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Within and Across County Variation in SNAP Misreporting: Evidence from Linked ACS and Administrative Records

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Within and Across County Variation in SNAP Misreporting: Evidence from Linked ACS and Administrative Records

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Abstract

This paper examines sub-state spatial and temporal variation in misreporting of participation in the Supplemental Nutrition Assistance Program (SNAP) using several years of the American Community Survey linked to SNAP administrative records from New York (2008–2010) and Texas (2006–2009). I calculate county false-negative (FN) and false-positive (FP) rates for each year of observation and find that, within a given state and year, there is substantial heterogeneity in FN rates across counties. In addition, I find evidence that FN rates (but not FP rates) persist over time within counties. This persistence in FN rates is strongest among more populous counties, suggesting that when noise from sampling variation is not an issue, some counties have consistently high FN rates while others have consistently low FN rates. This finding is important for understanding how misreporting might bias estimates of sub-state SNAP participation rates, changes in those participation rates, and effects of program participation.

Keywords: Food Stamps, Record Linkage, Survey Misreporting, Supplemental Nutrition Assistance Program (SNAP)

1 Introduction

During 2010, 40.3 million people participated in the Supplemental Nutrition Assistance Program (SNAP, formerly the Food Stamp Program), which is the largest federal program aimed to reduce domestic hunger (FNS, 2011, 2013). Nevertheless, an estimated 28 percent of eligible individuals did not participate in SNAP during that same year (FNS, 2012). Because of the direct benefit to participants as well as the estimated economic stimulus associated with redeeming benefits at grocery stores, the U.S. Department of Agriculture Food and Nutrition Service (USDA FNS) devotes considerable resources toward outreach to those who are eligible but—for whatever reason—do not participate in SNAP (FNS, 2012).[1] Effective

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‡*Disclaimer:* This report is released to inform interested parties of research and to encourage discussion. The views expressed are those of the author and not necessarily those of the U.S. Census Bureau.

[1]For example, the FNS will reimburse state SNAP agencies approximately 50 percent of their administrative costs for outreach to low-income individuals (FNS, 2009).

outreach depends, though, on the availability of reliable data regarding the characteristics of people who do and do not participate in SNAP. Responses to survey questions about SNAP participation, however, are known to suffer from measurement error due to non-random misreporting by survey respondents (see, for example, Bound *et al.*, 2001; Oberheu and Ono, 1975; Meyer *et al.*, 2009).

Misreporting of program participation in surveys most commonly takes the form of false-negative (FN) responses, when true participants report that they do not participate in the program. False-positive (FP) responses, when non-participants report that they do participate in the program, also corrupt survey data. Together, FN and FP responses yield net underreporting biases in estimates of what types of people use or do not use the program, the program's effect on poverty, and the program's effect on a variety of other outcomes such as health, food security, and labor market attachment. Understanding the direction and extent of the bias depends on knowing as much as possible about how misreporting varies along many dimensions. Previous research has shown how misreporting has varied nationally over time and that individual and household characteristics are good predictors for FN and FP responses. Research suggests that accurate responses are more likely if the respondent's program participation was more recent, pointing toward cognitive issues—such as misunderstanding the question or suffering from faulty recall—as a cause of misreporting (Taeuber *et al.*, 2004). But cognitive issues do not explain everything, since we have also learned that the likelihood of misreporting is correlated with individual characteristics like race, age, sex, and education (Meyer and Goerge, 2011). In longitudinal data, some households always misreport, while other households always give accurate responses, potentially signaling intentional misreporting (Bollinger and David, 2005).

This paper contributes to the literature by examining variation of misreporting between and within counties over time. Specifically, I answer the following three questions: First, how much do FN rates vary across counties in a given year? Second, to what extent do FN rates vary within counties over time? Are the patterns persistent? Finally, what are the main county-level correlates with FN rates?[2] To answer these questions, I calculate county-level FN rates by aggregating individual-level American Community Survey (ACS) records linked to administrative records from New York and Texas' state SNAP agencies. My data allow me to evaluate misreporting in the ACS in New York for each year from 2008 to 2010 and in Texas from 2006 to 2009. Aggregating individual responses from the linked data allows me to separately identify rates of FN responses from rates of FP responses, which would not be possible by comparing county-level counts from publicly available administrative data to survey counts. Observing misreporting in each county over several years allows me to examine the persistence of misreporting within counties.

Ultimately, this research can begin to tell us how informative misreporting measures are at the county level. If misreporting is highly variant between counties, then county-level estimates using survey responses will suffer from different degrees of bias. Furthermore, if misreporting rates persist within small geographies, then there is additional information that can help improve estimation strategies. For example, if certain counties have consistently high FN rates, those same counties will also have consistently downward-biased estimates of participation rates and program effects. As a result, resources and outreach may be misdirected.[3] Understanding the spatial and temporal dynamics of misreporting can help researchers and policy makers avoid the pitfalls associated with such systematic bias. In addition, if small geographies exhibit patterned misreporting over time, then that information can inform research about potential non-cognitive causes of misreporting such as institutions, culture, or stigma. Such information may also be useful for improving survey instruments.

The answer to my first research question is clear: I find substantial heterogeneity in misreporting across

[2] An extended version of this paper, available from the author upon request, also considers variation in FP rates. In general, I find FP rates are extremely low (1 to 2 percent), exhibit substantial heterogeneity across counties in a given year, and exhibit no persistence within counties over multiple years.

[3] As of a 2010, 12 states administer SNAP at the county level (Rowe *et al.*, 2010), and some counties, states, media, and advocacy groups are taking advantage of the ACS to conduct county-level analyses (e.g., Benton County, 2012; CAH, 2013; FRAC, 2010; Bloch *et al.*, 2009; Kirk, 2013).

counties within a given year. In fact, over all years, the smallest difference between the FN rates at the 10th and 90th percentiles in a given year was 21.7 percentage points. Furthermore, I find evidence that counties' FN rates are moderately persistent over time. Although somewhat small, correlation coefficients between FN rates in one year and the previous year (and the year before that) are positive and statistically significant. Finally, I estimate county FN rates conditional on the previous year's FN rate as well as several county characteristics. While previous FN rates remain positively correlated with current ones, point estimates become imprecise as I condition on successively more county characteristics. The strongest predictors of county-level FN rates are the percentage of the population reporting participation in other government transfer programs (as reported in the ACS) and the length of the average SNAP participation spell (derived from SNAP administrative data), both of which are negatively correlated with FN rates. This is consistent with Meyer and Goerge's (2011) finding that individuals' length of SNAP spell is an important predictor for whether or not they provide FN responses.

These findings represent three main empirical contributions. First, to the best of my knowledge, this is the first analysis of FN rates for sub-state geographies. Second, this is the first analysis of dynamics of FN response rates at the state- and sub-state levels.[4] Finally, my results show that county aggregates of the individual characteristics that predict FN responses are, themselves, strong predictors of county FN rates. This suggests that researchers interested in SNAP usage over small geographies may be able to correct for misreporting using county tabulations rather than linked microdata, which can be difficult to access.

2 Literature

There are two mechanisms thought to cause the observed misreporting rates. The first is cognitive, and the second is motivational. Cognitive issues leading to misreporting could arise from misunderstanding of the survey question or could be due to faulty memory, but the cognitive mechanism hypothesis ultimately assumes respondents make a good-faith effort to answer survey questions accurately. The motivational mechanism hypothesis, in contrast, states that some respondents willingly provide false information to survey questions. This could be due to principled unwillingness to cooperate with surveys or to social desirability bias, interviewer effects, or stigma.

The empirical literature suggests misreporting of SNAP (or, in the past, the Food Stamps Program (FSP)) is probably caused by a combination of both cognitive and also motivational mechanisms.[5] Taeuber *et al.* (2004) match administrative records from the Maryland SNAP Program to the 2001 Supplementary Survey and find that the likelihood of a FN report increases with the duration between when the participation period ended and when the survey was conducted, which supports the faulty memory hypothesis. Meyer and Goerge (2011) estimate individual FN and FP reporting regressions, controlling for family and household structure, age, sex, education, race, labor market characteristics, income, disability, language and citizenship, rural residence, whether the person reported receipt of other government transfers, the length of the person's spell on SNAP, and interview mode. Similar to Taeuber *et al.* (2004), Meyer and Goerge (2011) find that the longer households participated in SNAP prior to the interview, the more likely they were to provide an accurate response, even when conditioning on the rich set of controls listed above; thus their findings support a cognitive explanation for misreporting. However, estimates from the same models show that the likelihood of a FN response is conditionally correlated with demographic characteristics as well as

[4]Mittag (2013) reports underreporting rates in New York state for 2008 to 2009 but does not look at trends; Meyer *et al.* (2009) look closely at the dynamics of underreporting across many surveys and transfer programs, although their analysis is at the national level. Both studies evaluate net underreporting and do not distinguish between FN and FP responses.

[5]The 2008 Farm Bill changed the program name from the Food Stamp Program (FSP) to the Supplemental Nutrition Assistance Program (SNAP). I refer to the program using its current name, even when I discuss results from research conducted prior to the name change.

how individuals respond to questions about participation in other transfer programs, supporting the motivational hypothesis. Evaluating a linked panel of SIPP and administrative records, on the other hand, Bollinger and David (2005) find strong evidence that the response error structure is persistent within households over time, suggesting that—for whatever reason—respondents exhibit "...a latent tendency to cooperate (or not cooperate) with surveys."

Leaving aside for a moment the cause of misreporting, the degree of measurement error in survey responses about participation in SNAP is well-documented. A straightforward approach to measuring net misreporting is to compare counts of program recipients (possibly by geographic or demographic group) from public survey data to corresponding counts released by the agency administering the program.[6] This is the approach of Meyer *et al.* (2009), who compare survey estimates of total SNAP recipients from five surveys to aggregates provided by the FNS. They find that net national underreporting rates for participation in the SNAP were as high as 34 percent in the 1980 Current Population Survey (CPS) and increased to 47 percent in the 2006 CPS. Meyer and Sullivan (2008) compare the CPS to public SNAP Quality Control data from FNS, but they allow net underreporting rates to differ between demographic groups, which they show to be an important dimension along which survey reporting behavior can vary.

Another approach is to evaluate linked administrative records to individual responses in surveys. The major benefit of this method is that it allows researchers to distinguish between FN responses and FP responses. Due to the difficulties researchers face gaining access to administrative records as well as the high costs of record linkage, however, the scope of studies using linked data has been limited to states for which administrative data have been made available to researchers. The estimates of FN rates from this handful of states are consistently high and consistently exceed estimated FP rates by many orders of magnitude. For example, Meyer and Goerge (2011) evaluate data from the 2001 Supplemental Survey (a precursor to the ACS) linked to administrative records from Illinois and Maryland, and they find statewide FN rates of 32 and 37 percent, respectively. At the same time, their estimates of FP rates in the same states are 0.83 and 0.51 percent. Using the 1984 individual records from the Survey of Income and Program Participation (SIPP) linked to administrative records from Florida, New York, Pennsylvania, and Wisconsin, Marquis and Moore (1990) estimate FN rates for SNAP participation of 23 percent and FP rates of less than 1 percent. For other examples, see Bollinger and David (1997), Mittag (2013), Oberheu and Ono (1975), and Taeuber *et al.* (2004).

I am unaware of any research that reports FN, FP, or net underreporting rates by sub-state geographies, however there is evidence of significant heterogeneity in SNAP eligibility and participation across counties. Newman and Scherpf (2013) find that county-level SNAP access rates (defined as the percentage of modeled eligible ACS respondents who appear in SNAP administrative records) range from 47.7 to 79.8 percent across the 25 most populous counties of Texas in 2009. Harris and Scherpf (2013) use New York SNAP administrative data linked to records in the ACS and estimate that across all counties in 2010, the percentage of the population modeled to be eligible ranged from 10.0 to 63.8 percent, and access rates ranged from 37.2 to 81.0 percent. They also find that estimated county-level eligibility and access rates vary substantially by demographic group. Finally, Goetz *et al.* (2004) show that county-level variation in economic and demographic characteristics is an important consideration in estimating SNAP outlays.

3 Data

This paper uses person-level SNAP administrative data from Texas and New York state agencies linked to individual records in the ACS. The SNAP data for Texas cover the period from January 1, 2005 to December 31, 2009, and the New York SNAP data cover the period from January 1, 2007 to December 31, 2009. Each

[6]Comparing aggregates from one data source to those of another allows researchers to identify net misreporting, since FN as well as FP responses are combined to get aggregate counts.

of the SNAP data sets includes information on participation, dollar amounts of receipt, and the months of participation.

Individual records in the SNAP data are linked to the ACS by merging on a Protected Identification Key (PIK), which is a unique identifier used within the Census Bureau's Center for Administrative Records Research and Applications (CARRA) to link individual person records across data sets. These PIKs are determined through the Person Identification Validation System, which employs probability record linkage techniques (see Wagner and Layne (2012) for more information). CARRA uses Personally Identifiable Information (PII) such as name, date of birth, and address to assign a PIK. CARRA then removes the PII from the data file to anonymize the data and preserve confidentiality so it can be used for statistical purposes and research.

Rates of PIK assignment are high, but in some cases, observations in the administrative records or the survey data are unmatchable to a unique PIK. Whether or not a survey or administrative record matches to a PIK is non-random, and I follow Meyer and Goerge (2011) and Newman and Scherpf (2013) by adjusting the sample weights to account for the probability that an individual lives in a household where at least one person receives a PIK.[7] Specifically, I weight each observation by:

$$\widetilde{w_i} = w_i * (\widehat{P_i^{PIK}})^{-1} \tag{1}$$

where w_i is individual i's survey sample weight, and $\widehat{P_i^{PIK}}$ is the predicted probability that person i lives in a household where at least one member's ACS record was matched to a PIK. The predicted probabilities, $\widehat{P_i^{PIK}}$, are derived from a probit regression where the dependent variable is an indicator for living in a household with at least one member who received a PIK, and the controls include age, race, education, household structure, and other characteristics. Details on sample sizes and PIK rates, as well as the results from the Probit estimation, appear in Tables A1 and A2, respectively.[8]

After matching on PIKs, I set an individual-level indicator for SNAP participation equal to 1 if the most recent month of SNAP receipt in the administrative records is within 12 months of the ACS interview date.[9] Next, I create the indicator, $IN\_AR_i^{HH}$, equal to 1 if anyone in person i's household appears in the SNAP administrative records and received SNAP benefits during the 12 months preceding the interview. Finally, I define the two county-level concepts of interest: the county's False-Negative (FN) rate and the county's False-Positive (FP) rate. For each year, I calculate:

$$FN_j = \frac{1}{N_j^{AR}} \sum_{i=1}^{N_j^{AR}} \widetilde{w_i} * \mathbb{1}(FS_i = 2 | IN\_AR_i^{HH} = 1) \tag{2}$$

$$FP_j = \frac{1}{N_j^{ACS}} \sum_{i=1}^{N_j^{ACS}} \widetilde{w_i} * \mathbb{1}(FS_i = 1 | IN\_AR_i^{HH} = 0) \tag{3}$$

[7]Meyer and Goerge (2011) and Newman and Scherpf (2013) actually estimate the probability that an individual record receives a PIK. Since my sample selection depends not on whether an individual receives a PIK, but rather on whether an individual lives with someone who receives a PIK, I estimate the probability of living with at least one person with a PIK.

[8]Table A1 shows, in general, that at least 98 percent of the administrative records could be assigned a PIK, and between 88.4 and 92.8 percent of records in the ACS could be matched to a PIK. However, 94.0 to 95.7 percent of ACS records appeared in households with at least one member with a PIK. Table A2 demonstrates that PIK assignment in the ACS in non-random—instead it is a function of social, demographic, and economic characteristics—and reinforces the importance of accounting for this non-random assignement via our reweighting scheme.

[9]To determine whether a household participated in SNAP during the reference period, we need to match the year t ACS file to the year t and also the year $t-1$ administrative records, since the ACS question about SNAP receipt refers to the previous 12 months.

where N_j^{AR} is the number of ACS respondents in county j who lived in a household with at least one member who was matched to a SNAP administrative record from the previous year, $\mathbb{1}$ is the indicator function, FS_i is person i's response to the question about whether anyone in the household participated in SNAP in the previous year (2 indicates a negative response). Finally, N_j^{ACS} is the number of ACS respondents who lived in a household where no members participated in SNAP in the previous year. I drop all observations that had FS_i imputed, and I drop all county-years with $N_j^{AR} < 15$. In addition to annual county-level FN and FP rates, I calculate a variety of yearly county-level economic, demographic, and geographic characteristics. As with the calculation of FN and FP rates, all county-level variables are generated using the sample weights adjusted by the predicted probability of living in a household with at least one member who was assigned a PIK. I discuss these variables in Section 4.3 and list them in Table 7.

4 Analytic Framework

4.1 Variation in misreporting across counties

Assessing the degree to which county-level FN and FP rates vary within a state during a given year simply requires descriptive statistics such as the standard deviation, minimum and maximum, and the values of the FN and FP rates at various quantiles of their distributions. In addition to these statistics, I report the 90-10 ratio. The 90-10 ratio indicates how many times greater is the misreporting rate in the county at the 90th percentile than the misreporting rate of the county at the 10th percentile. The 90-10 ratio is bounded from below at 1 (if the middle 80 percent of the distribution were centered on a single mass point) and unbounded from above. In order to tell whether the 90-10 ratio is driven by variation at the bottom half or the top half of the distribution, I also decompose the 90-10 ratio into the product of the 50-10 and the 90-50 ratio.

4.2 Variation in misreporting within counties

The second question of this paper is whether FN and FP rates are stable within counties over time. That is, are counties with high (low) FN and FP rates in one year likely to have high (low) FN and FP rates in following years? More to the point, is observed persistence in FN and FP rates greater than what we would observe if the accuracy of individual responses about SNAP participation in the ACS were random?

If individuals responded randomly, there could still be cross-sectional differences in county-level FN and FP rates within a given year, due to sampling variation. Furthermore, this random response scenario may result in some counties having FN and FP rates within the same quantile over a multiple-year panel. Therefore, to frame the question of how persistent county FN and FP rates are over time, it will be useful to consider what the data would look like under two extreme scenarios. The first of these scenarios is one in which FN and FP rates are perfectly stable over time. I will refer to this as the "certainty scenario". The second scenario is one in which FN and FP rates are randomly distributed over counties and time; I will refer to this as the "lottery scenario." I generate simulated data for the lottery scenario as follows. For every year, I calculate the actual state-wide FN and FP rates. For every individual, I then generate 100 random FN and FP responses drawn from a binomial distribution whose mean is the actual state-wide mean for that sample year. I aggregate these random individual-level variables by county and year to attain 100 random county FN and FP rates. The within county-year mean from these 100 simulations is the final county-year mean FN or FP rate for the lottery scenario. Neither the certainty scenario nor the lottery scenario is likely to be an accurate description of reality; however the two scenarios provide a benchmark against which to evaluate reality.

A first heuristic approach to evaluating persistence of county misreporting rates follows Javdani (2013). This exercise compares the observed percentage of counties appearing in a particular quartile of the FN and FP distributions for $0, 1, 2, \ldots, T$ years to what things would look like under the certainty and the lottery scenarios. For example, under the certainty scenario, 75 percent of the counties will never appear in the top quartile of the FN distribution, and 25 percent of the counties will appear in the top quartile for all T years of the observation period. Clearly, the lottery scenario will have a much smaller percentage of counties appearing in the top quartile for all T years. In reality, the number of counties falling in the top quartile for all T years will likely be somewhere between the two extreme scenarios. Although very informative, I refer to this first approach as heuristic because there is no formal test to see where reality is relative to the two extreme scenarios.

We can also assess the persistence of FN and FP rates within counties (over time) by decomposing the total variance of each misreporting rate into the component due to within-county variation and the component due to between-county variation. To do so, we estimate a random intercept (or variation component) model:

$$y_{jt} = \mu_y + u_j + \epsilon_{jt} \tag{4}$$

$$u_j \sim N(0, \sigma_u^2) \tag{5}$$

$$\epsilon_{jt} \sim N(0, \sigma_\epsilon^2) \tag{6}$$

where y_{jt} is either the FN or FP rate of county j in year t, μ_y is the mean FN or FP rate over all t, u_j is county j's random effect (i.e., $\mu_y + u_j$ is county j's mean FN or FP rate over all t), and ϵ_{jt} is a county- and year-specific spherical error term. The proportion of the variance in y_{jt} that is due to between-county variation is therefore given by:

$$\rho = \frac{\sigma_u^2}{(\sigma_u^2 + \sigma_\epsilon^2)} \tag{7}$$

Within the context of our two extreme scenarios, we would have $\rho = 1$ if misreporting were certain, since there would be no variation within counties over time. On the other hand, if misreporting were generated randomly, as in a lottery, then all of the variation would be explained by within-county variation, and we would have $\rho = 0$.

The final method for examining persistence of misreporting within counties is to estimate autocorrelation coefficients between misreporting in years t, $t-1$, and $t-2$. The autocorrelation coefficient for a k year lag is estimated by:

$$r_y^k = \frac{\sum_{j=1}^{J-k}(y_{jt} - \overline{y})(y_{jt-k} - \overline{y})}{\sum_{j=1}^{J}(y_{jt} - \overline{y})^2} \tag{8}$$

where y_{jt} is the FN or FP rate in county j in year t, $\overline{y}$ is the sample mean of all y_{jt}, and J is the total number of counties. The autocorrelation coefficient is bound by $[-1, 1]$, and a value of 0 means counties' misreporting in year t is uncorrelated with misreporting in year $t-k$. Under the certainty scenario, $r_y^k = 0$. To formally assess whether misreporting is persistent within counties, we test the null hypothesis that $r_y^k = 0$.

4.3 Multivariate analysis of FN rates

The final objective of this paper is to determine main correlates with county misreporting rates. To do so, I estimate the following equation using OLS:

$$y_{jt} = \alpha + \beta y_{jt-1} + X_{jt}'\gamma + \delta_{st} + \epsilon_{jt} \tag{9}$$

where y_{jt} is the FN rate of county j in year t, y_{jt-1} is the 1 year lagged FN rate, X_{jt} is a vector of county-level characteristics in year t, δ_{st} are state-year fixed effects, and ϵ_{jt} is a spherical disturbance term.[10]

[10]Because the dependent variable is censored at 0 and 100, OLS may yield predicted values outside the realm of possibility. An alternative approach is to transform the dependent variable to a proportion and use the Generalized Linear Model (GLM) with a

County characteristics include labor market characteristics such as unemployment rates, demographic characteristics, and county-level rates of public program participation. The full list of variables included in X_{jt} appear in Table 7. To account for potential heteroskedasticity in ϵ_{jt}, I cluster standard errors on state and year in my main specification and by county in additional specifications. I focus on FN rates instead of FP rates because FP rates are negligibly small and because the previous results showed no temporal pattern in FP rates.[11]

5 Results

5.1 Variation in misreporting across counties

Table 1 shows distributional statistics of SNAP FN rates for each state and year. For comparability with previous research, the first column of Table 1 shows the weighted statewide mean of person-level FN responses. This column reproduces for New York and Texas the statewide FN rates reported for Illinois and Maryland in Table 1 of Meyer and Goerge (2011). The statewide FN rates for New York ranged from 27.4 to 30.2 percent between 2008 and 2010. In Texas, FN rates ranged from 32.4 to 40.4 percent between 2006 and 2009. These figures are similar to results for Illinois (31.9 percent) and Maryland (36.5 percent) presented in Meyer and Goerge (2011).

The remaining columns in Table 1 answer the first question of the paper: To what extent do misreporting rates of SNAP usage vary across counties? These columns present the mean, standard deviation, and minimum, maximum, and selected percentiles of county-level FN rates. While each county-level FN rate derives from person-level records using the augmented weights discussed in Section 3, the descriptive statistics attained from the county-level data do not use weights. That is, very populous counties have the same weight as small-population counties.

FN rates vary substantially across counties. For example, in New York in 2008, the county with the lowest FN rate had no instances of people who lived in households with SNAP participants reporting that no one in their household participated in SNAP. In that same year, the highest FN rate across all counties was 70.4 percent. In Texas in every year, county-level FN rates spanned the maximum range possible, from 0.0 to 100.0 percent. Focusing on the interior of the distribution (rather than the extremes) shows that over the 3 years of observations in New York the ratio of the 90th to the 10th percentile ranges from 2.2 to 2.9. In other words, the lowest FN rate in the top 10 percent of FN-rates was about two to three times as large as the highest FN rate in the lowest 10 percent of FN rates. In Texas from 2006-2008, 90:10 ratios ranged from 8.5 to 29.4.[12] The 90:10 ratio can be decomposed into the product of the 50:10 ratio and the 90:50 ratio to show from which side of the distribution the 90:10 ratio is most driven. This decomposition shows that the 90:10 ratio in New York is approximately equally driven by the top and bottom of the distribution, while in Texas variation at the bottom of the distribution plays the larger role in the state's 90:10 ratio.

Table 2 shows the same distributional statistics for FP rates in New York and Texas. The first column shows state-level FP rates that are again similar to those reported in Meyer and Goerge (2011) for Illinois and Maryland. Between 2008 and 2010, New York's FP rates ranged from 1.1 to 1.3 percent, and between 2006 and 2009, Texas had FP rates ranging from 0.4 to 2.0 percent. As is the case with FN rates, FP rates differ substantially across counties in New York and Texas. In fact, the 90:10 ratios are substantially larger for FP rates than they are for FN rates. In New York, the 90:10 ratio grows from 14.0 to 20.8 between 2008

logit link and binomial family to address the censoring issue. I estimate such a model and find very similar results to the OLS estimates. Furthermore, the predicted values from OLS are within the bounds of the dependent variable. For ease of exposition, I report only the OLS results, although GLM results are available upon request.

[11]For completeness, I estimated FP rates using an analogous model to the one used for FN rates. The model had very little predictive power and offered little insight into correlates of FP rates. Results are available upon request.

[12]In 2009, the 90:10 ratio could not be calculated because the FN rate at the 10th percentile was 0.0.

and 2010. In Texas, the 90:10 ratio could not be calculated, due to the fact that the value of the FP rate at the 10th percentile was 0.0 in every year.

5.2 Variation in misreporting within counties

We now turn to the question of how stable counties' FN and FP rates are over time. Figures 1–4 map county-level FN and FP rates in New York and Texas during each of the years of our observation period. These figures reinforce the findings above that there is substantial cross-sectional variation in county misreporting within a given year. However, they also show some evidence of spatial clustering of misreporting. For example, Figure 1 shows that FN rates tend to be very low in the westernmost counties of New York, while counties in the east tend to have FN rates in the third or fourth quartiles. Similarly, Figure 3 shows clusters of southern Texas counties that have FN rates in the 1st and 2nd quartiles. In both New York and Texas, these trends appear to be somewhat persistent across years. I examine this observation in greater detail below.

Tables 3 and 4 illustrate the persistence of counties' FN and FP rates over time by comparing the actual data to what things would look like under the certainty and lottery scenarios discussed in Section 4. Under the certainty scenario, every county would rank in the same quartile of the distribution of FN and FP rates every year. In this case, 25 percent of the counties would always be in the bottom quartile of the distribution, 25 percent would always be in the top quartile, and 50 percent would always be in the middle two quartiles. Under a lottery scenario in which FN and FP rates are aggregated from simulated random individual responses, it would be increasingly unlikely as years go on that a county will always rank in the same quartile.[13]

Table 3 shows that for FN rates, reality falls between the certainty and lottery scenarios. In New York, 8.1 percent of all counties appear in the bottom quartile of the FN rate distribution for 2 of the 3 years, and 8.1 percent appear in the bottom quartile in all 3 years. Under the lottery scenario, these figures would both be 0.0 percent. New York's FN rates are also more persistent at the top of the distribution than they would be under the lottery scenario. Over 16 percent of all counties appear in the top quartile of the FN rate distribution for 2 of the three years (as opposed to 0.0 percent under the lottery scenario), and 6.5 percent appear in the top quartile during all three years (as opposed to 0.0 percent under the lottery scenario). In Texas, as well, more counties appear in the bottom and top quartiles for 2 and 3 years than would have if FN responses were randomly distributed, however no county appears in the same quartile in all 4 years.

Table reffpjav repeats Table 3 for FP rates. In general, results are quite similar: more counties than we would expect under the lottery scenario appear in the same quartile for multiple years. In the case of FP rates in Texas, however, this appears to be especially true at the bottom quartile. While 12.2 percent of counties appear in the bottom quartile for 3 out of 4 years in Texas, only 14.6 percent of counties appear in the top quartile for 2 years, and no counties appear in the top quartile for 3 or 4 years.

Table 5 decomposes the total within-state variation in FN and FP rates into the component due to variation within counties (over time) and the component due to variation across counties. The results are attained by estimating random intercept models for each outcome and each state. Under the lottery scenario, 100 percent of the total variation would be due to within-county variation over time. Under the certainty scenario, 100 percent of the total variation would be due to between-county variation.

Analysis of FN rates in the top panel of Table 5 shows that, while the majority of the total variation FN rates is due to within-county variation, time-invariant variation across counties accounts for 30.7 percent of the total variation in New York and 13.9 percent of the variation in Texas. The implication is that county-level FN rates are noisy but somewhat patterned over time, which corroborates the results in Table 3. The

[13] Data for the lottery scenario were generated as follows. For every year, I calculate the actual state-wide FN and FP rates (as shown in the first columns of Tables 1 and 2). For each individual observation, I then generate random FN and FP response indicators drawn from a binomial distribution whose mean is the actual state-wide mean for that sample year. Finally, I aggregate these random individual-level variables by county and year to attain random county FN and FP rates.

bottom panel of Table 5 shows results for FP rates. Again we see a large percentage of the total variation in FP rates coming from within-county variation. In New York, we see some evidence of stability in FP rates within counties, although results for Texas suggest all the variation in FP rates is from within county (over time) volatility, which is consistent with random assignment of FP responses and is in line with the finding in Table 4 that Texas' FP rates were not persistent within counties at the top of the distribution.

Finally, Table 6 shows the autocorrelation coefficients between current, 1-year lagged, and 2-year lagged misreporting rates, calculated over all county-years for both states. The left-hand panel shows autocorrelation coefficients for FN rates that suggest a weak, but statistically significant and positive relationship between FN rates within counties over time. The autocorrelation coefficient between a county's FN rate in year t and year $t-1$ (as well as year $t-2$) is 0.1 and significant at the 5 percent error level or stronger. For FP rates, the cross-year correlation is less consistent. The autocorrelation coefficient between years t and $t-1$ is -0.0, and the autocorrelation coefficient between years $t-1$ and $t-2$ is -0.1. The former is imprecise, although the latter is significant at the 1 percent error level. Finally, the autocorrelation coefficient between years t and $t-2$ is precisely 0.1. This mix of positive and negative autocorrelation coefficients appears to suggest that FP rates regress toward the mean across years, which is also consistent with random FP responses.

Together, the results in Tables 3–6 suggest an unconditionally positive systematic relationship between a county's FN rate in one year and the next, while the results for FP rates appear suggest a distribution of FP rates across years that is much less systematic. The next section focuses on the conditional relationship between counties' FN rates and prior-year FN rates as well as other county-level correlates.

5.3 Multivariate analysis of FN rates

In this section, I build on the findings from the previous literature by attaining county-level aggregates of most of the variables used in Meyer and Goerge (2011).[14] I estimate county FN rates using OLS, with controls for county-level characteristics, lagged FN rates, and state-year controls. I also cluster standard errors by state and year.[15] The unit of observation in these regressions is the county-year, rather than the individual.

Descriptive statistics for the dependent and control variables are presented in Table 7. The total number of county-years included in the regressions is 828, and the total number of counties is 307 (all of New York's 62 counties and 245 of Texas' 254 counties). Summary statistics for the dependent variable are shown on the first line. The mean of the FN rate across all counties, years, and states is 34.1. As we noted in Table 1, the FN rate has substantial variability, with a standard deviation of 21.4 percentage points and a coefficient of variation equal to 0.6. The remaining variables in Table 7 are the controls.[16] Of note, the average length of SNAP receipt is 11.2 months and ranges from 0.0 to 21.1 months. The administrative data show that in some counties, SNAP receipt lasts nearly 2 years on average, while in other counties SNAP receipt appears to provide more temporary relief. This is an important source of variation, since Meyer and Goerge (2011) found increasing length of SNAP receipt was strongly correlated with more accurate reporting.

Column 1 of Table 8 shows results for a simple regression of current FN rates on lagged FN rates and state-year controls. Column 2 adds labor market characteristics of the county, percentage living in rural areas, population size (in tens of thousands), and the percentage of interviews that were Computer Assisted

[14]Meyer and Goerge (2011) include controls for whether the individual appeared in administrative records for TANF receipt, which I do not have. Point estimates for this control variable were positive but statistically insignificant.

[15]I also obtain estimates clustering standard errors by county, however point estimates are quite imprecise. This is most likely due to the small number of observations for each county. Results are available upon request.

[16]I exclude those whose ACS response about SNAP receipt was imputed, although I do control for the percentage of imputed responses in the county. Table 7 shows that rates of imputation of SNAP receipt are generally low, but in some counties as many as 1 in 4 respondents have SNAP receipt imputed in the ACS.

Telephone Interviews (CATI) and Computer Assisted Personal Interview (CAPI). Column 3 includes additional controls for county demographic and educational characteristics. Additional columns successively add controls for the percentage of the county that speaks English only as well as the percentage of the county that is foreign born (column 4); percent disabled and percent of disabled who are unemployed (column 5); household characteristics, including PIK rates (column 6); percentage reporting receipt of Supplemental Security Income (SSI) and public assistance (column 7); and finally percent modeled eligible for SNAP, percent of those modeled eligible who used SNAP, average length (in months) of the SNAP spell, and the percentage of ACS responses about SNAP usage that were imputed (column 8).

I find weak evidence that lagged FN rates are conditionally correlated with current FN rates. The sparsest specification in column 1 estimates that a 1 percentage point increase in a county's lagged FN rate implies a 0.068 percentage point increase in the county's current FN rate, holding state and year constant. While statistically significant at the 5 percent error level, this point estimate is very small in magnitude. As regional, economic, and demographic controls are added, the magnitude of the point estimate on lagged FN rate decreases by 43 percent to 0.039 in column 4. After including controls for disability rates and disabled unemployment rates in column 5, the point estimates on lagged FN rate again decrease and become statistically insignificant. In columns 6-8, the controls that turn out to have the strongest predictive power for current FN rates are percent female, the percentage of the population reporting SSI or public assistance, and the length of the average SNAP spell.

The strong point estimates on the percentage of the population reporting receipt of government transfers and the length of the average SNAP spell may be due to at least two underlying mechanisms. On one hand, participation in SNAP may be less stigmatized in counties that have high rates of participation in social programs, and therefore respondents may be less reluctant to report SNAP participation. Table 8, particularly in columns 4 and 5, provides some suggestive evidence that stigma plays a role in county FN rates. FN responses are more common in counties with high rates of in-person interviews than in counties with high rates of mail-based interviews. On the other hand, the result that FN rates are higher in counties with shorter SNAP spells could simply be an artifact of faulty recall. The longer the average SNAP spell, the more likely respondents were participating in the program immediately before or during their interviews. The shorter the average SNAP spell, the more likely the respondents' SNAP usage occurred many months before the interview, and therefore the more likely they are to forget about their SNAP usage at the time of the interview. Previous literature finds evidence for this second mechanism using individual-level data linking Maryland administrative records to the Census Bureau's 2001 Supplemental Survey (Taeuber *et al.*, 2004). Additional research is needed to determine how much of a role each of these two mechanisms plays in county-level misreporting.

5.3.1 Sampling variation

Less populous counties will be more subject to sampling variation in the ACS than more populous counties. To assess the degree to which sampling variation introduces noise to my analysis of FN rates in particular, I reproduce my estimates restricting my sample to those counties with populations of at least 60,000 and samples of at least 1,500. Table 9 reproduces the regression results shown in Table 8 using the sample of highly populous counties.[17] The point estimates on lagged FN rates are larger in magnitude than in Table 8 in all specifications and are statistically significant in all but the final specification. Together, these results suggest that, absent the effects of sampling variation, there is strong evidence for the persistence of FN rates (but not FP rates) within counties over time.

[17] All other tables using the sample of highly populous counties are available upon request.

6 Conclusion

This study is the first to calculate false-negative (FN) and false-positive (FP) response rates at the county-level. I find that during any given year, there is substantial heterogeneity in FN and FP rates across counties. I also find evidence that FN rates are moderately persistent within counties over time. Current FN rates are statistically significantly and positively correlated with their lags, although the autocorrelation coefficients are somewhat small. The predictive power of lagged FN rates is not very robust, however, in a multivariate regression analysis using all counties. Instead, the strongest predictors of current county FN rates are the percentage of the population reporting participation in other transfer programs and the length in months of the average SNAP spell within the county. However, in counties that are less subject to the effects of sampling variation, the persistence of FN rates is quite evident.

The cross-sectional heterogeneity in FN (and FP) rates implies that survey estimates of SNAP program participation will be biased downward in areas with high FN rates. Such bias could itself lead to underestimates of program access and program effectiveness. Furthermore, since some counties have consistently high FN rates, the bias will compound over time. Specifically, improvements in program access and program effectiveness may not be observable over time if counties have consistently high FN rates. However, survey data on participation in other transfer programs as well as demographic characteristics of the county can help researchers predict the direction and magnitude of the bias. Furthermore, researchers should be aware that the threat of compounding bias over time is greater in more populous counties that are less affected by sampling variation.

The main limitation of this paper is that it does not identify the cause of misreporting. Some of the results are consistent with the hypothesis that cognitive issues such as faulty recall lead to misreporting: counties with shorter average SNAP spells have greater rates of FN reporting. On the other hand, the results that FN rates persist over time and exhibit some spatial clustering are consistent with the hypothesis that misreporting is motivational or the product of cultures of stigma. Future research could incorporate the findings in this paper to examine how county patterns in FN rates might influence individual misreporting.

This paper is also limited in that it draws on data from only two states with relatively short and unbalanced time periods. Analysis of spatial and temporal patterns in misreporting would be enhanced by incorporating administrative records from more states, with more years, and with observation periods that are consistent across states. Such data could allow for analysis of how different states' policies around eligibility and outreach may (or may not) influence the likelihood that residents misreport.

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Figures

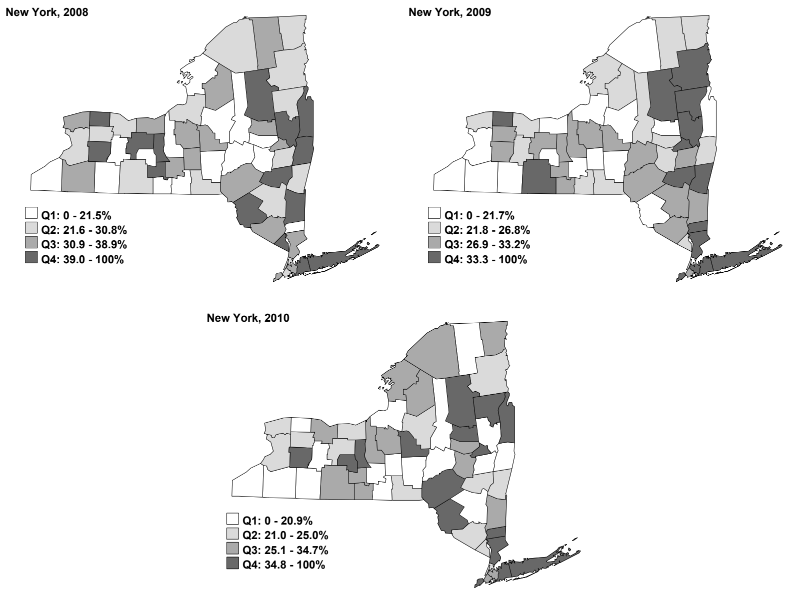

Figure 1: FN rates, New York (2009–2010)

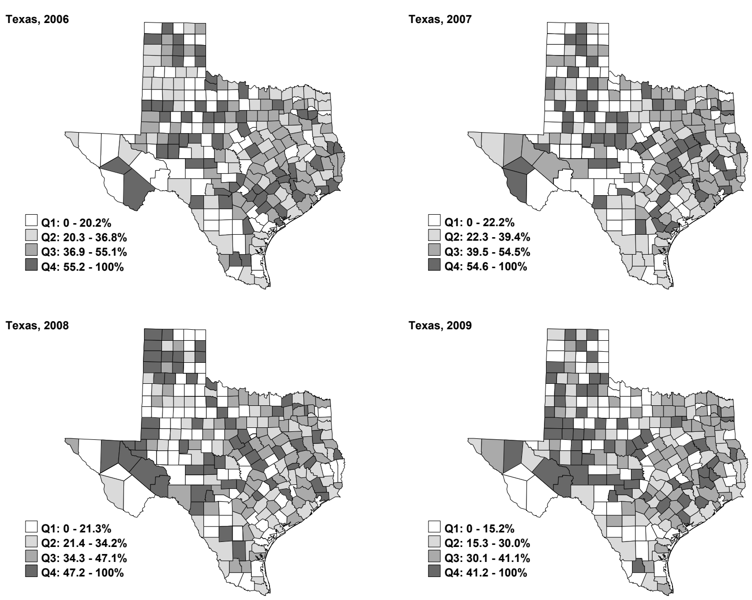

Figure 2: FN rates, Texas (2005–2009)

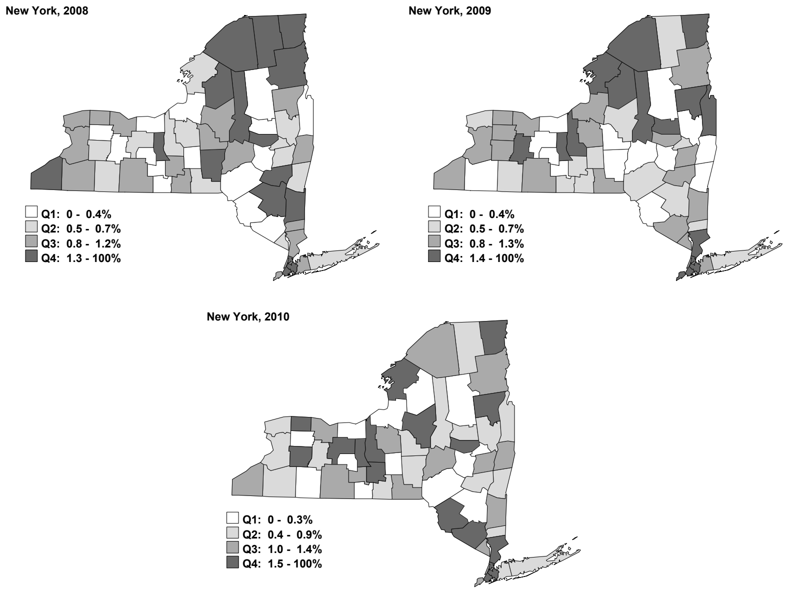

Figure 3: FP rates, New York (2009–2010)

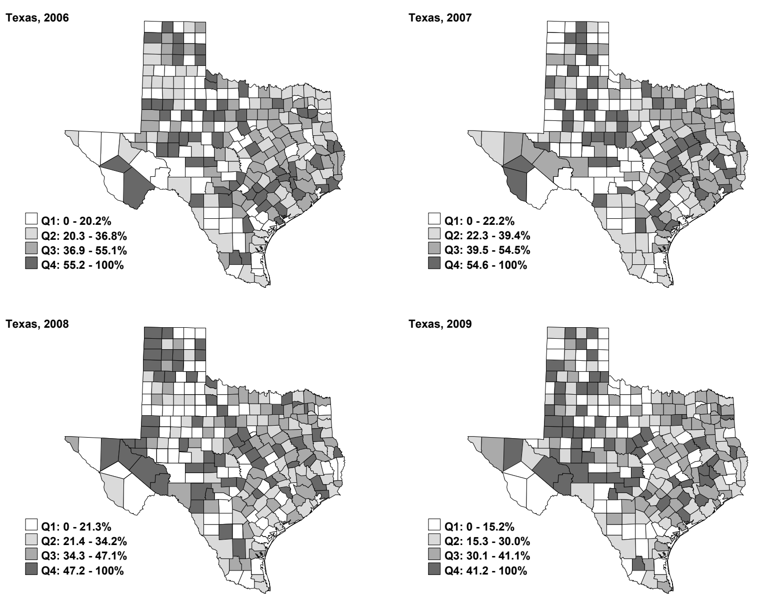

Figure 4: FP rates, Texas (2005–2009)

Tables

Table 1: Yearly Distribution of County-Level SNAP FN Rates

					Percentile				
	State Mean	Mean over Counties	Std. Dev. over Counties	Min	10	50	90	Max	90:10 ratio
New York									
2008	30.2	30.7	14.5	0.0	15.2	30.8	44.9	70.4	2.9
2009	27.4	28.1	10.5	7.6	16.8	26.8	38.7	75.3	2.3
2010	28.6	27.7	9.9	10.7	18.3	25.0	40.0	56.2	2.2
Texas									
2006	38.2	37.9	24.6	0.0	2.3	37.1	68.7	100.0	29.4
2007	40.4	40.1	24.5	0.0	4.9	39.6	73.1	100.0	15.0
2008	35.4	36.2	23.2	0.0	7.5	34.2	63.3	100.0	8.5
2009	32.4	30.8	21.5	0.0	0.0	30.0	56.3	100.0	-

Source: County aggregates from 2005-2009 TX and 2007-2010 NY SNAP administrative records linked with 2006-2010 ACS

Notes: County-year is unit of observation, except for the State Mean, which is calculated over individuals using augmented sample weights. County-years aggregated from fewer than 15 observations are omitted. Mean and Standard Deviation are calculated over all counties within a given year, with equal weights for each county. The $90 : 10$ ratio for Texas in 2009 is blank because the FN rate at the 10th percentile was 0.0, making the ratio undefined.

Table 2: Yearly Distribution of County-Level SNAP FP Rates

	State Mean	Mean over Counties	Std. Dev. over Counties	Min	Percentile 10	Percentile 50	Percentile 90	Max	90:10 ratio
New York									
2008	1.1	0.9	0.7	0.0	0.1	0.7	1.7	2.6	14.0
2009	1.2	0.9	0.8	0.0	0.1	0.7	1.8	4.0	14.0
2010	1.3	1.0	0.9	0.0	0.1	0.9	2.1	4.7	20.8
Texas									
2006	0.8	0.5	1.1	0.0	0.0	0.0	1.4	8.5	-
2007	0.4	0.5	1.6	0.0	0.0	0.0	1.5	17.2	-
2008	1.5	2.1	3.9	0.0	0.0	0.8	4.6	28.0	-
2009	2.0	1.9	2.6	0.0	0.0	1.1	4.8	13.8	-

Source: County aggregates from 2005-2009 TX and 2007-2010 NY SNAP administrative records linked with 2006-2010 ACS
Notes: County-year is unit of observation, except for the State Mean, which is calculated over individuals using augmented sample weights. County-years aggregated from fewer than 15 observations are omitted. Mean and Standard Deviation are calculated over all counties within a given year, with equal weights for each county. Some $90 : 10$ ratios are blank because the FP rates at the 10th percentile were 0.0, making the ratio undefined.

Table 3: Stability in the FN Rate Distribution

	Percentage of Counties Ranked in Quartile:					
	1st			4th		
	Certainty	Reality	Lottery	Certainty	Reality	Lottery
New York						
1 year	0.0	27.4	0.0	0.0	21.0	1.6
2 years	0.0	17.7	0.0	0.0	21.0	0.0
3 years	25.0	4.8	0.0	25.0	4.8	0.0
Texas						
1 year	0.0	40.2	18.5	0.0	44.1	20.1
2 years	0.0	14.6	5.5	0.0	11.4	1.6
3 years	0.0	5.9	2.0	0.0	1.6	0.0
4 years	25.0	0.0	0.0	25.0	0.0	0.0

Source: County aggregates from 2005-2009 TX and 2007-2010 NY SNAP administrative records linked with 2006-2010 ACS
Notes: County-year is unit of observation. County-years aggregated from fewer than 15 observations are omitted. Lottery results are attained by assigning individuals who used SNAP 100 random survey responses such that the state and year FN rate was preserved. 100 FN rates were calculated for each county, and the final county FN rate under the lottery scenario is the mean FN rate from the 100 simulations.

Table 4: Stability in the FP Rate Distribution

	Percentage of Counties Ranked in Quartile:					
	1st			4th		
	Certainty	Reality	Lottery	Certainty	Reality	Lottery
New York						
1 year	0.0	41.9	0.0	0.0	38.7	30.6
2 years	0.0	11.3	0.0	0.0	19.4	9.7
3 years	25.0	4.8	0.0	25.0	0.0	0.0
Texas						
1 year	0.0	42.5	28.3	0.0	44.9	56.7
2 years	0.0	28.0	13.8	0.0	14.6	7.1
3 years	0.0	12.2	2.8	0.0	0.0	0.8
4 years	25.0	0.0	0.0	25.0	0.0	0.0

Source: County aggregates from 2005-2009 TX and 2007-2010 NY SNAP administrative records linked with 2006-2010 ACS
Notes: County-year is unit of observation. County-years aggregated from fewer than 15 observations are omitted. Lottery results are attained by assigning individuals who did not use SNAP 100 random survey responses such that the state and year FP rate was preserved. 100 FP rates were calculated for each county, and the final county FP rate under the lottery scenario is the mean FP rate from the 100 simulations.

Table 5: Misreporting Variance Decomposition

		Percentage of overall Variance due to:	
	Number of County-Years	Across-County Variation ρ	Within-County Variation $(1-\rho)$
False Negative Rate			
New York	186	30.7	69.3
Texas	969	13.9	86.1
False Positive Rate			
New York	186	26.2	73.8
Texas	999	0.0	100.0

Source: County aggregates from 2005-2009 TX and 2007-2010 NY SNAP administrative records linked with 2006-2010 ACS
Notes: County-year is unit of observation. County-years aggregated from fewer than 15 observations are omitted. Mean and Standard Deviation are calculated over all county-years within a given state, with equal weights for each county-year.

Table 6: Autocorrelation of County Misreporting

	False-Negative Rates				False-Positive Rates		
	t	t-1	t-2		t	t-1	t-2
t	1.0			t	1.0		
t-1	0.1*	1.0		t-1	0.0	1.0	
t-2	0.1***	0.1***	1.0	t-2	0.1**	-0.1**	1.0

Source: County aggregates from 2005-2009 TX and 2007-2010 NY SNAP administrative records linked with 2006-2010 ACS
Notes: County-year is unit of observation. County-years aggregated from fewer than 15 observations are omitted. *$p<0.05$ **$p<0.01$ ***$p<0.001$

Table 7: Descriptive Statistics for County Regressions

Variable	Count	Mean	Std. Dev.	Min	Max
County False Negative Rate	828	34.1	21.4	0.0	100.0
Lag 1 County False Negative Rate	828	35.9	22.1	0.0	100.0
Percent unemployed	828	3.9	2.4	0.0	17.0
Percent not in the labor force	828	37.4	7.3	11.2	68.9
Avg. SU inc. as percentage of pov. cutoffs	828	347.5	87.3	140.3	848.5
Percent fifty years or older	828	34.9	7.8	8.9	67.6
Percent female	828	51.0	3.6	35.7	66.2
Percent Black or African American alone	828	6.1	7.3	0.0	40.3
Percent AIAN alone	828	0.6	1.3	0.0	15.7
Percent Asian alone	828	1.0	2.2	0.0	23.8
Percent SOR alone or NHPI alone	828	6.2	7.8	0.0	42.4
Percent Two or more races	828	1.3	1.9	0.0	20.4
Percent Hispanic	828	25.2	24.5	0.0	99.8
Percent with less than a high school degree	828	20.3	11.3	1.9	79.3
Percent with a high school degree	828	30.9	9.7	3.5	74.3
Percent with a bachelor's degree or higher	828	19.0	9.5	0.0	59.2
Percent who speak English only	828	77.8	20.5	2.6	100.0
Percent foreign born	828	7.0	7.1	0.0	57.5
Percent disabled	828	0.2	0.1	0.0	0.4
Percent of disabled unemployed	828	0.1	0.1	0.0	0.4
Percent in single-adult w/children SU	828	11.1	5.6	0.0	37.5
Percent in multiple-adult wo/children SU	828	35.1	7.5	8.1	81.4
Percent in multiple-adult w/children SU	828	38.0	9.0	0.0	78.4
Average number of children in SU	828	1.0	0.3	0.2	2.1
Average number of people with PIK in SU	828	3.0	0.3	1.7	4.2
Percent reporting receipt of cash PA	828	0.9	1.1	0.0	9.6
Percent reporting receipt of SSI	828	2.7	2.3	0.0	21.3
Percent modeled eligible for SNAP	828	30.4	11.6	5.8	80.0
SNAP Participation Rate	828	19.4	10.4	0.9	62.0
Average length of SNAP receipt (in months)	828	11.2	2.7	0.0	21.1
Percent whose SNAP usage was imputed	828	1.1	2.0	0.0	24.8
Percent living in a rural part of the county	828	52.9	29.9	0.0	100.0
Population size (in 10 thousands)	828	12.2	35.0	0.1	342.8
Percent of observations from CATI	828	11.2	5.4	0.0	36.7
Percent of observations from CAPI	828	47.9	15.9	13.2	100.0

Source: County aggregates from 2005-2009 TX and 2007-2010 NY SNAP administrative records linked with 2006-2010 ACS

Notes: County-year is unit of observation. County-years aggregated from fewer than 15 observations are omitted.

Table 8: OLS Estimates of County FN Rates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Co. FN Rate (11)	0.068**	0.050***	0.041**	0.039**	0.031	0.023	0.024	-0.018
	(0.02)	(0.01)	(0.011)	(0.011)	(0.017)	(0.024)	(0.022)	(0.011)
% reporting PA							-1.791***	-1.583***
							(0.338)	(0.068)
% reporting SSI							-0.964**	-0.661*
							(0.281)	(0.297)
Avg. mo. on SNAP								-2.364***
								(0.419)
Additional Controls:								
SNAP Usage								X
HHLD Structure						X	X	X
Disability					X	X	X	X
Language				X	X	X	X	X
Demo. & Educ.			X	X	X	X	X	X
Geo. & Econ.		X	X	X	X	X	X	X
Observations	828	828	828	828	828	828	828	828
Adjusted R-squared	0.042	0.055	0.072	0.072	0.088	0.097	0.11	0.182

Source: County aggregates from 2005-2009 TX and 2007-2010 NY SNAP administrative records linked with 2006-2010 ACS

Notes: Note: County-year is unit of observation. County-years aggregated from fewer than 15 observations are omitted. All models include state-year fixed effects. Standard errors are clustered by state-year. *p<0.1 **p<0.05 ***p<0.01

Table 9: OLS Estimates of County FN Rates, Populous Counties

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Co. FN Rate (11)	0.527***	0.409***	0.297**	0.279**	0.236**	0.207*	0.203*	0.201
	-0.064	-0.083	-0.083	-0.076	-0.084	-0.082	-0.089	-0.114
% reporting PA							-0.842	-0.906
							-1.353	-1.389
% reporting SSI							-0.612	-0.525
							-0.73	-0.747
Avg. mo. on SNAP								-0.148
								-0.611
Additional Controls:								
SNAP Usage								X
HHLD Structure						X	X	X
Disability					X	X	X	X
Language				X	X	X	X	X
Demo. & Educ.			X	X	X	X	X	X
Geo. & Econ.		X	X	X	X	X	X	X
Observations	159	159	159	159	159	159	159	159
Adjusted R-squared	0.509	0.537	0.584	0.593	0.605	0.604	0.6	0.589

Source: County aggregates from 2005-2009 TX and 2007-2010 NY SNAP administrative records linked with 2006-2010 ACS

Notes: Note: County-year is unit of observation.Sample includes only counties with a population of at least 60,000 and a sample size of at least 1,500. All models include state-year fixed effects. Standard errors are clustered by state-year. *p<0.1 **p<0.05 ***p<0.01

Appendix Tables

Table A1: Sample Sizes and Match Rates

	(1) Total Records	(2) Total Records with PIK	(3) % with PIK	(4) Unique PIKs	(5) In a HHLD with ≥1 PIKd member	(6) % In a HHLD with ≥1 PIKd member	(7) Matched to the ACS
SNAP							
NY 2007–2008	5,954,834	5,834,981	98.0	2,998,761			26,463
NY 2008–2009	6,740,531	6,611,830	98.1	3,408,191			30,431
NY 2009–2010	7,753,054	7,614,618	98.2	3,825,187			36,213
TX 2005–2006	7,327,507	7,298,759	99.6	4,413,601			38,426
TX 2006–2007	7,229,520	7,205,895	99.7	4,365,529			37,051
TX 2007–2008	7,269,888	7,206,216	99.1	4,283,236			35,889
TX 2008–2009	8,155,224	8,032,693	98.5	4,754,083			39,486
ACS							
NY 2008	265,384	241,035	90.8		249,891	94.2	
NY 2009	265,764	238,777	89.8		249,937	94.0	
NY 2010	265,493	246,336	92.8		252,376	95.1	
TX 2006	309,280	279,321	90.3		295,927	95.7	
TX 2007	304,360	273,251	89.8		289,251	95.0	
TX 2008	303,661	272,131	89.6		286,979	94.5	
TX 2009	306,081	270,579	88.4		289,251	94.5	

Source: New York SNAP administrative records, 2007–2010; Texas SNAP administrative records, 2005–2009; 1-Year ACS, 2006–2010

Table A2: Probit Estimates of Living with at least 1 Person with a PIK

	New York			Texas			
	2008	2009	2010	2006	2007	2008	2009
Married Couple	0.191***	0.240***	0.209***	0.435***	0.387***	0.373***	0.378***
	(8.96)	(11.17)	(9.29)	(19.87)	(18.22)	(17.76)	(17.52)
Male Head	0.196***	0.209***	0.160***	0.279***	0.189***	0.223***	0.243***
	(4.86)	(5.22)	(3.75)	(7.00)	(4.81)	(5.80)	(6.28)
Female Head	0.374***	0.417***	0.309***	0.506***	0.444***	0.413***	0.469***
	(12.56)	(14.11)	(10.11)	(15.97)	(14.52)	(14.04)	(15.62)
Children under 6	0.075*	0.093**	0.142***	0.140***	0.137***	0.133***	0.031
	(2.10)	(2.59)	(3.58)	(3.84)	(3.98)	(3.91)	(0.92)
Children 6 to 17	0.057*	0.168***	0.101***	0.039	0.011	0.025	0.069**
	(2.22)	(6.30)	(3.70)	(1.52)	(0.46)	(1.05)	(2.79)
Age 16 to 29	1.537*	1.935***	1.293	0.355	0.253	1.840***	1.680***
	(2.06)	(3.95)	(1.68)	(0.56)	(0.48)	(5.52)	(4.22)
Age 30 to 39	1.539*	1.985***	1.233	0.338	0.237	1.844***	1.713***
	(2.06)	(4.05)	(1.60)	(0.53)	(0.45)	(5.53)	(4.30)
Age 40 to 49	1.530*	2.017***	1.294	0.344	0.331	1.824***	1.724***
	(2.05)	(4.12)	(1.68)	(0.54)	(0.63)	(5.46)	(4.33)
Age 50 to 59	1.614*	2.076***	1.322	0.386	0.287	1.871***	1.725***
	(2.16)	(4.24)	(1.72)	(0.61)	(0.55)	(5.60)	(4.33)
Age 60 to 69	1.595*	2.144***	1.291	0.329	0.267	1.857***	1.745***
	(2.14)	(4.38)	(1.68)	(0.52)	(0.51)	(5.56)	(4.38)
Age 70+	1.606*	2.188***	1.296	0.360	0.296	1.902***	1.759***
	(2.15)	(4.46)	(1.68)	(0.57)	(0.57)	(5.68)	(4.41)
Less than HS Diploma	-0.009	-0.031	-0.029	-0.029	-0.039	-0.020	-0.046
	(-0.31)	(-1.04)	(-0.93)	(-0.99)	(-1.35)	(-0.72)	(-1.63)
HS Diploma	-0.099***	-0.132***	-0.090***	-0.062*	-0.053*	-0.058*	-0.127***
	(-4.30)	(-5.69)	(-3.71)	(-2.56)	(-2.27)	(-2.51)	(-5.50)
Bachelor's Degree	0.024	0.061*	0.021	-0.091***	-0.054*	-0.048*	-0.037
	(1.01)	(2.56)	(0.86)	(-3.58)	(-2.21)	(-2.05)	(-1.53)
White	-0.006	0.011	-0.181*	-0.065	0.081	0.011	0.181*
	(-0.08)	(0.15)	(-2.37)	(-0.85)	(1.32)	(0.17)	(2.53)
Black or African American	0.016	0.037	-0.097	-0.098	-0.004	-0.029	0.057
	(0.20)	(0.49)	(-1.23)	(-1.23)	(-0.05)	(-0.42)	(0.76)
AIAN	-0.458***	0.011	-0.330*	-0.114	-0.188	-0.148	-0.017
	(-3.37)	(0.07)	(-2.01)	(-0.90)	(-1.62)	(-1.24)	(-0.14)
Asian	0.024	-0.134	-0.274***	0.052	0.115	0.156	0.010
	(0.29)	(-1.66)	(-3.31)	(0.54)	(1.40)	(1.84)	(1.15)
Some Other Race or NHPI	0.123	0.130	-0.007	-0.162*	0.059	-0.169*	0.076
	(1.47)	(1.61)	(-0.08)	(-2.01)	(0.88)	(-2.36)	(0.99)
Hispanic Origin	0.072*	0.033	0.078*	0.054	0.093**	0.154***	0.145***
	(2.15)	(0.96)	(2.17)	(1.59)	(2.87)	(4.88)	(4.73)
Unemployed	-0.159***	-0.135***	-0.136***	-0.069*	-0.098***	-0.074**	-0.050
	(-5.75)	(-4.95)	(-4.77)	(-2.44)	(-3.50)	(-2.66)	(-1.85)
Full-time	-0.041	0.004	-0.111***	0.023	-0.056*	-0.012	-0.035
	(-1.75)	(0.16)	(-4.46)	(0.98)	(-2.53)	(-0.52)	(-1.53)
Non-citizen	-0.410***	-0.449***	-0.265***	-0.570***	-0.535***	-0.519***	-0.556***
	(-15.37)	(-16.91)	(-9.15)	(-19.24)	(-18.10)	(-18.00)	(-19.26)
HH inc $<$ 100% Poverty	-0.011	0.002	-0.030	-0.032	0.021	-0.009	-0.025
	(-0.37)	(0.08)	(-1.02)	(-1.15)	(0.76)	(-0.31)	(-0.93)
HH inc 100-130% Poverty	-0.025	0.076*	-0.021	-0.016	-0.020	-0.0003	-0.009
	(-0.64)	(2.00)	(-0.52)	(-0.45)	(-0.59)	(-0.01)	(-0.26)
HH inc 130-200% Poverty	-0.036	-0.009	0.030	-0.073**	-0.027	-0.0003	-0.012
	(-1.33)	(-0.32)	(1.08)	(-2.84)	(-1.07)	(-0.01)	(-0.47)
Speaks English	0.140***	0.050*	0.080**	-0.056	-0.074*	-0.010	-0.018
	(5.79)	(2.04)	(3.16)	(-1.82)	(-2.48)	(-0.35)	(-0.63)
Speaks English poorly	-0.216***	-0.178***	-0.093**	-0.317***	-0.351***	-0.287***	-0.189***
	(-6.50)	(-5.29)	(-2.59)	(-9.53)	(-10.71)	(-8.87)	(-5.81)
Disabled	0.158***	0.174***	0.187***	0.107***	0.132***	0.153***	0.175***
	(7.14)	(7.86)	(7.91)	(5.12)	(6.29)	(7.32)	(8.16)
Rural	0.065*	0.097***	0.049	-0.031	0.009	-0.001	0.005
	(2.57)	(3.80)	(1.83)	(-1.47)	(0.44)	(-0.03)	(0.22)
Mail	1.015***	1.055***	1.072***	0.741***	0.826***	0.849***	0.898***
	(50.97)	(53.09)	(51.53)	(34.78)	(39.95)	(42.14)	(45.14)
CATI	-0.263***	-0.199***	-0.258***	-0.265***	-0.256***	-0.331***	-0.266***
	(-13.10)	(-9.77)	(-12.08)	(-13.25)	(-13.51)	(-17.42)	(-13.63)
Constant	-0.521	-1.067*	0.003	1.078	0.961	-0.680*	-0.725
	(-0.69)	(-2.15)	(0.00)	(1.68)	(1.84)	(-1.99)	(-1.79)
Observations	107,306	107,250	106,646	118,276	116,476	116,726	117,221

Source: 2006–2010 ACS
Notes: Individual is the unit of observation. Estimated is Probit regression with individual sample weights. Regression coefficients appear outside of parentheses and standard errors appear in parentheses. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$