Estimating the Impacts of SNAP on Food Insecurity, Obesity, and Food Purchases with Imperfect Administrative Measures of Participation[1]

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Abstract

Administrative data are considered the "gold standard" when measuring program participation, but little evidence exists on the potential problems with administrative records or their implications for econometric estimates. We explore measurement error in administrative data using data from the FoodAPS, a unique dataset that contains two different administrative measures of Supplemental Nutrition Assistance Program (SNAP) participation as well as a survey-based measure. We first document substantial missing data in the two administrative participation variables and show that they are only slightly more strongly correlated with each other than with self-reported participation. Next, we find that estimated misreporting rates can vary considerably depending on assumptions used to consolidate the two administrative variables into a single "true" participation measure. We then show that instrumental variables estimates of the effects of SNAP on food insecurity, obesity, and the Healthy Eating Index are also quite sensitive to these assumptions. Using our preferred approach, which combines information from all three SNAP participation measures, SNAP is not statistically significantly associated with food security, BMI, or obesity, but increases severe obesity while worsening the healthfulness of food purchases.

Keywords: Supplemental Nutrition Assistance Program, food stamps, SNAP, food insecurity, obesity, body mass index, food purchases, food expenditures, healthy eating index, misreporting, measurement error

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I. Introduction

A growing literature documents the problems with relying on survey measures of program participation, which suffer from considerable reporting error, when conducting impact evaluations (Meyer et al., 2015; Mittag, 2016; Nguimkeu et al., 2016). Administrative data are generally assumed to be the "gold standard" to overcoming these econometric challenges, but relatively little evidence exists on the potential problems with administrative records or econometric strategies to address them. We investigate these issues using data from the FoodAPS, which combines a panel of household purchases with a survey and linked administrative data on Supplemental Nutrition Assistance Program (SNAP) participation from both state enrollment records and Electronic Benefit Transfer card expenditures. The data therefore provide the unique opportunity to evaluate the reliability of administrative records by comparing the two different administrative measures to each other as well as to self-reported participation. Moreover, the data also allow us to examine the sensitivity of estimated effects of SNAP on food security, obesity, and diet healthfulness to different assumptions about how to consolidate the available SNAP variables into a single "true" participation measure.

SNAP is the largest means-tested nutrition assistance program in the U.S., serving millions of low income individuals and households. It is administered by the U.S. Department of Agriculture (USDA) with the objective of increasing food security, reducing hunger, and improving health and well-being of low income individuals and households by expanding access to food, nutritious diets, and nutrition education (Mabli et al., 2013). Since 2000, the number of Americans receiving SNAP benefits has almost tripled from about 17 million to 46 million as of

2014 while total spending on SNAP has more than quadrupled from about $17 billion to almost $75 billion.[3]

Proponents assert that SNAP participation reduces food insecurity, lifts millions from poverty, and provides a fiscal boost to the economy during downturns (U.S. Department of Agriculture, 2012). However, the empirical literature on the causal impacts of SNAP has produced mixed results. Several studies have documented the expected negative relationship between SNAP and food insecurity (Van Hook & Ballistreri, 2006; Nord & Prell, 2011; Schmidt et al., 2016), but others have found statistically insignificant or even positive associations (Gundersen & Oliveira, 2001; Hofferth, 2004; Huffman & Jensen, 2003; Wilde et al., 2005; Hoynes & Schanzenbach, 2015). SNAP is also often found to be positively correlated with obesity, but some studies find insignificant or negative effects (Meyerhoefer and Pylypchuk, 2008; Gundersen, 2015; Almada et al., 2016; Almada & Tchernis, 2016; Nguimkeu et al., 2016; Denteh, 2017).

These mixed results reflect two major methodological challenges in evaluating the causal effects of SNAP. The first is non-random selection. SNAP participation is endogenous, so there is a strong likelihood that certain unobservable characteristics are correlated with both SNAP participation and nutrition-related outcomes. Such factors might include current and/or expected future health, human capital, financial stability, and attitudes toward work (Currie, 2003; Kreider et al., 2012).

The second identification problem, and the primary focus of our paper, is measurement error in SNAP participation, which occurs when SNAP participants are coded as receiving no benefits when they actually did (false negatives) or vice versa (false positives). Misreporting of SNAP participation in national surveys has been documented with false negatives being much

[3] Statistics are from http://www.fns.usda.gov/pd/supplemental-nutrition-assistance-program-snap.

more prevalent than false positives. For instance, the estimated false negative rates for SNAP in various surveys range from 20% to 50% (Mittag, 2013). There is a growing literature suggesting that the estimated effect of a misclassified binary explanatory variable (such as SNAP participation) may be substantially biased and may even yield “wrong signs” (Kreider, 2010; Kreider et al., 2012). This is even the case within an instrumental variables framework (Almada, McCarthy, and Tchernis, 2016). Most researchers using survey data do not account for the possibility of non-classical measurement error and the few that do so make assumptions akin to random misreporting.

A fundamental difficulty in dealing with misreporting is that true participation status is unobserved in almost all surveys and validation datasets that link survey responses to administrative records are scarce. Additionally, even linked administrative records are difficult to validate since true participation status is ultimately unobserved. While administrative data are generally considered the “gold standard”, they can still be missing, incorrectly entered, or outdated. Some measurement error may therefore remain. By linking survey responses to administrative data on SNAP participation from two different sources, FoodAPS provides a unique opportunity to investigate issues related to measurement error in both self-reported and administrative measures.

Specifically, we use data from the FoodAPS to offer a number of novel insights related to SNAP and measurement error. First, we provide evidence that administrative SNAP participation measures are not fully reliable, as they both are missing for a number of individuals, frequently disagree for a number of others, and only agree with each other slightly more often than with the self-reported measure. In other words, administrative data do not appear to be the “gold standard”, at least in this context. Second, we consider a variety of methods to consolidate the two administrative variables into a single “true” participation measure and show that estimated misreporting rates, particularly for false positives, can vary considerably. Next, we demonstrate similar sensitivity to assumptions about the administrative variables across estimates of the effects of SNAP on food insecurity, obesity, and the Healthy Eating Index (HEI). This is particularly true when we instrument for SNAP participation using state policies that influence enrollment. In our preferred instrumental variable regressions, which combine information from all three SNAP participation measures, we find that SNAP is not statistically significantly associated with food security, BMI, or obesity, but increases severe obesity while worsening healthfulness of food purchases.

II. Data

The FoodAPS survey is the first nationally representative survey of U.S. households to collect comprehensive data about household food purchases as well as health and nutrition outcomes. FoodAPS is sponsored by the Economic Research Service (ERS) and the Food and Nutrition Service (FNS) of the USDA to support critical research that informs policymaking on health and obesity, food insecurity, and nutrition assistance policy.

The FoodAPS surveyed 4,826 households through a multistage sampling design with a target population roughly equally divided into SNAP households, non-participating low income households with income less than the poverty guideline, non-participating households with income between 100 percent and 185 percent of the poverty guideline, and non-participating households with income at least equal to 185 percent of the poverty guideline.[4] Survey questions relate to demographic characteristics, income, program participation, food insecurity, health,

[4] The FoodAPS field operations were conducted from April 2012 through January, 2013, during which each participating household provided information on all acquisitions of all household members during a 7-day interview period.

weight, and height. In addition, FoodAPS contains detailed information about individual food purchases and acquisitions (merged with nutrition information), along with variables related to local food availability and prices. A unique feature of FoodAPS that makes it well-suited for our study is the linked administrative records on SNAP participation for consenting respondents. This presents an opportunity to study SNAP misreporting more thoroughly than past research.

Self-reported SNAP participation comes from the interview before the survey week. The primary respondent (PR) was asked about SNAP receipt, including information on the date of last receipt and the amount of benefits received. The PR was the designated “main food shopper” for the household. The specific question asking about SNAP participation states, “(Do you/Does anyone in your household) receive benefits from the SNAP program? This program used to be called food stamps. It puts money on a SNAP EBT card that you can use to buy food.” This question does not specify a reference period, and only respondents who answered “yes” were further asked to provide dates of last receipt as well as benefit amounts received. We consider this self-report to reflect current participation, but the exact timing is somewhat ambiguous.

The FoodAPS contains two distinct administrative measures of SNAP participation. The first is from state caseload files covering March 2012 to November 2012 (“ADMIN”). The second is from the electronic benefit transfer (EBT) ALERT database (“ALERT”).[5] The ALERT transaction data contain one recorded per swipe of an EBT Card per user from April through December, 2012.

While such administrative records sound appealing, they have several limitations that likely lead to measurement error. The quality and availability of the administrative data vary

[5] The EBT ALERT database is Anti-Fraud Locator EBT Retailer Transactions (ALERT) system of the Food and Nutrition Service (FNS) of the USDA designed to help detect signs of abuse, fraud, and waste in the SNAP program. Each record of the EBT ALERT data represents one swipe of the EBT card and contains information on the state, store ID, EBT account number, date/time of event, purchase amount, etc.

considerably across states. Households can fall into one of four (4) state groups: (a) one-to-one match was possible between ADMIN and ALERT data because they both contain the same case identifiers (13 states), (b) either the CASEIDs in the ALERT data were scrambled or they are different in the ALERT and caseload data (8 states), (c) CASEIDs are different in the caseload and ALERT data, and the former does not include benefit disbursement dates (2 states), and (d) the state did not provide SNAP enrollment data (5 states containing 880 sample households).

Another source of measurement error is that matching from the FoodAPS to administrative SNAP records was probabilistic. All the matches to ADMIN data were based on first name, last name, phone number, and house address (including apartment number) and links were considered "certain matches" if the associated matching score exceeded a pre-determined threshold.[6] The linkage to the ALERT data was similarly probabilistic, except in the state group (a) described above. In state group (a), if a household *first* matched probabilistically to caseload data, then a one-to-one match was possible to the ALERT data using CASEIDs. Thus, it is reasonable to presume that the quality of the administrative linkage would be highest in the 13 states in state group (a). Nonetheless, the quirks of probabilistic matching would suggest unknown degrees of error in the administrative measures of participation in all states. In other words, one can imagine that true SNAP households whose matching score was not high enough to be sufficiently definitive would be have to be classified as non-matches (non-participants), and vice versa.

Additionally, the ADMIN and ALERT data may contradict each other because of discrepancies in timing. In the ADMIN data, participation is in most cases defined based on current enrollment status during the interview week. However, in the two states in category (c)

[6] The probabilistic matching was implemented using LinkageWIZ record linkage software and resulted in Cartesian join of each survey household with all SNAP enrolment record (or EBT ALERT). The contractors determined a pre-specified score above which to classify a match as "certain." FoodAPS does not contain the raw matching scores.

mentioned above, exact dates are not available, thus, their current participation status was conditional on the results of the EBT ALERT linkage. For instance, in a few cases, an individual is considered a current participant if they matched at any point during the nine-month data availability window and also matched to the EBT ALERT, with date of last receipt (per ALERT) within 36 days of the end of the survey week.[7] Some former and future participants will therefore incorrectly be coded as current participants. The same logic is true for the EBT ALERT data. In the ALERT data, an individual is coded as a participant if she had an EBT card transaction during the survey week and matched to the EBT ALERT data. SNAP participants who did not use the EBT card that week – for instance because they stocked up on groceries the previous week, or because their monthly benefits already ran out (food stamp cycling) – were coded as non-participants if they were also current non-participants per ADMIN.[8]

Finally, another issue with the ALERT data is that no match is attempted (and therefore the variable is missing) if the household does not either report SNAP participation or a transaction during the survey week using an EBT card. While the majority of such individuals are likely true non-participants, some could be true participants who both denied participation in the program and also did not disclose that certain purchases during the survey week were made with an EBT card. Given the high prevalence of false negatives reported in the literature, the fraction of such individuals could be non-trivial.

Turning to a discussion of the other variables used in our analyses, our first three dependent variables relate to food insecurity. These come from the ten-question household food

[7] FoodAPS's measure of current SNAP participation based on the two administrative linkages is summarized in the SNAPNOWADMIN variable, which combines the results of the two administrative matches into a single variable.
[8] In the remainder (majority) of cases in the two states whose current SNAP participaton cannot be determined based on EBT ALERT matching (conditional on ADMIN) or ADMIN (conditional on ALERT) due to missing information or non-matches, their current SNAP participation is coded as "no match" in SNAPNOWADMIN.

security questionnaire included in FoodAPS based on USDA's 30-day Food Security Scale.[9] The specific outcomes are the number of affirmative responses (where a larger number indicates worse food security), a dummy for whether the household has low food security (defined as having affirmative responses to three to five questions), and a dummy for whether the household has very low food security (six or more affirmative responses).

The next several dependent variables relate to body weight. The FoodAPS contains self-reported height and weight for the household responder. We use this information to create five outcomes: body mass index (BMI) and indicators for overweight or obese (BMI≥25), obese (BMI≥30), severely obese (BMI≥35), and underweight (BMI<18.5).[10] Dichotomous variables are often used in addition to continuous BMI in the obesity literature since health is not monotonically decreasing in weight. Weight gain generally improves health at low levels of BMI, and the large increase in mortality risk from excess weight does not begin until around the severe obesity threshold (Courtemanche et al., 2016). The health implications of any impacts of SNAP would depend on which portion of the BMI distribution the effects are strongest (i.e., the health implications of SNAP's effects would potentially be more substantial if they are stronger on severe obesity).

The final dependent variable relates to food purchases. Following prior studies such as Volpe, Okrent, & Leibtag (2013), we use a summary measure of healthfulness of food purchases called the Healthy Eating Index (HEI-2010). The HEI-2010, designed by the USDA, aims to capture the degree of adherence to dietary guidelines. We use the total HEI-2010 scores for all

[9] Please see the Appendix for the list of question on the ten-question household food security question.
[10] Body mass index is defined as weight in kilograms divided by height in squared meters.

items for all the entire survey week for each household.[11] This HEI variable is computed by FoodAPS staff and available as a linkable auxiliary dataset.

The FoodAPS also contains a number of variables that we use as controls. These include dummy variables for gender, educational attainment (dummy variables for having less than high school diploma, high school diploma but no college education, and some college education, with college degree or higher being the omitted base category), race/ethnicity (non-Hispanic black and non-Hispanic white, with other being the base category), marital status (married and formerly married, with never married as the base category), whether any individuals under 5 years old or at least 65 years old are present in the household, whether the respondent worked last week, and whether the household lives in rural census tract. Continuous controls include respondent's age, household size, and household monthly gross total income.

Our final sample is subject to three restrictions. First, we include only households in which the primary respondent is at least 18 years old. Next, we drop households with missing values for any dependent or control variables. Finally, we exclude 122 households who did not provide consent for administrative verification. The resulting sample contains 4,491 households. The sample size will vary somewhat across analyses, though, as we will experiment with different ways to handle missing data in the SNAP variables.

Table 1 presents summary statistics for our final sample. Table 1 presents summary statistics for our final sample. From Table 1, FoodAPS's primary respondents have average BMI of 28.02 while 31 percent and are 33 percent likely to be overweight and obese, respectively. Also, almost 70 percent of the primary respondents are female, 44 percent are married, about one-half report having worked last week.

[11] Further information on HEI scores can be found at http://epi.grants.cancer.gov/hei.

III. Disagreement among SNAP Participation Measures

As discussed in Section II, the FoodAPS includes one self-reported measure of SNAP participation (REPORT) and two administratively verified participation measures (ADMIN and ALERT), and there are reasons to expect discrepancies among the three variables. This section documents the extent of disagreement among the three measures as well as the extent of missing data in each variable.

Table 2 presents information about the extent of disagreement. In addition, the last column of reports how we classify disagreements into various categories, which are explained below. There is 60.2% agreement among all three measures (i.e., all three variables either indicate participation or non-participation), which we label as Category A. The rest of the households with non-missing self-reported data have different types of disagreement among the three measures. In Category B, making up about 13.13% of households, two measures agree while the third is missing. Category C respondents, which account for 4.38%, have both administrative measures being in agreement but in conflict with the self-reported participation. Households with only the self-reported participation variable who are missing both administrative measures (Category D) make up 15.04% while the remaining 7.27% of respondents are lumped into miscellaneous types of disagreement in Category E.

Table 3 reports the numbers of individuals classified as non-SNAP participants, participants, and missing based on each of the three measures. Based on these numbers, we compute rates of SNAP participation and missing data. The participation rates are 30.5%, 29.8%, and 35.1% using REPORT, ADMIN, and ALERT, respectively. A striking result is that both administrative measures contain far more missing data than the self-reported variable. About 22.1% and 23.7% of consenting households are missing the ADMIN and ALERT participation measures, respectively, compared to hardly any that are missing the self-report. As discussed previously, these missing values occur for a variety of reasons, but the majority for ADMIN are due to states not providing caseload records, while the majority for ALERT are due to a probabilistic match not being attempted. Note that missing data may help to explain why the estimated participation rate is highest using ALERT. Recall that individuals for whom no match to the ALERT data was attempted are those who did not self-report either SNAP participation or EBT card use. Most, of those households are likely true non-participants, meaning that excluding them leads to an over-estimation of the participation rate. However, at least some of them are likely true participants due to the well-known issue of underreporting of SNAP participation. To illustrate, if we were to assume that all individuals who are missing ALERT information are true non-participators, the estimated participation rate would drop to 26.8%, which is below that of the other two measures.

In sum, the high frequency and potentially non-random nature of the missing data calls into question whether administrative data are preferable to self-reports even if they are more reliable in cases where the data are not missing. This also points to the potential appeal of combining all three measures into a predicted probability of participation rather than simply discarding the self-report. We will do this in Section V.

Table 4 reports pairwise Pearson correlation coefficient estimates for the three participation measures. The three measures are roughly equally positive correlated, although the correlation between the two administrative measures, 0.841, is slightly stronger than the correlations between each administrative measure and the self-reported measure, which are both slightly over 0.75. The key point, though, is that a non-trivial amount of disagreement exists even between the administrative variables.

IV. Misreporting Rates

This section introduces several approaches or ad hoc rules to consolidate the two administrative participation measures into a single "true" participation measure, and then evaluates how these rules influence the estimated rate of misreporting in the self-reported participation measure. The seven rules we used to consolidate ADMIN and ALERT participation variables are as follows:

1) **Always use ADMIN**: Here, we always consider the matching to ADMIN data as the "true" participation measure and completely ignore the linkage to ALERT data.
2) **Always use ALERT**: The ALERT participation variable takes precedence over the ADMIN measure in this scenario.
3) **Always use ADMIN unless missing**: This rule is similar to (1) but for households missing ADMIN data, their participation status is set to the ALERT participation measure.
4) **Always use ALERT unless missing**: Similarly, to (2), the ALERT data takes precedence but is set equal to the ADMIN participation measure for households missing ALERT data.
5) **Use ADMIN and ALERT only if they agree**: This rule sets the "true" participation measure to equal to both ADMIN and ALERT, *only* if they agree (i.e., if ADMIN =ALERT=i, i=0, 1). When they disagree, their values are set to missing.
6) **Use ADMIN and ALERT, assigning more weight to matches**: This rule is similar to (5) as it uses both if they are in agreement. However, when they disagree, we set the "true" status to participation, unless either is missing in which case the "true"

status is set to the value of the non-missing variable. In other words, this rule treats households as "true" participants if at least ADMIN or ALERT confirms participation. Otherwise, the household is considered a non-participant unless both are missing.

7) **Use ADMIN and ALERT, assigning more weight to non-matches**: This rule is similar to (6). However, when ADMIN and ALERT disagree, we set the "true" status to non-participation, unless either is missing in which case the "true" status is set to the value of the non-missing variable. In other words, this rule treats households as "true" non-participants if at least ADMIN or ALERT confirms non-participation. Else, the household is considered a participant unless both are missing.

Table 5 presents estimates of false negative and false positive reporting errors under each of these decision rules above. The table shows that estimates of reporting errors vary considerably, particularly for false positives. The false negative rate ranges from 15.8 percent to 18.4 percent and the false positive rate varies from 2.8 to 10.6 percent. Some patterns also emerge. First, while using ALERT to augment ADMIN reduces the rate of false negatives (going from Rule 1 to Rule 3), the false positive rate increases slightly. Second, on the contrary, using ALERT data to augment the ADMIN variable tends to increase (decrease) false negatives (false positives) slightly.

V. Econometric Analyses and Results

We next turn to our regression estimates of the effects of SNAP on food insecurity, weight outcomes, and dietary healthfulness. This section has two primary goals. The first is to illustrate the sensitivity of these estimates to the assumptions, introduced in the previous section, about how to code "true" participation in cases of disagreement between the two administrative measures. The second is to implement a "preferred specification" that utilizes all three SNAP participation measures – including the self-reported one – to predict true participation, while also utilizing instrumental variables (IVs) to address non-random selection into SNAP. The aim, then, is to improve on prior literature on these treatment effects by simultaneously addressing both measurement error and endogeneity.

We begin with naïve ordinary least squares (OLS) regressions of the form

$$y_{is} = \beta_0 + \beta_1 SNAP_{is} + \boldsymbol{\beta_2 X_{is}} + \varepsilon_{is} \quad (1)$$

where y_{is} is the outcome variable for individual/household *i* living in state *s* (separate regressions for each of the outcomes discussed in Section II), $SNAP_{is}$ is an indicator of SNAP participation (separate regressions for each decision rule from Section IV), $\boldsymbol{X_{is}}$ is a vector of the control variables from Section II, and ε_{is} is the error term. $\hat{\beta}_1$ could be a biased estimator for SNAP's treatment effect for two reasons. The first is measurement error from using only the sreported participation variables (which is potentially misclassfied) or applying a flawed decision rule to code SNAP participation. If this measurement error is classical $\hat{\beta}_1$ will be biased toward zero, but if the measurement error is non-classical the bias could go in either direction.[12] It might be reasonable to suspect that some of the inconsistencies among the administrative measures, such as the inability to match names with sufficient certainty, are as good as random. However, other inconsistencies, such as appearing in the caseload records but not using an EBT card in the past 30 days, arise from personal choices and may therefore be correlated with the error term. The second source of bias is the well-known issue of endogenous SNAP participation. To provide one of several possible scenarios, if eligible individuals with high unobserved demand for

[12] Note that measurement error in a binary variable is necessarily non-classical (see, for e.g., Aigner, 1973; Lewbel, 2007).

unhealthy food are the most likely to enroll, SNAP participation may be positively correlated with the error terms in the weight-related regressions and negatively correlated with the error terms in the food security and HEI regressions.

We next turn to IV regression in an attempt to address these issues. The first stage of the IV model takes the form

$$SNAP_{is} = \gamma_0 + \boldsymbol{\gamma_1 Z_s} + \boldsymbol{\gamma_2 X_{is}} + \varepsilon_{is} \tag{1}$$

where $\boldsymbol{Z_s}$ is the set of state-level instruments. Following prior literature (Meyerhoefer and Pylypchuk, 2008; Kabbani and Wilde, 2003), these include an indicator for whether the respondents' state requires SNAP applicants to be fingerprinted (biometric verification), the percentage of SNAP participants who are required to recertify within three months or less, and outreach program expenditures in nominal dollars ($1000s). If these state policies are uncorrelated with unobservable determinants of food security, weight, and HEI, then they solve the problem of endogenous participation. However, they are unlikely to adequately address the measurement error issue unless the error is classical. As shown by Almada et al. (2016), non-classical measurement error can substantially alter IV estimates and cause them to fall outside of non-parametric upper bounds. Measuring SNAP participation as accurately as possible therefore remains critical even in IV specifications, which is why our preferred strategy will leverage information from all three SNAP measures to compute a predicted probability of participation.

This preferred measure combines the three participation variables into a single variable based on the categories described in Section IV and reported in Table 4. Specifically, the new variable, which we name "SNAP-ABC", combines information from Categories A, B, and C and sets to missing observations in Categories D and E. For Category A, all three variables are in agreement, so we are comfortable setting the "true" participation variable equal to the associated value. For Category B, two of the three variables are in agreement while the third is missing. Again, we set our preferred participation variable, SNAP-ABC, equal to the associated value. Essentially, we do not place any weight on the third variable that is missing as long as the other two agree. Finally, we considere the self-reported participation value in Category C to be erroneous since the two administrative variables are in agreement but opposite to the self-report. Thus, we set SNAP-ABC to the particular value to which the two administrative values are equal.

We code the participation status of observations in Category D who have non-missing self-reported participation but missing both administrative measures as missing values (i.e., SNAP-ABC=.). Finally, we also set the participation status of respondents in Category E to missing because all three measures have various disagreements such that we are unwilling to classify them as participants or otherwise. For our preferred regression specifications, we use SNAP-ABC as the "true" measure of participation and perform a regression-based imputation (using all control variables) of participation probability for the missing values (Categories D and E). The present results do not account for the uncertainty introduced by imputing missing values; future versions of the paper will attempt to do so through multiple imputation or bootstrapping.

Table 6 reports OLS (linear probability models) and IV regressions for our food security and diet healthfulness outcomes. The first row reports the estimates using the self-reported participation variable. The next eight rows use the different approaches to combining the two administrative measures described in section IV. The last two rows then present estimates using: (1) our preferred participation measure, SNAP-ABC, with missing values dropped; and (2) the same SNAP-ABC measure but with imputations for the missing values. Tables 7 reports similar regression results but for our weight outcomes (BMI and the indicators for obese and severely obese).

The OLS estimates in Table 6 suggest a positive and statistically significant association between SNAP participation and food insecurity outcomes. This finding is not surprising given the well-known negative selection into SNAP participation (i.e. food insecure individuals are most likely to take up the program). While the estimates are always positive and significant, there is non-trivial variability in their magnitudes. The estimates range from 6.9 to 9.4 percentage points for food insecurity, meaning the largest one is 36% larger than the smallest. For very low food security, the magnitudes range from 3.4 to 6 percentage points – a 77% difference.

Columns (3) and (4) of Table 6 report the IV estimates for the food security outcomes. In all cases, the participation measures are statistically insignificant, which may be attributable to the inherent inefficiency of IV estimation (the standard errors are roughly ten-fold larger than those from OLS) combined with the relatively small sample size of the FoodAPS. More interestingly, the magnitudes vary substantially across the different participation measures. Eight of the coefficient estimates are negative for food insecurity, suggesting that SNAP improves food security. However, these negative coefficient estimates range from nearly zero using our preferred SNAP-ABC measure to a substantial 24.5 percentage points – over double the sample rate of food insecurity – using self-reported participation.[13] Moreover, the sign is positive under two of the decision rules. For very low food security, the sign of the coefficient estimate is counterintuitively positive in all cases, but with a very wide range of 3.8 to 17.8 percentage points. In sum, the IV estimates appear much more sensitive to construction of the participation

[13] We have reported only direction of effects and statistical significance for the IV estimates in Panel C that impute missing values for our preferred participation measure, SNAP-ABC, because they have not yet been cleared for disclosure by the USDA.

measure than those using OLS. This is consistent with Almada et al.'s (2016) simulations demonstrating the large swings in IV estimates that can occur with even modest measurement error in SNAP participation.

The results for the Healthy Eating Index reported in in Columns (5) and (6) of Table 6 suggest that SNAP participation reduces adherence to the 2010 Dietary Guidelines for America. The OLS and IV estimates are always negative, and all but one are statistically significant. Again, the mangitudes are much more sensitive to assumptions about the SNAP participation measures with IV than OLS. The OLS estimates range from -1.4 to -1.9, for a spread of 36%. The IV estimates fluctuate between -6.9 to -19 – nearly a three-fold difference.

The results for the weight outcomes are presented in Table 7. From the first three columns of Table 6, the OLS estimates suggest a positive and significant association between SNAP participation and BMI, the probability of being obese, and the probability of being severely obese. The coefficient estimates range from 1.2 to 1.6 units for BMI, 5.4 to 9.9 percentage points for Pr(Obese), and 3.5 to 6.1 percentage points for Pr(Severely Obese). Using IV, effects on BMI and obesity become insignificant in all cases, with the signs being positive in most cases for BMI but negative in most cases for obesity. The magnitudes are again relatively unstable using IV, as the effects on BMI range from essentially zero to almost 4 units, while those for Pr(Obese) vary from a huge -33 percentage points to 3.8. Interestingly, a more consistent pattern emerges with the IV estimates for severe obesity. The coefficient estimates are all positive and six are significant, including in the regression using our preferred SNAP-ABC measure. Moreover, the magnitudes are somewhat stable, ranging from 15.3 to 28.4. In sum, then, the IV results suggest that the effects of SNAP on BMI are unclear throughout much of the distribution, with the exception of the right tail where they are positive and large. In other words, SNAP appears to lead to weight gain among those individuals who are already at the most risk of weight-related health problems.

Table 8 reports the first stage F statistics and the over-identification test p-values for all our IV regressions. In most cases, the F statistics are always above the usual recommended level of 10 to deem one's instruments as sufficiently correlated with the treatment variable. Nonetheless, they are not overwhelmingly strong, as the largest F-statistic is 25, with those for our preferred SNAP-ABC measure being around 13-14. This likely contributes to the imprecision of the estimates. Our set of instruments passes the over-identification tests, as the p-values indicate statistical insignificance, for the majority of outcomes. However, the tests indicate the instruments are problematic for low food security and HEI-2010 score. Future versions of the paper will consider additional instruments in an effort to obtain more convincing diagnostic test results.

VI. Conclusion

This paper leverages the availability of self-reported and two different administrative measures of SNAP participation in the FoodAPS to investigate several issues related to SNAP and measurement error. We first present evidence that the two administrative SNAP variables are often missing or disagree with each other. We then demonstrate that different methods of combining the two administrative variables into a single "true" participation measure can lead to meaningfully different estimated misreporting rates. Next, we document similar sensitivity to assumptions about the administrative variables across instrumental variables estimates of the effects of SNAP on food insecurity, body weight, and healthfulness of food purchases. Finally, we propose a method of predicting probability of participation using the information from all three SNAP participation measures, including the self-report. In general, the IV estimates suggest that SNAP has unclear effects on food insecurity, reduces healthfulness of food purchases, and increases severe obesity.

Our work serves as a cautionary tale for using administrative records uncritically under the assumption that they represent the "gold standard" with regard to measurement. While some of the difficulties we observed with the linked administrative variables may be unique to FoodAPS, others likely generalize to other settings. For instance, challenges with obtaining data from all states and differences in data quality across states are hardly unique to SNAP caseload files, as many programs (such as Medicaid and public schools) are operated at the state or local levels and standards for data collection may differ across different geographic areas. Additionally, probabilistic matching between survey respondents and verified program participants would be necessary in other contexts as well since it is unlikely that both sources include universal identifiers such as social security numbers. Moreover, the fact that matches to EBT transaction data were not attempted for individuals who (perhaps erroneously) reported not participating in SNAP points to the broader tradeoff between rigor and budgetary/practical constraints during data collection. When faced with a choice between nationwide surveys and administrative records that are only available for certain areas or individuals and potentially flawed for others, it is not obvious that the administrative data are preferable.

With all that said, we do not stop at pointing out the flaws with administrative data. Instead, we propose a strategy to construct a probability of participation variable based on all available information from both adminsitrative and self-reported measures. This allows us to provide new evidence on SNAP's impacts on food security, body weight, and food purchase healthfulness that pushes further than prior studies toward addressing both misreporting and endogenous participation. Since measurement error and endogeneity are nearly ubiquitous issues in applied microeconometric research, similar strategies could be applied to study other topics.

Nonetheless, our study suffers from several limitations that should be addressed in future work. For instance, while we propose a method that intuitively should minimize measurement error, there is no way to directly test whether it indeed accomplishes that objective or whether other strategies could be superior. Additionally, the FoodAPS contains a relatively small number of households, which contributes to our IV estimates being relatively imprecise. Next, while we use policy-related IVs that have been suggsted by other researchers, they are not overly strong and it is also difficult to verify that they satisfy the exclusion restriction. Much is therefore left to be learned about both the impacts of SNAP and best practices for measurement when multiple flawed indicators of program participation are available.

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Table 1: Summary Statistics

Variable	Mean (Standard Deviation)
SNAP Participation Variables	
Self-Reported Participation	0.305 (0.461)
Administrative Participation using ADMIN	0.298 (0.457)
Administrative Participation using ALERT	0.351 (0.477)
Dependent Variables	
Low Food Security	0.09 (0.29)
Very Low Food Security	0.06 (0.24)
Total 2010 HEI Score	53.06 (13.89)
Body Mass Index	28.02 (6.39)
Obese	0.33 (0.47)
Severely Obese	0.13 (0.33)
Control Variables	
Age (years)	49.86 (16.53)
Female	0.67 (0.47)
Black	0.12 (0.32)
White	0.77 (0.42)
Other race (non-black, non-white)	0.11 (0.31)
Married	0.44 (0.50)
Formerly Married	0.34 (0.47)
Household Size	2.42 (1.51)
Rural Tract	0.35 (0.48)
High School Graduate	0.25 (0.43)
Some College Education	0.20 (0.40)
College Degree or Higher	0.46 (0.50)
Worked Last Week	0.53 (0.50)
Gross Monthly Family Income (Thousand Dollars)	4.94 (5.08)
Child Less than 5 years present in HH	0.48 (0.50)
Elderly at least 65 years present in HH	0.26 (0.44)
Never Married	0.22 (0.42)
Less than High School Education	0.10 (0.29)

Note: Statistics are from final analysis sample of 4491 observations, except the ADMIN and ALERT, which have only 3,665 and 3,590 valid observations, respectively.

Table 2: Extent of Disagreement among SNAP Participation Variables

REPORT	ADMIN	ALERT	Observations	Category
0	0	0	2075	A
0	0	1	26	E
0	0	.	314	B
0	1	0	33	E
0	1	1	146	C
0	1	.	22	E
0	.	0	22	B
0	.	1	27	E
0	.	.	600	D
1	0	0	60	C
1	0	1	81	E
1	0	.	15	E
1	1	0	81	E
1	1	1	753	A
1	1	.	55	B
1	.	0	57	E
1	.	1	226	B
1	.	.	107	D
Total			4,700	

Table 3: Tabulation of SNAP Participation Variables

Variable	Non-Participants	Participants	Participation Rate	Missing	Missing Rate
REPORT	3,265	1,435	30.5%	4	0.1%
ADMIN	2,574	1,091	29.8%	1,039	22.1%
ALERT	2,329	1,261	35.1%	1,114	23.7%

Table 4: Correlations among SNAP Participation Variables

Variable	REPORT	ADMIN	ALERT
REPORT	1		
ADMIN	0.764***	1	
ALERT	0.757***	0.841***	1

Note: *** indicates statistically significant at 1% level.

Table 5: Estimated Reporting Errors in SNAP Participation under Different Assumptions

Decision Rule when ADMIN and ALERT Differ	False Negative (%)	"True" Participants	False Positive (%)	"True" Non-Participants
1) Always use ADMIN	18.44	1090	6.07	2571
2) Always use ALERT	15.81	1259	8.51	2328
3) Always use ADMIN unless missing	16.98	1343	8.04	2650
4) Always use ALERT unless missing	16.54	1336	8.02	2657
5) Use ADMIN and ALERT only if they agree	16.24	899	2.81	2135
6) Use ADMIN and ALERT, assigning more weight to matches	17.52	1450	5.19	2543
7) Use ADMIN and ALERT, assigning more weight to non-matches	15.87	1229	10.64	2764

Table 6: Regression Results for Food Security and Healthy Eating Index (2010)

	OLS		IV		OLS	IV
	Food Insecurity	Very Low Food Sec.	Food Insecurity	Very Low Food Sec.	Healthy Eating Index	
	(1)	(2)	(3)	(4)	(5)	(6)
Self-reported participation (N=4491)	0.071***	0.060***	-0.245	0.178	-1.536***	-10.526*
	(0.015)	(0.013)	(0.164)	(0.135)	(0.477)	(5.709)
Rule 1 (ADMIN) (N=3519)	0.077***	0.052***	-0.105	0.080	-1.690***	-19.003***
	(0.017)	(0.015)	(0.106)	(0.090)	(0.516)	(4.125)
Rule 2 (ALERT) (N=3454)	0.085***	0.049***	-0.081	0.092	-1.751***	-15.034***
	(0.016)	(0.014)	(0.148)	(0.126)	(0.511)	(5.461)
Rule 3 (N=3834)	0.069***	0.049***	-0.047	0.094	-1.616***	-11.846**
	(0.016)	(0.014)	(0.131)	(0.113)	(0.482)	(4.703)
Rule 4 (N=3834)	0.084***	0.045***	0.067	0.093	-1.406***	-6.898
	(0.016)	(0.014)	(0.145)	(0.126)	(0.486)	(5.061)
Rule 5 (N=2926)	0.094***	0.058***	-0.076	0.038	-1.894***	-15.640***
	(0.019)	(0.016)	(0.106)	(0.087)	(0.580)	(3.992)
Rule 6 (N=3834)	0.082***	0.060***	-0.056	0.079	-1.655***	-8.178*
	(0.015)	(0.013)	(0.125)	(0.107)	(0.484)	(4.341)
Rule 7 (N=1380)	0.071***	0.034**	0.091	0.108	-1.378***	-11.079**
	(0.016)	(0.014)	(0.149)	(0.130)	(0.488)	(5.383)
SNAP-ABC (N=3512)	0.083***	0.052***	-0.003	0.100	-1.596***	-8.119*
	(0.017)	(0.014)	(0.136)	(0.116)	(0.521)	(4.840)
SNAP-ABC with Imputation (N=4491)	0.088***	0.053***	-	+	-1.638***	-
	(0.015)	(0.013)			(0.516)	

Notes: Heteroskedasticity-robust standard errors are in parentheses. *** indicates statistically significant at the 1% level, ** 5% level, * 10% level. Missing cells have not yet passed disclosure review; therefore only signs are shown.

Table 7: Regression Results for Weight Outcomes

	OLS			IV		
	BMI	Obese	Severely Obese	BMI	Obese	Severely Obese
	(1)	(2)	(3)	(4)	(5)	(6)
Self-reported participation (N=4491)	1.556***	0.096***	0.053***	-0.235	-0.331	0.153
	(0.263)	(0.018)	(0.014)	(2.892)	(0.216)	(0.156)
Rule 1 (ADMIN) (N=3519)	1.332***	0.064***	0.059***	1.111	0.018	0.173*
	(0.297)	(0.020)	(0.016)	(1.908)	(0.135)	(0.104)
Rule 2 (ALERT) (N=3454)	1.184***	0.067***	0.035**	3.387	-0.079	0.284*
	(0.285)	(0.019)	(0.015)	(2.738)	(0.188)	(0.151)
Rule 3 (N=3834)	1.394***	0.076***	0.054***	2.661	-0.075	0.236*
	(0.274)	(0.018)	(0.015)	(2.410)	(0.169)	(0.132)
Rule 4 (N=3834)	1.380***	0.075***	0.052***	3.336	-0.047	0.244
	(0.273)	(0.018)	(0.015)	(2.707)	(0.188)	(0.148)
Rule 5 (N=2926)	1.182***	0.054**	0.045**	1.821	0.038	0.223**
	(0.331)	(0.022)	(0.018)	(1.944)	(0.136)	(0.107)
Rule 6 (N=3834)	1.440***	0.079***	0.053***	2.119	-0.102	0.204
	(0.266)	(0.018)	(0.015)	(2.292)	(0.162)	(0.125)
Rule 7 (N=1380)	1.346***	0.072***	0.054***	3.971	-0.001	0.273*
	(0.282)	(0.019)	(0.015)	(2.803)	(0.193)	(0.154)
SNAP-ABC (N=3512)	1.565***	0.081***	0.061***	2.616	-0.070	0.242*
	(0.291)	(0.020)	(0.016)	(2.517)	(0.178)	(0.139)
SNAP-ABC with Imputation (N=4491)	1.561***	0.081***	0.061***	+	-	+
	(0.267)	(0.020)	(0.015)			

Notes: Heteroskedasticity-robust standard errors are in parentheses. *** indicates statistically significant at the 1% level, ** 5% level, * 10% level. Missing cells have not yet passed disclosure review; therefore only signs are shown.

Table 8: Diagnostic Test Results for IV Regressions

	First-Stage F-Statistics	Overidentification Test P-Values					
		Low Food Security	Very Low Food Security	HEI-2010	BMI	Obese	Severely Obese
Self-Reported	11.06	0.0164	0.2610	0.0000	0.1210	0.4870	0.2575
Rule 1 (ADMIN)	24.83	0.0050	0.8599	0.0001	0.1410	0.0500	0.5780
Rule 2 (ALERT)	11.75	0.0080	0.9060	0.0000	0.3960	0.2810	0.5900
Rule 3 (N=3834)	15.06	0.0003	0.8167	0.0000	0.3632	0.2670	0.6050
Rule 4 (N=3834)	11.97	0.0004	0.7588	0.0000	0.4277	0.2420	0.4813
Rule 5 (N=2926)	25.06	0.0004	0.5780	0.0028	0.0770	0.0320	0.5870
Rule 6 (N=3834)	16.36	0.0004	0.7557	0.0000	0.3003	0.2930	0.4518
Rule 7 (N=1380)	11.57	0.0003	0.8160	0.0000	0.5560	0.2320	0.6240
SNAP-ABC (N=3512)	14.16	0.0001	0.4804	0.0000	0.1832	0.1670	0.4817
SNAP-ABC with Imputation (N=4491)	12.583	0.0031	0.3398	0.1397	0.2430	0.3683	0.0000

Appendix Table A1: 10-Question Food Security Question in FoodAPS

Question	Description
E2	In last 30 days, worried food would run out before we got more money
E3	Food ran out and had no money to buy more, in last 30 days
E4	Couldn't afford to eat balanced meals, in last 30 days
E5	Adults skipped or cut size of meals b/c not enough money, in last 30 days (Y/N) Universe: Answered “Sometimes not enough to eat” or “Often not enough to eat” description of food sufficiency question within last 30 days, OR answered “Often true” or “Sometimes true” to E2, E3 or E4.
E5a	Number of days adults skipped/cut meal size b/c not enough money, last 30 days Universe: Answered “Yes” to E5
E6	Eat less than felt you should b/c not enough money, in last 30 days (Y/N) Universe: Answered “Sometimes not enough to eat” or “Often not enough to eat” description of food sufficiency question within last 30 days, OR answered “Often true” or “Sometimes true” to E2, E3 or E4.
E7	Ever hungry but didn't eat b/c not enough money, in last 30 days (Y/N) Universe: Answered “Sometimes not enough to eat” or “Often not enough to eat” description of food sufficiency question within last 30 days, OR answered “Often true” or “Sometimes true” to E2, E3 or E4.
E8	Lose weight b/c not enough money for food, in last 30 days (Y/N) Universe: Answered “Sometimes not enough to eat” or “Often not enough to eat” description of food sufficiency question within last 30 days, OR answered “Often true” or “Sometimes true” to E2, E3 or E4.
E9	Skip food all day b/c not enough money for food, in last 30 days (Y/N) Universe: Answered “Yes” to E5, E5a, E6, E7, or E8.
E9a	How often adults skipped food all day b/c not enough money, in last 30 days Universe: Answered “Yes” to E9