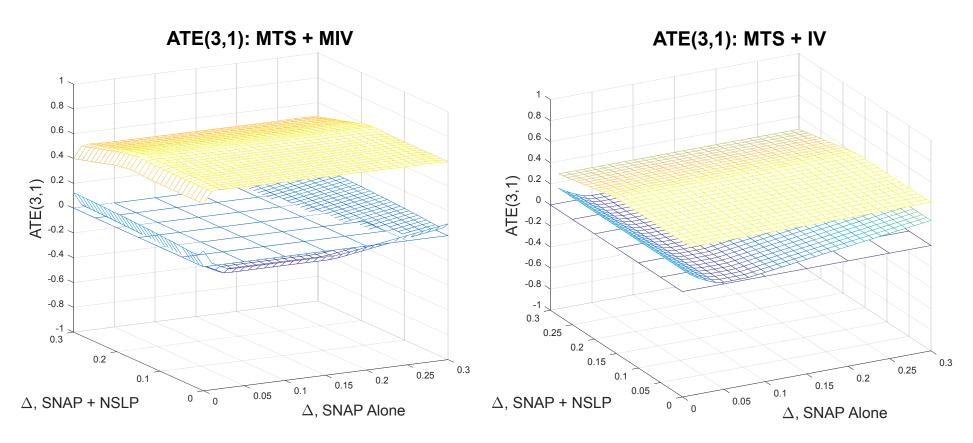
Results: Endog. vs. Exog. Selection

Bounds on ATE of participating in SNAP+NLSP vs. in SNAP only:



Results: MTS + MIV and MTS + IV

Bounds on ATE of participating in SNAP+NLSP vs. in SNAP only:



Summary

Motivating question: How do food programs interact in creating a food safety net?

Research goal: Quantify by how much SNAP+NSLP improves child food security relative to SNAP or NSLP only and relative to nonparticipation

Data: Large national sample drawn from FSS/CPS

Methodology: Nonparametric bounding approach handles endogeneity, misreporting, multiple treatments

Selected result: Bounding under MTS and IV indicates SNAP+NSLP improves child food security beyond effect of SNAP only $(ATE_{3,1} > 0)$

Thank you!

Appendix

More on Food Security

Conceptually, food security means access to enough food for active, healthy life. It implies:

- Ready availability of nutritionally adequate and safe foods, and
- Assured ability to acquire such foods in socially acceptable ways

In practice, food security status is assigned based on a survey module with questions on food-related behaviors under lack of resources:

- Example: "Did you ever cut the size of your meals or skip meals because there wasn't enough money for food?" (Yes/No)
- FSS/CPS uses 18 questions, other surveys may use ≤ 10 questions
- · Questions can focus on household, adults, or children

Answers are converted into # of food-insecure conditions. A threshold separates food secure from food insecure

Prevalence of Child Food Security

Unweighted prevalence by food program participation:

SNAP

		yes	no
NSLP	yes	0.8634	0.8777
	no	0.8691	0.9374

Weighted prevalence by food program participation:

SNAP

		yes	no
NSLP	yes	0.8626	0.8661
	no	0.8700	0.9386

- Reference period: past month. All variables are as reported
- Each cell shows fraction of households with given condition in subsample

Prevalence of No Very Low Child FS

Unweighted prevalence by food program participation:

SNAP

 yes
 no

 yes
 0.9783
 0.9881

 no
 0.9863
 0.9919

Weighted prevalence by food program participation:

SNAP

		yes	no
NSLP	yes	0.9782	0.9877
	no	0.9870	0.9921

- Reference period: past month. All variables are as reported
- Each cell shows fraction of households with given condition in subsample

Reported Program Participation (II)

Unweighted sample distribution by program participation, N = 10,390:

SNAP

		yes	no
LP	yes	34.5%	35.5%
NSLI	no	4.9%	25.0%

- Reference period for food assistance program participation: past month
- Sample: households with 1+ school-age child, income below 130% poverty line

QFAHPD, SNAP Policy Database: Details

QFAHPD is based on Nielsen Homescan: food purchase transactions by a large panel of households. ERS aggregated data within/across households by food group, area, time period

- Time coverage: every quarter between 1999 and 2010
- 54 food groups: e.g., fresh orange vegetables, low fat cheese
- 35 areas partitioning U.S. = 26 metro areas + 9 non-metro areas
- Food prices are expressed in \$ per 100 grams as purchased

SNAP Policy Database is compiled by ERS to provide state-level information on policies regarding program eligibility, reporting requirements, use of biometric technology, etc.

- Coverage: every state and DC, every month between 1996 and 2014
- Allows us to construct nearly all IVs used in previous literature:
 - Continuous: e.g., per capita SNAP outreach spending
 - Binary: e.g., fingerprinting, noncitizen eligibility

Restricting Selection Process

Exogenous selection: expected potential outcomes do not depend on realized treatment:

$$P[Y(j) = 1] = P[Y(j) = 1 | S^* = k] \ \forall j, k$$

Monotone instrumental variable (MIV):

$$u_1 \le u \le u_2 \Rightarrow P[Y(j) = 1 \mid v = u_1] \le P[Y(j) = 1 \mid v = u] \le P[Y(j) = 1 \mid v = u_2]$$

Monotone treatment selection (MTS) is a special case of MIV: decision to participate is monotonically related to food insecurity:

$$P[Y(j) = 1 | S^* = 3] \le P[Y(j) = 1 | S^* = k] \le P[Y(j) = 1 | S^* = 0] \quad \forall j; k = 1, 2$$

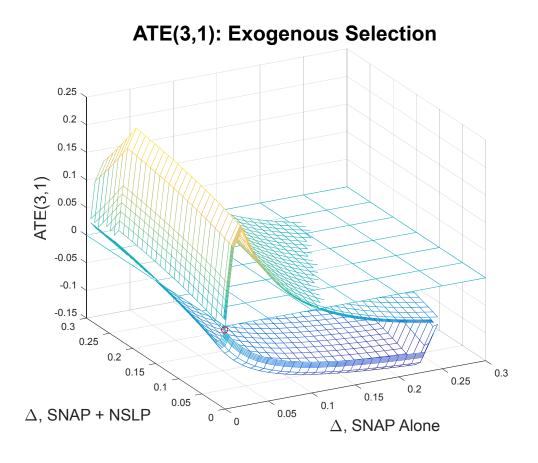
Monotone treatment response (MTR): potential participation in food programs would not harm food security:

$$P[Y(3) = 1 \mid S^*] \ge P[Y(1) = 1 \mid S^*] \ge P[Y(0) = 1 \mid S^*]$$

$$P[Y(3) = 1 \mid S^*] \ge P[Y(2) = 1 \mid S^*] \ge P[Y(0) = 1 \mid S^*]$$
24

Exogenous Selection: Closer View

Bounds on ATE of participating in SNAP+NSLP vs. in SNAP only:



Exog. Selection: Identification Decay

Bounds on ATE of participating in SNAP+NSLP vs. in SNAP only:

	$\Delta_1 = 0$		$\Delta_1 = 0.01$		∆ ₁ =	0.10	
Δ ₃ = 0	LB UB p.e. [-0.007, -0.007] CI [-0.040, 0.026]	width 0.000	LB UB [-0.029, 0.14] [-0.051, 0.16]	width 0.167	LB [-0.094, [-0.106,	-	width 0.101
$\Delta_3 = 0.01$	p.e. [-0.031, -0.004] CI [-0.057, 0.022]	0.028	[-0.053, 0.14] [-0.075, 0.17]	0.195	[-0.118, [-0.130,	_	0.129
$\Delta_3 = 0.10$	p.e. [-0.010, 0.023] CI [-0.036, 0.049]	0.034	[-0.032, 0.17] [-0.054, 0.19]	0.201	[-0.097, [-0.108,	-	0.134

Identification deteriorates with extent of underreporting of SNAP

MTS: Definition

Monotone treatment selection (MTS):

$$P[Y(j) = 1 | S^* = 3]$$

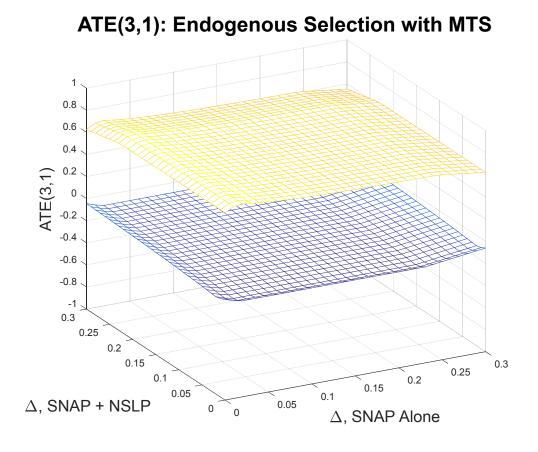
$$\leq P[Y(j) = 1 | S^* = k] \leq$$

$$P[Y(j) = 1 | S^* = 0] \quad \forall j; k = 1, 2$$

Under MTS assumption, decision to participate is monotonically related to food insecurity: households choose to participate in more programs in anticipation of worse food security situation

Endogenous Selection with MTS

Bounds on ATE of participating in SNAP+NSLP vs. in SNAP only:



MTR: Definition

Monotone treatment response (MTR):

$$P[Y(3) = 1 \mid S^*] \ge P[Y(1) = 1 \mid S^*] \ge P[Y(0) = 1 \mid S^*]$$

$$P[Y(3) = 1 | S^*] \ge P[Y(2) = 1 | S^*] \ge P[Y(0) = 1 | S^*]$$

Under MTR assumption, potential participation in (more) food programs would not harm food security on average

MIV: Definition

Monotone instrumental variable (MIV):

$$u_{1} \leq u \leq u_{2} \Rightarrow$$

$$P[Y(j) = 1 \mid v = u_{1}]$$

$$\leq P[Y(j) = 1 \mid v = u] \leq$$

$$P[Y(j) = 1 \mid v = u_{2}]$$

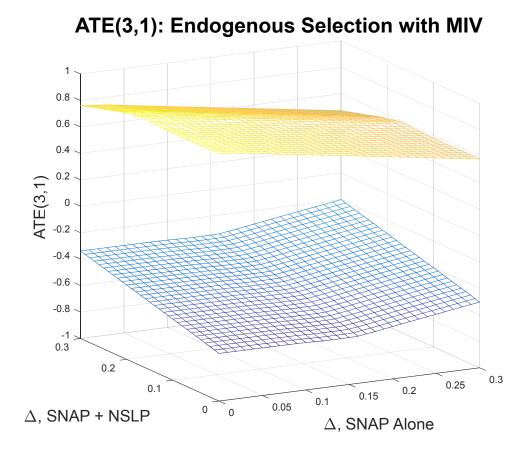
We construct and use:

$$v = \frac{\text{Usual household food expenditures}}{\text{TFP-based minimum expenditures}}$$

Assumption: higher v would not harm food security on average

Bounds under MIV

Bounds on ATE of participating in SNAP+NSLP vs. in SNAP only:



IV: Definition

Instrumental variable (IV):

$$\forall u_1, u_2$$
:
 $P[Y(j) = 1 \mid v = u_1] = P[Y(j) = 1 \mid v = u_2]$

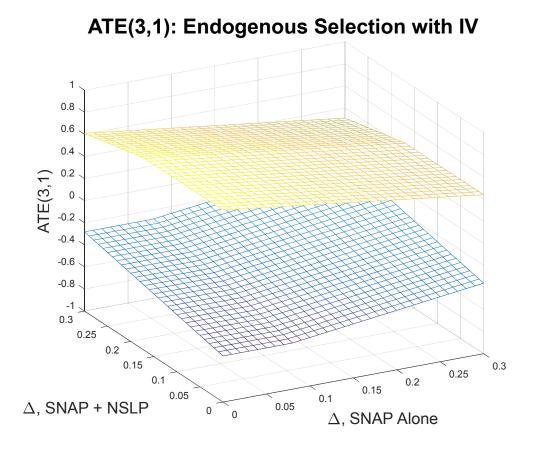
IV is a special case of MIV

We employ **SNAP Policy Database** to construct conventional IVs used in previous literature to instrument for SNAP participation. Many such IVs are binary

We create a multinomial scalar IV by combining seven conventional IVs

Bounds under IV

Bounds on ATE of participating in SNAP+NSLP vs. in SNAP only:



Combining Assumptions

We can combine monotonicity assumptions to **further tighten bounds**

In many cases, $ATE_{3,1}$ can be identified as **strictly positive** even in the presence of substantial classification error

Abbreviations

ATE: average treatment effect

CPS: Current Population Survey

ERS: Economic Research Service of USDA

FSM: food security module

FSS: Food Security Supplement of CPS

MIV: monotone instrumental variable

MTR: monotone treatment response

MTS: monotone treatment selection

NSLP: National School Lunch Program

QFAHPD: Quarterly Food-at-Home Price Database

SNAP: Supplemental Nutrition Assistance Program

TFP: Thrifty Food Plan