Errors in Reporting and Imputation of Government Benefits and Their Implications

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Abstract

Recent studies document extensive errors in household surveys that bias important estimates. We link administrative cash welfare and SNAP records to three major U.S. household surveys to answer important questions these studies raise. First, we show that survey data misrepresent patterns of participation in multiple programs and thereby distort total transfers to the poorest households and how households navigate the complex welfare system. On the positive side, survey data capture the reach of the safety net better than receipt of individual programs. Second, we examine error due to item non-response and imputation, as well as whether imputation improves estimates. Item non-respondents have higher receipt rates than the population, even conditional on many covariates. The assumptions for consistent estimates in multivariate models fail both when excluding item non-respondents and when using the imputed values. In models of program receipt, estimates from the linked data favor excluding item non-respondents rather than using their imputed values. We show that such analyses can help researchers make more informed decisions on the use of imputed values. Along the way, we extend prior work by documenting for other programs and geographies a pattern of pronounced misreporting that varies with key demographics. Our estimates allow researchers to gauge or correct bias in models of program participation, because they predict when these biases are (or are not) large. Most notably, the survey error we document cause the differences in receipt rates between Blacks or Hispanics and those of whites to be 1.4 to 6 times larger than survey estimates.

Key words: Linked Survey Data, Measurement Error, item non-response, imputation, program receipt.

JEL Codes: C81, D31, I32, I38

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1. Introduction

Both policy makers and academics heavily rely on household surveys. Survey statistics such as the rates of unemployment and poverty are the basis of important policy decisions. Survey data are also frequently used in more complex policy analyses such as documenting distributional impacts of taxes and transfers and assessing the likely consequences of new legislation (e.g. CBO 2013, 2016). Models of transfer receipt help to increase take-up and better target transfers (e.g. U.S. GAO, 2004). The surveys we examine here are also frequently used in academic studies of transfer receipt (e.g. Blank and Ruggles, 1996; Ganong and Liebman, 2018). Recent work has demonstrated that transfer receipt is severely underreported in survey data, with up to 50 percent of true SNAP recipients not reporting receipt, for example.[1] However, at least until other data sources become available, surveys are indispensable and continue to be used for studies of income, poverty and program participation. For example, recent research using survey data uncovered important differences by ethnicity and gender in program receipt (e.g. Moffit and Gotschalk, 2001; Gould-Werth and Shaefer 2012; Kuka and Stuart 2021; Forsythe and Yang 2021; U.S. GAO 2022) and measures of poverty and well-being (e.g. Burkhauser et al. 2022; U.S. Census Bureau 2022). For such analyses it is not only important that surveys capture resources and program receipt well overall, but also that survey accuracy does not vary with covariates. If covariates such as indicators for race or ethnicity predict survey error, then these analyses confound real differences with differences in survey error.

Therefore, it is crucial to understand for which types of analyses they are (more) reliable, as well as how we should use and improve survey data. Prior work shows that survey error severely distorts analyses of the ability of the safety net to reach those in need, resources available to poor households (Meyer and Mittag, 2019a) and extreme deprivation (Meyer et al. 2021). Such analyses crucially depend on whether surveys accurately reflect receipt of multiple transfer programs, but prior work on

[1] See e.g. Marquis and Moore (1990), Taeuber et al. (2004), Kirlin and Wiseman (2014), Meyer, Mittag and Goerge (2022) for SNAP, Lynch et al. (2007) for Public Assistance and Nicholas and Wiseman (2010), Gathright and Crabb (2014), Bee and Mitchell (2017) for social security and pensions.

misreporting has by and large only considered receipt of individual programs. This prior work on survey error has also documented alarming misclassification rates among imputed observations (Meyer, Mittag and Goerge, 2022). Yet the value of imputation and whether imputed values should be used depends on whether they improve survey estimates rather than the error rates that have been documented, which is less clear (see Bollinger et al. 2019).

In this paper, we focus on these two questions of multiple program receipt and imputation that are crucial to understand when and how surveys should be used. First, we examine reporting of participation in multiple programs. It is important to understand how the multitude of U.S. transfer programs interact and whether they jointly form an effective safety net. To obtain even basic facts such as how many individuals depend on this safety net or whom it misses, we need surveys to correctly capture patterns of participation in multiple programs. While we know that rates of underreporting are high, we do not know whether some recipients fail to report all program receipt or whether most recipients fail to report some of the programs they receive. Consequently, many crucial questions remain open: Does misreporting arise from program confusion (Gathright and Crabb, 2014, Giefer et al. 2015, Bollinger and Tasseva, 2022)? How does misreporting affect statistics that depend on the total amount a household receives, such as poverty rates and the income distribution? Does the multitude of transfer programs jointly form an effective safety net and how do people navigate this complex welfare system (e.g. Keane and Moffitt, 1998)? Do surveys accurately capture who is (not) reached by the safety net at all (e.g. Blank and Kovak, 2009, Bitler and Hoynes 2010)?

Second, we examine the nature of item non-response and the quality of imputation. Even though item non-response is frequent and imputed values are its main remedy (Meyer, Mok and Sullivan, 2015), we do not know how item non-respondents differ from respondents (Groves and Cooper 1998, Groves 2001). Consequently, we do not know whether the assumptions for common imputation methods to correct survey estimates are valid (Andridge and Little 2010). We also do not know to what extent imputed values reproduce the predictors of program receipt (Hirsch and Schumacher, 2004). In consequence, it is difficult to assess whether it is better to exclude item non-respondents or to use their imputed values (Angrist and Krueger, 2001). A better understanding of item non-response and imputation is also crucial to design better imputation methods.

To make progress on these open questions, we link administrative records from Supplemental Nutrition Assistance (SNAP), Temporary Assistance for Needy Families (TANF) and General Assistance (GA) covering New York State to the American Community Survey (ACS), the Current Population Survey Annual Social and Economic Supplement (CPS) and the Survey of Income and Program Participation (SIPP). We aggregate participation in either TANF or GA to participation in one program, TANF+GA, because they are in practice one program in New York. Along the way, we use this large linked sample to extend prior studies of survey error and its consequences.

In particular, validating receipt of two programs shows that surveys not only understate program receipt, but also misrepresent patterns of participation in multiple transfer programs. This error badly distorts how people navigate the complex welfare system, i.e. how they combine participation in multiple programs, because survey reports severely understate the probability of receiving a second program conditional on receiving one program. In consequence, one would expect large biases when using survey data to analyze decisions to participate in multiple programs and resources available to the poorest households. On the positive side, survey data capture the reach of the safety net, i.e. how many households receive any aid, better than the rate of underreporting individual programs suggests. Surveys may therefore be more reliable when studying whether individuals are connected to the safety net as a whole rather than when examining whether they receive a specific program. We also provide evidence that program confusion is not an important cause of misreporting for SNAP and TANF+GA.

Our linked data put us in a unique position to study item non-response and the merits of imputation as a remedy, because they provide us with an accurate measure of the outcome for both respondents and (item) non-respondents.[2] We first show that item non-respondents differ from the overall population, both unconditional as well as conditional on many covariates. In addition, the relationship between these covariates and program receipt differs between non-respondents and the overall population. But imputed program receipt also differs from actual receipt, so that imputed values reproduce neither receipt rates, nor the relationship between covariates and program receipt among non-respondents. Thereby, we soundly reject the assumptions usually required for consistency of excluding item non-respondents as well as for the alternative of including them along with their imputed values. Thus, data users face a choice between two strategies neither of which yields estimates close to the truth even in large samples. For models of program receipt for our three datasets and two programs, we provide evidence that using only respondents likely leads to less bias and thus seems preferable. More generally, our results suggest that analyses of the nature of item non-response and imputation error, such as the ones we conduct allow researchers to make more informed decisions whether to use observations with imputed values or not. Our analyses of imputed values and how they differ between surveys also suggests ways to improve imputation methods, for example by incorporating geographic information.

In addition to our two main questions regarding participation in multiple programs and imputations, we confirm and extend analyses of the nature of survey errors. We confirm high error rates for another state and an additional program and show key household characteristics tend to predict over- and underreporting of transfer receipt (Bollinger and David 1997, Meyer, Mittag and Goerge, 2022). When estimating binary choice models of program receipt, we indeed find sizeable bias especially for strong predictors of survey error. For example, we document stark differences in reporting by race and ethnicity, which make the surveys severely understate differences in receipt rates by minorities compared to whites. Such conditional differences in reporting accuracy are more concerning for the studies of program receipt

[2] Unit non-response or more generally coverage error is another important source of survey error. We do not examine coverage error here, since Meyer and Mittag (2021a) show that the surveys we examine here capture the population of SNAP and TANF+GA recipients well.

and inequality between racial and ethnic groups than the overall error rates emphasized by the previous literature. Researchers using survey data to study inequality between ethnic groups should thus either correct for misreporting or at least be aware of the fact that survey error likely biases the differences they find. Yet overall, there is a tendency for attenuation and robust signs as predicted by the theoretical results in Hausman, Abrevaya and Scott-Morton (1998) and Meyer and Mittag (2017). Thus, survey estimates preserve many substantive conclusions. Our estimates of the determinants of misreporting can explain exceptions from this pattern of attenuation. Thereby, our results can help researchers assess which conclusions are likely robust to misreporting and to gauge or correct the bias when information on the nature of misreporting is available (Bollinger and David 1997, Meyer and Mittag 2017). For example, the studies of differences between ethnic groups referenced above could use our results to better isolate actual differences from differences in reporting (e.g. using methods in Bollinger and David 1997, Meyer and Mittag 2017 or Mittag 2019). Throughout this paper, we will use the example of these studies of differences by race and ethnicity to illustrate the importance of understanding survey error and how our results can help improve research based on survey data.

The next section describes our data sources and linkage. Section 3 analyzes participation in multiple programs. Section 4 examines which covariates predict survey errors. Section 5 studies how this systematic misclassification translates into bias in models of program receipt. Section 6 analyzes item non-response and imputation. Section 7 summarizes our conclusions.

2. Data Sources and Linkage

Studying survey error at the household level requires an accurate measure of the variable of interest for each household. Linking administrative records to survey data can provide this measure.[3] We use the

[3] We believe that our measure is sufficiently accurate to study misreporting, even though it likely contains a small amount of error. We do not mean to argue that administrative or linked data are more accurate in general. There can be substantial error both due to errors in the administrative data, see e.g. Niehaus and Sukhtankar (2013) for an extreme case, and due to the linkage process, see e.g. Courtemanche, Denteh and Tchernis (2019) and Meyer and Mittag (2019b). See Meyer and Mittag (2021b) for further discussion.

same data as Celhay, Meyer and Mittag (2022), Meyer and Mittag (2019a, 2021a) and Mittag (2019), who provide further detail on the data sources, the linkage process and the accuracy of the final linked data.

a. Survey data

We study measurement error in program receipt in three major U.S. household surveys: the ACS, the CPS and the SIPP. The ACS is the largest household survey in the U.S., with more than 290,000 households selected each month to participate. We use the ACS for calendar years 2008 through 2012. The CPS is one of the most important economic surveys in the U.S. with 60,000 households participating in the survey each month of the year. It is the official source of labor force statistics. We use the Annual Social and Economic Supplement (ASEC) to the CPS for calendar years 2007 to 2012. The ASEC has a sample of about 98,000 households, and is the official source of income and poverty statistics in the U.S. Finally, the SIPP is the highest quality source of information on low income households and the receipt of government transfers. We use wave 10 through 12 of the 2004 SIPP panel (covering calendar year 2007) and wave 1 to 14 of the 2008 SIPP panel (covering August 2008 to December 2012). Both panels sampled approximately 50,000 households intended to be surveyed for a period of 4 years. For all three surveys, our sample is households in NY state, because our administrative records provide us with an accurate measure of receipt for them.

The three surveys are large-scale, general interest surveys, which makes them similar in survey design. Yet, there are also pronounced differences in survey design features known to be related to both non-response and measurement error. See Celhay, Meyer and Mittag (2022) for a discussion. The ACS questionnaire is administered by mail/internet, telephone, or in-person interview. The CPS conducts interviews in person and by phone. While the ACS and CPS only interview one household member, the SIPP strives to conduct in-person interviews with every member of the household over age 15 every four months. The documentation of the surveys (U.S. Census Bureau, 2006, 2008, 2014) provides further detail.

In terms of information on government transfers, all three surveys ask about receipt of SNAP and TANF+GA. For both programs, the questions in the ACS refer to the 12 months prior to the interview date. The CPS asks about the previous calendar year. The SIPP asks for monthly information in the four months before the interview. A large extent of misreporting in the SIPP is known to stem from seam bias, i.e. respondents correctly report receipt of the program, but in the wrong months within each four-month wave (Moore, 2008). To focus on whether households report or not rather than the timing of reports, we aggregate the monthly information on program receipt to one observation on receipt anytime during the four-month wave, like Ribar (2005) and Acs, Phillips, and Nelson (2005). We then analyze each wave as a separate cross section.

Following Meyer, Mittag and Goerge (2022), we analyze program receipt at the household level. We consider a household to receive a program according to the survey if any member reports program receipt at any time during the reference period. For the ACS and CPS, we thereby exactly match the survey question. For the SIPP, we aggregate the individual responses to one observation per household to obtain a variable for receipt by any household member.

Item non-response rates differ substantially between surveys and questions. For SNAP, our sample of imputed observations accounts for 1.1 percent of the population in the ACS, 13 percent in the CPS and 7.2 percent in the SIPP. The rates for TANF+GA are similar in the CPS (13 percent) and SIPP (7.1 percent), but higher in the ACS (6.1 percent).[4] All three surveys impute missing values using a hot deck procedure. In short, the hot deck sorts observations into cells based on categorical variables reported in the survey. If a value is missing for an observation, the value of a respondent from the same cell is assigned to this observation instead. The details of the implementation vary across surveys and variables. For example, for SNAP, the ACS constructs cells based on few demographic characteristics (family type,

[4] Our samples of imputed observations include block and whole imputes, i.e. cases where respondents failed to answer multiple questions that were imputed simultaneously. They do not include edited cases, i.e. when a response was provided, but changed by the survey producer.

presence of children, poverty status, and the race of the reference person). However, the ACS hot deck incorporates detailed geographic information by only using values from the same state and assigning the value of the most recent respondent in the corresponding cell at the smallest geographic level available. In contrast, the CPS hot deck for SNAP classifies households into a much larger number of cells (648), but at the national level. Different from its processing of SNAP, the CPS imputes TANF+GA jointly with other missing income components from a single donor. The SIPP hot deck uses a comparable number of cells (864) to impute SNAP at the national level, but also incorporates some geographic information and restricts imputed values to come from the same wave. For more details see U.S. Census Bureau (2006, 2008 and 2014) for the CPS, SIPP, and ACS, respectively, and Meyer, Mittag and Goerge (2022) for a summary.

b. Administrative Data and Data Linkage

Our administrative data are records of payments from the NY Office of Temporary and Disability Assistance (OTDA) for all SNAP and TANF+GA recipients in the state. They include monthly payment amounts and dates, as well as basic demographic information and addresses from 2007 through 2012. The monthly information allows us to exactly match the reference periods of each survey. The accuracy of the individual identifiers and amounts paid is crucial to the validity of our estimates and they appear to be of high quality. As part of eligibility determination, the individual information in these records is checked against social security records by OTDA. The data are from actual payments and audited. For SNAP, estimates of total amounts paid are also published by OTDA and the Bureau of Economic Analysis (BEA). The overall total from our administrative SNAP records matches aggregate reports by OTDA almost exactly and differs from the BEA numbers by less than a percent in all years.[5] That these numbers are virtually identical provides additional evidence of the accuracy of our administrative microdata.

[5] Published aggregates comparable to our administrative TANF+GA records are not available.

We link the administrative data to the three surveys at the household level using person identifiers created by the Person Identification Validation System (PVS) of the U.S. Census Bureau. Wagner and Layne (2014) discuss the PVS in detail. In short, the PVS uses the person data (such as address, name, gender, and date of birth) from the administrative records and survey data to search for a matching record in a reference file that contains all transactions recorded against a social security number (SSN). If a matching record is found, the SSN of the record from the reference file is transformed into a protected identification key (PIK)[6] and attached to the corresponding records in our data. For the administrative data, a PIK is obtained for more than 99 percent of the records from each program. The administrative data include records for each recipient person, so we can link the information from a program case to the correct survey household if any true recipient in the household is assigned a PIK.[7] Therefore, we consider a household to have a PIK if a PIK was obtained for someone in the household. The household-level PIK rates of our survey sample are 93 percent in the ACS, 91 percent in the CPS, and 95 percent in the SIPP.

We cannot validate receipt information for survey households without a PIK, so all analyses are based on the survey sample with a PIK (the "linked data"). Despite the low rate of missed links, PIKs are not missing completely at random in the survey data. To restore representativeness of the linked data for the NY survey population, we use inverse probability weighting (Wooldridge 2007) as in Meyer and Mittag (2019a, 2021a). To do so, we estimate probit models to predict the probability that a household has a PIK and multiply the survey weights by the inverse of this predicted probability. This correction assumes that conditional on the covariates in the probit model, whether a household has a PIK or not does not predict receipt or reporting. Meyer and Mittag (2021a) discuss this assumption. As the high rate of PIK-linking suggests, our results do not appreciably change when using the unadjusted weights.

[6] PIKs are perturbed SSNs used to protect the anonymity of individuals in the data.

[7] We cannot link households in which all members with a PIK are true non-recipients, but there are true recipients among those without a PIK. Usually only few PIKs are missing per household, as 89 percent of individuals have a PIK in the ACS and 86 percent in the CPS and SIPP, and only few non-recipients cohabit with recipients. See Meyer, Mittag and Goerge (2022) for arguments why these exceptions should be uncommon.

3. The Extent of Survey Error in Reporting Participation in Multiple Programs

Before using our unique data to study reporting of multiple programs, we briefly document the extent of misclassification and compare it to prior studies. Table 1 reports population estimates of the false negative, false positive and the net reporting rates (the ratio of the weighted number of survey recorded recipient households to administrative recipient households in the linked data) of SNAP and TANF+GA for NY in the ACS, the CPS and the SIPP. The uppermost panel presents error rates for the entire sample, while the middle panel restricts the sample to respondents and the lowermost panel restricts the sample to item non-respondents. Appendix Table A3 provides crosstabulations of administrative and reported receipt including error rates conditional on reported receipt status and unconditional rates.

Table 1: Error and Reporting Rates by Survey and Imputation Status (around here)

For SNAP, we confirm for another state alarmingly high rates of false negatives that are highest in the CPS (42 percent), followed by the ACS (26 percent) and the SIPP (19 percent). While substantial, these rates are 15 to 22 percent lower than the false negative rates Meyer, Mittag and Goerge (2022) document for the same surveys in IL and MD. The rates for TANF+GA, for which no prior evidence exists, are substantially higher at 46 to 63 percent. Also in line with prior work, we find much lower rates of false positives. Contrary to Meyer, Mittag and Goerge (2022), the false positive rates we find in the SIPP are similar to the other surveys for SNAP (and low for TANF+GA). The combination of high false negative rates and low false positive rates leads all three surveys to understate the number of participating households, ranging from understating SNAP recipients by 12 percent in the SIPP to understating TANF+GA receipt by 50 percent in the CPS.

Similar to Meyer, Mittag and Goerge (2022), the lower panel of Table 1 documents substantial imputation error at the household level. False negative rates among imputations reach up to 86 percent. Imputation is also an important source of false positives, with up to almost half of all false positive errors stemming from the small sample of imputed values. Without imputed observations, the false positive rates for SNAP become remarkably similar across surveys at around 1.1 percent. The goal of imputation is usually to improve aggregate statistics, rather than correctly predicting receipt of individual units. However, columns 5 and 6 of Table 1 show that imputation does not reproduce aggregate receipt rates among item non-respondents either.

The high rates of underreporting above by themselves say little about how survey error blurs our understanding of how the safety net works as a whole and the bias misreporting causes in statistics that depend on the total amount a household receives, such as poverty rates and the income distribution. Both issues crucially depend on whether some recipients fail to report all program receipt or whether most recipients fail to report some programs they receive. Our linked data contain accurate measures of receipt for both SNAP and TANF+GA, so we can examine whether the survey data correctly reproduce receipt of multiple programs.

Table 2 summarizes joint receipt rates for SNAP and TANF+GA according to the administrative and the survey variables in the linked data. Patterns of participation are similar across surveys when using the administrative receipt variables, but the survey data poorly reflect these patterns of participation. The first two columns show that all surveys understate how many households depend on government transfers. The share of households receiving either program is 20, 46 and 14 percent higher than the ACS, CPS and SIPP suggest. As the lower panel of Table 2 shows, the understatement of the number of households reached by SNAP or TANF+GA is more severe among imputed observations. Thus, the survey data overstate how many people are missed by the safety net, as one would expect given the high rates of underreporting of each program. However, while these differences are important in magnitude, they are smaller than rates of underreporting for each individual program. It seems likely that this difference would increase when looking at receipt of more than the two programs we consider here. The surveys thus yield more accurate estimates of receipt rates when looking at receipt of either program, than when looking at each program separately. Thereby, the surveys capture the reach of the safety net overall better than previous studies of one program suggest. Survey data thus seem more suitable to analyze who is reached by the safety net than to examine who receives any given program.

Capturing the reach of the safety net better than receipt of each program comes at the expense of understating joint program participation more severely than participation in one program only. Columns 7 and 8 show that the surveys understate receipt of both programs by slightly more than one-third (ACS and SIPP) and more than one-half (CPS). These rates are substantially higher than the net understatement of each program in Table 1. The surveys also underimpute joint program receipt. Imputations in the ACS and SIPP capture the probability of receiving both programs better than the survey reports but fall further short of it in the CPS. These large differences indicate that survey data severely understate total transfers and hence resources of the (likely) poorest households. This finding can help to explain why survey data are particularly problematic when analyzing extreme deprivation (Meyer et al. 2021).

Table 2: Joint Receipt Rates of SNAP and TANF+GA According to Survey Reports and Administrative Records (around here)

These differences are partly driven by the high rates of underreporting but reinforced by survey reports understating dependence in program participation. As columns 3 to 6 of Table 2 show, all three surveys still understate the fraction of households receiving SNAP, but not TANF+GA. However, the difference is smaller than the difference for all SNAP recipients in Table 1. The surveys overstate the fraction of households receiving TANF+GA only.[8] Both biases are even more pronounced in the imputed sample. There is a downward bias in the survey estimates of the probabilities of receiving the second program given receipt of the first. This problem holds for all conditional probabilities, i.e. the probability of receiving SNAP given receipt of TANF+GA, receiving TANF+GA given receipt of SNAP as well as receiving

[8] Separately looking at overreporting of each program explains the overstatement of receipt of TANF+GA only, which seems surprising given the high false negative rate among TANF+GA recipients. However, the overstatement is due to households that receive neither program, but mistakenly report TANF+GA receipt (false positives). The fraction of actual TANF+GA recipients who report TANF+GA only is small in all samples.

both programs given receipt of any of the two programs.[9] Survey data thus poorly capture patterns of receipt of multiple programs.

The bias is pronounced for the probability of receiving SNAP conditional on receiving TANF+GA. Households receiving TANF+GA are categorically eligible for SNAP receipt in NY, so as one would expect, most households that receive TANF+GA also receive SNAP (96 percent in the ACS and CPS, and 94 percent in the SIPP). However, the probability of reporting TANF+GA conditional on reporting SNAP is 77, 84 and 89 percent in the ACS, CPS and SIPP respectively. Thus, survey errors can explain the puzzling fact that many eligible households do not seem to receive all programs for which they are likely to be eligible.[10] This finding underlines that reporting errors make survey data problematic for analyses of which programs households choose to participate in and how they navigate the complex welfare system.

The linked data allow us to examine how survey errors at the household level lead to these aggregate differences in the joint distribution of program receipt. Table 3 summarizes error rates conditional on the number of programs the household receives according to our administrative measure of participation. For each group, we omit the column corresponding to those who correctly reported receipt. The upper panel presents error rates for the entire sample. The lower panel restricts the sample to item non-respondents. The rates of erroneously reporting one program only in columns 1 and 7 show that the high reported rates of receiving only one program we document above is driven by both recipients of no program and recipients of two programs often reporting one program. The overreporting rates in column 5 are higher than those in columns 1 and 2, but the population share of non-recipients is much larger than the population share of recipients of one program. Thus, most false positives are due to non-recipients recorded as recipients of one program. However, we should emphasize again that some

[9] These probabilities are ratios of columns of Table 2, e.g. the survey estimate of the conditional probability of receiving SNAP given TANF+GA receipt is the ratio of column 7 to the sum of columns 5 and 7.
[10] The high probability of receiving SNAP when receiving TANF+GA suggests that imputing or probing for SNAP receipt for those reporting TANF+GA may be worth examining as a strategy to improve survey accuracy.

households are likely to be erroneously classified as false positives due to unlinkable administrative records, leading to spurious false positives.

Column 4 reports the fraction of households that receive one program according to the administrative variable and report receipt of the other program in the survey. Both the rate among those receiving one program (0.1 to 0.8 percent) and the share in the population (0.01 to 0.1 percent) are small. Consequently, program confusion is rare and plays a minor role for aggregate error rates. However, SNAP and TANF+GA differ in very salient ways. Program confusion may play a larger role for programs that operate in more similar ways and may still contribute to the high rates of underreporting we document, for example if people confuse SNAP with free school meals. The rate of imputing the wrong program is two to four times higher, which is not surprising given that the recipient populations are similar.

Table 3: Reporting of Participation in Multiple Programs (around here)

Finally, columns 6 and 7 show that the fraction of households who correctly report both programs is low at 35 to 52 percent. Error rates are high for both programs, so getting both programs right is relatively uncommon. Yet the fraction correctly reporting both programs is higher than the product of the fraction correctly reporting each program. Thus, those receiving both programs report more accurately than the overall population: with the exception of TANF+GA in the SIPP, the false negative rates among those receiving both programs are lower than the false negative rates in the entire population. Most people who report two programs actually receive two programs, with a rate close to 80 percent in the CPS and SIPP and 63 percent in the ACS.

Errors are more frequent among imputed observations than among respondents in the CPS and SIPP throughout. Surprisingly, the ACS imputations for households that receive both programs are more accurate than the ACS reports of respondents who receive both programs. While the error rates in imputations are high, one may have expected worse for participation in multiple programs given that the imputation procedures use little information on other programs. It is important to keep in mind that our sample of imputed observations includes households where the entire income record was imputed in the CPS and households where some, but not all household members refused to answer the question on program receipt in the SIPP. Such observations preserve the reported patterns of joint participation. However, the fact that we do not find the imputations to be systematically worse in the ACS without this feature than in the other surveys suggests that these observations are not driving the patterns we find.

4. The Determinants of Survey Errors

We next examine how misreporting of SNAP and TANF+GA receipt differs between households. The previous section shows that misreporting rates differ by true receipt status. Therefore, we estimate probit models whether receipt status of the household is misclassified separately for recipients and non-recipients according to the administrative variable. We use the entire linked survey sample including imputed observations in order to provide a description of the accuracy of the entire data. Meyer, Mittag and Goerge (2022) estimate similar models[11] for SNAP using linked data from IL and MD. So after briefly summarizing similarities in the main predictors, we focus on extensions of and differences to prior work. Importantly, we show that the patterns of misreporting are qualitatively similar for a third state and a second program, TANF+GA. Table 4 reports probit marginal effects of the determinants of failure to report SNAP or TANF+GA among recipient households. Table 5 reports probit marginal effects of the determinants of reporting receipt among non-recipient households. We confirm that survey errors are systematically related to household characteristics, even conditional on true receipt status by rejecting the hypothesis that the coefficients are jointly zero with p-values below 0.001 in all models. Beyond describing the nature of measurement error, researchers can use these estimates to correct for survey error (Meyer and Mittag 2017, Mittag 2019).

[11] They exclude households with income above twice the poverty line. Mittag (2019) and Meyer and Mittag (2019a) document fairly high error rates among households with income higher than twice the poverty line, so we include these households in the analyses in this section. Parameter estimates of models that exclude these observations are provided in Appendix Tables A4 and A5.

Table 4: The Determinants of Mis-reporting, False Negatives, Probit Average Derivatives, Full Linked Sample (around here)
Table 5: The Determinants of Mis-reporting, False Positives, Probit Average Derivatives, Full Linked Sample (around here)

The marginal effects vary across surveys, but tend to be of similar magnitudes and usually have the same sign for a given program in all surveys. Key predictors are nearly the same as the variables with significant marginal effects on misreporting SNAP in Meyer, Mittag and Goerge (2022). We also find income, employment and reported receipt of other programs to be important predictors of misreporting. False negatives increase and false positives decrease as reported income relative to the poverty line rises. Thus, households with higher incomes report less program participation. The effects are large and precisely estimated. Whether anyone in the household is employed is significant with only one exception. With differences in false negatives of 3 to 22 percentage points between households with and without anyone employed, the differences are large enough to skew substantive conclusions. Reported receipt of other transfer programs (housing assistance and reported TANF+GA/SNAP receipt) is among the strongest predictors of misreporting. The marginal effects are significant in all but one case and consistently show that those who report one program are more likely to report other programs as well. This correlation is positive for both recipients and non-recipients, i.e. reporting receipt of another program is associated with lower false negatives and higher false positives. With lower false negatives of 6 to 20 percentage points for those with reported housing assistance receipt and 20 to 35 percentage points for those with reported TANF+GA/SNAP, the associations are very strong.

In addition, we find gender, disability, race and ethnicity to be important predictors of misreporting, but here our findings extend or differ from prior work. We extend the analyses of Meyer, Goerge and Mittag (2022), who find evidence that whites commit fewer reporting errors, by separately analyzing households with a Black, a non-Black Hispanic or other non-Hispanic household head. False negative rates are 4 to 8 percentage points higher among these minorities. These effects are pronounced and consistent across surveys and programs for households with a Black or Hispanic householder, but noisier for other minorities. With the exception of Hispanics who overreport TANF+GA less, false positive rates are also higher among minorities. Consequently, in most cases minorities report program participation worse and not just less. These sizeable differences in reporting are concerning for the numerous analyses that compare receipt rates or measures of resources that include transfers across racial and ethnic groups. For example, studies such as Burkhauser et al. (2022) or U.S. Census Bureau (2022) could use estimates such as ours to predict net differences in program receipt in order to gauge whether their estimates of disparities are likely to be over or understated due to systematic differences in reporting transfer receipt.

Contrary to Meyer, Mittag and Goerge (2022), who find large, but imprecise marginal effects for indicator variables for male and disabled householders, we find that false negative rates for households with a male householder are 3 to 8 percentage points higher. At the same time, they have lower false positive rates. Thus, households with a male householder tend to report less program receipt. All effects for a disabled householder go in the opposite direction, i.e. they report more program participation. The reduction in false negatives for the disabled is consistently significant and among the largest effect sizes we find. Contrary to Meyer, Mittag and Goerge (2022), we do not find reporting to be better in rural areas.

Finally, our more precise results provide some reassuring evidence on the important questions of misreporting by the elderly and whether misreporting is increasing over time. We do not find evidence of an age gradient for either program. The effect of age on false negatives is ambiguous for the elderly (60 and older), as they have fewer false negatives for SNAP in the ACS and SIPP, but more false negatives for SNAP in the CPS and TANF+GA in the SIPP. Yet, the elderly clearly commit fewer false positives. These findings suggest that the low estimated program participation rates of the elderly (Haider, Jacknowitz and Schoeni, 2003, Wu, 2010, Jones et al. 2021) are not due to greater underreporting. The lower false positive rates make understatement of receipt more severe among the elderly, but any reduction in receipt due to reporting errors stems from better, rather than worse reporting. Whether the problem of misreporting has increased over time is an important question. Meyer, Mittag and Goerge (2022) find that false negative rates are increasing over time and provide suggestive evidence that false positives are becoming more frequent. Our estimates confirm that false positive rates have increased over time, but at a slow pace. However, we do not find evidence of increasing false negative rates, even though the time trend is precisely estimated.

5. The Consequences of Survey Errors

Survey users are ultimately mainly concerned with the accuracy of their estimates. The high error rates and their relation to common covariates violate the conditions for consistency of most estimators, but analytic results on the size and direction of bias from such non-classical measurement error are rare, and at best, case specific. The linked data provide us with an accurate measure of the dependent variable in addition to the reports. Thus, we can analyze the bias from misreporting for any specific estimate by comparing estimates using the reported and the accurate administrative variable. In lieu of more general results, we examine the consequences of survey errors for probit models of program receipt. These models are frequently estimated to analyze program targeting (e.g. Currie 2006, Haider, Jacknowitz and Schoeni 2003). Meyer, Mittag and Goerge (2022) describe the bias in such models, employing the same approach we adopt here using data from IL and MD. Therefore, after briefly summarizing key differences and extensions, we focus on methodological issues that these results raise. Specifically, we examine when and why the survey data reproduce substantive conclusions as well as whether empirical estimates of the determinants of survey error in combination with asymptotic results help to explain exceptions from this pattern and thereby provide guidance on the consequences of misclassification to applied researchers.

Table 6 and Table 7 report results for models of SNAP and TANF+GA receipt. In both cases, we restrict the sample to households with income below twice the poverty line and include imputed observations to focus on a commonly used sample for which receipt is likely. For each survey and program, the tables contain three columns: The marginal effects according to the survey reports, the same estimates when using administrative receipt as the dependent variable instead and the p-value of a test of equality. We can reject the hypothesis that all estimates are jointly the same at conventional significance levels in all cases. Consequently, our results show that survey error indeed leads to bias.

Table 6: SNAP Receipt in Survey Data and Combined Data, Probit Average Derivatives, Households with Income less than Twice the Poverty Line (around here)

Table 7: TANF+GA Receipt in Survey Data and Combined Data, Probit Average Derivatives, Households with Income less than Twice the Poverty Line (around here)

In line with finding substantial misreporting by minorities, the most pronounced differences are for households with a Black or Hispanic householder, for whom receipt rates of both SNAP and TANF+GA are significantly biased downward in all cases. Receipt rates of minorities (conditional on observables) are 4 to 8 percentage points higher than the survey indicates. Thereby, survey data severely understate differences in receipt rates between these minorities and whites, which are 1.4 to 6 times higher when correcting for survey error. These differences are among the largest ones we find and clearly large enough to skew important conclusions. For example, prior work used the same models we estimate here to argue that higher welfare receipt rates by minorities almost vanish once conditioning on demographics (Moffitt and Gottschalk 2001). Yet our results suggest that such estimates may severely understate differences. Whether correcting for differential misreporting amplifies or reduces differences likely depends on the initial differences. In the case of unemployment insurance receipt (Gould-Werth and Shaefer 2012; Kuka and Stuart, 2021; Forsythe and Yang 2021; U.S. GAO 2022) surveys tend to find lower receipt rates by minorities, but our results suggest these differences may be smaller or even reverse once one accounts for misreporting of receipt. Like prior work, we find misreporting to bias the effects of income on program receipt.

Contrary to Meyer, Mittag and Goerge (2022), but in line with our results on the determinants of survey error, we do not find that the surveys understate receipt by the elderly. For SNAP, we do not find any systematic effect on the age profile. The survey data actually overstate the probability of receipt for the elderly in the ACS and SIPP, although the difference is not significant in the SIPP. This effect is more pronounced for TANF+GA, where the surveys overstate receipt by those 70 and older by 3 to 5 percentage points. Despite their large marginal effects on reporting errors, the marginal effects of reported receipt of other programs on TANF+GA and SNAP receipt are surprisingly accurate in the survey. So while the surveys severely misrepresent the patterns of multiple program participation in the unconditional analyses above, this problem appears less severe in our multivariate analyses.

Our results lend further support to the conjecture of Meyer, Mittag and Goerge (2022) that qualitative conclusions are similar despite the large and systematic error. Only 42 out of 152 estimated marginal effects are significantly different. So even with a much larger sample, we do not find a larger fraction of significant differences than Meyer, Mittag and Goerge (2022). The results are well-aligned with the asymptotic formulas of Meyer and Mittag (2017), which imply a tendency for robust signs and attenuation that would preserve qualitative conclusions. Only 15 out of our 152 pairs of point estimates switch sign when we replace the survey reports with the administrative values. The survey estimate is insignificant in 13 of these cases and there is only one case in which both estimates are significant. 99 out of 137 marginal effects (excluding the 15 marginal effects that change sign) are attenuated when using the survey reports. Only 3 of the marginal effects that are biased away from zero change significantly (at the 10 percent level) when using the administrative variable instead of the survey reports. Thus, most point estimates are indeed attenuated and we can only reject the hypothesis that they are biased toward zero for 3 out of 152 marginal effects. Consequently, our results provide evidence that it is very rare for the survey data to imply an incorrect direction of the marginal effects and confirm a strong tendency to attenuation.

Yet, this encouraging pattern does not always hold. While some coefficients, such as those on receipt of other programs, indeed accurately reproduce substantive conclusions, other key predictors of misreporting indeed translate into large biases in models of receipt, as the examples for minorities above shows. This finding raises the question whether and when we can expect the pattern of attenuation that preserves substantive conclusions to generalize and to what extent empirical analyses of the determinants of survey error and asymptotic results can help data users detect exceptions. The asymptotic formulas of Meyer and Mittag (2017) point to a potential reason why the severity of the bias differs so much between coefficients: If misreporting reinforces the true receipt gradient, i.e. when a variable predicts higher true receipt rates and also predicts more reporting (more false positives and fewer false negatives), two errors partially cancel: The correlation of misreporting with covariates biases estimates away from zero, which reduces the attenuation due to misreporting. Conversely, if a variable predicts lower true receipt rates and also predicts less reporting (fewer false positives and more false negatives), the errors partially cancel so that misreporting reinforces the (attenuated) true receipt gradient.

This relatively benign form of misreporting indeed reliably holds for the variables where we find surprisingly small bias. For example, misreporting consistently reinforces the effect of gender and receiving other programs. Very much in line with our findings, for income, it holds for SNAP, but not for TANF+GA. This alignment of misreporting and receipt also contributes to the low fraction of significant differences that we find. While misreporting reinforces receipt for roughly half of the marginal effects, less than one quarter of the significant differences are among these marginal effects. The theoretical results in Meyer and Mittag (2017) can also help to understand the exceptions we find. They predict that sign changes become more likely as the probability of misclassification rises. Indeed, the error rates for TANF+GA are higher and 11 out of 15 sign changes occur in the models of TANF+GA receipt. Meyer and Mittag (2017) also show that attenuation may not hold if misreporting is strongly and systematically related to the covariates, which explains the three marginal effects that are not attenuated: the pattern of receipt rates is reinforced by misreporting we discuss above in all three cases.

In consequence, a tendency to preserve qualitative conclusions is likely to generalize, but may be weaker in other applications: One may expect to find more significant differences in applications where the effects of the covariates on survey error and outcomes are less aligned. Yet in many studies, such as those of differences by race and ethnicity, the magnitude of estimates also matters. We also show that the theoretical results in Meyer and Mittag (2017) correctly predict key features of the bias in a typical application, which makes them useful to interpret estimates and the conditions under which significant survey estimates likely indicate larger and significant true effects. These results are useful for studies where not only significance, but also magnitude matters. However, the fact that the patterns predicted by the bias formulas is much clearer with the larger samples here than in Meyer, Mittag and Goerge (2022) also shows that one should be careful when using results on the asymptotic bias to interpret finite sample estimates of parameters.

6. Item Non-response and Imputation

Item non-response, i.e. respondents refusing to answer specific questions, is a pronounced problem for government transfers (Meyer, Mok and Sullivan, 2015) and other sources of income (Bollinger and Hirsch 2006). Applied researchers usually deal with the consequences of item non-response either by excluding observations with missing values or by using imputed values. Researchers frequently need to decide between these two options without much evidence on the relative merits of each strategy. Both strategies assume that the part of the true response that is not predicted by observed covariates does not predict the outcome of interest. For the problem of item non-response, the response is missing by definition, so with survey data alone these assumptions can only be partially assessed by examining proxy variables. Understanding the shortcomings of this assumption and hence of current imputation methods can help data producers devise improved imputation strategies. We know even less about the bias when these assumptions fail, which makes it difficult for researchers to decide between the two options. Fortunately, data linkage can provide us with an accurate measure of the variable in question for both respondents and non-respondents. In this section, we first use this accurate measure in our linked data to test the assumptions underlying each strategy. Then we examine and compare the bias from each strategy for a specific case, models of program receipt.

Specifically, we first examine whether item non-response is independent of the response conditional on covariates in the model the researcher estimates. If this assumption (usually referred to as MAR) fails, excluding item non-respondents will lead to bias. Compared to the prior literature that examines the nature and selectivity of non-response (Groves and Cooper 1998, Groves 2001), the linked data allows us to compare respondents and non-respondents in terms of the accurate program receipt variable from the administrative data. We then examine the nature of imputation error. Most imputation procedures require item non-response to be independent of the response conditional on the variables used to predict imputations. The advantage of using linked data to examine this assumption over previous studies (see e.g. Little and Rubin 2002; Andridge and Little 2010) is that the data contain both the imputed receipt status and the accurate receipt status from the administrative data. Thereby, data linkage enables us to compare imputed values to accurate values, just as we compared reported values to the linked administrative variable above.

Applied researchers are often particularly concerned with bias in their estimates, especially in large samples. Our results on the nature of item non-response and imputation error show that neither including imputations nor excluding non-respondents is likely to yield consistent estimates. Therefore, the key question is whether it is better to exclude non-respondents or to include them using the imputations provided in the data. Unfortunately, there is little general advice and considerable disagreement on this issue (see e.g. Angrist and Krueger, 2001). Analytic results on the bias from either strategy do not exist, so we use our linked data to directly examine the bias in a specific case, models of program receipt.

a. Differences Between Respondents and Item Non-Respondents

Using only the sample of respondents yields consistent estimates if non-response is (conditionally) independent of the value of the response. See Heitjan and Rubin (1991) and Heitjan (1994) for discussions. Similar conditions are required for the consistency of most corrections based on respondents only. Chenevert, Klee and Wilkin (2016) and Bollinger et al. (2019) compare administrative values from linked tax records of respondents and non-respondents to SIPP and CPS responses to earned income questions. Both reject the assumption that item non-response is conditionally random. Our linked data put us in a unique position to provide direct evidence on differences, both unconditional and conditional on covariates, between non-respondents and the overall population in terms of SNAP and TANF+GA receipt and its association with household characteristics.

Unconditional receipt rates according to the administrative variable are much higher among item non-respondents than in the overall population for both programs in all surveys. In the ACS, they are 16 percentage points higher for SNAP and 4.1 percentage points higher for TANF+GA, making receipt among item non-respondents almost twice as likely. The differences are smaller in the CPS (4 percentage points for SNAP and 0.5 percentage points for TANF+GA) and the SIPP (5 and 1.5 percentage points). Thus, item non-response is not completely random, so that respondents are not representative of the population. Consequently, excluding item non-respondents will bias estimated receipt rates. However, excluding non-respondents may still yield unbiased estimates of model parameters if non-response is conditionally random. To provide evidence on the presence and likely nature of this bias, we next examine whether these differences between non-respondents and the overall population are captured by covariates commonly used to study program receipt. That is, we test the MAR assumption and study the extent to which the outcomes of respondents and non-respondents differ conditional on covariates.

We conduct two sets of tests of the MAR assumption. We conduct both tests in the framework of probit models where administrative receipt is the dependent variable. First, we test whether the probability of program receipt among non-respondents still differs from the overall population after conditioning on the covariates from section 5 by testing whether the intercept differs by response status. Marginal effects of probit models that include an indicator for item non-response are in Appendix Table A8. The test rejects MAR in three of the six cases we examine and shows that unobserved factors causing program receipt are more prevalent among item non-respondents. The differences are smaller than the unconditional differences, but large enough to skew substantive conclusions. Even conditional on covariates, non-respondents are more likely to receive both programs in the ACS (by 6 percentage points for SNAP and 1.5 for TANF+GA) and SNAP in the SIPP (by 4 percentage points). At less than one percent, the difference is small and insignificant in the CPS for both programs and for TANF+GA in the SIPP.

The tests above examine whether non-respondents differ from the overall population in their (conditional) level of receipt. It is likely that not only the rates of receipt, but also the associations of receipt with covariates differ between respondents and non-respondents. If so, sample-selection bias in multivariate models depends on how the effects of the predictors of receipt differ for item non-respondents. If they do not differ, some common multivariate analyses still yield correct conclusions regarding the determinants of program receipt, because only the intercept is biased. Therefore, our second test of MAR examines whether the conditional distribution of program receipt differs between non-respondents and the entire population by testing whether the slope coefficients of the probit models differ by response status: We estimate the models of (administrative) program receipt from section 5 separately for the entire sample and for item non-respondents only and test coefficient equality. We reject the hypothesis that all coefficients are the same for all surveys and both programs. The p-values are below 0.001 for all models except for TANF+GA in the SIPP, which has a p-value of 0.017. Consequently, the relation between receipt and some covariates differs between non-respondents and the population, so that excluding non-respondents will affect estimates of the effect of these characteristics.[12]

Table 8: Examining How Non-Respondents Differ From the Population, Coefficients (around here)

To obtain a better understanding of how the determinants of program receipt differ between non-respondents and the overall population and hence which coefficient estimates are likely to be biased, we also test equality of individual coefficients. Table 8 reports coefficient estimates and the p-values of tests for coefficient equality.[13] We reject the hypothesis that non-respondents are the same as the overall population in their relation between program receipt and income. With the exception of TANF+GA in the SIPP, program receipt decreases more slowly with income among item non-respondents. Non-respondents to the question on SNAP who report TANF+GA are far less likely to receive SNAP than TANF+GA reporters in the population overall and the results suggest that the same pattern holds for reported receipt of housing assistance. Male non-respondents are less likely than male respondents to receive either program in the CPS and there is some evidence of higher receipt rates among non-respondents than respondents when the householder is non-white.

b. How well does imputation reproduce the (distribution of) missing values?

All three surveys include imputed values from the hot deck procedures described in section 2. Even though many researchers use these imputed values, little is known about their accuracy and, more generally, the conditions under which imputation works well. As Andridge and Little (2010) point out, the hot deck requires non-response to be random within each hot deck cell. The previous subsection provides evidence

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[12] The bias and its size depend on the model of interest and are usually intractable. It is plausible that bias arises in general, because the joint distribution of program receipt and the covariates for the entire population, $f(y, X)$ is a mixture of this joint distribution among respondents, $f(y, X|R = 1)$ and non-respondents, $f(y, X|R = 0)$, where R indicates whether the household provided a response. If they differ, using only respondents includes only one of the components, $f(y, X|R = 1)$, which differs from the distribution of interest, $f(y, X)$.

[13] Appendix Table A9 reports the corresponding marginal effects. We examine coefficients here, because differences in marginal effects could also arise from differences in the distributions of covariates between respondents and non-respondents, even when non-response is conditionally random.

that this assumption does not hold in the three surveys we examine. Thus, it is no surprise that our results from section 3 confirm the finding of Meyer, Mittag and Goerge (2022) that imputation biases estimated receipt rates. With the exception of TANF+GA in the ACS, imputation understates true rates of receipt, so that including imputed observations will bias estimates of receipt rates downward.

Many survey users are concerned with estimates of multivariate models rather than population statistics, which raises the question whether the imputed values accurately reproduce the joint distribution of receipt and other covariates among non-respondents. A necessary condition for consistency in multivariate models is that the imputation procedure correctly conditions on the other covariates in the model of interest. If the model that predicts the imputed values omits variables that are included in the model of interest, then the parameter estimates of the model of interest are affected by match bias (Hirsch and Schumacher, 2004). If the imputation model includes all variables in the model of interest, but misspecifies the functional form of the relation between the imputed variable and its predictors (for example by only including a linear term in the imputation model when the true function is quadratic), imperfect match bias (Bollinger and Hirsch 2006) may still affect the parameter estimates.

Like most other applications of hot deck methods, the imputation of transfer receipt only uses a small subset of the covariates of typical models as predictors. However, hot decks usually discretize all predictors and use all possible interactions. These flexible fully interacted models may allow the imputations to capture multivariate relationships well despite using only few predictors. In addition, the hot deck procedures are more complex than the assumed procedure for which Bollinger and Hirsch (2006) derive their results on bias: the ACS and SIPP use geographic information in the imputations in addition to other variables and the CPS uses a sequential hot deck, so that the cell variables can differ between observations. All three surveys simultaneously impute some related variables, such as cash income in the CPS, by assigning a block of responses from the same matched respondent. At the extreme, the CPS sometimes imputes the responses for all ASEC questions from the same matched record for households that provided answers to the other CPS questionnaires, but not the ASEC. Such block or whole imputes preserve correlations of the imputed values better than the theory for the standard hot deck suggests. Thus, it is not clear how applicable existing theory is to the bias in current methods as implemented.

Nevertheless, by showing examples where the effect of including imputed values on parameter estimates conforms to their theoretical expectations, Hirsch and Schumacher (2004) and Bollinger and Hirsch (2006) provide strong evidence that using imputed values in multivariate models is likely problematic. However, adding observations with imputed values also changes the sample to represent the entire population rather than just respondents. Thereby, the changes in the estimates combine match bias and selection bias. Our linked data provide us with an accurate measure of the response for the entire population, which allows us to isolate the bias due to imputation error. It also makes it possible to study how accurately imputed values reproduce the distribution of true values including the correlation with other covariates and thereby provide direct evidence on the nature of imputation error.

To do so, we compare models of program receipt with imputed and administrative receipt as the dependent variable as above but restrict the sample to item non-respondents. Table 9 reports the coefficient estimates as well as joint and individual tests of equality.[14] The tests of model equality reject that the imputations correctly reproduce the distribution of program receipt in all cases. Thus, including item non-respondents with imputed values in the sample yields a sample from a distribution different from that of the variables of interest in the overall population, which causes bias in most models.

Table 9: Examining Imputation Error, Coefficients (around here)

The differences between the coefficients when using the imputed dependent variable and the accurate dependent variable characterize the differences in the imputed and true distribution and are thereby informative about the likely bias. We reject the equality of individual coefficients in one-third of

[14] Appendix Table A10 reports the corresponding marginal effects.

all cases, which is impressive given the small samples of non-respondents. There are large differences in many coefficients, but they vary between surveys and programs as one would expect given the differences in item non-response rates and the imputation procedures. In line with the results on match bias and the fact that the hot decks do not include disability status, receipt by households with a disabled householder is systematically understated. As our findings on imputed participation in multiple programs from section 3 suggest, there are large differences in the estimated coefficients on reported receipt of other programs. However, the direction of the differences varies between surveys: imputations understate the importance of reporting receipt of other programs in the ACS and overstate it in the CPS and SIPP.

In addition to this evidence of match bias, the estimated coefficients on several variables used in the hot decks are badly biased nonetheless. Most notably, the imputations understate the difference between households with a white householder and a Black or Hispanic householder, even when this information is used in the hot deck. Similarly, imputations tend to understate receipt rates of single households with children and how much receipt rises with additional individuals, even though the hot decks include information on household composition. The results thereby also confirm that even for variables included in both the imputation and the outcome models, misspecifying the functional form of the imputation model can lead to imperfect match bias (Bollinger and Hirsch 2006).

The large differences in the estimated determinants of receipt based on imputations and true receipt status are concerning, but one may have expected worse based on Hirsch and Schumacher (2004) and Bollinger and Hirsch (2006). These authors show that, when conditioning on all predictors of the imputations, the coefficients on variables that are not used in the imputation procedure will be biased toward zero in the entire sample and zero among non-respondents. As pointed out above, their results do not directly apply to our case, but compared to this standard, our results are encouraging. Several variables that are not included in the hot deck procedures, such as disability, gender and receipt of other programs still significantly predict imputed receipt in several cases. We only find a tendency for attenuation and loss of significance in the CPS, but not in the ACS and SIPP. Yet it is not clear why the imputations capture multivariate relationships better than expected. A potential cause is that we include observations, such as entirely imputed records, that are likely to preserve the relevant correlations in the CPS and SIPP. However, this finding also applies to SNAP in the ACS, which is never imputed jointly with other variables. Therefore, other factors such as the use of geographic information in the ACS and SIPP are likely to play a role as well.

c. Do Imputed Observations Improve Estimates?

Applied researchers usually face the choice between excluding non-respondents or using the imputed values. Their main concern likely is the accuracy of the final estimates. However, our results above show that neither strategy is likely to yield consistent estimates. Item non-response is not conditionally random, so excluding item non-respondents causes bias from sample selection, but imputation error causes bias from measurement error. This impasse raises the question which of the two strategies yields more accurate estimates. To conceptualize the trade-off in minimizing bias, consider the following decomposition of a generic parameter estimate when imputed observations are included:

$$\hat{\beta}^{IMP} = \hat{\beta} + \hat{b}^{Non-Response} + \underbrace{\hat{b}^{Imputation\ Error} - \hat{b}^{Non-Response}}_{\text{Effect of Including Imputations}}$$

where $E[\hat{b}^{Non-Response}]$ is the bias from excluding non-respondents. Including imputations removes this bias, but introduces new bias from error in the imputed values, $E[\hat{b}^{Imputation\ Error}]$, to the equation. This bias from imputation error is one of the sources of the overall bias found in section 5, which we isolate and examine further here. The decomposition above underlines that one should include imputed observations when the bias from item non-response is larger than the bias from imputation error.[15]

Which of the two bias terms is larger and hence whether including imputed observations increases or decreases bias is case specific. It depends on how non-respondents differ from the population

[15] A complication this overlooks (that is discussed below), is that errors in opposite directions might cancel.

conditional on the covariates and on differences between the joint distribution of the imputed values and the true outcome for item non-respondents. Consequently, our results from above may allow researchers to form a reasonable opinion regarding which term is likely to be larger. However, the magnitude of the biases also depends on the model of interest. Neither the literature on missing data (e.g. Little and Rubin 2002) nor the literature on measurement error (e.g. Bound, Brown and Mathiowetz, 2001, and Carroll et al. 2006) provides results on the size of the bias under the conditions we examine.

In light of this lack of general results, we examine the bias from each source and whether excluding non-respondents or including imputed values improves estimates for the models of program receipt from section 5. We thereby provide guidance for a common application and show that the differences we document are indeed informative about the size of the bias. We can evaluate the merits and perils of each strategy by comparing estimates that exclude item non-respondents and estimates that replace the accurate measure from the administrative data by imputed values for non-respondents to the standard set by estimates using administrative receipt for the entire sample. To do so, we need a measure of distance between vectors of parameters. We adopt a χ^2 measure to put estimates of different size and precision on a common scale before aggregating the differences. We follow Meyer and Mittag (2017) and use the variance matrix of the accurate estimates as the weighting matrix. Compared to using the standard χ^2-test statistic, which uses the variance of the difference between the estimates, our measure does not suggest an improvement when the inaccurate estimates are less precisely estimated (without changing the point estimates).[16] In practice, researchers are likely to be concerned with specific coefficients rather than the entire coefficient vector, which makes the comparison easier.

[16] Note that we want to measure which of two vectors is further from a third vector, rather than the standard problem of testing whether two vectors are different. In our case, a standard hypothesis test using the variance of the difference would unduly favor the less precisely estimated vector. To see this, note that a comparison using χ^2 test statistics can be made to pick any vector by letting the variance go to infinity, as doing so makes the χ^2 statistic go to the ideal of 0.

Table 10: Comparing Bias From Item Non-response and Imputation (around here)

Table 10 reports the distance between probit coefficient estimates from models using the entire sample and administrative receipt as the dependent variable and estimates using respondents only (first row), as well as using imputations instead of administrative receipt for non-respondents (second row). All models use the same covariates as the models in section 5. Coefficient estimates from all three models are provided in Appendix Table A11. The last row of Table 10 reports the difference between the two measures, which can be interpreted as the change in the distance to the consistent coefficient estimates when adding the imputed values to the sample of respondents. Including imputed values minimally improves estimates for SNAP in the SIPP. In all other cases, the increase in the bias when including imputations is large at 50 to 500 percent of the non-response bias. Thus, these results clearly favor using only the sample of respondents.

In practice, researchers are often more concerned with specific parameters than with an overall assessment of a model. We begin by comparing the effects of variables for which we have found large differences in coefficient estimates between non-respondents and the overall population or between the imputed and administrative variable when predicting receipt. These results show that our analyses above of the assumptions required for each approach are informative about the accuracy of the estimated parameters of interest. For example, male non-respondents are substantially less likely to receive either program in the CPS. Accordingly, we find a strong upward bias in the estimates of program receipt for males when excluding non-respondents and less bias when including imputed observations. For the imputations, we found large differences between models using imputed and the accurate receipt for households with a Black or Hispanic householder and find large biases in the receipt rates of such households when using the imputed observations. This bias is particularly pronounced in the CPS. This finding strongly suggests that the studies of differences by race and ethnicity we cite throughout should exclude imputed observations (as Kuka and Stuart, 2021, indeed do based on the high error rates we documented) and address item non-response in other ways.

The effects of income are instructive regarding both sources of error. We find receipt to decline more slowly with income among non-respondents, with the exception of TANF+GA in the SIPP, where we find receipt to decline more quickly with income among non-respondents. As expected, the estimates that exclude non-respondents indeed overstate the decline with income, again with the anticipated exception of TANF+GA in the SIPP, where the sign of the bias in the model of receipt is reversed. However, the effect of income also illustrates that it is important to consider both sides of the trade-off, as the bias from using imputations is worse than the bias from excluding non-respondents in two out of six cases, TANF+GA in the ACS and SNAP in the SIPP, despite the differences in the income gradient between respondents and the overall population. These two cases are explained well by our results above: For TANF+GA in the ACS, non-respondents only differ minimally from the overall population in terms of the effect of income, so the bias from excluding them is smaller than the bias from using the imputed values. For SNAP in the SIPP, non-respondents differ from the overall population, but the difference in the income gradient between imputed and accurate receipt is enormous. As a consequence, using imputed observations leads to an even larger bias in the income gradient than excluding non-respondents, even though non-respondents differ substantially from the overall population.

The fact that the biases in the coefficients we discuss above are well aligned with our results from the previous two subsections demonstrates that understanding the nature of item non-response and imputation error can provide guidance on the decision whether to use imputed values or not. The accurate estimates from the linked data allow for other interesting comparisons and decompositions. The distances to the accurate model for additional approaches are in Appendix Table A12. For example, researchers who exclude non-respondents have more sophisticated strategies at their disposal than just dropping them from the sample. The effects of inverse probability weighting (Wooldridge 2007) to adjust for missing data on coefficient estimates are minimal and increase the bias, but marginal effects seem to improve slightly.

Our approaches above take the accurate estimates as the reference point and examine whether excluding non-respondents or using them with imputed values biases the estimates further from this reference point. Researchers usually do not have an accurate measure for the sample of respondents and use survey reports instead. Our results above show that adding non-respondents with imputed values to the sample of respondents moves estimates further away from the consistent estimates, which does not imply that doing so degrades estimates that are also biased by other sources of survey error. Thus, another important question is whether adding imputed observations to a model using survey reports of respondents as the dependent variable moves estimates closer to the accurate estimates. Rows 4 and 5 of Appendix Table A12 report our distance metric for these two models. In line with Meyer and Goerge (2011), this comparison favors including imputed observations. Some of the improvements are sizeable, but they tend to be small compared to the large bias from measurement error among respondents. This large bias from a different source of error affects the estimates both with and without non-respondents. Therefore, a major determinant of whether using imputed values improves estimates is the direction of sample selection and imputation bias. If they go in opposite directions, the strategy that mitigates rather than reinforces the additional bias from measurement error always yields lower overall bias. Thus, this comparison picks the strategy with a convenient sign of the bias, rather than being informative about which bias term is smaller. Consequently, this comparison may be of more interest for this specific case, but is less informative about the question of including or excluding imputed observations more generally.

7. Conclusions

We link administrative and survey data to answer two key questions raised by prior studies. First, we study how well surveys capture participation in multiple programs. After extending prior evidence of high false negative rates and low false positive rates that lead to severe net understatement of transfer receipt, we show that the survey reports severely understate the dependence in the probabilities of participating in multiple programs. Therefore, survey data most severely understate the fraction of the population that receives both programs we examine. As a consequence, survey data distort total transfers and hence resources of the (likely) poorest households. Understating the probability of receiving a second program given receipt of the first program also makes survey data poorly suited to study why some individuals do not receive programs they appear to be eligible for and the portfolio of programs in which households participate. In consequence, survey data are especially problematic when examining how households navigate the complex welfare system. On the positive side, understating dependence in program receipt implies less bias when using survey data to examine participation in any of multiple programs than when analyzing participation in a single program. Thereby, survey data are better suited to analyze the reach of the safety net and whom it misses than the high rates of underreporting for individual programs suggest. Our results also suggest that program confusion is only a minor source of survey error for the two programs we examine.

Second, we examine survey error due to item non-response and imputation. We show that the conditions for both unconditional analyses and those conditional on covariates to yield consistent estimates neither hold when excluding item non-respondents nor when replacing the missing values by imputed ones. Item non-respondents are more likely to be program recipients than the overall population both unconditionally and conditional on key covariates, so that estimated receipt rates are likely to be biased when excluding item non-respondents. The effects of important determinants of program receipt, such as income and receipt of other programs, also differ between non-respondents and the overall population. Therefore, the effects of these variables will be biased in analyses that do not include item non-respondents. However, we also find that imputed values reproduce neither the actual levels nor the associations of program receipt with covariates either. Imputation improves net reporting rates for TANF+GA, but makes them worse for SNAP. With a few exceptions, imputations fall even further short of reports in their ability to capture participation in multiple programs. Consequently, neither excluding non-respondents nor including them with imputed values is likely to yield consistent estimates. This finding raises the question which strategy causes less bias. Our results on the bias for models of program receipt suggest that it is better to use only respondents than to include imputations. More generally, these analyses provide guidance for a common application and show that a better understanding of the nature of item non-response and imputations could allow researchers to make more informed decisions on whether to use imputed values or not.

Along the way, we confirm and extend work showing that errors are systematically related to many key covariates, which leads to bias that is difficult to assess and address. Most importantly, we document large differences in survey error by race and ethnicity that likely bias many important analyses of differences in program receipt, poverty, and well-being. On the positive side, models of program receipt using survey reports reproduce many qualitative conclusions about the actual relationships. Our results show that key predictions of the asymptotic results in Meyer and Mittag (2017) hold in common applications, namely a strong tendency for effect signs to be robust, but marginal effects to be attenuated. Combining theory with our empirical evidence on misreporting also helps to predict bias in common applications: As suggested by the large reporting differences, we find pronounced survey biases in receipt by race and ethnicity.

Our results have several implications for both survey producers trying to improve survey quality and survey users trying to make better use of error ridden data. For survey producers, the results are informative about who misreports and which patterns of misreporting greatly affect data quality. Our findings thereby not only help survey producers direct efforts for improvements toward the most important problems, but also point to ways to improve data quality. For example, the fact that surveys understate the probability of reporting a second program given receipt of a first program suggests that instructing interviewers to probe for receipt of other programs among those who report receipt of one program could improve some of the problems we document. The results directly point to the potential to improve surveys by developing better imputation methods. Using administrative data or geographic information to predict missing values may be promising paths to improve imputations. Survey producers should be encouraged to provide results similar to ours to survey users whenever possible to help survey users gauge the strengths and weaknesses of the data.

This study shows that such results can help survey users assess the accuracy of their estimates and the likely biases, as we find bias to be well predicted by the patterns of survey errors. For example, based on our results for transfer receipt, survey users should be skeptical of survey estimates of receipt rates and total resources from transfers. This problem becomes worse when studying patterns of receipt of multiple programs, but better when examining participation in any program. Survey estimates of the determinants of program receipt are likely more reliable and in fact often larger in absolute value than the true effect. Our results on the determinants of survey errors can help to predict exceptions from this general pattern of attenuation, such as the marginal effects for minorities, so they can help survey users assess whether estimates are likely to suffer from large bias and whether substantive conclusions are robust to survey error. For example, Kuka and Stuart (2021) estimate unemployment insurance take-up to be much lower for Blacks. They argue that this difference would likely persist when correcting for survey error based on prior estimates of unconditional (net) error rates. These analyses are laudable and underline the value of understanding survey error. However, estimates of the conditional differences in reporting rates such as the ones we provide here are the key determinants of bias in such studies and therefore crucial to assess the validity of their conclusions. Studies examining the same programs as we do here (e.g. Moffitt and Gottschalk, 2001; Burkhauser et al. 2022) can even use our results on the determinants of survey error to correct for bias. The differences by race in Burkhauser et al. for example could be estimated more accurately using our results. The analysis of item non-response and imputation shows that linked data can provide survey users with the needed information to make more informed decisions to exclude item non-respondents or not. For the case of program receipt, the results favor excluding them at least in multivariate analyses.

In conclusion, this study substantially expands mounting evidence of large and systematic survey error. Failing to take survey error into account makes the survey data likely to mislead both policy makers and academics in need of accurate information regarding who benefits from programs, who chooses not to participate, and which characteristics deter participation. However, our results also imply two positive messages. First, the findings show that we can still obtain reliable substantive insights from the error-ridden survey data if we account for survey error. Second, data linkage enables us to better understand how to use contaminated data and provides the needed information to account for survey error.

References

Acs, G., Phillips, K.R. and Nelson, S. 2005. "The Road Not Taken?: Changes in Welfare Entry during the 1990s." *Social Science Quarterly*, 86(S1), 1060-1079.

Andridge, R.R. and Little, R.J.A. 2010. "A Review of Hot Deck Imputation for Survey Non-response." *International Statistical Review*, 78(1), 40–64.

Angrist, J. D., and Krueger, A.B. 2001. "Empirical Strategies in Labor Economics", in O. Ashenfelter and D. Card (Eds.), *Handbook of Labor Economics*, Vol 3A. Elsevier: Amsterdam.

Bee, C. A., and Mitchell, J. 2017. The Hidden Resources of Women Working Longer: Evidence from Linked Survey-Administrative Data. In C. Goldin and L.F. Katz (Eds.), *Women Working Longer: Increased Employment at Older Ages*. Chicago: University of Chicago Press.

Bitler, M., and Hoynes, H. 2010. "The State of the Social Safety Net in the Post–Welfare Reform Era." *Brookings Papers on Economic Activity*.

Blank, R.M. and Ruggles, P. 1996. "When Do Women Use AFDC & Food Stamps? The Dynamics of Eligibility vs. Participation," *Journal of Human Resources* 31, 57-89.

Blank, R.M. and Kovak, B.K. 2009. "The Growing Problem of Disconnected Single Mothers." In C. J. Heinrich and J. K. Scholz (Eds.) *Making the Work-Based Safety Net Work Better*. New York: Russell Sage Press.

Bollinger, C.R. and David, M.H. 1997. "Modeling Discrete Choice with Response Error: Food Stamp Participation." *Journal of the American Statistical Association*, 92 (439), 827-835.

Bollinger, C.R., and Hirsch, B.T. 2006. "Match bias from earnings imputation in the Current Population Survey: The case of imperfect matching." *Journal of Labor Economics* 24 (3), 483-519.

Bollinger, C.R., Hirsch, B.T., Hokayem, C.M., & Ziliak, J.P. 2019. "Trouble in the Tails? What We Know about Earnings Nonresponse Thirty Years after Lillard, Smith, and Welch." *Journal of Political Economy.* 127(5), 2143-2185.

Bollinger, C.R. and Tasseva, I.V., 2022. Income source confusion using the SILC. ISER Working Paper No. 2022-04.

Bound, J., Brown, C. and Mathiowetz, N. 2001. "Measurement error in survey data." In *Handbook of Econometrics*. Vol. 5, eds. J.J. Heckman and E. Leamer, Cp. 59, 3705–3843. Amsterdam: Elsevier.

Burkhauser, R.V., Corinth, K., Elwell, J. and Larrimore, J. 2022. "Evaluating the Success of President Johnson's War on Poverty: Revisiting the Historical Record Using an Absolute Full-Income Poverty Measure." NBER Working Paper 26532, Revised August 2022.

Carroll, R.J., Ruppert, D., Stefanski, L.A., Crainiceanu, C.M. 2006. "*Measurement Error in Nonlinear Models: A Modern Perspective*." 2nd ed. Chapman & Hall: Boca Raton.

Celhay, Pablo, Bruce D. Meyer and Nikolas Mittag. 2022. "What Leads to Measurement Error? Evidence from Reports of Program Participation in Three Surveys." NBER Working Paper 29652.

Chenevert, R.L., Klee, M.A. and Wilkin, K.R. 2016. "Do Imputed Earnings Earn Their Keep? Evaluating SIPP Earnings and Nonresponse with Administrative Records." U.S. Census Bureau Working Paper.

Congressional Budget Office (CBO). 2013. "The Distribution of Federal Spending and Taxes, 2006." Congressional Budget Office Report 44698, Washington, D.C.

Congressional Budget Office (CBO). 2016. "The Distribution of Household Income and Federal Taxes, 2013." Congressional Budget Office Report 51361, Washington, D.C.

Courtemanche, C., Denteh, A. and Tchernis, R. 2019. "Estimating the Associations between SNAP and Food Insecurity, Obesity, and Food Purchases with Imperfect Administrative Measures of Participation*." Southern Economic Journal* 86 (1): 202–228.

Currie, J. 2006. "The Take-up of Social Benefits," in A.J. Auterbach, D. Card, and J.M. Quigley (Eds.) *Public Policy and the Income Distribution*, Russell Sage Foundation: New York.

Forsythe, E., and Yang, H. 2021. "Understanding Disparities in Unemployment Insurance Recipiency," Report to the Department of Labor.

Ganong, P. and Liebman, J.B. 2018. "The Decline, Rebound, and Further Rise in SNAP Enrollment: Disentangling Business Cycle Fluctuations and Policy Changes," *American Economic Journal: Economic Policy*, 10(4), 153-176.

Gathright, G.M.R., and Crabb, T.A. 2014. "Reporting of SSA Program Participation in SIPP." Working Paper, U.S. Census Bureau.

Giefer, K., Williams, A., Benedetto, G. and Motro, J., 2015. "Program confusion in the 2014 SIPP: Using administrative records to correct false positive SSI reports." In *FCSM 2015 Proceedings*.

Gould-Werth, A., and Shaefer, H.L. 2012. "Unemployment Insurance Participation by Education and by Race and Ethnicity." *Monthly Labor Review* 135: 28.

Groves, R.M. 2001. "*Survey nonresponse*." New York: Wiley.

Groves, R.M., and Couper, M.P. 1998. "*Nonresponse in household interview surveys*." New York: Wiley.

Haider, S., Jacknowitz, A. and Schoeni, R. 2003. "Food Stamps and the Elderly: Why is Participation so Low?" *Journal of Human Resources*, 38:S, 1180-1220.

Hausman, J.A., Abrevaya, J., Scott-Morton, F.M., 1998. "Misclassification of the dependent variable in a discrete-response setting." *Journal of Econometrics*, 87(2): 239-269.

Heitjan, D.F. 1994. "Ignorability in General Incomplete-Data Models." *Biometrika*, 81, 701-708.

Heitjan, D. F., and Rubin, D. B. 1991, "Ignorability and Coarse Data." *Annals of Statistics*, 19, 2244-2253.

Hirsch, B.T., and Schumacher, E. 2004. "Match Bias in Wage Gap Estimates Due to Earnings Imputation." *Journal of Labor Economics*, 22(3): 689–722.

Jones, J.W., Courtemanche, C., Denteh, A., Marton, J. and Tchernis, R., 2022. "Do state Supplemental Nutrition Assistance Program policies influence program participation among seniors?" *Applied Economic Perspectives and Policy,* 44(2): 591-608*.*

Keane, M. and Moffitt, R., 1998. "A structural model of multiple welfare program participation and labor supply." *International Economic Review*, 39(3): 553-589.

Kirlin, J.A., and Wiseman, M. 2014. "Getting it Right, or at Least Better: Improving Identification of Food Stamp Participants in the National Health and Nutrition Examination Survey." Working Paper.

Kuka, E., and Stuart, B.A. 2021 "Racial Inequality in Unemployment Insurance Receipt and Take-Up." NBER Working Paper 29595.

Little, R.J.A. and Rubin, D.B. 2002. "*Statistical analysis with missing data*." 2nd ed., New York: John Wiley.

Lynch, V., Resnick, D.M., Stavely, J. and Taeuber, C.M. 2007. "Differences in Estimates of Public Assistance Recipiency Between Surveys and Administrative Records." U.S. Census Bureau Working paper.

Marquis, K. H., and Moore, J.C. 1990. "Measurement Errors in SIPP Program Reports." In *Proceedings of the 1990 Annual Research Conference*. 721–745. Washington, D.C.: U.S. Bureau of the Census.

Meyer, B.D. and Goerge, R. 2011. "Errors in Survey Reporting and Imputation and Their Effects on Estimates of Food Stamp Program Participation". U.S. Census Bureau CES Working Paper 11-14.

Meyer, B.D., Mittag, N. and Goerge, R. 2022. “Errors in Survey Reporting and Imputation and Their Effects on Estimates of Food Stamp Program Participation.” *Journal of Human Resources* 57(5): 1605-1644.

Meyer, B.D. and Mittag, N. 2017. “Misclassification in Binary Choice Models.” *Journal of Econometrics.* 200(2), 295-311.

Meyer, B.D., and Mittag, N. 2019a. “Using Linked Survey and Administrative Data to Better Measure Income: Implications for Poverty, Program Effectiveness and Holes in the Safety Net.” *American Economic Journal: Applied Economics* 11(2): 176-204.

Meyer, B.D. and Mittag, N. 2019b. “Misreporting of Government Transfers: How Important are Survey Design and Geography?” *Southern Economic Journal*. 86(1), 230-253.

Meyer, B.D. and Mittag, N. 2021a. “An Empirical Total Survey Error Decomposition Using Data Combination.” *Journal of Econometrics*. 224(2), 286-305.

Meyer, B.D. and Mittag, N. 2021b. "Combining Administrative and Survey Data to Improve Income Measurement." In *Administrative Records for Survey Methodology*, edited by Asap Y. Chun, Michael D. Larsen, Gabriela Durrant and Jerome P. Reiter, cp. 12: 297-322. New York: John Wiley and Sons.

Meyer, B.D., Wu, D., Mooers, V., Medalia, C. 2021. “The Use and Misuse of Income Data and Extreme Poverty in the United States.” *Journal of Labor Economics*, 39(S1): S5-S58.

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

Mittag, N. 2019. “Correcting for Misreporting of Government Benefits.” *American Economic Journal: Economic Policy* 11(2): 142-16.

Moffitt, R.A. and Gottschalk, P.T., 2001. Ethnic and racial differences in welfare receipt in the United States. In *America becoming: Racial trends and their consequences*, Vol. 2, Chapter 7, pp.152-173. Washington, DC: The National Academies Press.

Moore, J.C. 2008. “Seam Bias in the 2004 SIPP Panel: Much Improved, but Much Bias Still Remains.” U.S. Census Bureau Statistical Research Division Survey Methodology Research Report Series 2008-3.

Nicholas, J. and Wiseman, M. 2010 “Elderly Poverty and Supplemental Security Income, 2002-2005.” *Social Security Bulletin*

Niehaus, P. and Sukhtankar, S. 2013. “Corruption dynamics: The golden goose effect.” *American Economic Journal: Economic Policy*, 5 (4): 230-269.70(2), 1-29.

Ribar, D.C. 2005. “Transitions from Welfare and the Employment Prospects of Low-Skill Workers.” *Southern Economic Journal* 71(3), 514–33.

Taeuber, C., Resnick, D.M., Love, S.P., Stavely, J. Wilde, P. and Larson, R. 2004. “Differences in Estimates of Food Stamp Program Participation Between Surveys and Administrative Records” Working Paper, U.S. Census Bureau.

U.S. Census Bureau. 2006. “Design and Methodology: Current Population Survey.” Technical Paper 66, U.S. Census Bureau.

U.S. Census Bureau. 2008. “Survey of Income and Program Participation: User’s Guide.” U.S. Census Bureau.

U.S. Census Bureau. 2014. “American Community Survey: Design and Methodology.” U.S. Census Bureau.

U.S. Census Bureau. 2022. “Poverty in the United States: 2021.” Current Population Report P60-277. U.S. Census Bureau.

U.S. General Accounting Office (GAO). 2004. “Food Stamp Program: Steps Have Been Taken to Increase Participation of Working Families, but Better Tracking of Efforts is Needed.” GAO-04-346. Washington, DC: GAO.

U.S. General Accounting Office (GAO) 2022. “Pandemic Unemployment Assistance: Federal Program Supported Contingent Workers Amid Historic Demand, but DOL Should Examine Racial Disparities in Benefit Receipt” Report to Congressional Committee GAO-22-104438, Washington, D.C.

Wagner, D., and Layne, M. 2014. “The Person Identification Validation System (PVS): Applying the Center for Administrative Records Research and Applications’ (CARRA) Record Linkage Software.” U.S. Census Bureau.

Wooldridge, J.M. 2007. “Inverse Probability Weighted Estimation for General Missing Data Problems.” *Journal of Econometrics*, 141(2), 1281–1301.

Wu, Yanyuan 2010. “Essays on the Economic Well-Being of the Elderly and Public Policy.” Ph.D. Dissertation, University of Chicago.

Table 1 - Error Rate by True Receipt Status and Net Reporting Rate

	False Negative Rate		False Positive Rate		Net Reporting Rate	
	(1)	(2)	(3)	(4)	(5)	(6)
	SNAP	*TANF+GA*	*SNAP*	*TANF+GA*	*SNAP*	*TANF+GA*
			Full Sample			
ACS	26%	57%	1.2%	1.6%	80%	82%
CPS	42%	63%	2.0%	0.6%	67%	50%
SIPP	19%	46%	1.5%	0.5%	88%	68%
			Respondents			
ACS	25%	59%	1.1%	1.3%	80%	75%
CPS	37%	59%	1.2%	0.3%	69%	49%
SIPP	18%	46%	1.3%	0.4%	88%	66%
			Imputed Observations			
ACS	67%	44%	13.7%	6.2%	60%	126%
CPS	68%	86%	7.6%	2.4%	60%	61%
SIPP	33%	51%	4.9%	1.9%	83%	84%

Note: Approved for release by the Census Bureau's Disclosure Review Board, approvals dated August 3, 2015 and August 18, 2016. The false negative rate is the estimated fraction of true recipient households with receipt not recorded in the survey. The false positive rate is the estimated fraction of true non-recipient households recorded as recipients in the survey. The net reporting rate is the ratio of the (weighted) number of recipient households according to the survey and the administrative variable in the linked data. Our samples of imputed observations include block and whole imputes, but do not include edited observations. In the SIPP, we collapse receipt to the wave level. All analyses use household weights adjusted for incomplete linkage. Appendix Table A3 provides full cross-tabulations of administrative and reported receipt.

Table 2: Reported and Administrative Rates of Joint Receipt of SNAP and TANF+GA

	No program		SNAP Only		TANF+GA Only		Both Programs	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Source	*Report*	*Admin.*	*Report*	*Admin.*	*Report*	*Admin.*	*Report*	*Admin.*
	Full Sample							
ACS	85.4%	82.5%	11.4%	13.5%	0.7%	0.1%	2.5%	3.9%
CPS	87.7%	82.0%	10.1%	13.6%	0.3%	0.2%	1.9%	4.2%
SIPP	84.2%	82.0%	13.3%	14.4%	0.3%	0.2%	2.2%	3.4%
	Imputed Observations							
ACS	75.6%	73.0%	14.4%	19.0%	2.9%	0.2%	7.1%	7.9%
CPS	86.5%	78.5%	10.7%	16.4%	1.1%	0.2%	1.7%	4.9%
SIPP	80.3%	76.8%	15.5%	18.2%	0.3%	0.1%	3.9%	4.9%

Note: Approved for release by the Census Bureau's Disclosure Review Board, approvals dated August 3, 2015 and August 18, 2016. The sample of imputed observations includes all households where receipt of either of the two programs was imputed (according to the definition of being imputed in Table 1 and section 2a). All numbers are in percent of the number of households in NY. All analyses use household weights adjusted for incomplete linkage.

Table 3 - Reporting of Participation in Multiple Programs by True Number of Programs Received

True Receipt	No Program		One Program			Two Programs	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Reported Receipt	*One Program*	*Two Programs*	*No Program*	*The Wrong Program*	*Two Programs*	*No Program*	*One Program*
				Full Sample			
ACS	1.7%	0.1%	26.9%	0.8%	6.1%	17.9%	41.0%
CPS	2.1%	0.1%	45.5%	0.4%	2.2%	28.9%	35.9%
SIPP	1.4%	0.1%	20.7%	0.1%	2.2%	13.2%	35.1%
				Imputed Observations			
ACS	5.7%	0.5%	31.1%	3.2%	14.0%	15.7%	33.7%
CPS	7.6%	0.4%	69.4%	1.4%	4.9%	56.1%	31.0%
SIPP	4.8%	0.5%	36.6%	0.1%	6.0%	18.3%	32.5%

Note: Approved for release by the Census Bureau's Disclosure Review Board, approvals dated August 3, 2015 and August 18, 2016. All numbers are in percent of the population receiving the number of programs stated in the first row according to the administrative data. The omitted group in each case are those correctly reporting receipt of the programs they receive according to the administrative data. The sample of imputed observations includes all households where receipt of either of the two programs was imputed (according to the definition of being imputed in Table 1 and section 2a). All analyses use household weights adjusted for incomplete linkage.

Table 4: The Determinants of False Negatives, Probit Marginal Effects, Full Linked Sample of True Recipients

	ACS		CPS		SIPP	
	(1)	(2)	(3)	(4)	(5)	(6)
	SNAP	*TANF+GA*	*SNAP*	*TANF+GA*	*SNAP*	*TANF+GA*
Single adult, no children	-0.0592***	-0.0148	-0.0035	0.2271***	-0.0454*	0.1950**
	(0.0081)	(0.0180)	(0.0388)	(0.0711)	(0.0271)	(0.0937)
Single adult, with children	-0.0306***	-0.0427***	0.0227	0.0577	-0.0392*	-0.0008
	(0.0069)	(0.0136)	(0.0293)	(0.0573)	(0.0233)	(0.0594)
Multiple adults, no children	-0.0303***	-0.0474***	-0.0485	0.1370**	0.0604***	0.0397
	(0.0065)	(0.0145)	(0.0325)	(0.0582)	(0.0220)	(0.0653)
Number of members under 18	-0.0211***	-0.0202***	-0.0222*	0.0405***	-0.0058	-0.0919***
	(0.0023)	(0.0041)	(0.0116)	(0.0150)	(0.0078)	(0.0198)
Number of members 18 or older	0.0031	-0.0149***	0.0307***	0.0726**	-0.0086	0.0480*
	(0.0022)	(0.0053)	(0.0112)	(0.0298)	(0.0077)	(0.0259)
Rural	0.0040	-0.0026	-0.0146	-0.0248	0.0776***	0.0096
	(0.0065)	(0.0183)	(0.0326)	(0.0689)	(0.0208)	(0.0686)
Hispanic	0.0410***	0.0467***	0.0554***	0.0744*	0.0382**	0.0508
	(0.0059)	(0.0145)	(0.0208)	(0.0450)	(0.0171)	(0.0512)
Black non-hispanic	0.0678***	0.0877***	0.0958***	0.0683	0.0841***	0.0800*
	(0.0049)	(0.0114)	(0.0210)	(0.0451)	(0.0135)	(0.0430)
Other non-hispanic	0.0343***	0.0132	0.0953**	0.0014	-0.0031	0.1229
	(0.0085)	(0.0230)	(0.0376)	(0.1271)	(0.0198)	(0.0749)
Male	0.0485***	0.0384***	0.0312*	0.0767**	0.0791***	-0.0436
	(0.0038)	(0.0100)	(0.0172)	(0.0376)	(0.0127)	(0.0509)
Disabled	-0.0947***	-0.0594***	-0.0531		-0.1439***	-0.1215**
	(0.0045)	(0.0097)	(0.0691)		(0.0187)	(0.0472)
Age 16-29	-0.0295***	0.0361***	0.0340	-0.0530	-0.0113	0.0189
	(0.0066)	(0.0131)	(0.0279)	(0.0446)	(0.0239)	(0.0539)
Age 30-39	-0.0005	0.0111	0.0227	-0.0366	-0.0297	0.2616***
	(0.0058)	(0.0123)	(0.0252)	(0.0422)	(0.0196)	(0.0470)
Age 50-59	-0.0158***	0.0053	-0.0046	-0.0116	-0.0225	-0.0291
	(0.0057)	(0.0124)	(0.0267)	(0.0468)	(0.0179)	(0.0515)
Age 60-69	-0.0164**	0.0713***	0.0294	0.0717	-0.0806***	-0.0444
	(0.0065)	(0.0162)	(0.0304)	(0.0627)	(0.0218)	(0.0691)
Age 70 or more	0.0009	0.0784***	0.0562*	0.2028	-0.0697***	-0.0191
	(0.0068)	(0.0224)	(0.0315)	(0.1450)	(0.0211)	(0.0804)
Less than high school	-0.0370***	-0.0137	-0.0842***	-0.0502	-0.0288*	0.0033
	(0.0051)	(0.0109)	(0.0222)	(0.0407)	(0.0171)	(0.0476)
High school graduate	0.0074	-0.0094	-0.0091	-0.0308	-0.0082	0.0270
	(0.0047)	(0.0108)	(0.0210)	(0.0408)	(0.0136)	(0.0418)
Complete graduate and beyond	0.0106*	0.0040	0.0225	-0.0525	0.0346*	-0.3240***
	(0.0061)	(0.0162)	(0.0278)	(0.0554)	(0.0198)	(0.0634)
Household language is English only	0.0136**	-0.0402***				
	(0.0054)	(0.0126)				
Speaks English poorly	-0.0781***	0.0128			-0.0000	0.1285*
	(0.0062)	(0.0158)			(0.0192)	(0.0711)
Non-citizen	0.0257***	0.0080			0.0310	-0.0295
	(0.0060)	(0.0136)			(0.0215)	(0.0579)
Household income/poverty line	0.0449***	0.0150***	0.0798***	0.0273*	0.0529***	-0.0196
	(0.0014)	(0.0038)	(0.0085)	(0.0157)	(0.0050)	(0.0160)
Household income/poverty line >10	-0.2396***	-0.1358*	-0.4967***		-0.2854***	0.1404
	(0.0231)	(0.0720)	(0.1598)		(0.1102)	(0.2035)
Anyone in household employed	0.0697***	0.1733***	0.0627***	0.0281	-0.0284*	-0.2194***
	(0.0049)	(0.0096)	(0.0206)	(0.0349)	(0.0168)	(0.0454)
Reported housing assistance receipt			-0.1957***	-0.0593*	-0.1130***	-0.0604
			(0.0175)	(0.0314)	(0.0134)	(0.0406)
Reported TANF+GA receipt	-0.2189***		-0.3252***		-0.2074***	
	(0.0065)		(0.0331)		(0.0270)	
Reported SNAP receipt		-0.3115***		-0.3479***		-0.3320***
		(0.0105)		(0.0338)		(0.0469)
Linear time trend	-0.0085***	0.0147***	-0.0096**	-0.0027	0.0000***	0.0001**
	(0.0013)	(0.0029)	(0.0046)	(0.0091)	(0.0000)	(0.0000)
Number of observations	81,772	16,962	3,539	908	4,771	931
chi2 statistic of joint significance	9,337	3,451	1,269	385	1,173	658
p-value of joint significance	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001

Notes: Approved for release by the Census Bureau's Disclosure Review Board, approvals dated August 3, 2015 and August 18, 2016. The samples include imputed observations, but are restricted to recipients according to the linked data. The dependent variable is an indicator for failure to report receipt in the survey. All demographic characteristics refer to the reference person. The time trend is measured in years for the ACS and CPS, but in waves for the SIPP. The omitted categories are Multiple Adults with Children, Age 40-49, College Graduate and White. All analyses use household weights adjusted for PIK probability. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 5: The Determinants of False Positives, Probit Marginal Effects, Full Linked Sample of Non-Recipients

	ACS		CPS		SIPP	
	(1)	(2)	(3)	(4)	(5)	(6)
	SNAP	*TANF+GA*	*SNAP*	*TANF+GA*	*SNAP*	*TANF+GA*
Single adult, no children	-0.0029***	-0.0024**	-0.0084	-0.0041	-0.0014	-0.0040**
	(0.0010)	(0.0010)	(0.0053)	(0.0026)	(0.0039)	(0.0020)
Single adult, with children	0.0022**	0.0029***	0.0057	-0.0033	0.0079*	0.0029
	(0.0011)	(0.0010)	(0.0050)	(0.0022)	(0.0043)	(0.0019)
Multiple adults, no children	-0.0026***	-0.0001	-0.0085*	-0.0011	0.0041	-0.0052***
	(0.0008)	(0.0008)	(0.0046)	(0.0019)	(0.0035)	(0.0017)
Number of members under 18	0.0005	-0.0000	-0.0014	0.0016***	-0.0010	-0.0014*
	(0.0003)	(0.0003)	(0.0018)	(0.0006)	(0.0015)	(0.0008)
Number of members 18 or older	0.0025***	0.0043***	0.0020	0.0016**	0.0046***	0.0001
	(0.0003)	(0.0002)	(0.0017)	(0.0008)	(0.0012)	(0.0005)
Rural	-0.0024***	-0.0017***	0.0012	-0.0033	0.0007	0.0021
	(0.0006)	(0.0006)	(0.0045)	(0.0023)	(0.0027)	(0.0019)
Hispanic	0.0085***	-0.0028***	0.0139***	-0.0017	0.0044	-0.0027*
	(0.0007)	(0.0008)	(0.0031)	(0.0015)	(0.0033)	(0.0014)
Black non-hispanic	0.0098***	0.0005	0.0116***	0.0015	0.0137***	0.0059***
	(0.0006)	(0.0006)	(0.0031)	(0.0014)	(0.0022)	(0.0010)
Other non-hispanic	0.0060***	0.0046***	0.0060	-0.0070**	0.0093***	-0.0056**
	(0.0008)	(0.0008)	(0.0043)	(0.0031)	(0.0029)	(0.0023)
Male	-0.0019***	0.0006	-0.0034	-0.0020*	-0.0069***	0.0004
	(0.0004)	(0.0004)	(0.0024)	(0.0012)	(0.0017)	(0.0009)
Disabled	0.0069***	0.0006	0.0274***		0.0076*	-0.0010
	(0.0006)	(0.0006)	(0.0088)		(0.0042)	(0.0014)
Age 16-29	0.0071***	-0.0000	0.0011	0.0062***	0.0041	-0.0038
	(0.0008)	(0.0008)	(0.0043)	(0.0017)	(0.0037)	(0.0024)
Age 30-39	0.0023***	0.0009	0.0029	-0.0006	0.0130***	-0.0037**
	(0.0007)	(0.0007)	(0.0038)	(0.0017)	(0.0034)	(0.0016)
Age 50-59	0.0005	-0.0012*	0.0045	0.0002	0.0000	-0.0003
	(0.0007)	(0.0007)	(0.0042)	(0.0018)	(0.0028)	(0.0012)
Age 60-69	-0.0006	-0.0054***	-0.0032	-0.0058**	-0.0041	-0.0038**
	(0.0008)	(0.0008)	(0.0045)	(0.0026)	(0.0035)	(0.0015)
Age 70 or more	-0.0040***	-0.0072***	-0.0087*	-0.0074***	-0.0021	-0.0046***
	(0.0009)	(0.0008)	(0.0049)	(0.0028)	(0.0033)	(0.0018)
Less than high school	0.0068***	0.0035***	0.0088**	0.0023	0.0056*	0.0021*
	(0.0007)	(0.0007)	(0.0036)	(0.0017)	(0.0030)	(0.0012)
High school graduate	0.0031***	0.0012**	0.0011	0.0025*	0.0050**	0.0004
	(0.0006)	(0.0006)	(0.0031)	(0.0014)	(0.0023)	(0.0011)
Complete graduate and beyond	-0.0017***	-0.0004	-0.0075*	-0.0045**	-0.0043*	-0.0026*
	(0.0006)	(0.0006)	(0.0039)	(0.0021)	(0.0022)	(0.0015)
Household language is English only	-0.0006	0.0004				
	(0.0006)	(0.0006)				
Speaks English poorly	0.0051***	-0.0008			0.0058	-0.0033**
	(0.0008)	(0.0008)			(0.0036)	(0.0015)
Non-citizen	0.0003	-0.0032***			0.0063**	0.0034**
	(0.0007)	(0.0008)			(0.0031)	(0.0015)
Household income/poverty line	-0.0030***	-0.0010***	-0.0121***	-0.0010***	-0.0035***	0.0002
	(0.0002)	(0.0001)	(0.0015)	(0.0004)	(0.0006)	(0.0003)
Household income/poverty line >10	0.0112***	-0.0007	0.0517***		0.0095	-0.0021
	(0.0017)	(0.0011)	(0.0164)		(0.0076)	(0.0039)
Anyone in household employed	-0.0038***	-0.0094***	-0.0094***	-0.0035**	0.0137***	0.0075***
	(0.0007)	(0.0006)	(0.0031)	(0.0015)	(0.0027)	(0.0017)
Reported housing assistance receipt			0.0089**	0.0029**	0.0222***	0.0029***
			(0.0036)	(0.0014)	(0.0027)	(0.0010)
Reported TANF+GA receipt	0.0341***		0.0461***		0.0479***	
	(0.0010)		(0.0075)		(0.0047)	
Reported SNAP receipt		0.0334***		0.0103***		0.0123***
		(0.0006)		(0.0016)		(0.0015)
Linear time trend	0.0008***	0.0003**	0.0029***	0.0003	0.0000***	0.0000***
	(0.0001)	(0.0001)	(0.0007)	(0.0003)	(0.0000)	(0.0000)
Number of observations	461,756	526566	14,525	17,156	20,226	24,066
chi2 statistic of joint significance	2,546	5,025	257	121	344	162
p-value of joint significance	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001

Notes: Approved for release by the Census Bureau's Disclosure Review Board, approvals dated August 3, 2015 and August 18, 2016. The samples include imputed observations, but are restricted to non-recipients according to the linked data. The dependent variable is an indicator for reporting in the survey. All demographic characteristics refer to the reference person. The time trend is measured in years for the ACS and CPS, but in waves for the SIPP. The omitted categories are Multiple Adults with Children, Age 40-49, College Graduate and White. All analyses use household weights adjusted for PIK probability. Standard errors in parentheses,*** p<0.01, ** p<0.05. * p<0.1

Table 6: The Determinants of Reported and Administrative SNAP Receipt, Probit Marginal Effects, Linked Households with Income less than Twice the

	ACS			CPS			SIPP		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent Variable	Survey Report	Admin. Receipt	P-value (1)=(2)	Survey Report	Admin. Receipt	P-value (4)=(5)	Survey Report	Admin. Receipt	P-value (7)=(8)
Single adult, no children	-0.0711***	-0.0854***	0.137	-0.0293	-0.0101	0.648	-0.0411	-0.0409	0.997
	(0.0067)	(0.0069)		(0.0294)	(0.0302)		(0.0258)	(0.0271)	
Single adult, with children	0.0313***	0.0480***	0.062	0.0290	0.1173***	0.013	0.1063***	0.1333***	0.400
	(0.0062)	(0.0064)		(0.0242)	(0.0259)		(0.0225)	(0.0229)	
Multiple adults, no children	-0.0567***	-0.0592***	0.762	-0.0121	-0.0252	0.719	-0.0418*	-0.0227	0.546
	(0.0059)	(0.0060)		(0.0256)	(0.0257)		(0.0222)	(0.0226)	
Number of members under 18	0.0297***	0.0335***	0.162	0.0312***	0.0424***	0.383	0.0266***	0.0382***	0.282
	(0.0019)	(0.0019)		(0.0091)	(0.0090)		(0.0075)	(0.0078)	
Number of members 18 or older	0.0081***	0.0202***	0.001	0.0028	0.0393***	0.017	0.0194**	0.0198**	0.976
	(0.0025)	(0.0025)		(0.0107)	(0.0110)		(0.0097)	(0.0100)	
Rural	-0.0228***	-0.0276***	0.407	0.0333	0.0569***	0.434	-0.0101	0.0027	0.513
	(0.0041)	(0.0042)		(0.0211)	(0.0216)		(0.0138)	(0.0139)	
Hispanic	0.0987***	0.1405***	<0.001	0.0743***	0.1445***	0.001	0.0697***	0.1096***	0.078
	(0.0044)	(0.0044)		(0.0148)	(0.0151)		(0.0156)	(0.0163)	
Black non-hispanic	0.1098***	0.1708***	<0.001	0.0291*	0.1075***	<0.001	0.0759***	0.1232***	0.005
	(0.0038)	(0.0038)		(0.0157)	(0.0160)		(0.0119)	(0.0122)	
Other non-hispanic	-0.0397***	-0.0438***	0.637	-0.0363	-0.0003	0.298	0.0704***	0.0773***	0.770
	(0.0060)	(0.0061)		(0.0244)	(0.0244)		(0.0166)	(0.0163)	
Male	-0.0550***	-0.0593***	0.282	-0.0531***	-0.0640***	0.540	-0.0722***	-0.0293***	0.004
	(0.0029)	(0.0029)		(0.0125)	(0.0128)		(0.0105)	(0.0107)	
Disabled	0.1599***	0.1544***	0.222	0.1263**	0.0937	0.704	0.2535***	0.2549***	0.945
	(0.0031)	(0.0032)		(0.0580)	(0.0633)		(0.0145)	(0.0147)	
Age 16-29	0.0531***	0.0475***	0.447	-0.0219	0.0229	0.138	0.0319*	0.0356*	0.888
	(0.0051)	(0.0053)		(0.0210)	(0.0217)		(0.0187)	(0.0189)	
Age 30-39	0.0271***	0.0365***	0.178	-0.0034	0.0002	0.899	0.0943***	0.0817***	0.611
	(0.0048)	(0.0050)		(0.0191)	(0.0201)		(0.0170)	(0.0178)	
Age 50-59	0.0113**	0.0047	0.331	0.0279	0.0528**	0.395	0.0174	0.0140	0.880
	(0.0047)	(0.0048)		(0.0202)	(0.0212)		(0.0157)	(0.0157)	
Age 60-69	-0.0045	-0.0109**	0.389	-0.0463**	-0.0310	0.637	0.0421**	0.0246	0.516
	(0.0053)	(0.0053)		(0.0224)	(0.0234)		(0.0191)	(0.0191)	
Age 70 or more	-0.1041***	-0.1262***	0.003	-0.1053***	-0.0987***	0.837	0.0506***	0.0354*	0.565
	(0.0052)	(0.0053)		(0.0224)	(0.0230)		(0.0186)	(0.0187)	
Less than high school	0.0735***	0.0745***	0.853	0.0829***	0.0882***	0.824	0.0574***	0.0762***	0.380
	(0.0039)	(0.0039)		(0.0164)	(0.0172)		(0.0150)	(0.0152)	
High school graduate	0.0143***	0.0238***	0.061	-0.0075	0.0060	0.541	0.0157	0.0270**	0.503
	(0.0035)	(0.0036)		(0.0155)	(0.0160)		(0.0119)	(0.0119)	
Complete graduate and beyond	-0.0790***	-0.0862***	0.275	-0.0780***	-0.0654***	0.664	-0.0885***	-0.0908***	0.914
	(0.0046)	(0.0047)		(0.0202)	(0.0206)		(0.0145)	(0.0158)	
Household language is English only	-0.0157***	-0.0187***	0.602						
	(0.0039)	(0.0041)							
Speaks English poorly	0.1558***	0.1478***	0.242				0.1300***	0.1503***	0.341
	(0.0048)	(0.0050)					(0.0177)	(0.0185)	
Non-citizen	-0.1096***	-0.1302***	0.002				-0.0809***	-0.0982***	0.565
	(0.0047)	(0.0048)					(0.0190)	(0.0188)	
Household income/poverty line	-0.1346***	-0.1394***	0.186	-0.0912***	-0.0957***	0.774	-0.0938***	-0.0973***	0.774
	(0.0026)	(0.0026)		(0.0107)	(0.0115)		(0.0085)	(0.0087)	
Anyone in household employed	-0.1018***	-0.1066***	0.370	-0.1058***	-0.1304***	0.267	0.0677***	0.0689***	0.951
	(0.0037)	(0.0039)		(0.0152)	(0.0161)		(0.0130)	(0.0132)	
Reported housing assistance receipt				0.2191***	0.2349***	0.402	0.2367***	0.2223***	0.517
				(0.0127)	(0.0139)		(0.0105)	(0.0109)	
Reported TANF+GA receipt	0.3616***	0.3481***	0.130	0.3792***	0.3277***	0.253	0.3794***	0.3181***	0.127
	(0.0060)	(0.0066)		(0.0291)	(0.0344)		(0.0286)	(0.0282)	
Linear time trend	0.0247***	0.0268***	0.109	0.0192***	0.0177***	0.738	-0.0000***	-0.0000***	0.428
	(0.0009)	(0.0009)		(0.0033)	(0.0034)		(0.0000)	(0.0000)	
Number of observations	149,318	149,318		5,711	5,711		8,819	8,819	
Joint test of equality chi2 statistic			533			68			39
Joint test of equality p-value			<0.001			<0.001			0.0443

Notes: Approved for release by the Census Bureau's Disclosure Review Board, approvals dated August 3, 2015 and August 18, 2016. For each survey, the first column contains estimates from a probit model using reported receipt as the dependent variable. The second column estimates the same model using the administrative receipt measure as the dependent variable. The thrid column contains p-values of a chi-square test whether the estimates are equal. All demographic characteristics refer to the reference person. The time trend is measured in years for the ACS and CPS, but in waves for the SIPP. The omitted categories are Multiple Adults with Children, Age 40-49, College Graduate and White. All analyses conducted using household weights adjusted for PIK probability. Standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1

Table 7: The Determinants of Reported and Administrative TANF+GA Receipt, Probit Marginal Effects, Linked Households with Income less than Twice the Poverty Line

	ACS			CPS			SIPP		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent Variable	Survey Report	Admin. Receipt	P-value (1)=(2)	Survey Report	Admin. Receipt	P-value (4)=(5)	Survey Report	Admin. Receipt	P-value (7)=(8)
Single adult, no children	-0.0236***	-0.0545***	<0.001	-0.0284*	-0.0179	0.643	-0.0266**	-0.0359***	0.610
	(0.0037)	(0.0041)		(0.0147)	(0.0172)		(0.0118)	(0.0138)	
Single adult, with children	0.0225***	0.0332***	0.020	0.0082	0.0601***	0.004	0.0447***	0.0549***	0.480
	(0.0031)	(0.0033)		(0.0118)	(0.0135)		(0.0094)	(0.0110)	
Multiple adults, no children	-0.0054*	-0.0250***	<0.001	-0.0024	-0.0158	0.478	0.0039	0.0258**	0.164
	(0.0033)	(0.0035)		(0.0119)	(0.0147)		(0.0102)	(0.0120)	
Number of members under 18	0.0063***	0.0064***	0.936	0.0047	0.0065*	0.717	0.0127***	0.0134***	0.853
	(0.0009)	(0.0010)		(0.0032)	(0.0038)		(0.0027)	(0.0032)	
Number of members 18 or older	0.0110***	0.0174***	0.001	-0.0022	0.0164***	0.034	0.0070*	0.0118**	0.431
	(0.0013)	(0.0014)		(0.0063)	(0.0061)		(0.0037)	(0.0049)	
Rural	-0.0104***	-0.0281***	<0.001	0.0120	0.0304*	0.358	0.0187*	0.0232*	0.780
	(0.0028)	(0.0036)		(0.0119)	(0.0161)		(0.0138)	(0.0139)	
Hispanic	0.0114***	0.0579***	<0.001	0.0122	0.0761***	<0.001	-0.0011	0.0286***	0.006
	(0.0027)	(0.0030)		(0.0077)	(0.0100)		(0.0070)	(0.0082)	
Black non-hispanic	0.0177***	0.0753***	<0.001	0.0204**	0.0835***	<0.001	0.0258***	0.0647***	<0.001
	(0.0022)	(0.0025)		(0.0081)	(0.0102)		(0.0057)	(0.0072)	
Other non-hispanic	0.0147***	0.0076*	0.216	-0.0290	-0.0270	0.943	-0.0160*	0.0274**	0.002
	(0.0035)	(0.0044)		(0.0179)	(0.0216)		(0.0091)	(0.0109)	
Male	-0.0051***	-0.0058***	0.790	-0.0049	0.0105	0.168	0.0014	-0.0147**	0.073
	(0.0018)	(0.0021)		(0.0071)	(0.0086)		(0.0058)	(0.0069)	
Disabled	0.0099***	0.0136***	0.222	-0.0535*	0.0057	0.209	0.0175**	0.0317***	0.209
	(0.0020)	(0.0023)		(0.0323)	(0.0344)		(0.0074)	(0.0085)	
Age 16-29	-0.0030	0.0122***	<0.001	0.0232***	0.0136	0.516	-0.0075	0.0028	0.416
	(0.0028)	(0.0029)		(0.0090)	(0.0118)		(0.0082)	(0.0096)	
Age 30-39	-0.0044*	-0.0052*	0.819	-0.0025	-0.0219**	0.134	-0.0408***	-0.0104	0.009
	(0.0026)	(0.0028)		(0.0080)	(0.0101)		(0.0078)	(0.0087)	
Age 50-59	-0.0100***	-0.0043	0.147	-0.0156	-0.0251**	0.531	-0.0142*	-0.0234**	0.444
	(0.0027)	(0.0029)		(0.0096)	(0.0118)		(0.0077)	(0.0093)	
Age 60-69	-0.0517***	-0.0546***	0.565	-0.0657***	-0.0849***	0.346	-0.0519***	-0.0860***	0.034
	(0.0033)	(0.0037)		(0.0132)	(0.0155)		(0.0103)	(0.0124)	
Age 70 or more	-0.0708***	-0.1187***	<0.001	-0.1105***	-0.1654***	0.030	-0.0582***	-0.0922***	0.051
	(0.0032)	(0.0043)		(0.0172)	(0.0185)		(0.0115)	(0.0131)	
Less than high school	0.0151***	0.0175***	0.471	0.0174**	0.0090	0.526	0.0200***	0.0285***	0.447
	(0.0023)	(0.0025)		(0.0082)	(0.0105)		(0.0073)	(0.0086)	
High school graduate	0.0045**	0.0023	0.502	0.0190**	0.0077	0.395	0.0009	-0.0018	0.791
	(0.0022)	(0.0024)		(0.0082)	(0.0105)		(0.0067)	(0.0075)	
Complete graduate and beyond	-0.0085***	-0.0218***	0.005	-0.0022	-0.0045	0.902	0.0131	-0.0097	0.099
	(0.0031)	(0.0036)		(0.0115)	(0.0143)		(0.0091)	(0.0105)	
Household language is English only	0.0107***	0.0160***	0.145						
	(0.0025)	(0.0027)							
Speaks English poorly	-0.0120***	-0.0237***	0.005				-0.0289***	-0.0392***	0.435
	(0.0028)	(0.0031)					(0.0084)	(0.0102)	
Non-citizen	-0.0035	-0.0007	0.476				0.0132	0.0006	0.193
	(0.0027)	(0.0028)					(0.0084)	(0.0102)	
Household income/poverty line	-0.0147***	-0.0487***	<0.001	-0.0221***	-0.0521***	0.003	-0.0127**	-0.0322***	0.012
	(0.0017)	(0.0020)		(0.0067)	(0.0078)		(0.0053)	(0.0057)	
Anyone in household employed	-0.0607***	-0.0466***	<0.001	-0.0256***	-0.0447***	0.112	0.0549***	0.0498***	0.674
	(0.0022)	(0.0024)		(0.0074)	(0.0095)		(0.0086)	(0.0086)	
Reported housing assistance receipt				0.0219***	0.0228***	0.925	0.0179***	0.0110	0.341
				(0.0061)	(0.0079)		(0.0054)	(0.0069)	
Reported SNAP receipt	0.1234***	0.1208***	0.380	0.0958***	0.1041***	0.444	0.0996***	0.0984***	0.915
	(0.0020)	(0.0020)		(0.0075)	(0.0080)		(0.0077)	(0.0073)	
Linear time trend	-0.0029***	-0.0039***	0.261	0.0002	-0.0033	0.197	-0.0000	-0.0000**	0.436
	(0.0006)	(0.0006)		(0.0017)	(0.0022)		(0.0000)	(0.0000)	
Number of observations	149,318	149,318		5,711	5,711		8,819	8,819	
Joint test of equality chi2 statistic			1,558			120			96
Joint test of equality p-value			<0.001			<0.001			<0.001

Notes: Approved for release by the Census Bureau's Disclosure Review Board, approvals dated August 3, 2015 and August 18, 2016. For each survey, the first column contains estimates from a probit model using reported receipt as the dependent variable. The second column estimates the same model using the administrative receipt measure as the dependent variable. The thrid column contains p-values of a chi-square test whether the estimates are equal. All demographic characteristics refer to the reference person. The time trend is measured in years for the ACS and CPS, but in waves for the SIPP. The omitted categories are Multiple Adults with Children, Age 40-49, College Graduate and White. All analyses use household weights adjusted for PIK probability. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 8: Differences Between the Full Sample and Item Non-Respondents in the Determinants of Program Receipt, Probit Coefficients

	ACS						CPS						SIPP					
	SNAP			TANF+GA			SNAP			TANF+GA			SNAP			TANF+GA		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Sample:	Full Sample	Non-respondents	P-value (1)=(2)	Full Sample	Non-respondents	P-value (4)=(5)	Full Sample	Non-respondents	P-value (7)=(8)	Full Sample	Non-respondents	P-value (10)=(11)	Full Sample	Non-respondents	P-value (13)=(14)	Full Sample	Non-respondents	P-value (16)=(17)
Single adult, no children	-0.093***	-0.054	0.723	-0.381***	-0.265***	0.087	0.099	0.115	0.914	-0.132	0.230	0.104	-0.078	-0.817***	<0.001	-0.604***	0.205	0.016
	(0.016)	(0.110)		(0.025)	(0.071)		(0.067)	(0.168)		(0.097)	(0.246)		(0.069)	(0.218)		(0.107)	(0.355)	
Single adult, with children	0.348***	0.378***	0.793	0.303***	0.368***	0.275	0.455***	0.296**	0.228	0.496***	0.414**	0.619	0.593***	0.400**	0.302	0.437***	0.710***	0.205
	(0.015)	(0.117)		(0.020)	(0.062)		(0.061)	(0.147)		(0.078)	(0.179)		(0.061)	(0.196)		(0.081)	(0.221)	
Multiple adults, no children	-0.069***	-0.064	0.956	-0.158***	-0.025	0.023	0.043	-0.108	0.229	-0.071	-0.052	0.915	-0.027	-0.409***	0.007	-0.049	0.257	0.185
	(0.013)	(0.095)		(0.020)	(0.061)		(0.057)	(0.137)		(0.078)	(0.195)		(0.060)	(0.153)		(0.093)	(0.238)	
Number of members under 18	0.109***	0.143***	0.372	0.056***	0.069***	0.466	0.145***	0.148***	0.943	0.070***	0.170***	0.056	0.119***	0.002	0.033	0.082***	0.112	0.642
	(0.005)	(0.038)		(0.006)	(0.019)		(0.022)	(0.051)		(0.024)	(0.058)		(0.022)	(0.059)		(0.026)	(0.070)	
Number of members 18 or older	0.180***	0.119***	0.023	0.122***	0.116***	0.773	0.217***	0.158***	0.209	0.139***	0.167***	0.628	0.198***	0.171***	0.559	0.032	0.090	0.398
	(0.005)	(0.027)		(0.007)	(0.020)		(0.021)	(0.052)		(0.031)	(0.061)		(0.022)	(0.050)		(0.031)	(0.074)	
Rural	-0.114***	-0.232***	0.146	-0.196***	-0.185***	0.873	0.123**	0.462***	0.002	0.201**	0.327	0.474	0.000***	0.000**	0.127	0.000***	0.000	0.597
	(0.010)	(0.082)		(0.020)	(0.068)		(0.050)	(0.127)		(0.085)	(0.200)		(0.000)	(0.000)		(0.000)	(0.000)	
Hispanic	0.493***	0.477***	0.811	0.400***	0.351***	0.308	0.560***	0.725***	0.055	0.471***	0.345**	0.363	0.386***	0.571***	0.149	0.383***	0.311	0.713
	(0.011)	(0.067)		(0.018)	(0.050)		(0.037)	(0.094)		(0.058)	(0.152)		(0.045)	(0.133)		(0.063)	(0.206)	
Black non-hispanic	0.678***	0.670***	0.899	0.604***	0.586***	0.660	0.463***	0.652***	0.024	0.595***	0.682***	0.469	0.494***	0.409***	0.435	0.670***	0.529***	0.387
	(0.009)	(0.059)		(0.015)	(0.043)		(0.038)	(0.092)		(0.058)	(0.132)		(0.037)	(0.113)		(0.058)	(0.170)	
Other non-hispanic	0.022	0.012	0.920	0.099***	0.038	0.434	0.085	0.253*	0.213	-0.175	-0.005	0.485	0.422***	0.078	0.054	0.207**	0.666***	0.044
	(0.015)	(0.095)		(0.027)	(0.081)		(0.059)	(0.147)		(0.120)	(0.280)		(0.048)	(0.185)		(0.086)	(0.249)	
Male	-0.207***	-0.168***	0.384	-0.042***	-0.085**	0.196	-0.122***	-0.342***	0.001	0.013	-0.409***	<0.001	-0.105***	-0.052	0.539	-0.149***	-0.337**	0.215
	(0.007)	(0.045)		(0.012)	(0.035)		(0.030)	(0.075)		(0.048)	(0.122)		(0.029)	(0.090)		(0.053)	(0.157)	
Disabled	0.479***	0.309***	0.002	0.083***	0.120***	0.337	0.346**	0.636**	0.320	0.079	0.923***	0.001	1.027***	1.219***	0.321	0.293***	0.243	0.819
	(0.008)	(0.054)		(0.015)	(0.040)		(0.139)	(0.316)		(0.179)	(0.327)		(0.046)	(0.200)		(0.068)	(0.227)	
Age 16-29	0.223***	0.137	0.404	0.107***	0.218***	0.033	0.183***	0.437***	0.030	0.080	0.218	0.341	0.306***	0.362**	0.709	0.132	0.082	0.804
	(0.013)	(0.103)		(0.018)	(0.054)		(0.051)	(0.131)		(0.066)	(0.162)		(0.060)	(0.161)		(0.087)	(0.201)	
Age 30-39	0.124***	-0.060	0.028	-0.034**	-0.032	0.975	0.156***	0.394***	0.022	-0.165***	0.014	0.173	0.275***	0.267**	0.952	-0.051	-0.009	0.816
	(0.011)	(0.084)		(0.017)	(0.051)		(0.047)	(0.115)		(0.060)	(0.150)		(0.047)	(0.129)		(0.067)	(0.188)	
Age 50-59	0.029***	0.095	0.374	0.010	-0.037	0.301	0.094*	-0.008	0.374	-0.043	-0.135	0.568	0.091**	0.072	0.877	0.097	0.090	0.974
	(0.011)	(0.074)		(0.017)	(0.048)		(0.048)	(0.125)		(0.068)	(0.179)		(0.044)	(0.131)		(0.070)	(0.216)	
Age 60-69	-0.056***	0.041	0.211	-0.304***	-0.455***	0.010	-0.082	0.015	0.449	-0.332***	-0.471**	0.500	0.062	-0.107	0.288	-0.522***	-1.001**	0.260
	(0.013)	(0.078)		(0.022)	(0.062)		(0.056)	(0.142)		(0.087)	(0.223)		(0.054)	(0.164)		(0.098)	(0.433)	
Age 70 or more	-0.425***	-0.231***	0.019	-0.764***	-0.915***	0.021	-0.298***	-0.242	0.680	-1.066***	-1.241***	0.579	0.100**	0.127	0.872	-0.645***	-0.553**	0.711
	(0.013)	(0.083)		(0.026)	(0.070)		(0.059)	(0.149)		(0.128)	(0.331)		(0.051)	(0.177)		(0.097)	(0.259)	
Less than high school	0.291***	0.023	<0.001	0.143***	0.055	0.034	0.305***	0.437***	0.185	0.103	0.174	0.633	0.342***	0.745***	0.005	0.186***	0.174	0.949
	(0.010)	(0.065)		(0.016)	(0.044)		(0.043)	(0.107)		(0.063)	(0.164)		(0.046)	(0.149)		(0.070)	(0.203)	
High school graduate	0.105***	0.027	0.195	0.043***	-0.021	0.119	0.031	0.196**	0.055	0.085*	0.142	0.662	0.175***	0.267***	0.339	-0.053	0.142	0.224
	(0.008)	(0.061)		(0.014)	(0.043)		(0.037)	(0.095)		(0.059)	(0.145)		(0.034)	(0.101)		(0.060)	(0.167)	
Complete graduate and beyond	-0.188***	-0.110	0.258	-0.149***	-0.246***	0.088	-0.237***	-0.253**	0.882	0.006	-0.076	0.601	-0.323***	-0.072	0.029	-0.170**	-0.019	0.485
	(0.010)	(0.069)		(0.018)	(0.059)		(0.044)	(0.113)		(0.071)	(0.174)		(0.040)	(0.122)		(0.074)	(0.230)	
Household language is English only	-0.121***	-0.141**	0.729	0.086***	0.105**	0.655							0.153***	0.002	0.167	0.036	0.105	0.744
	(0.009)	(0.059)		(0.016)	(0.045)								(0.039)	(0.119)		(0.079)	(0.220)	
Speaks English poorly	0.419***	0.374***	0.560	-0.201***	-0.167***	0.553							0.489***	0.293	0.344	-0.417***	-0.234	0.520
	(0.013)	(0.078)		(0.020)	(0.061)								(0.060)	(0.213)		(0.090)	(0.292)	
Non-citizen	-0.348***	-0.158**	0.009	-0.014	0.031	0.387							-0.292***	-0.315*	0.891	0.122	-0.290	0.062
	(0.013)	(0.073)		(0.018)	(0.054)								(0.066)	(0.170)		(0.098)	(0.217)	
Household income/poverty line	-0.250***	-0.108***	<0.001	-0.119***	-0.098***	0.046	-0.222***	-0.143***	0.001	-0.110***	-0.041	0.039	-0.250***	-0.176***	0.004	-0.088***	-0.197***	0.069
	(0.003)	(0.012)		(0.004)	(0.011)		(0.012)	(0.025)		(0.019)	(0.037)		(0.013)	(0.027)		(0.022)	(0.060)	
Anyone in household employed	-0.428***	-0.246***	0.004	-0.368***	-0.335***	0.417	-0.487***	-0.519***	0.722	-0.395***	-0.530***	0.291	0.245***	0.328***	0.437	0.502***	0.374**	0.478
	(0.010)	(0.064)		(0.015)	(0.043)		(0.041)	(0.096)		(0.058)	(0.137)		(0.037)	(0.112)		(0.067)	(0.185)	
Reported housing assistance receipt							0.810***	0.420***	<0.001	0.187***	0.017	0.246						
							(0.043)	(0.113)		(0.053)	(0.154)							
Reported TANF+GA receipt	1.307***	0.604***	<0.001				1.121***	0.247	<0.001				1.157***	0.860***	0.144			
	(0.017)	(0.100)					(0.099)	(0.187)					(0.085)	(0.215)				
Reported SNAP receipt				1.032***	1.091***	<0.001				0.830***	0.405***	0.794				0.890***	0.920***	0.840
				(0.013)	(0.036)					(0.053)	(0.131)					(0.055)	(0.155)	
Linear time trend	0.084***	0.074***	0.483	-0.022***	-0.025**	0.773	0.058***	0.064***	0.771	-0.005	-0.036	0.255	0.820***	0.659***	0.261	0.138**	-0.155	0.122
	(0.002)	(0.016)		(0.004)	(0.011)		(0.008)	(0.020)		(0.013)	(0.031)		(0.039)	(0.147)		(0.058)	(0.197)	
Constant	-0.798***	-0.693***	0.510	-1.875***	-1.694***	0.076	-1.093***	-1.225***	0.545	-1.922***	-1.842***	<0.001	-1.587***	-1.077***	0.025	-2.447***	-2.537***	0.827
	(0.023)	(0.160)		(0.036)	(0.107)		(0.098)	(0.240)		(0.138)	(0.340)		(0.091)	(0.239)		(0.149)	(0.427)	
Number of observations	543,528	6,096		543,528	35,589		18,064	2,336		18,064	2,346		24,997	1,941		24,997	1,928	
Chi2 distance measure			19,313			2,554			460			354			656			267
Joint test of equality chi2 statistic			753.21			319.28			107.71			88.12			109.97			44.86
Joint test of equality p-value			<0.001			<0.001			<0.001			<0.001			<0.001			0.017

Notes: Approved for release by the Census Bureau's Disclosure Review Board, approvals dated August 3, 2015 and August 18, 2016. The dependent variable is receipt according to the administrative data in all columns. For each survey and program, the first column estimates the model using the full linked sample, the second column estimates the same model using the sample of item non-respondents. The third column contains p-values of chi-square tests whether the estimates in the first two columns are equal. All demographic characteristics refer to the reference person. The time trend is measured in years for the ACS and CPS, but in waves for the SIPP. The omitted categories are Multiple Adults with Children, Age 40-49, College Graduate and White. All analyses use household weights adjusted for PIK probability. The distance measure is the squared distance between the two coefficient vectors, weighted by the variance matrix of the coefficients from using the full sample with the administrative dependent variable. SEs in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 9: The Determinants of Administrative and Imputed Program Receipt Among Item Non-Respondents, Probit Coefficients

	ACS						CPS						SIPP					
	SNAP			TANF+GA			SNAP			TANF+GA			SNAP			TANF+GA		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Dependent variable:	Admin. Receipt	Imputed Receipt	P-value (1)=(2)	Admin. Receipt	Imputed Receipt	P-value (4)=(5)	Admin. Receipt	Imputed Receipt	P-value (7)=(8)	Admin. Receipt	Imputed Receipt	P-value (10)=(11)	Admin. Receipt	Imputed Receipt	P-value (13)=(14)	Admin. Receipt	Imputed Receipt	P-value (16)=(17)
Single adult, no children	-0.054	-0.298**	0.102	-0.265***	-0.181***	0.338	0.115	0.178	0.804	0.230	-0.898***	0.004	-0.817***	-0.306	0.027	0.205	0.600*	0.345
	(0.110)	(0.119)		(0.071)	(0.063)		(0.168)	(0.202)		(0.246)	(0.284)		(0.218)	(0.212)		(0.355)	(0.362)	
Single adult, with children	0.378***	0.048	0.049	0.368***	0.199***	0.025	0.296**	0.163	0.547	0.414**	-0.168	0.030	0.400**	0.201	0.274	0.710***	0.537**	0.541
	(0.117)	(0.124)		(0.062)	(0.057)		(0.147)	(0.168)		(0.179)	(0.212)		(0.196)	(0.200)		(0.221)	(0.266)	
Multiple adults, no children	-0.064	-0.258**	0.124	-0.025	-0.012	0.860	-0.108	0.160	0.203	-0.052	-0.376*	0.276	-0.409***	-0.205	0.206	0.257	0.260	0.993
	(0.095)	(0.103)		(0.061)	(0.054)		(0.137)	(0.175)		(0.195)	(0.216)		(0.153)	(0.158)		(0.238)	(0.272)	
Number of members under 18	0.143***	0.016	0.011	0.069***	0.073***	0.866	0.148***	0.058	0.180	0.170***	0.086	0.398	0.002	0.078	0.103	0.112	0.240***	0.120
	(0.038)	(0.039)		(0.019)	(0.018)		(0.051)	(0.062)		(0.058)	(0.070)		(0.059)	(0.060)		(0.070)	(0.088)	
Number of members 18 or older	0.119***	-0.102***	<0.001	0.116***	0.082***	0.185	0.158***	-0.012	0.033	0.167***	0.041	0.243	0.171***	0.082	0.139	0.090	0.013	0.396
	(0.027)	(0.034)		(0.020)	(0.019)		(0.052)	(0.069)		(0.061)	(0.082)		(0.050)	(0.059)		(0.074)	(0.079)	
Rural	-0.232***	-0.142	0.481	-0.185***	-0.121**	0.381	0.462***	0.067	0.049	0.327	-0.296	0.036	0.000**	0.000***	0.660	0.000	0.000	0.412
	(0.082)	(0.094)		(0.068)	(0.047)		(0.127)	(0.153)		(0.200)	(0.232)		(0.000)	(0.000)		(0.000)	(0.000)	
Hispanic	0.477***	0.310***	0.080	0.351***	-0.003	<0.001	0.725***	0.207*	<0.001	0.345**	-0.164	0.023	0.571***	0.533***	0.760	0.311	-0.325	0.006
	(0.067)	(0.075)		(0.050)	(0.046)		(0.094)	(0.114)		(0.152)	(0.168)		(0.133)	(0.143)		(0.206)	(0.207)	
Black non-hispanic	0.670***	0.434***	0.007	0.586***	0.160***	<0.001	0.652***	0.084	<0.001	0.682***	0.115	0.006	0.409***	0.358***	0.702	0.529***	0.256	0.214
	(0.059)	(0.064)		(0.043)	(0.036)		(0.092)	(0.112)		(0.132)	(0.162)		(0.113)	(0.122)		(0.170)	(0.187)	
Other non-hispanic	0.012	0.249**	0.057	0.038	-0.030	0.454	0.253*	0.104	0.488	-0.005	-0.936**	0.047	0.078	0.240	0.485	0.666***	-0.506	0.003
	(0.095)	(0.100)		(0.081)	(0.062)		(0.147)	(0.175)		(0.280)	(0.367)		(0.185)	(0.180)		(0.249)	(0.406)	
Male	-0.168***	-0.217***	0.459	-0.085**	-0.174***	0.028	-0.342***	-0.208**	0.248	-0.409***	-0.212	0.297	-0.052	-0.083	0.747	-0.337**	-0.097	0.236
	(0.045)	(0.050)		(0.035)	(0.029)		(0.075)	(0.094)		(0.122)	(0.142)		(0.090)	(0.096)		(0.157)	(0.172)	
Disabled	0.309***	0.078	0.003	0.120***	0.125***	0.911	0.636**	0.479	0.678	0.923***	-0.115	0.096	1.219***	0.909***	0.108	0.243	-0.208	0.042
	(0.054)	(0.059)		(0.040)	(0.034)		(0.316)	(0.366)		(0.327)	(0.445)		(0.200)	(0.199)		(0.227)	(0.247)	
Age 16-29	0.137	0.054	0.588	0.218***	0.252***	0.596	0.437***	-0.225	<0.001	0.218	0.748***	0.038	0.362**	0.313**	0.775	0.082	0.094	0.962
	(0.103)	(0.114)		(0.054)	(0.052)		(0.131)	(0.149)		(0.162)	(0.190)		(0.161)	(0.156)		(0.201)	(0.259)	
Age 30-39	-0.060	0.132	0.096	-0.032	0.116**	0.014	0.394***	-0.275*	<0.001	0.014	0.108	0.700	0.267**	0.508***	0.067	-0.009	-0.210	0.415
	(0.084)	(0.087)		(0.051)	(0.046)		(0.115)	(0.146)		(0.150)	(0.194)		(0.129)	(0.142)		(0.188)	(0.240)	
Age 50-59	0.095	0.020	0.478	-0.037	-0.100**	0.272	-0.008	0.043	0.791	-0.135	0.243	0.159	0.072	0.324**	0.111	0.090	-0.013	0.688
	(0.074)	(0.082)		(0.048)	(0.044)		(0.125)	(0.154)		(0.179)	(0.205)		(0.131)	(0.144)		(0.216)	(0.219)	
Age 60-69	0.041	-0.143	0.107	-0.455***	-0.372***	0.257	0.015	-0.302*	0.150	-0.471**	-0.037	0.198	-0.107	0.090	0.268	-1.001**	-0.683*	0.314
	(0.078)	(0.089)		(0.062)	(0.050)		(0.142)	(0.172)		(0.223)	(0.268)		(0.164)	(0.185)		(0.433)	(0.358)	
Age 70 or more	-0.231***	-0.251***	0.863	-0.915***	-0.606***	<0.001	-0.242	-0.424**	0.429	-1.241***	-0.394	0.072	0.127	0.107	0.915	-0.553**	-0.018	0.098
	(0.083)	(0.093)		(0.070)	(0.051)		(0.149)	(0.190)		(0.331)	(0.332)		(0.177)	(0.182)		(0.259)	(0.264)	
Less than high school	0.023	0.190***	0.084	0.055	0.102***	0.354	0.437***	0.228*	0.171	0.174	0.292	0.614	0.745***	0.886***	0.347	0.174	0.554***	0.112
	(0.065)	(0.072)		(0.044)	(0.039)		(0.107)	(0.123)		(0.164)	(0.180)		(0.149)	(0.154)		(0.203)	(0.212)	
High school graduate	0.027	0.170**	0.112	-0.021	-0.016	0.910	0.196**	-0.145	0.016	0.142	-0.056	0.359	0.267***	0.316***	0.654	0.142	0.153	0.959
	(0.061)	(0.068)		(0.043)	(0.036)		(0.095)	(0.112)		(0.145)	(0.156)		(0.101)	(0.110)		(0.167)	(0.196)	
Complete graduate and beyond	-0.110	0.036	0.158	-0.246***	-0.146***	0.161	-0.253**	-0.334**	0.673	-0.076	-0.684***	0.040	-0.072	0.108	0.164	-0.019	-0.109	0.752
	(0.069)	(0.080)		(0.059)	(0.047)		(0.113)	(0.163)		(0.174)	(0.243)		(0.122)	(0.120)		(0.230)	(0.300)	
Household language is English only	-0.141**	0.001	0.117	0.105**	0.101**	0.939							0.002	-0.100	0.447	0.105	1.229***	0.005
	(0.059)	(0.070)		(0.045)	(0.040)								(0.119)	(0.127)		(0.220)	(0.380)	
Speaks English poorly	0.374***	0.314***	0.581	-0.167***	0.067	0.001							0.293	0.087	0.396	-0.234	-0.140	0.702
	(0.078)	(0.079)		(0.061)	(0.052)								(0.213)	(0.211)		(0.292)	(0.295)	
Non-citizen	-0.158**	-0.031	0.215	0.031	-0.026	0.387							-0.315*	-0.013	0.085	-0.290	-0.091	0.506
	(0.073)	(0.080)		(0.054)	(0.051)								(0.170)	(0.169)		(0.217)	(0.268)	
Household income/poverty line	-0.108***	-0.149***	0.053	-0.098***	-0.065***	0.010	-0.143***	-0.518***	0.001	-0.041	-0.011	0.553	-0.176***	-0.138***	0.269	-0.197***	-0.149*	0.604
	(0.012)	(0.019)		(0.011)	(0.008)		(0.025)	(0.113)		(0.037)	(0.035)		(0.027)	(0.027)		(0.060)	(0.079)	
Anyone in household employed	-0.246***	-0.164**	0.379	-0.335***	-0.592***	<0.001	-0.519***	-0.189	0.029	-0.530***	-0.282*	0.245	0.328***	0.372***	0.721	0.374**	0.661**	0.291
	(0.064)	(0.071)		(0.043)	(0.036)		(0.096)	(0.129)		(0.137)	(0.159)		(0.112)	(0.113)		(0.185)	(0.260)	
Reported housing assistance receipt							0.420***	0.307**	0.444	0.017	0.355**	0.135						
							(0.113)	(0.120)		(0.154)	(0.172)							
Reported TANF+GA receipt	0.604***	0.195**	0.002				0.247	1.096***	<0.001				0.860***	1.675***	<0.001			
	(0.100)	(0.099)					(0.187)	(0.182)					(0.215)	(0.269)				
Reported SNAP receipt				1.091***	0.947***	0.001				0.405***	0.942***	0.008				0.920***	1.440***	0.015
				(0.036)	(0.031)					(0.131)	(0.151)					(0.155)	(0.192)	
Linear time trend	0.074***	0.063***	0.660	-0.025**	-0.021**	0.758	0.064***	0.016	0.129	-0.036	0.042	0.084	0.659***	1.210***	<0.001	-0.155	0.194	0.106
	(0.016)	(0.018)		(0.011)	(0.009)		(0.020)	(0.025)		(0.031)	(0.036)		(0.147)	(0.150)		(0.197)	(0.185)	
Constant	-0.693***	-0.419**	<0.001	-1.694***	-1.126***	<0.001	-1.225***	-0.091	<0.001	-1.842***	-2.023***	<0.001	-1.077***	-1.529***	<0.001	-2.537***	-4.463***	<0.001
	(0.160)	(0.175)		(0.107)	(0.093)		(0.240)	(0.281)		(0.340)	(0.366)		(0.239)	(0.274)		(0.427)	(0.647)	
Number of observations			29,610			4,514			4,688			1,209			867			1,355
Chi2 distance measure			359.75			436.72			172.10			62.71			79.86			52.65
Joint test of equality chi2 statistic			<0.001			<0.001			<0.001			<0.001			<0.001			0.002
Joint test of equality p-value	6096	6096		35589	35589		2336	2336		2346	2346		1941	1941		1928	1928	

Notes: Approved for release by the Census Bureau's Disclosure Review Board, approvals dated August 3, 2015 and August 18, 2016. The sample is restricted to item non-respondents in all columns. For each survey and program, the first column uses the administrative receipt measure as the dependent variable. The second column estimates the same model using the imputed receipt variable. The third column contains p-values of chi-square tests whether the estimates in the first two columns are equal. All demographic characteristics refer to the reference person. The time trend is measured in years for the ACS and CPS, but in waves for the SIPP. The omitted categories are Multiple Adults with Children, Age 40-49, College Graduate and White. All analyses use household weights adjusted for PIK probability. The distance measure is the squared distance between the two coefficient vectors, weighted by the variance matrix of the coefficients using the administrative dependent variable. SEs in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 10 – Bias From Item Non-response and Imputation in Probit Coefficients of the Determinants of Program Receipt

		ACS		CPS		SIPP	
Sample	**Dependent Variable**	*SNAP*	*TANF+GA*	*SNAP*	*TANF+GA*	*SNAP*	*TANF+GA*
Respondents	Administrative Receipt	8.5	27.2	25.7	15.6	12.7	3.2
Full	Admin/Imputed	14.0	163.5	57.0	23.1	11.9	7.1
Effect of Including Imputed Observations		5.5	136.3	31.3	7.5	-0.8	3.9

Note: Approved for release by the Census Bureau's Disclosure Review Board, approvals dated August 3, 2015 and August 18, 2016. The first two rows report distances between the estimated coefficients from the model using the full sample and the administrative dependent variable and using the sample and dependent variable in the first two columns. Coefficient estimates are reported in Appendix Table A6. Distances are the squared distance to the coefficients from the model using the full sample and the administrative receipt variable, weighted by the variance matrix of the coefficients from this model. The effect of including imputed observations in the third row is the difference between the two lines above.

Table A1: The Determinants of a Household Having a PIK, Probit Coefficients and Marginal Effects

	ACS		CPS		SIPP	
	(1)	(2)	(3)	(4)	(5)	(6)
	Coefficients	Marg. Eff.	Coefficients	Marg. Eff.	Coefficients	Marg. Eff.
Single adult, no children	-0.3077***	-0.0390***	-0.4146***	-0.0650***	-0.3882***	-0.0400***
	(0.0185)	(0.0024)	(0.0709)	(0.0112)	(0.0868)	(0.0090)
Single adult, with children	0.0207	0.0026	0.0416	0.0065	0.0909	0.0094
	(0.0205)	(0.0026)	(0.0721)	(0.0113)	(0.0888)	(0.0092)
Multiple adults, no children	-0.1170***	-0.0148***	-0.2023***	-0.0317***	-0.1861**	-0.0192**
	(0.0160)	(0.0020)	(0.0605)	(0.0095)	(0.0744)	(0.0077)
Number of members under 18	0.0399***	0.0051***	0.0473*	0.0074*	0.1018***	0.0105***
	(0.0068)	(0.0009)	(0.0266)	(0.0042)	(0.0330)	(0.0034)
Number of members 18 or older	0.0163***	0.0021***	0.0523**	0.0082**	0.0891***	0.0092***
	(0.0061)	(0.0008)	(0.0246)	(0.0039)	(0.0313)	(0.0032)
Rural	0.0278***	0.0035***	0.0978*	0.0153*	-0.0941*	-0.0097*
	(0.0106)	(0.0013)	(0.0559)	(0.0088)	(0.0513)	(0.0053)
Hispanic	0.0364***	0.0046***	-0.1765***	-0.0276***	-0.2091***	-0.0215***
	(0.0129)	(0.0016)	(0.0376)	(0.0058)	(0.0530)	(0.0056)
Black non-hispanic	-0.1423***	-0.0181***	-0.0929**	-0.0146**	-0.0305	-0.0031
	(0.0108)	(0.0014)	(0.0385)	(0.0060)	(0.0474)	(0.0049)
Other non-hispanic	-0.0778***	-0.0099***	-0.4893***	-0.0767***	-0.2112***	-0.0218***
	(0.0147)	(0.0019)	(0.0452)	(0.0070)	(0.0499)	(0.0052)
Male	-0.0033	-0.0004			0.0682**	0.0070**
	(0.0073)	(0.0009)			(0.0321)	(0.0033)
Disabled	0.1047***	0.0133***	0.0890	0.0140	0.1923***	0.0198***
	(0.0106)	(0.0013)	(0.1577)	(0.0247)	(0.0633)	(0.0065)
Age 16-29	-0.0916***	-0.0116***	-0.0694	-0.0109	-0.2617***	-0.0270***
	(0.0136)	(0.0017)	(0.0489)	(0.0077)	(0.0617)	(0.0064)
Age 30-39	-0.0853***	-0.0108***	-0.1104***	-0.0173***	-0.3849***	-0.0397***
	(0.0118)	(0.0015)	(0.0423)	(0.0066)	(0.0520)	(0.0054)
Age 50-59	0.1265***	0.0161***	0.1678***	0.0263***	0.0306	0.0032
	(0.0116)	(0.0015)	(0.0450)	(0.0071)	(0.0542)	(0.0056)
Age 60-69	0.2048***	0.0260***	0.3751***	0.0588***	0.1200**	0.0124**
	(0.0130)	(0.0017)	(0.0538)	(0.0084)	(0.0593)	(0.0061)
Age 70 or more	0.2618***	0.0332***	0.2849***	0.0446***	0.0663	0.0068
	(0.0141)	(0.0018)	(0.0575)	(0.0090)	(0.0609)	(0.0063)
Less than high school	-0.0503***	-0.0064***	-0.0880*	-0.0138*	-0.0624	-0.0064
	(0.0125)	(0.0016)	(0.0475)	(0.0075)	(0.0570)	(0.0059)
High school graduate	-0.1357***	-0.0172***	-0.1567***	-0.0246***	-0.0068	-0.0007
	(0.0097)	(0.0012)	(0.0377)	(0.0059)	(0.0420)	(0.0043)
Complete graduate and beyond	0.0664***	0.0084***	-0.0045	-0.0007	-0.0117	-0.0012
	(0.0101)	(0.0013)	(0.0409)	(0.0064)	(0.0405)	(0.0042)
Household language is English only	0.1150***	0.0146***				
	(0.0103)	(0.0013)				
Speaks English poorly	-0.2504***	-0.0318***			-0.5738***	-0.0591***
	(0.0144)	(0.0018)			(0.0555)	(0.0058)
Non-citizen	-0.3705***	-0.0470***			-0.4976***	-0.0513***
	(0.0116)	(0.0015)			(0.0520)	(0.0054)
Household income/poverty line	0.0092***	0.0012***	0.0199***	0.0031***	-0.0007	-0.0001
	(0.0009)	(0.0001)	(0.0059)	(0.0009)	(0.0005)	(0.0001)
Anyone in household employed	0.0595***	0.0076***	0.0579	0.0091	0.0535	0.0055
	(0.0105)	(0.0013)	(0.0417)	(0.0065)	(0.0382)	(0.0039)
Linear time trend	0.0136***	0.0017***	0.0134*	0.0021*	0.0163***	0.0017***
	(0.0025)	(0.0003)	(0.0081)	(0.0013)	(0.0036)	(0.0004)
Constant	1.4072***		1.3093***		1.7288***	
	(0.0276)		(0.1003)		(0.1222)	
Number of observations	573,459	573,459	19,852	19,852	26,349	26,349
chi2 statistic of joint significance	255.3	5806.8	22.8	490.8	34.4	651.2
p-value of joint significance	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001

Note: The dependent variable is an indicator whether someone in the household was assigned a PIK. All demographic characteristics refer to the reference person. The time trend is measured in years for the ACS and CPS, but in waves for the SIPP. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A2: Summary Statistics, Full Linked Sample

	ACS		CPS		SIPP	
	(1)	(2)	(3)	(4)	(5)	(6)
	Mean	*SD*	*Mean*	*SD*	*Mean*	*SD*
Reported SNAP receipt	0.139	0.346	0.120	0.325	0.155	0.362
Reported TANF+GA receipt	0.033	0.178	0.022	0.147	0.024	0.154
Fale Positive Rate SNAP	0.012	0.109	0.020	0.141	0.015	0.122
Fale Negative Rate SNAP	0.257	0.437	0.421	0.494	0.194	0.395
Imputed SNAP receipt	0.011	0.103	0.130	0.336	0.072	0.258
Fale Positive Rate TANF+GA	0.016	0.126	0.006	0.078	0.005	0.073
Fale Negative Rate TANF+GA	0.568	0.495	0.629	0.483	0.463	0.499
Imputed TANF+GA receipt	0.061	0.239	0.130	0.336	0.071	0.258
Single adult, no children	0.296	0.456	0.311	0.463	0.331	0.470
Single adult, with children	0.054	0.227	0.056	0.230	0.065	0.247
Multiple adults, no children	0.386	0.487	0.379	0.485	0.347	0.476
Number of members under 18	0.591	1.037	0.568	1.004	0.583	0.996
Number of members 18 or older	1.926	0.943	1.898	0.921	1.845	0.900
Rural	0.131	0.337	0.087	0.282	0.853	0.354
Hispanic	0.147	0.354	0.140	0.347	0.146	0.354
Black non-hispanic	0.136	0.343	0.147	0.354	0.134	0.340
Other non-hispanic	0.069	0.253	0.073	0.261	0.066	0.249
Male	0.497	0.500			0.451	0.498
Disabled	0.153	0.360	0.009	0.093	0.077	0.267
Age 16-29	0.096	0.295	0.119	0.324	0.097	0.296
Age 30-39	0.169	0.375	0.171	0.377	0.161	0.368
Age 50-59	0.210	0.408	0.199	0.399	0.216	0.411
Age 60-69	0.154	0.361	0.154	0.361	0.143	0.350
Age 70 or more	0.158	0.365	0.156	0.363	0.166	0.372
Less than high school	0.134	0.341	0.131	0.337	0.089	0.285
High school graduate	0.254	0.435	0.288	0.453	0.274	0.446
Complete graduate and beyond	0.350	0.477	0.344	0.475	0.331	0.470
Household language is English only	0.699	0.459				
Speaks English poorly	0.067	0.249			0.055	0.229
Non-citizen	0.095	0.293			0.069	0.253
Anyone in household employed	0.741	0.438	0.714	0.452	0.525	0.499
Household income/poverty line	4.122	2.941	3.972	2.899	3.644	2.730
Reported housing assistance receipt			0.090	0.286	0.110	0.313

Note: All demographic characteristics refer to the reference person. All estimates use household weights adjusted for PIK probability.

Table A3: Cross-tabulations of SNAP and TANF+GA Receipt According to Reports and Administrative Records, Full Linked Sample

SNAP					TANF+GA				
American Community Survey									
Admin record		**Survey report**			**Admin record**		**Survey report**		
		No SNAP	*SNAP*	*Total*			*No TANF+GA*	*TANF+GA*	*Total*
No SNAP	Pop Est. (1000s)	29333830	358630	29692460	No TANF+GA	Pop Est. (1000s)	33931820	556972	34488792
	Overall (%)	81.6%	1.0%	82.6%		Overall (%)	94.4%	1.5%	96.0%
	Row (%)	98.8%	1.2%	100%		Row (%)	98.4%	1.6%	100%
	Colum (%)	94.8%	7.2%	82.6%		Colum (%)	97.6%	47.1%	96.0%
	Sample count	457061	4695	461756		Sample count	518011	8555	526566
SNAP	Pop Est. (1000s)	1607057	4637630	6244686	TANF+GA	Pop Est. (1000s)	822890	625464	1448354
	Overall (%)	4.5%	12.9%	17.4%		Overall (%)	2.3%	1.7%	4.0%
	Row (%)	25.7%	74.3%	100%		Row (%)	56.8%	43.2%	100%
	Colum (%)	5.2%	92.8%	17.4%		Colum (%)	2.4%	52.9%	4.0%
	Sample count	18674	63098	81772		Sample count	9365	7597	16962
Total	Pop Est. (1000s)	30940887	4996259	35937146	Total	Pop Est. (1000s)	34754710	1182436	35937146
	Overall (%)	86.1%	13.9%	100%		Overall (%)	96.7%	3.3%	100%
	Row (%)	86.1%	13.9%	100%		Row (%)	96.7%	3.3%	100%
	Colum (%)	100%	100%	100%		Colum (%)	100%	100%	100%
	Sample count	475735	67793	543528		Sample count	527376	16152	543528
Current Population Survey									
Admin record		**Survey report**			**Admin record**		**Survey report**		
		No SNAP	*SNAP*	*Total*			*No TANF+GA*	*TANF+GA*	*Total*
No SNAP	Pop Est. (1000s)	36720	761	37481	No TANF+GA	Pop Est. (1000s)	43328	269	43597
	Overall (%)	80.5%	1.7%	82.2%		Overall (%)	95.0%	0.6%	95.6%
	Row (%)	98.0%	2.0%	100%		Row (%)	99.4%	0.6%	100%
	Colum (%)	91.5%	13.9%	82.2%		Colum (%)	97.2%	26.5%	95.6%
	Sample count	14214	311	14525		Sample count	17033	123	17156
SNAP	Pop Est. (1000s)	3422	4703	8125	TANF+GA	Pop Est. (1000s)	1264	745	2009
	Overall (%)	7.5%	10.3%	17.8%		Overall (%)	2.8%	1.6%	4.4%
	Row (%)	42.1%	57.9%	100%		Row (%)	62.9%	37.1%	100%
	Colum (%)	8.5%	86.1%	17.8%		Colum (%)	2.8%	73.5%	4.4%
	Sample count	1509	2030	3539		Sample count	575	333	908
Total	Pop Est. (1000s)	40142	5464	45606	Total	Pop Est. (1000s)	44592	1014	45606
	Overall (%)	88.0%	12.0%	100%		Overall (%)	97.8%	2.2%	100%
	Row (%)	88.0%	12.0%	100%		Row (%)	97.8%	2.2%	100%
	Colum (%)	100%	100%	100%		Colum (%)	100%	100%	100%
	Sample count	15723	2341	18064		Sample count	17608	456	18064
Survey of Income and Program Participation									
Admin record		**Survey report**			**Admin record**		**Survey report**		
		No SNAP	*SNAP*	*Total*			*No TANF+GA*	*TANF+GA*	*Total*
No SNAP	Pop Est. (1000s)	101572296	1555772	103128068	No TANF+GA	Pop Est. (1000s)	120200782	644334	120845116
	Overall (%)	81.0%	1.2%	82.3%		Overall (%)	95.9%	0.5%	96.4%
	Row (%)	98.5%	1.5%	100%		Row (%)	99.5%	0.5%	100%
	Colum (%)	95.9%	8.0%	82.3%		Colum (%)	98.3%	21.1%	96.4%
	Sample count	19840	386	20226		Sample count	23896	170	24066
SNAP	Pop Est. (1000s)	4309415	17909836	22219251	TANF+GA	Pop Est. (1000s)	2085904	2416299	4502203
	Overall (%)	3.4%	14.3%	17.7%		Overall (%)	1.7%	1.9%	3.6%
	Row (%)	19.4%	80.6%	100%		Row (%)	46.3%	53.7%	100%
	Colum (%)	4.1%	92.0%	17.7%		Colum (%)	1.7%	78.9%	3.6%
	Sample count	898	3873	4771		Sample count	422	509	931
Total	Pop Est. (1000s)	105881711	19465608	125347319	Total	Pop Est. (1000s)	122286686	3060633	125347319
	Overall (%)	84.5%	15.5%	100%		Overall (%)	97.6%	2.4%	100%
	Row (%)	84.5%	15.5%	100%		Row (%)	97.6%	2.4%	100%
	Colum (%)	100%	100%	100%		Colum (%)	100%	100%	100%
	Sample count	20738	4259	24997		Sample count	24318	679	24997

Notes: In the SIPP, we collapse receipt to the wave level. Estimates use household weights adjusted for PIK probability.

Table A4: The Determinants of False Negatives, Probit Marginal Effects, Linked Sample of True Recipients Below 200% of the Poverty Line

	ACS		CPS		SIPP	
	(1)	(2)	(3)	(4)	(5)	(6)
	SNAP	*TANF+GA*	*SNAP*	*TANF+GA*	*SNAP*	*TANF+GA*
Single adult, no children	-0.0209**	-0.0216	-0.0208	0.2381***	-0.0282	0.1090
	(0.0091)	(0.0217)	(0.0486)	(0.0874)	(0.0279)	(0.0989)
Single adult, with children	-0.0130*	-0.0404**	0.0233	0.0609	-0.0080	-0.0283
	(0.0076)	(0.0168)	(0.0358)	(0.0695)	(0.0238)	(0.0637)
Multiple adults, no children	0.0072	-0.0350*	-0.0343	0.0732	0.0553**	-0.0507
	(0.0078)	(0.0184)	(0.0414)	(0.0726)	(0.0236)	(0.0796)
Number of members under 18	-0.0151***	-0.0213***	-0.0305**	0.0401**	-0.0021	-0.1100***
	(0.0024)	(0.0047)	(0.0144)	(0.0173)	(0.0072)	(0.0212)
Number of members 18 or older	0.0118***	-0.0169**	0.0240	0.0812**	-0.0015	0.0425
	(0.0030)	(0.0077)	(0.0157)	(0.0367)	(0.0093)	(0.0296)
Rural	0.0008	-0.0074	-0.0011	-0.0824	0.0687***	-0.0364
	(0.0073)	(0.0224)	(0.0383)	(0.0870)	(0.0225)	(0.0813)
Hispanic	0.0445***	0.0396**	0.0598**	0.0806	0.0319*	0.0785
	(0.0065)	(0.0170)	(0.0242)	(0.0538)	(0.0178)	(0.0574)
Black non-hispanic	0.0635***	0.0735***	0.1076***	0.0615	0.0803***	0.1144**
	(0.0055)	(0.0138)	(0.0247)	(0.0546)	(0.0134)	(0.0475)
Other non-hispanic	0.0606***	0.0211	0.1346***	-0.0080	0.0117	0.1265
	(0.0093)	(0.0284)	(0.0425)	(0.1602)	(0.0200)	(0.0808)
Male	0.0330***	0.0453***	0.0208	0.0581	0.0991***	-0.0565
	(0.0043)	(0.0122)	(0.0209)	(0.0464)	(0.0130)	(0.0579)
Disabled	-0.0799***	-0.0658***	-0.0462		-0.1036***	-0.1085**
	(0.0048)	(0.0112)	(0.0813)		(0.0194)	(0.0494)
Age 16-29	-0.0202***	0.0369**	0.0420	-0.0572	-0.0088	0.0167
	(0.0070)	(0.0149)	(0.0325)	(0.0523)	(0.0240)	(0.0588)
Age 30-39	0.0030	0.0124	0.0103	-0.0457	-0.0250	0.2751***
	(0.0064)	(0.0142)	(0.0299)	(0.0488)	(0.0194)	(0.0502)
Age 50-59	-0.0110*	0.0089	-0.0051	0.0125	-0.0256	0.0079
	(0.0066)	(0.0149)	(0.0320)	(0.0580)	(0.0180)	(0.0578)
Age 60-69	-0.0089	0.1019***	0.0513	0.0756	-0.0796***	-0.0097
	(0.0075)	(0.0205)	(0.0361)	(0.0828)	(0.0223)	(0.0795)
Age 70 or more	-0.0050	0.1096***	0.0628*	0.2257	-0.0516**	-0.0522
	(0.0076)	(0.0292)	(0.0367)	(0.1655)	(0.0220)	(0.0993)
Less than high school	-0.0249***	-0.0139	-0.0766***	-0.0724	0.0017	-0.0074
	(0.0054)	(0.0125)	(0.0260)	(0.0478)	(0.0160)	(0.0551)
High school graduate	0.0114**	-0.0052	0.0076	-0.0412	0.0117	0.0112
	(0.0052)	(0.0128)	(0.0250)	(0.0479)	(0.0141)	(0.0467)
Complete graduate and beyond	0.0192**	0.0067	0.0359	-0.0670	0.0415*	-0.3570***
	(0.0077)	(0.0221)	(0.0351)	(0.0711)	(0.0219)	(0.0849)
Household language is English only	0.0052	-0.0361**				
	(0.0061)	(0.0152)				
Speaks English poorly	-0.0763***	0.0092			0.0013	0.1491**
	(0.0065)	(0.0179)			(0.0177)	(0.0737)
Non-citizen	0.0307***	0.0137			0.0184	-0.0461
	(0.0063)	(0.0156)			(0.0192)	(0.0682)
Anyone in household employed	0.0475***	0.1805***	0.0644***	0.0232	-0.0075	-0.2568***
	(0.0052)	(0.0112)	(0.0241)	(0.0422)	(0.0186)	(0.0495)
Household income/poverty line	0.0605***	0.0440***	0.0580***	0.0806**	0.0132	-0.0257
	(0.0044)	(0.0107)	(0.0203)	(0.0395)	(0.0142)	(0.0370)
Reported housing assistance receipt			-0.1838***	-0.0524	-0.0792***	-0.0653
			(0.0190)	(0.0361)	(0.0126)	(0.0441)
Reported TANF+GA receipt	-0.1670***		-0.3199***		-0.1765***	
	(0.0068)		(0.0357)		(0.0241)	
Reported SNAP receipt		-0.3165***		-0.4028***		-0.3117***
		(0.0140)		(0.0436)		(0.0537)
Linear time trend	-0.0101***	0.0159***	-0.0118**	-0.0107	0.0000**	0.0001***
	(0.0014)	(0.0034)	(0.0052)	(0.0106)	(0.0000)	(0.0000)
Number of observations	60,231	13,024	2,660	729	3,784	796
chi2 statistic of joint significance	2743	1959	382	194	313	466
p-value of joint significance	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001

Notes: The samples only include recipients according to the linked data with reported household income less than twice the household poverty line. The dependent variable is an indicator for failure to report receipt in the survey. All demographic characteristics refer to the reference person. The time trend is measured in years for the ACS and CPS, but in waves for the SIPP. The omitted categories are Multiple Adults with Children, Age 40-49, College Graduate and White. All analyses use household weights adjusted for PIK probability. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A5: The Determinants of False Positives, Probit Marginal Effects, Linked Sample of Non-Recipients Below 200% of the Poverty Line

	ACS		CPS		SIPP	
	(1)	(2)	(3)	(4)	(5)	(6)
	SNAP	*TANF+GA*	*SNAP*	*TANF+GA*	*SNAP*	*TANF+GA*
Single adult, no children	-0.0212***	-0.0074***	-0.0497**	-0.0079	-0.0090	-0.0038
	(0.0036)	(0.0029)	(0.0225)	(0.0084)	(0.0133)	(0.0060)
Single adult, with children	-0.0041	0.0018	0.0098	-0.0108	0.0109	0.0062
	(0.0036)	(0.0026)	(0.0209)	(0.0071)	(0.0128)	(0.0054)
Multiple adults, no children	-0.0165***	-0.0020	-0.0340*	0.0000	-0.0076	-0.0053
	(0.0032)	(0.0025)	(0.0200)	(0.0067)	(0.0119)	(0.0048)
Number of members under 18	0.0009	0.0010	-0.0051	0.0047***	-0.0032	-0.0024
	(0.0011)	(0.0008)	(0.0071)	(0.0016)	(0.0047)	(0.0020)
Number of members 18 or older	0.0029**	0.0039***	-0.0009	0.0010	0.0113***	0.0031*
	(0.0012)	(0.0009)	(0.0085)	(0.0032)	(0.0043)	(0.0018)
Rural	-0.0064**	-0.0010	-0.0016	-0.0057	0.0080	0.0098
	(0.0025)	(0.0018)	(0.0195)	(0.0073)	(0.0087)	(0.0065)
Hispanic	0.0278***	-0.0043**	0.0460***	-0.0002	-0.0195*	-0.0050
	(0.0026)	(0.0021)	(0.0135)	(0.0044)	(0.0101)	(0.0035)
Black non-hispanic	0.0250***	0.0007	0.0404***	0.0051	0.0218***	0.0119***
	(0.0023)	(0.0017)	(0.0132)	(0.0046)	(0.0063)	(0.0030)
Other non-hispanic	0.0180***	0.0110***	0.0145	-0.0105	0.0085	-0.0116**
	(0.0030)	(0.0023)	(0.0180)	(0.0087)	(0.0091)	(0.0054)
Male	-0.0033**	0.0006	-0.0229**	-0.0063	-0.0175***	0.0057**
	(0.0016)	(0.0013)	(0.0107)	(0.0039)	(0.0054)	(0.0025)
Disabled	0.0206***	-0.0003	0.1010**		0.0156	-0.0034
	(0.0020)	(0.0015)	(0.0459)		(0.0100)	(0.0039)
Age 16-29	0.0209***	-0.0038*	-0.0010	0.0159***	0.0090	-0.0080
	(0.0029)	(0.0022)	(0.0184)	(0.0055)	(0.0115)	(0.0057)
Age 30-39	0.0061**	-0.0010	0.0053	-0.0032	0.0427***	-0.0071*
	(0.0027)	(0.0021)	(0.0167)	(0.0052)	(0.0092)	(0.0040)
Age 50-59	0.0053*	-0.0050**	0.0030	-0.0035	0.0043	-0.0065*
	(0.0028)	(0.0021)	(0.0172)	(0.0058)	(0.0091)	(0.0033)
Age 60-69	0.0003	-0.0169***	-0.0127	-0.0205**	-0.0023	-0.0106**
	(0.0032)	(0.0023)	(0.0190)	(0.0084)	(0.0109)	(0.0042)
Age 70 or more	-0.0084**	-0.0225***	-0.0397**	-0.0297***	0.0045	-0.0204***
	(0.0033)	(0.0023)	(0.0201)	(0.0092)	(0.0097)	(0.0058)
Less than high school	0.0154***	0.0083***	0.0220	0.0068	0.0038	0.0013
	(0.0023)	(0.0017)	(0.0148)	(0.0050)	(0.0098)	(0.0030)
High school graduate	0.0053**	0.0043***	-0.0034	0.0108**	0.0038	0.0001
	(0.0021)	(0.0016)	(0.0134)	(0.0047)	(0.0065)	(0.0031)
Complete graduate and beyond	-0.0093***	-0.0017	-0.0466***	-0.0155*	-0.0039	-0.0067
	(0.0027)	(0.0021)	(0.0173)	(0.0084)	(0.0077)	(0.0045)
Household language is English only	0.0054**	0.0025				
	(0.0022)	(0.0018)				
Speaks English poorly	0.0136***	-0.0013			0.0201**	-0.0024
	(0.0027)	(0.0020)			(0.0095)	(0.0034)
Non-citizen	-0.0033	-0.0044**			0.0128	0.0059
	(0.0023)	(0.0021)			(0.0089)	(0.0036)
Household income/poverty line	-0.0143***	0.0068***	-0.0293***	0.0013	-0.0110**	-0.0029
	(0.0014)	(0.0013)	(0.0089)	(0.0036)	(0.0044)	(0.0026)
Anyone in household employed	-0.0090***	-0.0216***	-0.0357***	-0.0098**	0.0242***	0.0122**
	(0.0023)	(0.0018)	(0.0132)	(0.0048)	(0.0075)	(0.0049)
Reported housing assistance receipt			0.0234*	0.0068*	0.0552***	0.0094***
			(0.0137)	(0.0037)	(0.0074)	(0.0026)
Reported TANF+GA receipt	0.0835***		0.1582***		0.0909***	
	(0.0034)		(0.0296)		(0.0140)	
Reported SNAP receipt		0.0567***		0.0243***		0.0252***
		(0.0015)		(0.0041)		(0.0043)
Linear time trend	0.0024***	0.0002	0.0109***	0.0002	0.0000***	0.0000***
	(0.0005)	(0.0004)	(0.0030)	(0.0009)	(0.0000)	(0.0000)
Number of observations	89,087	136,294	3,051	4,982	5,035	8,023
chi2 statistic of joint significance	1258	1986	163	90	204	98
p-value of joint significance	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001

Notes: The samples only include non-recipients according to the linked data with reported household income less than twice the household poverty line. The dependent variable is an indicator for reporting in the survey. All demographic characteristics refer to the reference person. The time trend is measured in years for the ACS and CPS, but in waves for the SIPP. The omitted categories are Multiple Adults with Children, Age 40-49, College Graduate and White. All analyses use household weights adjusted for PIK probability. Standard errors in parentheses,*** p<0.01, ** p<0.05. * p<0.1

Table A6: The Determinants of Reported and Administrative SNAP Receipt, Probit Coefficients, Linked Households with Income less than Twice the Poverty

	ACS			CPS			SIPP		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent Variable	Survey Report	Admin. Receipt	P-value (1)=(2)	Survey Report	Admin. Receipt	P-value (4)=(5)	Survey Report	Admin. Receipt	P-value (7)=(8)
Single adult, no children	-0.2454***	-0.2874***	0.034	-0.1037	-0.0334	0.495	-0.1578	-0.1544	0.961
	(0.0232)	(0.0232)		(0.1040)	(0.0999)		(0.0991)	(0.1024)	
Single adult, with children	0.1081***	0.1614***	0.004	0.1025	0.3879***	0.002	0.4084***	0.5032***	0.132
	(0.0215)	(0.0216)		(0.0856)	(0.0859)		(0.0871)	(0.0870)	
Multiple adults, no children	-0.1955***	-0.1991***	0.833	-0.0429	-0.0834	0.664	-0.1604*	-0.0856	0.191
	(0.0204)	(0.0201)		(0.0906)	(0.0850)		(0.0851)	(0.0852)	
Number of members under 18	0.1025***	0.1127***	0.075	0.1104***	0.1402***	0.350	0.1020***	0.1443***	0.025
	(0.0067)	(0.0065)		(0.0324)	(0.0300)		(0.0289)	(0.0298)	
Number of members 18 or older	0.0279***	0.0680***	<0.001	0.0099	0.1300***	0.001	0.0745**	0.0748**	0.991
	(0.0085)	(0.0084)		(0.0377)	(0.0366)		(0.0374)	(0.0377)	
Rural	-0.0785***	-0.0927***	0.157	0.1179	0.1884***	0.317	-0.0390	0.0101	0.053
	(0.0140)	(0.0140)		(0.0746)	(0.0715)		(0.0530)	(0.0525)	
Hispanic	0.3404***	0.4726***	<0.001	0.2626***	0.4781***	<0.001	0.2676***	0.4135***	<0.001
	(0.0151)	(0.0151)		(0.0528)	(0.0513)		(0.0600)	(0.0614)	
Black non-hispanic	0.3790***	0.5746***	<0.001	0.1027*	0.3555***	<0.001	0.2917***	0.4650***	<0.001
	(0.0132)	(0.0132)		(0.0557)	(0.0539)		(0.0459)	(0.0461)	
Other non-hispanic	-0.1371***	-0.1473***	0.534	-0.1282	-0.0010	0.119	0.2706***	0.2916***	0.628
	(0.0208)	(0.0207)		(0.0862)	(0.0809)		(0.0637)	(0.0617)	
Male	-0.1896***	-0.1996***	0.205	-0.1876***	-0.2118***	0.570	-0.2772***	-0.1106***	<0.001
	(0.0099)	(0.0099)		(0.0443)	(0.0426)		(0.0407)	(0.0406)	
Disabled	0.5518***	0.5194***	<0.001	0.4464**	0.3098	0.538	0.9736***	0.9618***	0.750
	(0.0112)	(0.0111)		(0.2055)	(0.2097)		(0.0590)	(0.0589)	
Age 16-29	0.1831***	0.1597***	0.120	-0.0775	0.0756	0.043	0.1225*	0.1344*	0.818
	(0.0176)	(0.0177)		(0.0742)	(0.0717)		(0.0718)	(0.0715)	
Age 30-39	0.0935***	0.1228***	0.039	-0.0118	0.0006	0.862	0.3621***	0.3084***	0.327
	(0.0167)	(0.0169)		(0.0674)	(0.0666)		(0.0656)	(0.0669)	
Age 50-59	0.0390**	0.0158	0.083	0.0985	0.1745**	0.289	0.0667	0.0529	0.738
	(0.0164)	(0.0162)		(0.0714)	(0.0702)		(0.0605)	(0.0592)	
Age 60-69	-0.0155	-0.0368**	0.140	-0.1635**	-0.1025	0.436	0.1618**	0.0927	0.129
	(0.0182)	(0.0179)		(0.0792)	(0.0776)		(0.0733)	(0.0723)	
Age 70 or more	-0.3591***	-0.4246***	<0.001	-0.3723***	-0.3265***	0.546	0.1943***	0.1336*	0.196
	(0.0180)	(0.0179)		(0.0796)	(0.0764)		(0.0716)	(0.0706)	
Less than high school	0.2537***	0.2507***	0.783	0.2932***	0.2918***	0.980	0.2207***	0.2875***	0.066
	(0.0134)	(0.0133)		(0.0584)	(0.0571)		(0.0578)	(0.0577)	
High school graduate	0.0493***	0.0799***	0.002	-0.0267	0.0200	0.395	0.0604	0.1018**	0.149
	(0.0122)	(0.0121)		(0.0547)	(0.0528)		(0.0457)	(0.0450)	
Complete graduate and beyond	-0.2726***	-0.2899***	0.149	-0.2756***	-0.2164***	0.385	-0.3398***	-0.3425***	0.950
	(0.0160)	(0.0159)		(0.0716)	(0.0684)		(0.0556)	(0.0602)	
Household language is English only	-0.0542***	-0.0627***	0.432						
	(0.0136)	(0.0137)							
Speaks English poorly	0.5377***	0.4971***	0.003				0.4992***	0.5671***	0.158
	(0.0167)	(0.0170)					(0.0690)	(0.0713)	
Non-citizen	-0.3782***	-0.4381***	<0.001				-0.3106***	-0.3707***	0.265
	(0.0163)	(0.0163)					(0.0736)	(0.0713)	
Household income/poverty line	-0.4644***	-0.4691***	0.529	-0.3223***	-0.3165***	0.888	-0.3603***	-0.3671***	0.790
	(0.0092)	(0.0093)		(0.0384)	(0.0385)		(0.0334)	(0.0339)	
Anyone in household employed	-0.3512***	-0.3586***	0.490	-0.3741***	-0.4313***	0.296	0.2602***	0.2599***	0.993
	(0.0131)	(0.0132)		(0.0540)	(0.0542)		(0.0502)	(0.0504)	
Reported housing assistance receipt				1.3405***	1.0840***	0.957	1.4572***	1.2004***	0.013
				(0.1075)	(0.1168)		(0.1141)	(0.1089)	
Reported TANF+GA receipt	1.2478***	1.1711***	0.001	0.0680***	0.0584***	0.045	0.9093***	0.8389***	0.006
	(0.0223)	(0.0233)		(0.0117)	(0.0114)		(0.0445)	(0.0445)	
Linear time trend	0.0852***	0.0902***	0.050	0.7745***	0.7771***	0.405	-0.0001***	-0.0001***	0.241
	(0.0032)	(0.0032)		(0.0486)	(0.0497)		(0.0000)	(0.0000)	
Constant	-0.2796***	-0.1618***		-0.4732***	-0.5515***		-0.8775***	-0.9463***	
	(0.0355)	(0.0355)		(0.1508)	(0.1474)		(0.1378)	(0.1425)	
Number of observations	149,318	149,318		5,711	5,711		8,819	8,819	
Joint test of equality chi2 statistic			45			3			6
Joint test of equality p-value			<0.001			<0.001			<0.001

Notes: For each survey, the first column contains estimates from a probit model using reported receipt as the dependent variable. The second column estimates the same model using the administrative receipt measure as the dependent variable. The thrid column contains p-values of a chi-square test whether the estimates are equal. All demographic characteristics refer to the reference person. The time trend is measured in years for the ACS and CPS, but in waves for the SIPP. The omitted categories are Multiple Adults with Children, Age 40-49, College Graduate and White. All analyses conducted using household weights adjusted for PIK probability. Standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1

Table A7: The Determinants of Reported and Administrative TANF+GA Receipt, Probit Coefficients, Linked Households with Income less than Twice the Poverty Line

	ACS			CPS			SIPP		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent Variable	Survey Report	Admin. Receipt	P-value (1)=(2)	Survey Report	Admin. Receipt	P-value (4)=(5)	Survey Report	Admin. Receipt	P-value (7)=(8)
Single adult, no children	-0.1972***	-0.4158***	<0.001	-0.3239*	-0.1322	0.294	-0.3194**	-0.3345***	0.913
	(0.0314)	(0.0314)		(0.1696)	(0.1272)		(0.1398)	(0.1275)	
Single adult, with children	0.1884***	0.2531***	0.027	0.0931	0.4430***	0.013	0.5363***	0.5115***	0.802
	(0.0264)	(0.0253)		(0.1346)	(0.1006)		(0.1149)	(0.1043)	
Multiple adults, no children	-0.0451*	-0.1904***	<0.001	-0.0270	-0.1166	0.548	0.0464	0.2402**	0.099
	(0.0273)	(0.0267)		(0.1355)	(0.1088)		(0.1221)	(0.1122)	
Number of members under 18	0.0528***	0.0489***	0.641	0.0538	0.0480*	0.891	0.1522***	0.1253***	0.355
	(0.0076)	(0.0073)		(0.0360)	(0.0278)		(0.0321)	(0.0299)	
Number of members 18 or older	0.0923***	0.1323***	0.001	-0.0250	0.1206***	0.058	0.0835*	0.1101**	0.583
	(0.0109)	(0.0105)		(0.0715)	(0.0454)		(0.0449)	(0.0463)	
Rural	-0.0868***	-0.2139***	<0.001	0.1372	0.2246*	0.514	0.2248*	0.2161*	0.930
	(0.0237)	(0.0277)		(0.1361)	(0.1191)		(0.0530)	(0.0525)	
Hispanic	0.0956***	0.4412***	<0.001	0.1385	0.5611***	<0.001	-0.0131	0.2667***	<0.001
	(0.0224)	(0.0226)		(0.0886)	(0.0774)		(0.0843)	(0.0761)	
Black non-hispanic	0.1478***	0.5740***	<0.001	0.2330**	0.6163***	<0.001	0.3093***	0.6030***	<0.001
	(0.0186)	(0.0192)		(0.0931)	(0.0786)		(0.0697)	(0.0678)	
Other non-hispanic	0.1226***	0.0583*	0.093	-0.3300	-0.1988	0.514	-0.1918*	0.2551**	<0.001
	(0.0296)	(0.0337)		(0.2035)	(0.1595)		(0.1082)	(0.1013)	
Male	-0.0426***	-0.0443***	0.922	-0.0554	0.0776	0.110	0.0164	-0.1374**	0.024
	(0.0151)	(0.0157)		(0.0811)	(0.0636)		(0.0692)	(0.0644)	
Disabled	0.0829***	0.1038***	0.263	-0.6100*	0.0420	<0.001	0.2104**	0.2957***	0.269
	(0.0167)	(0.0174)		(0.3672)	(0.2538)		(0.0895)	(0.0793)	
Age 16-29	-0.0249	0.0934***	<0.001	0.2649***	0.1004	0.132	-0.0900	0.0259	0.190
	(0.0230)	(0.0221)		(0.1022)	(0.0867)		(0.0980)	(0.0896)	
Age 30-39	-0.0364*	-0.0398*	0.889	-0.0282	-0.1612**	0.151	-0.4895***	-0.0972	<0.001
	(0.0216)	(0.0211)		(0.0913)	(0.0749)		(0.0922)	(0.0814)	
Age 50-59	-0.0838***	-0.0329	0.038	-0.1781	-0.1855**	0.946	-0.1700*	-0.2180**	0.544
	(0.0225)	(0.0219)		(0.1095)	(0.0870)		(0.0925)	(0.0866)	
Age 60-69	-0.4328***	-0.4159***	0.600	-0.7487***	-0.6263***	0.442	-0.6230***	-0.8018***	0.114
	(0.0273)	(0.0282)		(0.1491)	(0.1167)		(0.1230)	(0.1153)	
Age 70 or more	-0.5928***	-0.9053***	<0.001	-1.2591***	-1.2203***	0.851	-0.6980***	-0.8592***	0.218
	(0.0269)	(0.0326)		(0.1949)	(0.1362)		(0.1381)	(0.1198)	
Less than high school	0.1265***	0.1336***	0.734	0.1981**	0.0661	0.165	0.2395***	0.2661***	0.739
	(0.0189)	(0.0189)		(0.0930)	(0.0774)		(0.0886)	(0.0805)	
High school graduate	0.0375**	0.0175	0.335	0.2169**	0.0569	0.100	0.0103	-0.0169	0.715
	(0.0182)	(0.0184)		(0.0933)	(0.0774)		(0.0810)	(0.0696)	
Complete graduate and beyond	-0.0712***	-0.1665***	0.002	-0.0253	-0.0331	0.951	0.1574	-0.0908	0.001
	(0.0256)	(0.0272)		(0.1312)	(0.1058)		(0.1091)	(0.0976)	
Household language is English only	0.0897***	0.1223***	0.172						
	(0.0206)	(0.0205)							
Speaks English poorly	-0.1000***	-0.1803***	0.003				-0.3463***	-0.3652***	0.848
	(0.0234)	(0.0233)					(0.0998)	(0.0948)	
Non-citizen	-0.0292	-0.0054	0.347				0.1587	0.0060	0.117
	(0.0227)	(0.0214)					(0.1009)	(0.0950)	
Household income/poverty line	-0.1228***	-0.3716***	<0.001	-0.2517***	-0.3844***	0.082	-0.1526**	-0.2999***	0.011
	(0.0145)	(0.0151)		(0.0768)	(0.0581)		(0.0639)	(0.0534)	
Anyone in household employed	-0.5083***	-0.3550***	<0.001	-0.2914***	-0.3297***	0.648	0.6587***	0.4640***	0.028
	(0.0188)	(0.0186)		(0.0856)	(0.0715)		(0.1067)	(0.0811)	
Reported housing assistance receipt				0.2492***	0.1683***	0.240	1.1948***	0.9173***	0.076
				(0.0702)	(0.0589)		(0.0875)	(0.0675)	
Reported SNAP receipt	1.0323***	0.9212***	<0.001	1.0916***	0.7682***	<0.001	0.2144***	0.1029	<0.001
	(0.0167)	(0.0163)		(0.0830)	(0.0601)		(0.0659)	(0.0640)	
Linear time trend	-0.0245***	-0.0297***	0.347	0.0026	-0.0245	0.175	-0.0001	-0.0001**	0.172
	(0.0048)	(0.0049)		(0.0188)	(0.0162)		(0.0001)	(0.0001)	
Constant	1.0323***	0.9212***		-1.8903***	-1.4785***		0.2144***	0.1029	
	(0.0482)	(0.0482)		(0.1508)	(0.1474)		(0.1378)	(0.1425)	
Number of observations	149,318	149,318		5,711	5,711		8,819	8,819	
Joint test of equality chi2 statistic			67			3			5
Joint test of equality p-value			<0.001			<0.001			<0.001

Notes: For each survey, the first column contains estimates from a probit model using reported receipt as the dependent variable. The second column estimates the same model using the administrative receipt measure as the dependent variable. The thrid column contains p-values of a chi-square test whether the estimates are equal. All demographic characteristics refer to the reference person. The time trend is measured in years for the ACS and CPS, but in waves for the SIPP. The omitted categories are Multiple Adults with Children, Age 40-49, College Graduate and White. All analyses use household weights adjusted for PIK probability. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A8: Testing Whether Item Non-Response is Conditionally Random by Adding an Response Indicator to Models of Program Receipt According to the Administrative Measure, Probit Marginal Effects, Full Linked Sample

	ACS		CPS		SIPP	
	SNAP	TANF+GA	SNAP	TANF+GA	SNAP	TANF+GA
	(1)	(2)	(3)	(4)	(5)	(6)
Item Non-Respondent	0.058***	0.015***	0.004	0.005	0.036***	-0.001
	(0.004)	(0.001)	(0.007)	(0.004)	(0.007)	(0.004)
Single adult, no children	-0.015***	-0.022***	0.017	-0.008	-0.012	-0.030***
	(0.003)	(0.001)	(0.011)	(0.006)	(0.010)	(0.005)
Single adult, with children	0.056***	0.017***	0.076***	0.031***	0.087***	0.021***
	(0.002)	(0.001)	(0.010)	(0.005)	(0.009)	(0.004)
Multiple adults, no children	-0.011***	-0.009***	0.007	-0.004	-0.004	-0.002
	(0.002)	(0.001)	(0.009)	(0.005)	(0.009)	(0.005)
Number of members under 18	0.018***	0.003***	0.024***	0.004***	0.018***	0.004***
	(0.001)	(0.000)	(0.004)	(0.001)	(0.003)	(0.001)
Number of members 18 or older	0.029***	0.007***	0.036***	0.009***	0.028***	0.002
	(0.001)	(0.000)	(0.004)	(0.002)	(0.003)	(0.002)
Rural	-0.018***	-0.011***	0.020**	0.012**	0.000***	0.000***
	(0.002)	(0.001)	(0.008)	(0.005)	(0.000)	(0.000)
Hispanic	0.079***	0.022***	0.094***	0.030***	0.058***	0.019***
	(0.002)	(0.001)	(0.006)	(0.003)	(0.007)	(0.003)
Black non-hispanic	0.109***	0.033***	0.077***	0.037***	0.074***	0.033***
	(0.001)	(0.001)	(0.006)	(0.004)	(0.006)	(0.003)
Other non-hispanic	0.003	0.005***	0.014	-0.011	0.064***	0.010**
	(0.002)	(0.002)	(0.010)	(0.008)	(0.007)	(0.004)
Male	-0.033***	-0.002***	-0.020***	0.001	-0.015***	-0.007***
	(0.001)	(0.001)	(0.005)	(0.003)	(0.004)	(0.003)
Disabled	0.077***	0.005***	0.058**	0.004	0.154***	0.014***
	(0.001)	(0.001)	(0.023)	(0.011)	(0.007)	(0.003)
Age 16-29	0.036***	0.006***	0.031***	0.005	0.044***	0.006
	(0.002)	(0.001)	(0.009)	(0.004)	(0.009)	(0.004)
Age 30-39	0.020***	-0.002*	0.026***	-0.010***	0.041***	-0.002
	(0.002)	(0.001)	(0.008)	(0.004)	(0.007)	(0.003)
Age 50-59	0.005***	0.001	0.016*	-0.003	0.014**	0.005
	(0.002)	(0.001)	(0.008)	(0.004)	(0.007)	(0.003)
Age 60-69	-0.009***	-0.017***	-0.014	-0.021***	0.010	-0.026***
	(0.002)	(0.001)	(0.009)	(0.005)	(0.008)	(0.005)
Age 70 or more	-0.069***	-0.043***	-0.050***	-0.066***	0.016**	-0.032***
	(0.002)	(0.001)	(0.010)	(0.008)	(0.008)	(0.005)
Less than high school	0.047***	0.008***	0.051***	0.006	0.052***	0.009***
	(0.002)	(0.001)	(0.007)	(0.004)	(0.007)	(0.003)
High school graduate	0.017***	0.002***	0.005	0.005	0.027***	-0.003
	(0.001)	(0.001)	(0.006)	(0.004)	(0.005)	(0.003)
Complete graduate and beyond	-0.030***	-0.008***	-0.040***	0.001	-0.048***	-0.008**
	(0.002)	(0.001)	(0.007)	(0.004)	(0.006)	(0.004)
Household language is English only	-0.019***	0.005***			0.023***	0.002
	(0.002)	(0.001)			(0.006)	(0.004)
Speaks English poorly	0.068***	-0.011***			0.074***	-0.020***
	(0.002)	(0.001)			(0.009)	(0.004)
Non-citizen	-0.056***	-0.001			-0.044***	0.006
	(0.002)	(0.001)			(0.010)	(0.005)
Household income/poverty line	-0.040***	-0.007***	-0.037***	-0.007***	-0.038***	-0.004***
	(0.000)	(0.000)	(0.002)	(0.001)	(0.002)	(0.001)
Anyone in household employed	-0.069***	-0.020***	-0.081***	-0.025***	0.035***	0.025***
	(0.002)	(0.001)	(0.007)	(0.004)	(0.005)	(0.003)
Reported housing assistance receipt			0.135***	0.012***		
			(0.007)	(0.003)		
Reported TANF+GA receipt	0.211***		0.187***		0.172***	
	(0.003)		(0.016)		(0.013)	
Reported SNAP receipt		0.058***		0.052***		0.044***
		(0.001)		(0.003)		(0.003)
Linear time trend	0.014***	-0.001***	0.010***	0.000	0.122***	0.007**
	(0.000)	(0.000)	(0.001)	(0.001)	(0.006)	(0.003)
Observations	543,528	543,528	18,064	18,064	24,997	24,997

Notes: The dependent variable is program receipt according to the administrative variable in all columns. Each column contains the same covariates as the models of receipt in Tables 7 and 8 and additionally include an indicator for responding to the survey question on program receipt. All demographic characteristics refer to the reference person. The time trend is measured in years for the ACS and CPS, but in waves for the SIPP. The omitted categories are Multiple Adults with Children, Age 40-49, College Graduate and White. All analyses use household weights adjusted for PIK probability. SEs in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A9: Differences Between the Full Sample and Item Non-Respondents in the Determinants of Program Receipt, Probit Marginal Effects

	ACS				CPS				SIPP			
	SNAP		TANF+GA		SNAP		TANF+GA		SNAP		TANF+GA	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Sample:	Full Sample	Non-Respondents	Full Sample	Non-Respondents	Full Sample	Non-Respondents	Full Sample	Non-Respondents	Full Sample	Non-Respondents	Full Sample	Non-Respondents
Single adult, no children	-0.015***	-0.016	-0.021***	-0.025***	0.017	0.024	-0.008	0.017	-0.012	-0.157***	-0.030***	0.014
	(0.003)	(0.032)	(0.001)	(0.007)	(0.011)	(0.035)	(0.006)	(0.019)	(0.010)	(0.041)	(0.005)	(0.024)
Single adult, with children	0.056***	0.111***	0.017***	0.035***	0.076***	0.062**	0.031***	0.031**	0.089***	0.077**	0.021***	0.048***
	(0.002)	(0.034)	(0.001)	(0.006)	(0.010)	(0.031)	(0.005)	(0.013)	(0.009)	(0.038)	(0.004)	(0.015)
Multiple adults, no children	-0.011***	-0.019	-0.009***	-0.002	0.007	-0.022	-0.004	-0.004	-0.004	-0.079***	-0.002	0.017
	(0.002)	(0.028)	(0.001)	(0.006)	(0.009)	(0.029)	(0.005)	(0.015)	(0.009)	(0.030)	(0.005)	(0.016)
Number of members under 18	0.018***	0.042***	0.003***	0.007***	0.024***	0.031***	0.004***	0.013***	0.018***	0.000	0.004***	0.008
	(0.001)	(0.011)	(0.000)	(0.002)	(0.004)	(0.011)	(0.001)	(0.004)	(0.003)	(0.011)	(0.001)	(0.005)
Number of members 18 or older	0.029***	0.035***	0.007***	0.011***	0.036***	0.033***	0.009***	0.013***	0.030***	0.033***	0.002	0.006
	(0.001)	(0.008)	(0.000)	(0.002)	(0.004)	(0.011)	(0.002)	(0.005)	(0.003)	(0.010)	(0.002)	(0.005)
Rural	-0.018***	-0.068***	-0.011***	-0.017***	0.020**	0.097***	0.013**	0.025	0.000***	0.000**	0.000***	0.000
	(0.002)	(0.024)	(0.001)	(0.006)	(0.008)	(0.026)	(0.005)	(0.015)	(0.000)	(0.000)	(0.000)	(0.000)
Hispanic	0.080***	0.140***	0.022***	0.033***	0.094***	0.152***	0.029***	0.026**	0.058***	0.110***	0.019***	0.021
	(0.002)	(0.019)	(0.001)	(0.005)	(0.006)	(0.018)	(0.003)	(0.011)	(0.007)	(0.025)	(0.003)	(0.014)
Black non-hispanic	0.110***	0.197***	0.034***	0.055***	0.077***	0.136***	0.037***	0.051***	0.074***	0.079***	0.033***	0.036***
	(0.001)	(0.017)	(0.001)	(0.004)	(0.006)	(0.018)	(0.004)	(0.010)	(0.006)	(0.022)	(0.003)	(0.012)
Other non-hispanic	0.003	0.004	0.006***	0.004	0.014	0.053*	-0.011	0.000	0.063***	0.015	0.010**	0.045***
	(0.002)	(0.028)	(0.001)	(0.008)	(0.010)	(0.031)	(0.008)	(0.021)	(0.007)	(0.036)	(0.004)	(0.017)
Male	-0.033***	-0.049***	-0.002***	-0.008**	-0.020***	-0.071***	0.001	-0.031***	-0.016***	-0.010	-0.007***	-0.023**
	(0.001)	(0.013)	(0.001)	(0.003)	(0.005)	(0.016)	(0.003)	(0.010)	(0.004)	(0.017)	(0.003)	(0.011)
Disabled	0.077***	0.091***	0.005***	0.011***	0.058**	0.133**	0.005	0.070***	0.154***	0.235***	0.014***	0.016
	(0.001)	(0.016)	(0.001)	(0.004)	(0.023)	(0.066)	(0.011)	(0.025)	(0.007)	(0.037)	(0.003)	(0.015)
Age 16-29	0.036***	0.040	0.006***	0.021***	0.031***	0.091***	0.005	0.016	0.046***	0.070**	0.006	0.006
	(0.002)	(0.030)	(0.001)	(0.005)	(0.009)	(0.027)	(0.004)	(0.012)	(0.009)	(0.031)	(0.004)	(0.014)
Age 30-39	0.020***	-0.018	-0.002**	-0.003	0.026***	0.082***	-0.010***	0.001	0.041***	0.051**	-0.002	-0.001
	(0.002)	(0.025)	(0.001)	(0.005)	(0.008)	(0.024)	(0.004)	(0.011)	(0.007)	(0.025)	(0.003)	(0.013)
Age 50-59	0.005***	0.028	0.001	-0.004	0.016*	-0.002	-0.003	-0.010	0.014**	0.014	0.005	0.006
	(0.002)	(0.022)	(0.001)	(0.005)	(0.008)	(0.026)	(0.004)	(0.014)	(0.007)	(0.025)	(0.003)	(0.015)
Age 60-69	-0.009***	0.012	-0.017***	-0.043***	-0.014	0.003	-0.021***	-0.036**	0.009	-0.021	-0.026***	-0.068**
	(0.002)	(0.023)	(0.001)	(0.006)	(0.009)	(0.030)	(0.005)	(0.017)	(0.008)	(0.032)	(0.005)	(0.030)
Age 70 or more	-0.069***	-0.068***	-0.043***	-0.086***	-0.050***	-0.051	-0.067***	-0.094***	0.015**	0.024	-0.032***	-0.037**
	(0.002)	(0.024)	(0.001)	(0.007)	(0.010)	(0.031)	(0.008)	(0.026)	(0.008)	(0.034)	(0.005)	(0.018)
Less than high school	0.047***	0.007	0.008***	0.005	0.051***	0.091***	0.006	0.013	0.051***	0.143***	0.009***	0.012
	(0.002)	(0.019)	(0.001)	(0.004)	(0.007)	(0.022)	(0.004)	(0.012)	(0.007)	(0.028)	(0.003)	(0.014)
High school graduate	0.017***	0.008	0.002***	-0.002	0.005	0.041**	0.005	0.011	0.026***	0.051***	-0.003	0.010
	(0.001)	(0.018)	(0.001)	(0.004)	(0.006)	(0.020)	(0.004)	(0.011)	(0.005)	(0.019)	(0.003)	(0.011)
Complete graduate and beyond	-0.030***	-0.032	-0.008***	-0.023***	-0.040***	-0.053**	0.000	-0.006	-0.048***	-0.014	-0.008**	-0.001
	(0.002)	(0.020)	(0.001)	(0.006)	(0.007)	(0.024)	(0.004)	(0.013)	(0.006)	(0.024)	(0.004)	(0.016)
Household language is English only	-0.020***	-0.042**	0.005***	0.010**					0.023***	0.000	0.002	0.007
	(0.002)	(0.017)	(0.001)	(0.004)					(0.006)	(0.023)	(0.004)	(0.015)
Speaks English poorly	0.068***	0.110***	-0.011***	-0.016***					0.073***	0.056	-0.020***	-0.016
	(0.002)	(0.023)	(0.001)	(0.006)					(0.009)	(0.041)	(0.004)	(0.020)
Non-citizen	-0.056***	-0.046**	-0.001	0.003					-0.044***	-0.061*	0.006	-0.020
	(0.002)	(0.022)	(0.001)	(0.005)					(0.010)	(0.032)	(0.005)	(0.015)
Household income/poverty line	-0.040***	-0.032***	-0.007***	-0.009***	-0.037***	-0.030***	-0.007***	-0.003	-0.037***	-0.034***	-0.004***	-0.013***
	(0.000)	(0.003)	(0.000)	(0.001)	(0.002)	(0.005)	(0.001)	(0.003)	(0.002)	(0.005)	(0.001)	(0.004)
Anyone in household employed	-0.069***	-0.072***	-0.021***	-0.032***	-0.081***	-0.108***	-0.025***	-0.040***	0.037***	0.063***	0.025***	0.025**
	(0.002)	(0.019)	(0.001)	(0.004)	(0.007)	(0.020)	(0.004)	(0.010)	(0.005)	(0.022)	(0.003)	(0.013)
Reported housing assistance receipt					0.135***	0.088***	0.012***	0.001				
					(0.007)	(0.023)	(0.003)	(0.012)				
Reported TANF+GA receipt	0.211***	0.178***			0.187***	0.052			0.173***	0.166***		
	(0.003)	(0.029)			(0.016)	(0.039)			(0.013)	(0.041)		
Reported SNAP receipt			0.058***	0.103***			0.052***	0.031***			0.044***	0.062***
			(0.001)	(0.003)			(0.003)	(0.010)			(0.003)	(0.011)
Linear time trend	0.014***	0.022***	-0.001***	-0.002**	0.010***	0.013***	0.000	-0.003	0.123***	0.127***	0.007**	-0.011
	(0.000)	(0.005)	(0.000)	(0.001)	(0.001)	(0.004)	(0.001)	(0.002)	(0.006)	(0.028)	(0.003)	(0.013)
Number of observations	543,528	6,096	543,528	35,589	18,064	2,336	18,064	2,346	24,997	1,941	24,997	1,928
Chi2 distance measure		18,326		11,704		684		383		1,192		617

Notes: The dependent variable is receipt according to the administrative data in all columns. For each survey and program, the first column estimates the model using the full linked sample, the second column estimates the same model using the sample of item non-respondents. All demographic characteristics refer to the reference person. The time trend is measured in years for the ACS and CPS, but in waves for the SIPP. The omitted categories are Multiple Adults with Children, Age 40-49, College Graduate and White. All analyses use household weights adjusted for PIK probability. The distance measure is the squared distance between the two coefficient vectors, weighted by the variance matrix of the coefficients from using the full sample with the administrative dependent variable. SEs in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A10: The Determinants of Administrative and Imputed Program Receipt Among Item Non-Respondents, Probit Marginal Effects

	ACS				CPS				SIPP			
	SNAP		TANF+GA		SNAP		TANF+GA		SNAP		TANF+GA	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent variable:	Admin. Receipt	Imputed Receipt	Admin. Receipt	Imputed Receipt	Admin. Receipt	Imputed Receipt	Admin. Receipt	Imputed Receipt	Admin. Receipt	Imputed Receipt	Admin. Receipt	Imputed Receipt
Single adult, no children	-0.016	-0.072**	-0.025***	-0.023***	0.024	0.025	0.017	-0.043***	-0.157***	-0.049	0.014	0.031*
	(0.032)	(0.028)	(0.007)	(0.008)	(0.035)	(0.029)	(0.019)	(0.014)	(0.041)	(0.034)	(0.024)	(0.019)
Single adult, with children	0.111***	0.011	0.035***	0.025***	0.062**	0.023	0.031**	-0.008	0.077**	0.032	0.048***	0.028**
	(0.034)	(0.030)	(0.006)	(0.007)	(0.031)	(0.024)	(0.013)	(0.010)	(0.038)	(0.032)	(0.015)	(0.014)
Multiple adults, no children	-0.019	-0.062**	-0.002	-0.002	-0.022	0.023	-0.004	-0.018*	-0.079***	-0.033	0.017	0.014
	(0.028)	(0.025)	(0.006)	(0.007)	(0.029)	(0.025)	(0.015)	(0.010)	(0.030)	(0.025)	(0.016)	(0.014)
Number of members under 18	0.042***	0.004	0.007***	0.009***	0.031***	0.008	0.013***	0.004	0.000	0.012	0.008	0.013***
	(0.011)	(0.009)	(0.002)	(0.002)	(0.011)	(0.009)	(0.004)	(0.003)	(0.011)	(0.010)	(0.005)	(0.004)
Number of members 18 or older	0.035***	-0.024***	0.011***	0.011***	0.033***	-0.002	0.013***	0.002	0.033***	0.013	0.006	0.001
	(0.008)	(0.008)	(0.002)	(0.002)	(0.011)	(0.010)	(0.005)	(0.004)	(0.010)	(0.009)	(0.005)	(0.004)
Rural	-0.068***	-0.034	-0.017***	-0.015**	0.097***	0.009	0.025	-0.014	0.000**	0.000***	0.000	0.000
	(0.024)	(0.023)	(0.006)	(0.006)	(0.026)	(0.022)	(0.015)	(0.011)	(0.000)	(0.000)	(0.000)	(0.000)
Hispanic	0.140***	0.074***	0.033***	0.000	0.152***	0.029*	0.026**	-0.008	0.110***	0.085***	0.021	-0.017
	(0.019)	(0.018)	(0.005)	(0.006)	(0.018)	(0.016)	(0.011)	(0.008)	(0.025)	(0.023)	(0.014)	(0.011)
Black non-hispanic	0.197***	0.104***	0.055***	0.021***	0.136***	0.012	0.051***	0.005	0.079***	0.057***	0.036***	0.013
	(0.017)	(0.015)	(0.004)	(0.005)	(0.018)	(0.016)	(0.010)	(0.008)	(0.022)	(0.020)	(0.012)	(0.010)
Other non-hispanic	0.004	0.060**	0.004	-0.004	0.053*	0.015	0.000	-0.045**	0.015	0.038	0.045***	-0.027
	(0.028)	(0.024)	(0.008)	(0.008)	(0.031)	(0.025)	(0.021)	(0.018)	(0.036)	(0.029)	(0.017)	(0.021)
Male	-0.049***	-0.052***	-0.008**	-0.022***	-0.071***	-0.029**	-0.031***	-0.010	-0.010	-0.013	-0.023**	-0.005
	(0.013)	(0.012)	(0.003)	(0.004)	(0.016)	(0.013)	(0.010)	(0.007)	(0.017)	(0.015)	(0.011)	(0.009)
Disabled	0.091***	0.019	0.011***	0.016***	0.133**	0.068	0.070***	-0.005	0.235***	0.145***	0.016	-0.011
	(0.016)	(0.014)	(0.004)	(0.004)	(0.066)	(0.051)	(0.025)	(0.021)	(0.037)	(0.032)	(0.015)	(0.013)
Age 16-29	0.040	0.013	0.021***	0.032***	0.091***	-0.032	0.016	0.036***	0.070**	0.050**	0.006	0.005
	(0.030)	(0.027)	(0.005)	(0.007)	(0.027)	(0.021)	(0.012)	(0.009)	(0.031)	(0.025)	(0.014)	(0.014)
Age 30-39	-0.018	0.032	-0.003	0.015**	0.082***	-0.039*	0.001	0.005	0.051**	0.081***	-0.001	-0.011
	(0.025)	(0.021)	(0.005)	(0.006)	(0.024)	(0.021)	(0.011)	(0.009)	(0.025)	(0.022)	(0.013)	(0.012)
Age 50-59	0.028	0.005	-0.004	-0.013**	-0.002	0.006	-0.010	0.012	0.014	0.052**	0.006	-0.001
	(0.022)	(0.020)	(0.005)	(0.006)	(0.026)	(0.022)	(0.014)	(0.010)	(0.025)	(0.023)	(0.015)	(0.011)
Age 60-69	0.012	-0.034	-0.043***	-0.048***	0.003	-0.043*	-0.036**	-0.002	-0.021	0.014	-0.068**	-0.036*
	(0.023)	(0.021)	(0.006)	(0.006)	(0.030)	(0.025)	(0.017)	(0.013)	(0.032)	(0.029)	(0.030)	(0.019)
Age 70 or more	-0.068***	-0.060***	-0.086***	-0.078***	-0.051	-0.060**	-0.094***	-0.019	0.024	0.017	-0.037**	-0.001
	(0.024)	(0.022)	(0.007)	(0.007)	(0.031)	(0.028)	(0.026)	(0.016)	(0.034)	(0.029)	(0.018)	(0.014)
Less than high school	0.007	0.046***	0.005	0.013***	0.091***	0.032*	0.013	0.014	0.143***	0.141***	0.012	0.029***
	(0.019)	(0.017)	(0.004)	(0.005)	(0.022)	(0.018)	(0.012)	(0.009)	(0.028)	(0.024)	(0.014)	(0.011)
High school graduate	0.008	0.041**	-0.002	-0.002	0.041**	-0.020	0.011	-0.003	0.051***	0.050***	0.010	0.008
	(0.018)	(0.016)	(0.004)	(0.005)	(0.020)	(0.016)	(0.011)	(0.007)	(0.019)	(0.017)	(0.011)	(0.010)
Complete graduate and beyond	-0.032	0.009	-0.023***	-0.019***	-0.053**	-0.047**	-0.006	-0.033***	-0.014	0.017	-0.001	-0.006
	(0.020)	(0.019)	(0.006)	(0.006)	(0.024)	(0.022)	(0.013)	(0.012)	(0.024)	(0.019)	(0.016)	(0.016)
Household language is English only	-0.042**	0.000	0.010**	0.013**					0.000	-0.016	0.007	0.065***
	(0.017)	(0.017)	(0.004)	(0.005)					(0.023)	(0.020)	(0.015)	(0.020)
Speaks English poorly	0.110***	0.075***	-0.016***	0.009					0.056	0.014	-0.016	-0.007
	(0.023)	(0.019)	(0.006)	(0.007)					(0.041)	(0.034)	(0.020)	(0.015)
Non-citizen	-0.046**	-0.007	0.003	-0.003					-0.061*	-0.002	-0.020	-0.005
	(0.022)	(0.019)	(0.005)	(0.007)					(0.032)	(0.027)	(0.015)	(0.014)
Household income/poverty line	-0.032***	-0.036***	-0.009***	-0.008***	-0.030***	-0.073***	-0.003	-0.001	-0.034***	-0.022***	-0.013***	-0.008*
	(0.003)	(0.004)	(0.001)	(0.001)	(0.005)	(0.013)	(0.003)	(0.002)	(0.005)	(0.004)	(0.004)	(0.004)
Anyone in household employed	-0.072***	-0.039**	-0.032***	-0.076***	-0.108***	-0.027	-0.040***	-0.013*	0.063***	0.059***	0.025**	0.035**
	(0.019)	(0.017)	(0.004)	(0.005)	(0.020)	(0.019)	(0.010)	(0.008)	(0.022)	(0.018)	(0.013)	(0.014)
Reported housing assistance receipt					0.088***	0.043**	0.001	0.017**				
					(0.023)	(0.017)	(0.012)	(0.008)				
Reported TANF+GA receipt	0.178***	0.047**			0.052	0.155***			0.166***	0.267***		
	(0.029)	(0.024)			(0.039)	(0.026)			(0.041)	(0.042)		
Reported SNAP receipt			0.103***	0.121***			0.031***	0.045***			0.062***	0.076***
			(0.003)	(0.004)			(0.010)	(0.008)			(0.011)	(0.012)
Linear time trend	0.022***	0.015***	-0.002**	-0.003**	0.013***	0.002	-0.003	0.002	0.127***	0.193***	-0.011	0.010
	(0.005)	(0.004)	(0.001)	(0.001)	(0.004)	(0.004)	(0.002)	(0.002)	(0.028)	(0.022)	(0.013)	(0.010)
Number of observations	6,096	6,096	35,589	35,589	2,336	2,336	2,346	2,346	1,941	1,941	1,928	1,928
Chi2 distance measure		45,999		13,161		2,375		769		1,085		1,442

Notes: The sample is restricted to item non-respondents in all columns. For each survey and program, the first column uses the administrative receipt measure as the dependent variable. The second column estimates the same model using the imputed receipt variable. All demographic characteristics refer to the reference person. The time trend is measured in years for the ACS and CPS, but in waves for the SIPP. The omitted categories are Multiple Adults with Children, Age 40-49, College Graduate and White. All analyses use household weights adjusted for PIK probability. The distance measure is the squared distance between the two coefficient vectors, weighted by the variance matrix of the coefficients using the administrative dependent variable. SEs in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A11: The Determinants of Program Receipt in the Full Linked Sample, When Excluding Item Non-Respondents and When Using Imputated Values, Probit Coefficients

	ACS						CPS						SIPP					
	SNAP			TANF+GA			SNAP			TANF+GA			SNAP			TANF+GA		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Dependent Variable	Admin	Admin	Admin/Imp	Admin	Admin	Admin/Imp	Admin	Admin	Admin/Imp	Admin	Admin	Admin/Imp	Admin	Admin	Admin/Imp	Admin	Admin	Admin/Imp
Sample	Full	Respondents	Full	Full	Respondents	Full	Full	Respondents	Full	Full	Respondents	Full	Full	Respondents	Full	Full	Respondents	Full
Single adult, no children	-0.0931***	-0.0985***	-0.1008***	-0.3812***	-0.4058***	-0.3368***	0.0988	0.0699	0.0820	-0.1316	-0.2331**	-0.2742***	-0.0778	-0.0165	-0.0626	-0.6038***	-0.6863***	-0.5998***
	(0.0157)	(0.0159)	(0.0157)	(0.0250)	(0.0268)	(0.0241)	(0.0670)	(0.0736)	(0.0679)	(0.0972)	(0.1077)	(0.1001)	(0.0689)	(0.0751)	(0.0698)	(0.1065)	(0.1121)	(0.1062)
Single adult, with children	0.3477***	0.3445***	0.3413***	0.3031***	0.2934***	0.2928***	0.4551***	0.4766***	0.4147***	0.4957***	0.5023***	0.4221***	0.5926***	0.6052***	0.5562***	0.4365***	0.4080***	0.4121***
	(0.0152)	(0.0154)	(0.0153)	(0.0200)	(0.0212)	(0.0197)	(0.0606)	(0.0669)	(0.0611)	(0.0777)	(0.0873)	(0.0804)	(0.0609)	(0.0649)	(0.0615)	(0.0807)	(0.0862)	(0.0817)
Multiple adults, no children	-0.0693***	-0.0712***	-0.0734***	-0.1580***	-0.1758***	-0.1520***	0.0430	0.0531	0.0565	-0.0710	-0.0853	-0.1169	-0.0274	0.0428	0.0062	-0.0493	-0.0986	-0.0730
	(0.0134)	(0.0136)	(0.0134)	(0.0196)	(0.0208)	(0.0191)	(0.0568)	(0.0626)	(0.0580)	(0.0785)	(0.0866)	(0.0798)	(0.0599)	(0.0650)	(0.0599)	(0.0930)	(0.1000)	(0.0944)
Number of members under 18	0.1092***	0.1078***	0.1066***	0.0561***	0.0543***	0.0581***	0.1451***	0.1439***	0.1281***	0.0695***	0.0431*	0.0465*	0.1191***	0.1380***	0.1238***	0.0817***	0.0736**	0.0831***
	(0.0049)	(0.0049)	(0.0049)	(0.0063)	(0.0067)	(0.0062)	(0.0220)	(0.0243)	(0.0223)	(0.0236)	(0.0261)	(0.0250)	(0.0221)	(0.0240)	(0.0222)	(0.0263)	(0.0289)	(0.0267)
Number of members 18 or older	0.1795***	0.1808***	0.1757***	0.1217***	0.1219***	0.1160***	0.2173***	0.2282***	0.1958***	0.1394***	0.1215***	0.1141***	0.1976***	0.1805***	0.1643***	0.0322	0.0302	0.0181
	(0.0048)	(0.0049)	(0.0048)	(0.0066)	(0.0070)	(0.0065)	(0.0215)	(0.0237)	(0.0218)	(0.0309)	(0.0370)	(0.0335)	(0.0216)	(0.0237)	(0.0220)	(0.0312)	(0.0341)	(0.0314)
Rural	-0.1136***	-0.1126***	-0.1128***	-0.1958***	-0.1933***	-0.1891***	0.1226**	0.0393	0.0416	0.2009**	0.1717*	0.1186	-0.0001***	-0.0001***	-0.0001***	-0.0001***	-0.0001***	-0.0001***
	(0.0097)	(0.0098)	(0.0097)	(0.0203)	(0.0213)	(0.0191)	(0.0501)	(0.0550)	(0.0509)	(0.0848)	(0.0932)	(0.0863)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Hispanic	0.4931***	0.4916***	0.4853***	0.4000***	0.4017***	0.3451***	0.5604***	0.5230***	0.4946***	0.4710***	0.4798***	0.4133***	0.3861***	0.3638***	0.3803***	0.3834***	0.3961***	0.3327***
	(0.0108)	(0.0110)	(0.0109)	(0.0181)	(0.0194)	(0.0176)	(0.0373)	(0.0410)	(0.0380)	(0.0575)	(0.0627)	(0.0577)	(0.0446)	(0.0474)	(0.0449)	(0.0634)	(0.0675)	(0.0635)
Black non-hispanic	0.6778***	0.6760***	0.6675***	0.6042***	0.5976***	0.5399***	0.4634***	0.4249***	0.3690***	0.5949***	0.5728***	0.5008***	0.4942***	0.5001***	0.4906***	0.6700***	0.6919***	0.6362***
	(0.0092)	(0.0093)	(0.0092)	(0.0147)	(0.0157)	(0.0141)	(0.0381)	(0.0424)	(0.0391)	(0.0584)	(0.0654)	(0.0599)	(0.0367)	(0.0391)	(0.0370)	(0.0584)	(0.0617)	(0.0584)
Other non-hispanic	0.0217	0.0198	0.0231	0.0990***	0.1008***	0.0858***	0.0851	0.0510	0.0599	-0.1747	-0.2210*	-0.2804**	0.4215***	0.4583***	0.4515***	0.2073**	0.1506	0.1107
	(0.0153)	(0.0155)	(0.0153)	(0.0267)	(0.0283)	(0.0253)	(0.0589)	(0.0647)	(0.0600)	(0.1199)	(0.1310)	(0.1241)	(0.0477)	(0.0496)	(0.0484)	(0.0860)	(0.0929)	(0.0889)
Disabled	0.4789***	0.4819***	0.4746***	0.0833***	0.0824***	0.0809***	0.3455**	0.3144**	0.3044**	0.0792	-0.2408	-0.2404	1.0267***	1.0099***	0.9984***	0.2934***	0.3041***	0.2632***
	(0.0083)	(0.0084)	(0.0083)	(0.0146)	(0.0156)	(0.0141)	(0.1391)	(0.1544)	(0.1436)	(0.1791)	(0.2130)	(0.1971)	(0.0457)	(0.0472)	(0.0456)	(0.0682)	(0.0717)	(0.0686)
Male	-0.2068***	-0.2083***	-0.2085***	-0.0419***	-0.0388***	-0.0560***	-0.1223***	-0.0860***	-0.0924***	0.0132	0.0905*	0.0618	-0.1052***	-0.1082***	-0.1058***	-0.1494***	-0.1212**	-0.1291**
	(0.0069)	(0.0070)	(0.0069)	(0.0120)	(0.0128)	(0.0116)	(0.0296)	(0.0323)	(0.0300)	(0.0478)	(0.0521)	(0.0485)	(0.0293)	(0.0312)	(0.0295)	(0.0528)	(0.0560)	(0.0530)
Age 16-29	0.2231***	0.2240***	0.2221***	0.1072***	0.1022***	0.1114***	0.1833***	0.1425**	0.0871*	0.0801	0.0532	0.1541**	0.3061***	0.2788***	0.2936***	0.1316	0.1477	0.1296
	(0.0129)	(0.0131)	(0.0129)	(0.0182)	(0.0194)	(0.0179)	(0.0510)	(0.0555)	(0.0516)	(0.0662)	(0.0726)	(0.0671)	(0.0602)	(0.0644)	(0.0592)	(0.0868)	(0.0954)	(0.0881)
Age 30-39	0.1236***	0.1278***	0.1277***	-0.0336**	-0.0294*	-0.0179	0.1556***	0.1085**	0.0701	-0.1651***	-0.2158***	-0.1650***	0.2748***	0.2661***	0.3007***	-0.0507	-0.0453	-0.0622
	(0.0113)	(0.0115)	(0.0113)	(0.0168)	(0.0178)	(0.0164)	(0.0467)	(0.0518)	(0.0479)	(0.0604)	(0.0659)	(0.0616)	(0.0466)	(0.0499)	(0.0470)	(0.0673)	(0.0716)	(0.0682)
Age 50-59	0.0294***	0.0267**	0.0284**	0.0099	0.0157	-0.0005	0.0937*	0.1191**	0.1073**	-0.0433	-0.0292	0.0069	0.0910**	0.0937**	0.1220***	0.0968	0.1091	0.1005
	(0.0110)	(0.0112)	(0.0111)	(0.0168)	(0.0180)	(0.0165)	(0.0482)	(0.0524)	(0.0486)	(0.0683)	(0.0742)	(0.0692)	(0.0441)	(0.0471)	(0.0446)	(0.0702)	(0.0743)	(0.0705)
Age 60-69	-0.0563***	-0.0608***	-0.0618***	-0.3038***	-0.2824***	-0.2913***	-0.0821	-0.0916	-0.1199**	-0.3319***	-0.3111***	-0.2756***	0.0622	0.0778	0.0833	-0.5224***	-0.4983***	-0.5000***
	(0.0125)	(0.0127)	(0.0126)	(0.0216)	(0.0230)	(0.0207)	(0.0562)	(0.0617)	(0.0567)	(0.0871)	(0.0949)	(0.0889)	(0.0537)	(0.0569)	(0.0542)	(0.0984)	(0.1022)	(0.0981)
Age 70 or more	-0.4247***	-0.4332***	-0.4292***	-0.7641***	-0.7426***	-0.6608***	-0.2979***	-0.3076***	-0.3243***	-1.0656***	-1.0536***	-0.9767***	0.0997**	0.0921*	0.0946*	-0.6447***	-0.6452***	-0.5572***
	(0.0134)	(0.0136)	(0.0134)	(0.0255)	(0.0274)	(0.0236)	(0.0590)	(0.0649)	(0.0597)	(0.1283)	(0.1396)	(0.1292)	(0.0508)	(0.0538)	(0.0510)	(0.0969)	(0.1041)	(0.0986)
Less than high school	0.2911***	0.2955***	0.2914***	0.1429***	0.1431***	0.1517***	0.3051***	0.2819***	0.2729***	0.1029	0.0909	0.1080*	0.3422***	0.3165***	0.3607***	0.1863***	0.1873**	0.2068***
	(0.0101)	(0.0102)	(0.0101)	(0.0158)	(0.0169)	(0.0154)	(0.0429)	(0.0471)	(0.0435)	(0.0630)	(0.0687)	(0.0642)	(0.0458)	(0.0482)	(0.0459)	(0.0702)	(0.0752)	(0.0703)
High school graduate	0.1054***	0.1054***	0.1057***	0.0430***	0.0430***	0.0460***	0.0309	-0.0085	-0.0217	0.0849	0.0685	0.0568	0.1745***	0.1717***	0.1880***	-0.0526	-0.0769	-0.0519
	(0.0085)	(0.0086)	(0.0085)	(0.0144)	(0.0153)	(0.0140)	(0.0373)	(0.0407)	(0.0378)	(0.0585)	(0.0642)	(0.0594)	(0.0336)	(0.0357)	(0.0338)	(0.0595)	(0.0641)	(0.0604)
Complete graduate and beyond	-0.1879***	-0.1884***	-0.1862***	-0.1495***	-0.1366***	-0.1467***	-0.2374***	-0.2414***	-0.2384***	0.0057	0.0250	-0.0281	-0.3230***	-0.3545***	-0.3004***	-0.1696**	-0.1806**	-0.1840**
	(0.0099)	(0.0100)	(0.0099)	(0.0179)	(0.0189)	(0.0172)	(0.0437)	(0.0474)	(0.0447)	(0.0709)	(0.0770)	(0.0725)	(0.0405)	(0.0430)	(0.0407)	(0.0740)	(0.0776)	(0.0745)
Household language is English only	-0.1209***	-0.1194***	-0.1179***	0.0857***	0.0842***	0.0786***							0.1526***	0.1824***	0.1489***	0.0364	0.0412	0.0908
	(0.0094)	(0.0095)	(0.0094)	(0.0158)	(0.0168)	(0.0153)							(0.0389)	(0.0399)	(0.0388)	(0.0793)	(0.0851)	(0.0814)
Speaks English poorly	0.4191***	0.4193***	0.4157***	-0.2012***	-0.2013***	-0.1740***							0.4895***	0.5225***	0.4881***	-0.4166***	-0.4503***	-0.4133***
	(0.0132)	(0.0133)	(0.0132)	(0.0203)	(0.0215)	(0.0198)							(0.0595)	(0.0622)	(0.0593)	(0.0899)	(0.0970)	(0.0894)
Non-citizen	-0.3477***	-0.3538***	-0.3446***	-0.0141	-0.0141	-0.0138							-0.2923***	-0.3039***	-0.2651***	0.1220	0.1691	0.1504
	(0.0126)	(0.0127)	(0.0126)	(0.0178)	(0.0188)	(0.0175)							(0.0661)	(0.0724)	(0.0668)	(0.0983)	(0.1067)	(0.0986)
Household income/poverty line	-0.2503***	-0.2547***	-0.2523***	-0.1186***	-0.1227***	-0.1082***	-0.2221***	-0.2359***	-0.2430***	-0.1097***	-0.1280***	-0.1121***	-0.2503***	-0.2636***	-0.2483***	-0.0884***	-0.0774***	-0.0806***
	(0.0028)	(0.0029)	(0.0029)	(0.0044)	(0.0048)	(0.0041)	(0.0120)	(0.0137)	(0.0135)	(0.0186)	(0.0220)	(0.0191)	(0.0128)	(0.0140)	(0.0128)	(0.0220)	(0.0232)	(0.0221)
Anyone in household employed	-0.4276***	-0.4309***	-0.4259***	-0.3684***	-0.3645***	-0.4089***	-0.4873***	-0.4911***	-0.4604***	-0.3954***	-0.3744***	-0.3520***	0.2449***	0.2200***	0.2395***	0.5022***	0.5223***	0.5038***
	(0.0098)	(0.0099)	(0.0098)	(0.0154)	(0.0165)	(0.0149)	(0.0411)	(0.0458)	(0.0415)	(0.0576)	(0.0639)	(0.0590)	(0.0369)	(0.0388)	(0.0367)	(0.0668)	(0.0712)	(0.0689)
Reported housing assistance receipt							0.8097***	0.8645***	0.8126***	0.1869***	0.1943***	0.2371***						
							(0.0428)	(0.0467)	(0.0425)	(0.0530)	(0.0576)	(0.0539)						
Reported TANF+GA receipt	1.3066***	1.3217***	1.2872***				1.1208***	1.4576***	1.2369***				1.1566***	1.2213***	1.2497***			
	(0.0173)	(0.0176)	(0.0172)				(0.0987)	(0.1326)	(0.0974)				(0.0850)	(0.0929)	(0.0875)			
Reported SNAP receipt				1.0322***	1.0197***	1.0027***				0.8296***	0.9067***	0.9047***				0.8902***	0.9074***	0.9193***
				(0.0131)	(0.0140)	(0.0127)				(0.0528)	(0.0585)	(0.0541)				(0.0554)	(0.0594)	(0.0562)
Linear time trend	0.0845***	0.0846***	0.0839***	-0.0217***	-0.0224***	-0.0190***	0.0582***	0.0553***	0.0457***	-0.0046	-0.0012	0.0037	0.8196***	0.8303***	0.8577***	0.1378**	0.1601***	0.1656***
	(0.0023)	(0.0023)	(0.0023)	(0.0038)	(0.0041)	(0.0037)	(0.0082)	(0.0090)	(0.0083)	(0.0126)	(0.0139)	(0.0128)	(0.0387)	(0.0403)	(0.0388)	(0.0585)	(0.0618)	(0.0580)
Constant	-0.7977***	-0.7896***	-0.7826***	-1.8749***	-1.8789***	-1.8033***	-1.0927***	-1.0394***	-0.9379***	-1.9221***	-1.8780***	-1.9114***	-1.5872***	-1.6127***	-1.5827***	-2.4472***	-2.4752***	-2.5076***
	(0.0235)	(0.0238)	(0.0235)	(0.0361)	(0.0384)	(0.0349)	(0.0976)	(0.1076)	(0.0987)	(0.1380)	(0.1545)	(0.1411)	(0.0907)	(0.0997)	(0.0928)	(0.1486)	(0.1618)	(0.1525)
Number of observations	543,528	537,432	543,528	543,528	507,939	543,528	18,064	15,728	18,064	18,064	15,718	18,064	24,997	23,056	24,997	24,997	23,069	24,997
Chi2 distance measure	0	8.5	14.0	0	27.2	163.5	0	25.7	57.0	0	15.6	23.1	0	12.7	11.9	0	3.2	7.1

Notes: There are 3 models per program per survey that differ in the dependent variable and the sample used as noted in the rows at the top of the table. For each survey and program, the first column uses the full sample with the administrative dependent variable. The second column excludes item non-respoondents from the sample. The third column uses their imputed values instead of the administrative dependent variable. All demographic characteristics refer to the reference person. The time trend is measured in years for the ACS and CPS, but in waves for the SIPP. The omitted categories are Multiple Adults with Children, Age 40-49, College Graduate and White. All analyses use household weights adjusted for PIK probability. The distance measure is the squared distance between the coefficient vector and the coefficients from the model using the full sample with the administrative dependent variable (in the first column for each survey and program), weighted by the variance matrix of the coefficients of the latter model. SEs in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A12 – Comparing Bias in Probit Coefficients of the Determinants of Program Receipt Using Different Methods to Address Item Non-response

		ACS		CPS		SIPP	
Sample	Dependent Variable	SNAP	TANF+GA	SNAP	TANF+GA	SNAP	TANF+GA
Chi2-Distance Measure of Coefficients							
Respondents	Admin Receipt	8.5	27.2	25.7	15.6	12.7	3.2
Respondents, reweighted	Admin Receipt	8.6	30.9	25.9	15.2	13.3	3.3
Full	Admin/Imputed	14.0	163.5	57.0	23.1	11.9	7.1
Full	Reports/Imputed	6,677.2	4,619.4	1,602.4	960.5	285.2	440.9
Respondents	Reports	6,761.0	6,004.0	1,449.5	1,427.5	376.7	481.0
Respondents, reweighted	Reports	6,765.7	5,950.7	1,455.7	1,431.7	374.7	489.2
Chi2-Distance Measure of Marginal Effects							
Respondents	Admin Receipt	4.8	66.2	23.0	11.5	10.0	3.3
Respondents, reweighted	Admin Receipt	3.2	27.8	21.2	11.3	9.9	2.8
Full	Admin/Imputed	12.5	102.7	46.7	17.7	10.0	6.9
Full	Reports/Imputed	4,365.5	3,452.3	643.6	330.0	172.7	191.5
Respondents	Reports	4,364.6	4,146.8	664.7	344.7	201.0	205.4
Respondents, reweighted	Reports	4,248.5	4,007.2	588.6	345.2	199.8	197.6

Note: The first and third row of each panel are identical to Table 10. The row with reweighted estimates use inverse probability weights predicted from probit models of item non-response including all covariates of the receipt models. Distances are the squared distance to the coefficients from the model using the full sample and the administrative receipt variable, weighted by the variance matrix of the coefficients from this model. The distances for the coefficients include the intercept of the model, but the ones for the marginal effects do not.