Revision in process

Errors in Survey Reporting and Imputation and their Effects on Estimates of Food Stamp Program Participation*

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Abstract

Measuring government benefit receipt in household surveys is important to assess the economic circumstances of disadvantaged populations, program takeup, the distributional effects of government programs, and other program effects. Receipt of food stamps is especially important given the large and growing size of the program and evidence of its effects on labor supply, health and other outcomes. We use administrative data on food stamp participation in two states matched to American Community Survey (ACS), Current Population Survey (CPS), and Survey of Income and Program Participation (SIPP) household data. We find that 23 percent of true recipient households do not report receipt in the SIPP, 35 percent in the ACS, and fully 50 percent do not report receipt in the CPS. Both false negative and false positive reports vary with individual characteristics, leading to complicated biases in food stamp analyses. Our results are also informative about the reasons for misreporting and the success of different survey methods. We then directly examine biases in research finding, in particular the determinants of program receipt using our combined administrative and survey data. Our results differ from conventional estimates in showing higher participation by single parents, non-whites, middle-income households, and other groups. We directly examine one source of potential error, Census Bureau imputations, finding that excluding the imputed observations leads to worse ACS estimates, but has little effect on the CPS and SIPP estimates.

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KEY WORDS: Measurement error, Survey errors, program takeup, food stamps, under-reporting, imputation, poverty.

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Table 1 – Mis-reporting of Food Stamp Receipt, 2001 ACS, Full Sample

		ACS Report		
Administrative Receipt		No Food Stamps	Food Stamps	Total
Illinois				
No Food Stamps	Sample Count	19,630	88	19,718
	Population Est.	4,193,387	34,883	4,228,270
	Overall %	91.15%	0.76%	91.91%
	Row %	99.18%	0.83%	100.00%
	Column %	97.24%	12.10%	91.91%
Food Stamps	Sample Count	321	728	1,049
	Population Est.	118,834	253,289	372,123
	Overall %	2.58%	5.51%	8.09%
	Row %	31.93%	68.07%	100.00%
	Column %	2.76%	87.90%	8.09%
Total	Sample Count	19,951	816	20,767
	Population Est.	4,312,222	288,172	4,600,393
	Overall %	93.74%	6.26%	100.00%
	Row %	93.74%	6.26%	100.00%
	Column %	100.00%	100.00%	100.00%
Maryland				
No Food Stamps	Sample Count	9,042	33	9,075
	Population Est.	1,880,871	9,615	1,890,485
	Overall %	93.39%	0.48%	93.86%
	Row %	99.49%	0.51%	100.00%
	Column %	97.66%	10.92%	93.86%
Food Stamps	Sample Count	163	296	459
	Population Est.	45,121	78,454	123,574
	Overall %	2.24%	3.90%	6.14%
	Row %	36.51%	63.49%	100.00%
	Column %	2.34%	89.08%	6.14%
Total	Sample Count	9,205	329	9,534
	Population Est.	1,925,991	88,069	2,014,060
	Overall %	95.63%	4.37%	100.00%
	Row %	95.63%	4.37%	100.00%
	Column %	100.00%	100.00%	100.00%

Notes: Estimates are weighted by household weight adjusted for PIK probability.

Table 2 – Mis-reporting of Food Stamp Receipt, 2001 ACS, Imputed Food Stamp Receipt Sample

		ACS Report		
Administrative Receipt		No Food Stamps	Food Stamps	Total
Illinois				
No Food Stamps	Sample Count	146	37	183
	Population Est.	29,905	14,181	44,086
	Overall %	30.74%	14.58%	45.32%
	Row %	67.83%	32.17%	100.00%
	Column %	94.55%	21.60%	45.32%
Food Stamps	Sample Count	6	154	160
	Population Est.	1,723	51,463	53,186
	Overall %	1.77%	52.91%	54.68%
	Row %	3.24%	96.76%	100.00%
	Column %	5.45%	78.40%	54.68%
Total	Sample Count	152	191	343
	Population Est.	31,629	65,644	97,273
	Overall %	32.52%	67.48%	100.00%
	Row %	32.52%	67.48%	100.00%
	Column %	100.00%	100.00%	100.00%
Maryland				
No Food Stamps	Sample Count	60	9	69
	Population Est.	12,060	2,494	14,553
	Overall %	42.26%	8.74%	51.00%
	Row %	82.86%	17.14%	100.00%
	Column %	96.54%	15.54%	51.00%
Food Stamps	Sample Count	3	56	59
	Population Est.	432	13,553	13,985
	Overall %	1.51%	47.49%	49.00%
	Row %	3.09%	96.91%	100.00%
	Column %	3.46%	84.46%	49.00%
Total	Sample Count	63	65	128
	Population Est.	12,491	16,047	28,538
	Overall %	43.77%	56.23%	100.00%
	Row %	43.77%	56.23%	100.00%
	Column %	100.00%	100.00%	100.00%

Notes: Estimates are weighted by household weight adjusted for PIK probability.

Table 3 – Mis-reporting of Food Stamp Receipt, CPS, Full Sample

		CPS Report		
Administrative Receipt		No Food Stamps	Food Stamps	Total
Illinois 2002-2005				
No Food Stamps	Sample Count	6,836	78	6,914
	Population Est.	17,267,477	170,642	17,438,119
	Overall %	89.32%	0.88%	90.21%
	Row %	99.02%	0.98%	100.00%
	Column %	94.98%	14.84%	90.21%
Food Stamps	Sample Count	452	459	911
	Population Est.	912,736	980,703	1,918,714
	Overall %	4.72%	5.07%	9.80%
	Row %	48.21%	51.79%	100.00%
	Column %	5.02%	85.18%	9.80%
Total	Sample Count	7,288	537	7,825
	Population Est.	18,180,213	1,151,345	19,331,558
	Overall %	94.04%	5.96%	100.00%
	Row %	94.04%	5.96%	100.00%
	Column %	100.00%	100.00%	100.00%
Maryland 2002-2004				
No Food Stamps	Sample Count	2,884	13	2,897
	Population Est.	5,921,409	24,700	5,946,109
	Overall %	94.32%	0.39%	94.71%
	Row %	99.58%	0.42%	100.00%
	Column %	97.09%	13.77%	94.71%
Food Stamps	Sample Count	103	90	193
	Population Est.	177,371	154,684	332,055
	Overall %	2.83%	2.46%	5.29%
	Row %	53.42%	46.58%	100.00%
	Column %	2.91%	86.23%	5.29%
Total	Sample Count	2,987	103	3,090
	Population Est.	6,098,780	179,384	6,278,164
	Overall %	97.14%	2.86%	100.00%
	Row %	97.14%	2.86%	100.00%
	Column %	100.00%	100.00%	100.00%

Notes: Estimates are weighted by household weight adjusted for PIK probability.

Table 4 – Mis-reporting of Food Stamp Receipt, CPS, Imputed Food Stamp Receipt Sample

		CPS Report		
Administrative Receipt		No Food Stamps	Food Stamps	Total
Illinois 2002-2005				
No Food Stamps	Sample Count	195	27	222
	Population Est.	510,438	56,398	566,834
	Overall %	68.62%	7.58%	76.20%
	Row %	90.05%	9.95%	100.00%
	Column %	78.19%	61.96%	76.20%
Food Stamps	Sample Count	68	22	90
	Population Est.	142,388	34,918	177,006
	Overall %	19.14%	4.65%	23.80%
	Row %	80.44%	19.56%	100.00%
	Column %	21.81%	38.04%	23.80%
Total	Sample Count	263	49	312
	Population Est.	652,826	91,016	743,842
	Overall %	87.76%	12.24%	100.00%
	Row %	87.76%	12.24%	100.00%
	Column %	100.00%	100.00%	100.00%
Maryland 2002-2004				
No Food Stamps	Sample Count	56	7	63
	Population Est.	136,636	12,705	149,341
	Overall %	75.62%	7.03%	82.65%
	Row %	91.49%	8.51%	100.00%
	Column %	85.31%	61.89%	82.65%
Food Stamps	Sample Count	12	6	18
	Population Est.	23,526	7,825	31,350
	Overall %	13.02%	4.33%	17.35%
	Row %	75.04%	24.96%	100.00%
	Column %	14.69%	38.11%	17.35%
Total	Sample Count	68	13	81
	Population Est.	160,162	20,530	180,692
	Overall %	88.64%	11.36%	100.00%
	Row %	88.64%	11.36%	100.00%
	Column %	100.00%	100.00%	100.00%

Notes: Estimates are weighted by household weight adjusted for PIK probability.

Table 5 – Misreporting of Food Stamp Receipt, SIPP, Full Sample

Administrative Receipt		SIPP Report: No Food Stamps	SIPP Report: Food Stamps	SIPP Report: Total
IL and MD Pooled				
No Food Stamps	Sample Count	9,973	189	10,162
	Population Est.	54,731,963	912,735	55,644,698
	Overall %	92.50%	1.54%	94.05%
	Row %	98.36%	1.64%	100.00%
	Column %	98.55%	25.13%	94.05%
Food Stamps	Sample Count	165	628	793
	Population Est.	803,748	2,718,842	3,522,590
	Overall %	1.36%	4.60%	5.95%
	Row %	22.82%	77.18%	100.00%
	Column %	1.45%	74.87%	5.95%
Total	Sample Count	10,138	817	10,955
	Population Est.	55,535,712	3,631,577	59,167,288
	Overall %	93.86%	6.14%	100.00%
	Row %	93.86%	6.14%	100.00%
	Column %	100.00%	100.00%	100.00%

Notes: Estimates are weighted by household weight adjusted for PIK probability.

Table 6 – Misreporting of Food Stamp Receipt, SIPP, Imputed Food Stamp Receipt Sample

Administrative Receipt		SIPP Report: No Food Stamps	SIPP Report: Food Stamps	SIPP Report: Total
IL and MD Pooled				
No Food Stamps	Sample Count	683	51	734
	Population Est.	3,586,349	276,607	3,862,956
	Overall %	82.63%	6.37%	89.00%
	Row %	92.84%	7.16%	100.00%
	Column %	96.30%	44.88%	89.00%
Food Stamps	Sample Count	29	79	108
	Population Est.	137,610	339,735	477,345
	Overall %	3.17%	7.83%	11.00%
	Row %	28.83%	71.17%	100.00%
	Column %	3.70%	55.12%	11.00%
Total	Sample Count	712	130	842
	Population Est.	3,723,958	616,342	4,340,300
	Overall %	85.80%	14.20%	100.00%
	Row %	85.80%	14.20%	100.00%
	Column %	100.00%	100.00%	100.00%

Notes: Estimates are weighted by household weight adjusted for PIK probability.

Table 7 - The Determinants of Mis-reporting, 2001 ACS, Probit Average Derivatives, Households with Income Less Than Twice the Poverty Line

	False Negative		False Positive	
	Illinois	Maryland	Illinois	Maryland
Single, no children	-0.0862	0.0437	omitted	omitted
	(0.0716)	(0.0877)		
Single, with children	-0.0802	0.1203	omitted	omitted
	(0.0539)	(0.0753)		
Multiple adults, no children	-0.1036	-0.0135	omitted	omitted
	(0.0857)	(0.1067)		
Number of members 18 or older	-0.0248	0.0405	-0.0024	0.0053
	(0.0341)	(0.0363)	(0.0034)	(0.0050)
Number of members under 18	-0.0306	-0.0185	0.0069	-0.0020
	(0.0264)	(0.0329)	(0.0033)	(0.0036)
Number of members PIKed	0.0308	0.0358	-0.0085	0.0060
	(0.0268)	(0.0333)	(0.0038)	(0.0040)
Age >= 50	0.1514	0.1319	-0.0225	-0.0063
	(0.0513)	(0.0663)	(0.0075)	(0.0086)
Male	0.0877	-0.0335	-0.0106	0.0032
	(0.0356)	(0.0483)	(0.0061)	(0.0080)
Less than high school	0.0688	0.0659	0.0140	0.0063
	(0.0431)	(0.0589)	(0.0068)	(0.0099)
High School graduate	-0.0001	0.1147	-0.0032	0.0111
	(0.0425)	(0.0576)	(0.0085)	(0.0126)
College graduate and beyond	0.2197	-0.0586	omitted	omitted
	(0.0745)	(0.1201)		
White	-0.0897	-0.1110	-0.0239	-0.0082
	(0.0368)	(0.0422)	(0.0071)	(0.0083)
Employed	omitted	omitted	-0.0054	-0.0261
			(0.0066)	(0.0151)
Unemployed	-0.0206	-0.2504	omitted	omitted
	(0.0554)	(0.0668)		
Not in labor force	-0.0077	-0.0627	omitted	omitted
	(0.0404)	(0.0513)		
Income/poverty line	0.0010	0.0008	-0.0001	-0.0001
	(0.0003)	(0.0004)	(0.0000)	(0.0001)
Disabled	-0.0637	-0.0333	0.0076	-0.0069
	(0.0386)	(0.0584)	(0.0084)	(0.0084)
Disabled, not working	-0.0382	0.1179	0.0159	0.0226
	(0.0465)	(0.0505)	(0.0082)	(0.0097)
Speaks English only	0.0455	-0.1448	omitted	omitted
	(0.0507)	(0.0838)		
Non-U.S. Citizen	-0.1545	0.0697	omitted	omitted
	(0.0327)	(0.1011)		
Rural	-0.1000	-0.1079	-0.0051	
	(0.0472)	(0.0476)	(0.0088)	not disclosed
Reported public assistance receipt	-0.2693	-0.2453	0.0442	0.0622
	(0.0549)	(0.0632)	(0.0091)	(0.0186)
Reported housing assistance receipt	-0.0336	-0.0248	0.0108	0.0007
	(0.0397)	(0.0481)	(0.0070)	(0.0081)
FS receipt imputed	-0.3115	-0.3833	0.0700	0.0447
	(0.0647)	(0.0899)	(0.0110)	(0.0139)
Length of FS receipt spell	-0.0275	-0.0384	omitted	omitted
	(0.0034)	(0.0036)		
Administrative TANF receipt	0.0658	0.0273	omitted	omitted
	(0.0446)	(0.0514)		
Observations	789	344	3,357	1,455

Notes: Delta-method standard errors in parentheses. All specifications also include controls for mode of interview (mail-back, CATI, CAPI). All analyses conducted using household weights adjusted for PIK probability. For the false negative probits, the unreported omitted family type is multiple adults with children, the education category is some college, the employment category is employed, the race group is nonwhite, and the geographic area is within-MSA. The unreported omitted education category for the false negative probits is some college or more, the race group is nonwhite, the employment category is not employed, and the geographic area is within-MSA. Rural status was also controlled for in the false positive Maryland regression.

Table 8 - The Determinants of Mis-reporting, CPS, Probit Average Derivatives, Households with Income Less Than Twice the Poverty Line

	False Negative		False Positive	
	Illinois	Maryland	Illinois	Maryland
Single, no children	-0.1312	0.0558	omitted	omitted
	(0.0779)	(0.1755)		
Single, with children	-0.0227	-0.0323	omitted	omitted
	(0.0620)	(0.1203)		
Multiple adults, no children	-0.0245	0.0668	omitted	omitted
	(0.0739)	(0.1416)		
Number of members 18 or over	0.0391	0.0370	0.0092	-0.0170
	(0.0371)	(0.0794)	(0.0067)	(0.0130)
Number of members under 18	-0.0230	-0.0968	0.0044	-0.0251
	(0.0224)	(0.0616)	(0.0049)	(0.0120)
Number of members PIKed	-0.0171	0.0484	-0.0047	0.0222
	(0.0194)	(0.0433)	(0.0044)	(0.0118)
Age >= 50	0.0881	-0.1418	-0.0382	-0.0010
	(0.0525)	(0.0832)	(0.0147)	(0.0109)
Male	-0.0603	0.0195	-0.0130	0.0106
	(0.0446)	(0.0858)	(0.0104)	(0.0094)
Less than high school	-0.0695	-0.0620	0.0193	not disclosed
	(0.0479)	(0.1111)	(0.0134)	
High School graduate	-0.0293	-0.0002	-0.0001	0.0008
	(0.0463)	(0.0926)	(0.0117)	(0.0079)
College graduate and beyond	0.0373	-0.0295	omitted	omitted
	(0.1103)	(0.1223)		
White	-0.0503	-0.0509	0.0046	0.0094
	(0.0415)	(0.0810)	(0.0098)	(0.0096)
Employed	omitted	omitted	-0.0016	0.0012
			(0.0117)	(0.0089)
Unemployed	0.0396	0.0235	omitted	omitted
	(0.0664)	(0.1532)		
Not in labor force	0.0199	-0.0074	omitted	omitted
	(0.0447)	(0.0832)		
Income/poverty line	0.0010	-0.0003	-0.0003	-0.0002
	(0.0004)	(0.0008)	(0.0001)	(0.0001)
Rural	-0.0276	-0.0684	omitted	omitted
	(0.0548)	(0.1346)		
Reported public assistance receipt	-0.3293	not disclosed	0.0957	0.0872
	(0.0722)		(0.0197)	(0.0332)
Reported housing assistance receipt	-0.1753	-0.2732	0.0571	-0.0032
	(0.0409)	(0.0871)	(0.0146)	(0.0116)
FS receipt imputed	0.3580	0.1932	0.0544	0.0443
	(0.0552)	(0.1103)	(0.0113)	(0.0156)
Length of FS receipt spell	-0.0281	-0.0196	omitted	omitted
	(0.0051)	(0.0086)		
Administrative TANF receipt	0.0986	0.2466	omitted	omitted
	(0.0580)	(0.0766)		
Linear time trend	0.0222	0.0980	0.0018	-0.0000
	(0.0157)	(0.0373)	(0.0047)	(0.0056)
Observations	689	136	1,462	504

Notes: Delta-method standard errors in parentheses. Samples are pooled across all years for both states (IL:2002-2005, MD:2002-2004). All analyses conducted using household weights adjusted for PIK probability. For the false negative probits, the unreported omitted family type is multiple adults with children, the education category is some college, the employment category is employed, the race group is nonwhite, and the geographic area is within-MSA. The unreported omitted education category for the false negative probits is some college or more, the race group is nonwhite, and the employment category is not employed. Reported public assistance receipt was controlled for in the Maryland false negative regression. Less than high school was controlled for in the Maryland false positive regression. Disabled status was controlled for in all false positive regressions.

Table 9 - The Determinants of Mis-reporting, SIPP, Probit Average Derivatives, Households with Income Less Than Twice the Poverty Line

	False Negative	False Positive
Single, no children	-0.1644	0.0026
	(0.0662)	(0.0177)
Single, with children	-0.1426	0.0214
	(0.0481)	(0.0124)
Married, no children	0.0323	-0.0337
	(0.0843)	(0.0174)
Number of members 18 or over	0.0159	0.0130
	(0.0210)	(0.0061)
Number of members under 18	-0.0361	0.0142
	(0.0219)	(0.0065)
Number of members interviewed	0.0009	0.0130
	(0.0313)	(0.0075)
Number of members PIKed	-0.0060	-0.0117
	(0.0205)	(0.0048)
Age >=50	-0.0044	-0.0100
	(0.0347)	(0.0103)
Male	-0.0798	-0.0032
	(0.0359)	(0.0084)
Less than high school	-0.1572	0.0091
	(0.0517)	(0.0089)
High School Graduate	0.0425	0.0086
	(0.0327)	(0.0081)
College Graduate and Beyond	-0.0460	-0.0051
	(0.0463)	(0.0127)
White	-0.0672	-0.0207
	(0.0355)	(0.0083)
Employed	0.0428	-0.0003
	(0.0273)	(0.0070)
Poverty Index	-0.0082	-0.0257
	(0.0304)	(0.0069)
Disabled	0.0249	0.0441
	(0.0280)	(0.0073)
Speaks no or poor English	0.1690	0.0027
	(0.0454)	(0.0125)
Non-U.S. Citizen	-0.2039	-0.0129
	(0.1162)	(0.0132)
Rural	0.0145	0.0120
	(0.0542)	(0.0095)
Reported TANF receipt	-0.2283	0.1020
	(0.0749)	(0.0210)
Reported housing assistance receipt	-0.1180	0.0523
	(0.0305)	(0.0089)
FS receipt imputed	-0.1029	0.0470
	(0.0525)	(0.0130)
Number of months of aministrative FS receipt	-0.0452	omitted
	(0.0158)	
Administrative TANF receipt	0.0812	-0.1093
	(0.0676)	(0.0422)
2001	-0.0892	-0.0008
	(0.0425)	(0.0091)
2002	-0.0146	0.0021
	(0.0386)	(0.0103)
2003	-0.0166	0.0046
	(0.0424)	(0.0100)
2005	-0.1288	0.0102
	(0.0606)	(0.0120)
No interview with reference person	-0.0667	0.0144
	(0.0695)	(0.0115)
HH had bad data record	0.0936	-0.0039
	(0.0450)	(0.0116)
Reference Person had bad data record	-0.0047	-0.0003
	(0.0411)	(0.0123)
Number of months since last administrative FS receipt	0.0414	omitted
	(0.0132)	
Interview with someone who did not have a PIK	-0.0235	0.0147
	(0.0762)	(0.0132)
HH in Maryland	0.0893	-0.0309
	(0.0442)	(0.0163)
Observations	640	2,333

Notes: Delta-method standard errors in parentheses. Samples include both states and are pooled across all years (IL: 10/2000-10/2004, MD: 10/2000-12/2003). All analyses conducted using household weights adjusted for PIK probability. The omitted family type is married with children, the omitted education category is some college and the omitted year is 2004

Table 10 – Food Stamp Receipt in Survey Data and Combined Data, 2001 ACS, Probit Average Derivatives, Households with Income less than Twice the Poverty Line

	Illinois			Maryland		
	Survey Food Stamp Measure	Admin. Food Stamp Measure	Equality Test p-value	Survey Food Stamp Measure	Admin. Food Stamp Measure	Equality Test p-value
Single, no children	0.0670	0.1164	0.0901	0.0861	0.1485	0.1685
	(0.0320)	(0.0361)		(0.0461)	(0.0515)	
Single, with children	0.1076	0.1429	0.0941	0.1083	0.1965	0.0294
	(0.0247)	(0.0272)		(0.0351)	(0.0389)	
Multiple adults, no children	0.0696	0.0959	0.3628	0.0547	0.0975	0.3601
	(0.0344)	(0.0392)		(0.0500)	(0.0547)	
Number of members under 18	0.0188	-0.0066	0.0420	0.0202	0.0027	0.2658
	(0.0099)	(0.0145)		(0.0144)	(0.0191)	
Number of members 18 or older	0.0027	-0.0201	0.0562	0.0039	0.0153	0.6115
	(0.0111)	(0.0138)		(0.0174)	-0.0208	
Number of members PIKed	0.0145	0.0692	0.0000	0.0165	0.0612	0.0082
	(0.0076)	(0.0131)		(0.0118)	(0.0183)	
Age 16-29	-0.0208	-0.0055	0.4209	0.0274	0.0141	0.6357
	(0.0231)	(0.0264)		(0.0300)	(0.0332)	
Age 30-39	0.0061	0.0061	0.9956	-0.0386	-0.0454	0.8105
	(0.0221)	(0.0262)		(0.0288)	(0.0323)	
Age 50-59	-0.0981	-0.0405	0.0245	-0.0315	-0.0375	0.8662
	(0.0261)	(0.0294)		(0.0366)	(0.0369)	
Age 60-69	-0.1144	-0.0806	0.2454	-0.0856	-0.0702	0.6623
	(0.0278)	(0.0320)		(0.0358)	(0.0384)	
Age >= 70	-0.1641	-0.1619	0.9656	-0.1346	-0.1354	0.9984
	(0.0278)	(0.0321)		(0.0359)	(0.0386)	
Less than high school	0.0648	0.0687	0.7580	0.0739	0.1089	0.0969
	(0.0184)	(0.0218)		(0.0237)	(0.0271)	
High School graduate	0.0239	0.0318	0.5690	0.0130	0.0510	0.1081
	(0.0186)	(0.0212)		(0.0232)	(0.0255)	
College graduate and beyond	-0.0584	-0.0569	0.9905	0.0114	-0.0147	0.4343
	(0.0313)	(0.0329)		(0.0361)	(0.0407)	
White	-0.0380	-0.0801	0.0053	0.0055	-0.0355	0.0204
	(0.0178)	(0.0191)		(0.0187)	(0.0211)	
Employed	-0.0380	-0.0217	0.2792	-0.0488	-0.0078	0.0832
	(0.0164)	(0.0188)		(0.0227)	(0.0247)	
Income/poverty line	-0.0007	-0.0007	0.5801	-0.0010	-0.0013	0.0338
	(0.0001)	(0.0001)		(0.0001)	(0.0002)	
Disabled	0.0906	0.0774	0.4844	0.0773	0.0933	0.4667
	(0.0182)	(0.0209)		(0.0235)	(0.0249)	
Disabled, not working	0.0271	0.0086	0.3507	0.0093	0.0465	0.1086
	(0.0193)	(0.0224)		(0.0242)	(0.0266)	
Speaks English only	0.0343	0.0850	0.0048	0.0716	0.0772	0.8855
	(0.0207)	(0.0245)		(0.0306)	(0.0393)	
Rural	0.0293	0.0458	0.2486	0.0499	0.0491	0.9462
	(0.0191)	(0.0189)		(0.0183)	(0.0225)	
Reported public assistance receipt	0.3189	0.2386	0.0197	0.3020	0.3728	0.1119
	(0.0240)	(0.0315)		(0.0324)	(0.0408)	
Reported housing assistance receipt	0.1461	0.1811	0.0457	0.1021	0.1337	0.1356
	(0.0184)	(0.0217)		(0.0198)	(0.0241)	
Observations	4,591	4,146		1,945	1,799	
Joint significance test P-value			0.0000			0.0004

Notes: Delta-method standard errors in parentheses. All analyses conducted using household weights adjusted for PIK probability. The unreported omitted family type is multiple adults with children, the age group is 40-49, the education group is some college, the race group is nonwhite, the employment group is not employed, and the geographic area is within MSA.

Table 11 – Food Stamp Receipt in Survey Data and Combined Data, 2001 CPS, Probit Average Derivatives, Households with Income less than Twice the Poverty Line

	Illinois			Maryland		
	Survey Food Stamp Measure	Admin. Food Stamp Measure	Equality Test p-value	Survey Food Stamp Measure	Admin. Food Stamp Measure	Equality Test p-value
Single, no children	-0.0119	0.0001	0.7372	-0.0687	-0.0229	0.4302
	(0.0256)	(0.0386)		(0.0511)	(0.0623)	
Single, with children	0.0547	0.1333	0.0164	0.0133	0.0775	0.1847
	(0.0214)	(0.0308)		(0.0437)	(0.0491)	
Multiple adults, no children	0.0192	0.0664	0.1803	-0.0509	0.0235	0.1533
	(0.0226)	(0.0346)		(0.0413)	(0.0560)	
Number of members under 18	0.0227	0.0309	0.4445	0.0235	0.0541	0.0725
	(0.0058)	(0.0087)		(0.0117)	(0.0181)	
Number of members 18 or older	-0.0069	0.0128	0.1745	-0.0213	0.0055	0.3562
	(0.0104)	(0.0143)		(0.0258)	(0.0246)	
Age 16-29	-0.0111	-0.0378	0.3634	-0.0086	-0.0428	0.3599
	(0.0198)	(0.0291)		(0.0287)	(0.0431)	
Age 30-39	-0.0118	0.0040	0.5257	-0.0285	-0.0043	0.5404
	(0.0194)	(0.0280)		(0.0257)	(0.0419)	
Age 50-59	0.0016	0.0287	0.4431	0.0249	0.0382	0.7735
	(0.0228)	(0.0369)		(0.0291)	(0.0461)	
Age 60-69	-0.0110	-0.0625	0.1389	0.0372	-0.0052	0.3747
	(0.0240)	(0.0353)		(0.0344)	(0.0519)	
Age >= 70	-0.1313	-0.1579	0.5931	-0.0714	-0.1675	0.0714
	(0.0254)	(0.0352)		(0.0353)	(0.0599)	
Less than high school	0.0503	0.0455	0.7299	-0.0056	0.0073	0.6685
	(0.0165)	(0.0248)		(0.0262)	(0.0405)	
High School graduate	0.0266	0.0409	0.5613	0.0031	-0.0085	0.6934
	(0.0158)	(0.0236)		(0.0241)	(0.0360)	
College graduate and beyond	-0.0892	-0.1557	0.1836	0.0191	-0.0420	0.1491
	(0.0267)	(0.0442)		(0.0300)	(0.0510)	
White	-0.0211	-0.0762	0.0038	0.0048	-0.0118	0.4967
	(0.0133)	(0.0196)		(0.0182)	(0.0261)	
Employed	-0.0399	-0.0665	0.2421	-0.0391	-0.0633	0.3914
	(0.0141)	(0.0207)		(0.0191)	(0.0280)	
Income/poverty line	-0.0009	-0.0015	0.0011	-0.0003	-0.0003	0.7260
	(0.0001)	(0.0002)		(0.0001)	(0.0002)	
Disabled	0.0466	0.0377	0.8699	0.1046	0.0022	0.0602
	(0.0451)	(0.0719)		(0.0629)	(0.0867)	
Rural	0.0275	0.0383	0.7132	0.0495	0.0682	0.5421
	(0.0167)	(0.0262)		(0.0278)	(0.0388)	
Reported public assistance receipt	0.2179	0.2077	0.6018	0.1934	0.2246	0.6295
	(0.0268)	(0.0432)		(0.0327)	(0.0590)	
Reported housing assistance receipt	0.1517	0.1999	0.1054	0.1378	0.1593	0.5765
	(0.0147)	(0.0243)		(0.0221)	(0.0364)	
Linear time trend	0.0039	0.0180	0.0606	-0.0002	0.0329	0.0190
	(0.0053)	(0.0079)		(0.0096)	(0.0164)	
Observations	2,981	2,151		808	640	
Joint significance test P-value			0.0000			0.0085

Notes: Delta-method standard errors in parentheses. Samples are pooled across all years (2002-2005). All analyses conducted using household weights adjusted for PIK probability. The unreported omitted family type is multiple adults with children, the age group is 40-49, the education group is some college, the race group is nonwhite, the employment group is not employed, and the geographic area is within MSA.

Table 12 – Food Stamp Receipt in Survey Data and Combined Data, SIPP, Probit Average Derivatives, Households with Income Less Than Twice the Poverty Line

	Illinois and Maryland pooled		
	Survey Food Stamp Measure	Administrative Food Stamp Measure	Equality Test p-value
Single, no children	0.0505	0.0329	0.4812
	(0.0223)	(0.0278)	
Single, with children	0.1262	0.1280	0.9065
	(0.0149)	(0.0185)	
Married, no children	0.0186	-0.0064	0.3635
	(0.0245)	(0.0307)	
Number of members under 18	0.0199	0.0052	0.1068
	(0.0065)	(0.0113)	
Number of members 18 or over	0.0155	-0.0121	0.0010
	(0.0074)	(0.0096)	
Number of members PIKed	0.0048	0.0281	0.0010
	(0.0036)	(0.0069)	
Age 16-29	0.0298	0.0210	0.6194
	(0.0159)	(0.0205)	
Age 30-39	0.0338	-0.0151	0.0044
	(0.0150)	(0.0188)	
Age 50-59	0.0112	-0.0269	0.0462
	(0.0171)	(0.0190)	
Age 60-69	-0.0039	-0.0075	0.8460
	(0.0175)	(0.0219)	
Age >=70	0.0080	0.0316	0.1894
	(0.0174)	(0.0206)	
Less than high school	0.0100	0.0077	0.8668
	(0.0122)	(0.0155)	
High School Graduate	0.0137	0.0387	0.0505
	(0.0114)	(0.0139)	
College Graduate and Beyond	-0.0223	0.0004	0.1326
	(0.0152)	(0.0187)	
White	-0.0767	-0.1069	0.0031
	(0.0100)	(0.0112)	
Employed	-0.0146	-0.0275	0.1796
	(0.0092)	(0.0112)	
Poverty Index	-0.0841	-0.1028	0.0505
	(0.0083)	(0.0100)	
Disabled	0.1220	0.1550	0.0134
	(0.0116)	(0.0143)	
Speaks no or poor English	0.0393	0.0814	0.0099
	(0.0138)	(0.0167)	
Rural	0.0386	0.0384	0.9877
	(0.0122)	(0.0160)	
Reported TANF receipt	0.1676	0.0883	0.0016
	(0.0244)	(0.0262)	
Reported housing assistance receipt	0.1522	0.1355	0.1913
	(0.0116)	(0.0132)	
2001	-0.0373	-0.0687	0.0153
	(0.0124)	(0.0152)	
2002	-0.0360	-0.0517	0.2540
	(0.0133)	(0.0164)	
2003	-0.0228	-0.0581	0.0144
	(0.0137)	(0.0180)	
2005	0.0188	-0.0207	0.0088
	(0.0167)	(0.0195)	
HH in Maryland	-0.0493	-0.0008	0.0011
	(0.0146)	(0.0161)	
Observations	4177	2973	
Joint significance test P-value			0.0000

Notes: Delta-method standard errors in parentheses. Samples include both states and are pooled across all years (IL: 10/2000-10/2004, MD: 10/2000-12/2003). All analyses conducted using household weights adjusted for PIK probability. The omitted family type is married with children, the omitted age category is 40-49, the omitted education category is some college and the omitted year is 2004.

Table 13 – Food Stamp Receipt in Survey Data and Combined Data Compared, with and without Imputed Observations, 2001 ACS, Probit Average Derivatives, Households with Income less than Twice the Poverty Line

	Illinois				Maryland			
	Difference with imputed (survey-admin)	Equality test p-value	Difference without imputed (survey-admin)	Equality test p-value	Difference with imputed (survey-admin)	Equality test p-value	Difference without imputed (survey-admin)	Equality test p-value
Single, no children	-0.0494	0.0901	-0.0470	0.1051	-0.0624	0.1685	-0.0728	0.1157
Single, with children	-0.0353	0.0941	-0.0438	0.0424	-0.0882	0.0294	-0.1085	0.0086
Multiple adults, no children	-0.0263	0.3628	-0.0447	0.1519	-0.0428	0.3601	-0.0553	0.2487
Number of members under 18	0.0254	0.0420	0.0196	0.1415	0.0175	0.2658	0.0233	0.1653
Number of members 18 or older	0.0228	0.0562	0.0227	0.0529	-0.0114	0.6115	-0.0254	0.2977
Number of members PIKed	-0.0547	0.0000	-0.0544	0.0000	-0.0447	0.0082	-0.0476	0.0082
Age 16-29	-0.0153	0.4209	-0.0253	0.2197	0.0133	0.6357	0.0167	0.5723
Age 30-39	0.0000	0.9956	-0.0209	0.3472	0.0068	0.8105	-0.0079	0.7884
Age 50-59	-0.0576	0.0245	-0.0538	0.0440	0.0060	0.8662	0.0217	0.5483
Age 60-69	-0.0338	0.2454	-0.0199	0.5427	-0.0154	0.6623	-0.0130	0.7232
Age >= 70	-0.0022	0.9656	0.0212	0.3037	0.0008	0.9984	0.0066	0.8646
Less than high school	-0.0039	0.7580	-0.0165	0.2863	-0.0350	0.0969	-0.0562	0.0114
High School graduate	-0.0079	0.5690	-0.0057	0.6594	-0.0380	0.1081	-0.0408	0.0941
College graduate and beyond	-0.0015	0.9905	0.0028	0.8972	0.0261	0.4343	0.0328	0.3433
White	0.0421	0.0053	0.0383	0.0153	0.0410	0.0204	0.0397	0.0333
Employed	-0.0163	0.2792	-0.0057	0.7497	-0.0410	0.0832	-0.0484	0.0533
Income/poverty line	0.0000	0.5801	0.0000	0.8840	0.0003	0.0338	0.0005	0.0002
Disabled	0.0132	0.4844	0.0043	0.9183	-0.0160	0.4667	-0.0190	0.4044
Disabled, not working	0.0185	0.3507	0.0165	0.4215	-0.0372	0.1086	-0.0367	0.1327
Speaks English only	-0.0507	0.0048	-0.0533	0.0041	-0.0056	0.8855	-0.0248	0.4957
Rural	-0.0165	0.2486	-0.0134	0.3731	0.0008	0.9462	0.0070	0.6907
Reported public assistance receipt	0.0803	0.0197	0.0584	0.0969	-0.0708	0.1119	-0.0974	0.0279
Reported housing assistance receipt	-0.0350	0.0457	-0.0489	0.0068	-0.0316	0.1356	-0.0394	0.0644
Chi-square test of equality	84.94	0.0000	105.59	0.0000	52.68	0.0004	72.23	0.0000

Notes: Delta-method standard errors in parentheses. All analyses conducted using household weights adjusted for PIK probability. The unreported omitted family type is multiple adults with children, the age group is 40-49, the education group is some college, the race group is nonwhite, the employment group is not employed, and the geographic area is within MSA.

Table 14 – Food Stamp Receipt in Survey Data and Combined Data Compared, with and without Imputed Observations, 2001 CPS, Probit Average Derivatives, Households with Income less than Twice the Poverty Line

	Illinois				Maryland			
	Difference with imputed (survey-admin)	Equality test p-value	Difference without imputed (survey-admin)	Equality test p-value	Difference with imputed (survey-admin)	Equality test p-value	Difference without imputed (survey-admin)	Equality test p-value
Single, no children	-0.0120	0.7372	-0.0043	0.9046	-0.0458	0.4302	-0.0193	0.7301
Single, with children	-0.0786	0.0164	-0.0652	0.0555	-0.0642	0.1847	-0.0486	0.3169
Multiple adults, no children	-0.0472	0.1803	-0.0547	0.1142	-0.0744	0.1533	-0.0514	0.3028
Number of members under 18	-0.0197	0.1745	-0.0170	0.2500	-0.0268	0.3562	-0.0245	0.4055
Number of members 18 or older	-0.0082	0.4445	-0.0100	0.3328	-0.0306	0.0725	-0.0270	0.0869
Age 16-29	0.0267	0.3634	0.0155	0.6204	0.0342	0.3599	0.0293	0.4319
Age 30-39	-0.0158	0.5257	-0.0100	0.6845	-0.0242	0.5404	-0.0285	0.4558
Age 50-59	-0.0271	0.4431	-0.0302	0.3836	-0.0133	0.7735	-0.0179	0.6789
Age 60-69	0.0515	0.1389	0.0568	0.1007	0.0424	0.3747	0.0226	0.6237
Age >= 70	0.0266	0.5931	0.0317	0.4952	0.0961	0.0714	0.0860	0.0964
Less than high school	0.0048	0.7299	-0.0063	0.8844	-0.0129	0.6685	-0.0159	0.5944
High School graduate	-0.0143	0.5613	-0.0138	0.5754	0.0116	0.6934	0.0005	0.9914
College graduate and beyond	0.0665	0.1836	0.0431	0.4246	0.0611	0.1491	0.0442	0.2782
White	0.0551	0.0038	0.0486	0.0103	0.0166	0.4967	0.0159	0.5070
Employed	0.0266	0.2421	0.0269	0.2391	0.0242	0.3914	0.0178	0.5114
Income/poverty line	0.0006	0.0011	0.0006	0.0009	0.0000	0.7260	0.0000	0.7191
Disabled	0.0089	0.8699	0.0046	0.9226	0.1024	0.0602	0.0677	0.2960
Rural	-0.0108	0.7132	-0.0148	0.5668	-0.0187	0.5421	-0.0149	0.6224
Reported public assistance receipt	0.0102	0.6018	0.0106	0.5924	-0.0312	0.6295	-0.0472	0.3745
Reported housing assistance receipt	-0.0482	0.1054	-0.0409	0.1878	-0.0215	0.5765	-0.0193	0.6110
Linear time trend	-0.0141	0.0606	-0.0111	0.1429	-0.0331	0.0190	-0.0281	0.0448
Chi-square test of equality	62.10	0.0000	58.35	0.0000	39.52	0.0085	39.72	0.0079

Notes: Delta-method standard errors in parentheses. Samples are pooled across all years (2002-2005). All analyses conducted using household weights adjusted for PIK probability. The unreported omitted family type is multiple adults with children, the age group is 40-49, the education group is some college, the race group is nonwhite, the employment group is not employed, and the geographic area is within MSA.

Table 15 – Food Stamp Receipt in Survey Data and Combined Data Compared, with and without Imputed Observations, SIPP, Probit Average Derivitives, Households with Income Less Than Twice the Poverty Line

	Illinois and Maryland pooled			
	Difference with imputed (survey-admin)	Equality test p-value	Difference without imputed (survey-admin)	Equality test p-value
Married, no children	0.0250	0.3635	0.0046	0.8717
Single, no children	0.0176	0.4812	0.0141	0.5861
Single, with children	-0.0018	0.9065	-0.0064	0.7171
Number of members under 18	0.0147	0.1068	0.0149	0.1017
Number of members 18 or over	0.0276	0.0010	0.0279	0.0032
Number of members PIKed	-0.0233	0.0010	-0.0254	0.0004
Age 16-29	0.0088	0.6194	0.0154	0.3949
Age 30-39	0.0489	0.0044	0.0462	0.0078
Age 50-59	0.0381	0.0462	0.0430	0.0322
Age 60-69	0.0036	0.8460	-0.0051	0.7890
Age >=70	-0.0236	0.1894	-0.0143	0.4348
Less than high school	0.0023	0.8668	0.0060	0.6664
High School Graduate	-0.0250	0.0505	-0.0184	0.1602
College Graduate and Beyond	-0.0227	0.1326	-0.0179	0.2303
White	0.0302	0.0031	0.0380	0.0003
Employed	0.0129	0.1796	0.0119	0.2114
Poverty Index	0.0187	0.0505	0.0144	0.1317
Disabled	-0.0330	0.0134	-0.0320	0.0230
Speaks no or poor English	-0.0421	0.0099	-0.0497	0.0014
Rural	0.0002	0.9877	-0.0060	0.6644
Reported TANF receipt	0.0793	0.0016	0.0793	0.0009
Reported housing assistance receipt	0.0167	0.1913	0.0098	0.4362
2001	0.0314	0.0153	0.0262	0.0470
2002	0.0157	0.2540	0.0192	0.1572
2003	0.0353	0.0144	0.0363	0.0156
2005	0.0395	0.0088	0.0337	0.0280
HH in Maryland	-0.0485	0.0011	-0.0502	0.0005
Chi-square test of equality	79.28	0.0000	79.21	0.0000

Notes: Samples include both states and are pooled across all years (IL: 10/2000-10/2004, MD: 10/2000-12/2003). All analyses conducted using household weights adjusted for PIK probability. The omitted family type is married with children, the omitted age category is 40-49, the omitted education category is some

Appendix Table 1 – The Determinants of a Household having a PIK, ACS, Probit Average Derivatives

	Illinois	Maryland
Single, no children	-0.0124	-0.0032
	(0.0119)	(0.0169)
Single, with children	0.0215	0.0039
	(0.0122)	(0.0138)
Multiple adults, no children	0.0032	0.0115
	(0.0126)	(0.0166)
Number of members under 18	0.0243	0.0207
	(0.0053)	(0.0076)
Number of members 18 or older	0.0322	0.0219
	(0.0047)	(0.0052)
Age 16-29	-0.0130	0.0240
	(0.0084)	(0.0104)
Age 30-39	-0.0084	-0.0027
	(0.0080)	(0.0087)
Age 50-59	0.0065	0.0080
	(0.0082)	(0.0089)
Age 60-69	-0.0022	0.0152
	(0.0092)	(0.0104)
Age >= 70	-0.0192	0.0187
	(0.0093)	(0.0106)
Less than high school	-0.0000	-0.0184
	(0.0075)	(0.0100)
High School graduate	0.0052	-0.0172
	(0.0064)	(0.0084)
College graduate and beyond	0.0071	-0.0220
	(0.0065)	(0.0075)
Hispanic	-0.0435	-0.0782
	(0.0104)	(0.0151)
Black	-0.0298	-0.0082
	(0.0075)	(0.0071)
Other	-0.0710	-0.0779
	(0.0107)	(0.0113)
Unemployed	-0.0101	0.0023
	(0.0125)	(0.0158)
Not in the labor force	-0.0019	-0.0243
	(0.0066)	(0.0080)
Income/poverty line	0.0000	0.0000
	(0.0000)	(0.0000)
Disabled	-0.0119	0.0165
	(0.0067)	(0.0090)
Disabled, not working	-0.0080	-0.0048
	(0.0081)	(0.0091)
Speaks English only	0.0162	-0.0048
	(0.0092)	(0.0111)
Speaks English poorly	0.0097	-0.0107
	(0.0110)	(0.0141)
Non-U.S. Citizen	-0.0300	0.0055
	(0.0102)	(0.0123)
Rural	0.0142	-0.0042
	(0.0077)	(0.0078)
Reported housing assistance receipt	-0.0106	0.0110
	(0.0106)	(0.0125)
Observations	21,957	9,996

Notes: Delta-method standard errors in parentheses. All specifications also include controls for mode of interview (mail-back, CATI, CAPI). All analyses conducted using household weights. For the false negative probits, the unreported omitted family type is multiple adults with children, the education category is some college, the age category is 40-49, the employment category is employed, the race group is non-Hispanic white, and the geographic area is within-MSA.

Appendix Table 2 – The Determinants of a Household Having a PIK, CPS, Probit Average Derivatives

	Illinois	Maryland
Single, no children	-0.2860	-0.1697
	(0.0263)	(0.0447)
Single, with children	-0.0269	-0.0648
	(0.0252)	(0.0393)
Multiple adults, no children	-0.2737	-0.1307
	(0.0230)	(0.0398)
Number of members under 18	0.0610	0.0553
	(0.0118)	(0.0217)
Number of members 18 or over	0.0248	0.0034
	(0.0089)	(0.0129)
Age 16-29	-0.0282	-0.0098
	(0.0165)	(0.0271)
Age 30-39	-0.0034	-0.0219
	(0.0148)	(0.0235)
Age 50-59	-0.0168	-0.0448
	(0.0149)	(0.0224)
Age 60-69	-0.0380	-0.0318
	(0.0178)	(0.0277)
Age >= 70	-0.0322	-0.0343
	(0.0190)	(0.0291)
Less than high school	-0.0194	0.0257
	(0.0165)	(0.0252)
High School graduate	-0.0299	-0.0270
	(0.0123)	(0.0203)
College graduate and beyond	-0.0071	-0.0274
	(0.0128)	(0.0196)
Hispanic	-0.0268	-0.1032
	(0.0157)	(0.0290)
Black	0.0428	-0.0150
	(0.0126)	(0.0154)
Other	0.0537	-0.0056
	(0.0237)	(0.0345)
Unemployed	0.0702	0.0045
	(0.0246)	(0.0524)
Not in labor force	0.0223	-0.0158
	(0.0133)	(0.0212)
Poverty index	0.0000	0.0000
	(0.0000)	(0.0000)
Disabled	0.0172	0.1547
	(0.0456)	(0.0805)
Rural	0.0922	0.0828
	(0.0151)	(0.0278)
Reported housing assistance receipt	0.1844	0.0481
	(0.0278)	(0.0320)
Linear time trend	-0.0307	-0.0484
	(0.0041)	(0.0084)
Observations	10,836	3,744

Notes: Delta-method standard errors in parentheses. Samples are pooled across all years for both states (IL:2002-2005, MD:2002-2004). All analyses conducted using household weights. The unreported omitted family type is multiple adults with children, the age category is 40-49, the education category is some college, the employment category is employed, the race group is non-Hispanic white, and the geographic area is within-MSA.

Appendix Table 3 – The Determinants of a Household Having A PIK, SIPP 01 and 04 Panel, Probit Average Derivatives

	2001: IL and MD pooled	2004: IL only
Single, no children	-0.0503	-0.0391
	(0.0217)	(0.0226)
Single, with children	-0.0329	-0.0105
	(0.0191)	(0.0164)
Married, no children	-0.0665	0.0618
	(0.0215)	(0.0235)
Number of members under 18	-0.0399	0.0090
	(0.0084)	(0.0094)
Number of members 18 or over	0.0357	0.0239
	(0.0067)	(0.0064)
Age 16-29	0.1237	-0.0293
	(0.0200)	(0.0137)
Age 30-39	-0.0120	0.0227
	(0.0150)	(0.0143)
Age 50-59	0.0059	-0.0049
	(0.0151)	(0.0143)
Age 60-69	-0.0275	0.0667
	(0.0185)	(0.0198)
Age >=70	0.0232	-0.0458
	(0.0201)	(0.0150)
Less than high school	-0.0690	-0.0428
	(0.0168)	(0.0147)
High School Graduate	-0.0700	-0.0376
	(0.0130)	(0.0117)
College Graduate and Beyond	-0.0176	-0.0354
	(0.0135)	(0.0121)
White	0.0234	0.0359
	(0.0133)	(0.0107)
Employed	0.0676	-0.0050
	(0.0141)	(0.0102)
Poverty Index	0.0007	0.0046
	(0.0012)	(0.0027)
Disabled	-0.0024	-0.0111
	(0.0183)	(0.0154)
Speaks no or poor English	-0.0117	-0.0544
	(0.0144)	(0.0190)
Non-U.S. Citizen	0.0790	-0.0517
	(0.0242)	(0.0171)
Rural	-0.1061	0.0148
	(0.0128)	(0.0124)
Reported receipt of any transfers	0.0815	0.0048
	(0.0157)	(0.0133)
Reported housing assistance receipt	0.0906	0.0898
	(0.0288)	(0.0286)
HH in Maryland	-0.0026	omitted
	(0.0112)	
Observations	10,354	4,486

Notes: Delta-method standard errors in parenteses. All analyses conducted using household weights. The omitted family type is married with children, the omitted age category is 40-49 and the omitted education category is some college. 2004 contains only HH from IL, so the MD dummy is omitted.

Appendix Table 4 – Summary Statistics, 2001 ACS, PIKed Households with Income Less than Twice the Poverty Lin

	Illinois			Maryland		
Variable	Mean	Standard Deviation	Sample Size	Mean	Standard Deviation	Sample Size
Number of members PIKed	2.1410	1.4885	4,146	2.1357	1.4431	1,799
Administrative food stamp receipt	0.2432	0.4291	4,146	0.2323	0.4224	1,799
Number of months of food stamp receipt	9.1006	4.1855	789	8.9877	4.2661	344
ACS-reported food stamp receipt	0.2035	0.4027	4,146	0.1745	0.3797	1,799
Food stamp receipt imputed	0.0512	0.2205	4,146	0.0426	0.2020	1,799
Administrative TANF receipt	0.0634	0.2438	4,146	0.0787	0.2694	1,799
ACS-reported public assistance receipt	0.0601	0.2377	4,146	0.0565	0.2310	1,799
ACS-reported housing assistance receipt	0.1429	0.3500	4,146	0.1732	0.3785	1,799
Single, no children	0.5227	0.4995	4,146	0.5515	0.4975	1,799
Single, with children	0.1944	0.3958	4,146	0.2258	0.4182	1,799
Multiple adults, no children	0.1263	0.3323	4,146	0.1046	0.3062	1,799
Multiple adults, with children	0.1566	0.3635	4,146	0.1180	0.3227	1,799
Number of members under 18	0.8757	1.3459	4,146	0.8510	1.3016	1,799
Number of members over 18	1.5941	0.8070	4,146	1.4988	0.7065	1,799
Rural	0.1852	0.3885	4,146	0.1286	0.3349	1,799
Income/poverty line	111.67	56.62	4,146	114.14	55.63	1,799
Age 17-29	0.2034	0.4025	4,146	0.1699	0.3756	1,799
Age 30-39	0.1796	0.3839	4,146	0.1896	0.3921	1,799
Age 40-49	0.1677	0.3736	4,146	0.1655	0.3717	1,799
Age 50-59	0.1134	0.3171	4,146	0.1157	0.3199	1,799
Age 60-69	0.1112	0.3144	4,146	0.1316	0.3381	1,799
Age >= 70	0.2249	0.4176	4,146	0.2278	0.4195	1,799
Age>=50	0.4494	0.4975	4,146	0.4751	0.4995	1,799
Less than high school	0.3436	0.4750	4,146	0.3330	0.4714	1,799
High school	0.3264	0.4690	4,146	0.3409	0.4741	1,799
Some college	0.2298	0.4207	4,146	0.2319	0.4222	1,799
College graduate and beyond	0.1002	0.3003	4,146	0.0942	0.2922	1,799
Male	0.4043	0.4908	4,146	0.3585	0.4797	1,799
Non-Hispanic white	0.5762	0.4942	4,146	0.5149	0.4999	1,799
Noncitizen	0.1113	0.3145	4,146	0.0631	0.2433	1,799
Speaks English only	0.7738	0.4184	4,146	0.8836	0.3208	1,799
Employed	0.4263	0.4946	4,146	0.3967	0.4894	1,799
Unemployed	0.0676	0.2511	4,146	0.0674	0.2508	1,799
Not in labor force	0.5061	0.5000	4,146	0.5359	0.4988	1,799
Disabled	0.3038	0.4599	4,146	0.3475	0.4763	1,799
Disabled, not working	0.1790	0.3834	4,146	0.2018	0.4015	1,799
CATI	0.0927	0.2900	4,146	0.0962	0.2949	1,799
CAPI	0.4625	0.4987	4,146	0.4138	0.4927	1,799
Mail-back	0.4448	0.4970	4,146	0.4900	0.5000	1,799

Notes: All analyses conducted using household weights corrected for PIK probability. Reported demographic characteristics are for the household head.

Appendix Table 5 – Summary Statistics, CPS, PIKed Households with Income Less than Twice the Poverty Li

	Illinois			Maryland		
	Mean	Standard Deviation	Sample Size	Mean	Standard Deviation	Sample Size
Number of members PIKed	2.0670	1.4670	2,151	1.8763	1.3195	640
Administrative food stamp receipt	0.2744	0.4463	2,151	0.1721	0.3777	640
Number of months of food stamp receipt	9.4111	3.3482	689	8.7004	4.0234	136
CPS-reported food stamp receipt	0.1947	0.3960	2,151	0.1175	0.3223	640
Food Stamp receipt imputed	0.0963	0.2951	2,151	0.0793	0.2704	640
Administrative TANF receipt	0.0416	0.1998	2,151	0.0482	0.2144	640
CPS-reported public assistance receipt	0.0415	0.1995	2,151	0.0349	0.1838	640
CPS-reported housing assistance receipt	0.1348	0.3416	2,151	0.1713	0.3771	640
Single adult, no children	0.4194	0.4936	2,151	0.4861	0.5002	640
Single adult, with children	0.1358	0.3426	2,151	0.1143	0.3184	640
Multiple adults, no children	0.2014	0.4011	2,151	0.2119	0.4090	640
Multiple adults, with children	0.2435	0.4293	2,151	0.1877	0.3907	640
Number of members under 18	0.8709	1.3472	2,151	0.6069	1.0789	640
Number of members over 18	1.5845	0.7965	2,151	1.5087	0.7572	640
Rural	0.2118	0.4087	2,151	0.0653	0.2472	640
Income/poverty line	116.93	54.61	2,151	116.35	56.57	640
Age 17-29	0.1775	0.3821	2,151	0.1220	0.3275	640
Age 30-39	0.1821	0.3860	2,151	0.1614	0.3682	640
Age 40-49	0.1467	0.3539	2,151	0.1442	0.3516	640
Age 50-59	0.1041	0.3055	2,151	0.1370	0.3441	640
Age 60-69	0.1331	0.3397	2,151	0.1151	0.3195	640
Age >= 70	0.2565	0.4368	2,151	0.3203	0.4670	640
Age >= 50	0.4937	0.5001	2,151	0.5724	0.4951	640
Less than high school	0.3024	0.4594	2,151	0.2827	0.4507	640
High school graduate	0.3658	0.4818	2,151	0.3921	0.4886	640
Some college	0.2255	0.4180	2,151	0.1744	0.3798	640
College graduate and beyond	0.1063	0.3083	2,151	0.1508	0.3581	640
Male	0.3912	0.4881	2,151	0.3939	0.4890	640
Non-Hispanic white	0.5917	0.4916	2,151	0.6033	0.4896	640
Employed	0.3894	0.4877	2,151	0.3707	0.4834	640
Unemployed	0.0517	0.2215	2,151	0.0372	0.1894	640
Not in labor force	0.5588	0.4966	2,151	0.5921	0.4918	640
Disabled	0.0113	0.1055	2,151	0.0129	0.1130	640
Linear time trend	3.5455	1.1136	2,151	3.0543	0.8323	640

Notes: All analyses conducted using household weights corrected for PIK probability. Samples are pooled across all years for both states (IL:2002-2005, MD:2002-2004). Reported demographic characteristics are for the household head.

Appendix Table 6 – Summary Statistics, SIPP, PIKed Households with Income Less Than Twice the Povert
Line

	IL and MD Pooled		
	Mean	Standard Deviation	Sample Size
Number of members PIKed	2.0982	1.4857	2,973
Administrative Food Stamp Receipt	0.1819	0.3859	2,973
Number of months of aministrative FS receipt	0.6652	1.4502	2,973
Number of months since last administrative FS receipt	3.5746	1.0286	2,973
Reported FS receipt	0.1861	0.3892	2,973
FS receipt imputed	0.0737	0.2614	2,973
Administrative TANF receipt	0.0284	0.1661	2,973
Reported TANF receipt	0.0357	0.1855	2,973
Reported receipt of any transfers	0.4397	0.4964	2,973
Reported housing assistance receipt	0.1216	0.3269	2,973
Single, no children	0.4884	0.4999	2,973
Single, with children	0.1926	0.3944	2,973
Married, no children	0.1262	0.3321	2,973
Married, with children	0.1928	0.3946	2,973
Number of members under 18	0.8038	1.2485	2,973
Number of members 18 or over	1.6384	0.8266	2,973
Rural	0.1681	0.3740	2,973
Poverty Index	1.1575	-0.5678	2,973
Age of reference person	53.2478	19.2355	2,973
Age 16-29	0.1254	0.3313	2,973
Age 30-39	0.17	0.38	2,973
Age 50-59	0.1461	0.3533	2,973
Age 60-69	0.1187	0.3235	2,973
Age >=70	0.2613	0.4394	2,973
Less than high school	0.2476	0.4317	2,973
High School Graduate	0.3477	0.4763	2,973
Some College	0.2384	0.4262	2,973
College Graduate and Beyond	0.1664	0.3725	2,973
Reference Person male	0.3913	0.4881	2,973
White	0.7057	0.4558	2,973
Non-U.S. Citizen	0.0692	0.2538	2,973
Speaks no or poor English	0.1328	0.3394	2,973
Disabled	0.1820	0.3859	2,973
Employed	0.4447	0.4970	2,973
Number of members interviewed	1.1218	0.3942	2,973
No interview with reference person	0.1245	0.3303	2,973
Interview with someone who did not have a PIK	0.0737	0.2614	2,973
HH had bad data record	0.4704	0.4992	2,973
Reference Person had bad data record	0.1575	0.3644	2,973
2001	2.6756	1.2913	2,973
2002	0.2478	0.4318	2,973
2003	0.2281	0.4196	2,973
2004	0.2016	0.4012	2,973
2005	0.2458	0.4306	2,973
HH in Maryland	0.0767	0.2662	2,973

Notes: Samples include both states and are pooled across all years (IL: 10/2000-10/2004, MD: 10/2000-12/2003). All analyses conducted using household weights corrected for PIK probability. Reported demographic characteristics are for the household head.

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I. Introduction

Measuring government benefit receipt in household surveys is important to assess the economic circumstances of disadvantaged populations, program takeup, the distributional effects of government programs, and other program effects. The Food Stamp Program (FSP, now SNAP) is especially important given its large and growing size and findings of its effects on health, labor supply, food security, consumption and other outcomes.[1] Recognizing that surveys may have errors, this study examines the misreporting of Food Stamp Program (FSP) benefits using a unique linkage of administrative microdata to three major survey datasets. We examine rates of misreporting and how misreporting varies with household characteristics. We test theories of misreporting and examine the success of different survey methods. We then examine how misreporting affects estimates of program receipt. We also directly examine biases due to one source of error, imputed observations.

There is growing evidence that program receipt is badly reported in household surveys. The most extensive and frequently cited evidence compares weighted totals of dollars or recipients in household surveys to analogous figures provided by government agencies. The most comprehensive study of this form is Meyer, Mok and Sullivan (2009) which provides many cites to earlier studies.[2] They find in the vast majority of cases substantial net underreporting of program receipt that has often been growing sharply over time. A common criticism of these aggregate studies is that they cannot separately distinguish false positive and false negative reporting since they identify net under-reporting. The results are also potentially biased by errors in the sample design or weighting. Furthermore, such aggregate studies have a limited ability to use interview and respondent characteristics to identify the determinants of misreporting and correct the problem.

Linking of survey and administrative microdata provides a potential solution to these limitations. Unfortunately, surveys of the literature have noted that there are very few of the "complete record check" studies that are needed to assess false positive reports

[1] See Hoynes and Schanzenbach (2009), Almond, Hoynes and Schanzenbach (2011), and Schmidt, Shore-Sheppard and Watson (2012) for example.
[2] Also see Coder and Scoon-Rogers (1996), Roemer (2000), and Wheaton (2007).

and net reporting of receipt (Bound et al. 2001). The few studies that do complete record checks tend to suffer from small sample sizes and are often specialized to a single state and survey. In addition, the record linkage they rely on may be inaccurate and they are rarely able to correct for imperfect linkage or analyze possible biases that might result from linkage problems.

In this study we link administrative data on food stamp receipt from two states to three of the most important economic surveys, the Current Population Survey (CPS), the American Community Survey (ACS) and the Survey of Income and Program Participation (SIPP). The CPS is the most used labor economics survey and the source of our official income and poverty statistics. The ACS replaces the Census long form data and is the largest general household survey, allowing fine geographic analyses. The SIPP is the most detailed survey of program receipt and commonly thought to have the highest quality data. The Social Security Numbers on the food stamp records that we use have been verified (compared to SSA records) as a necessary condition for receipt of benefits, so the accuracy of the match is very high. We also analyze likely biases do to linkage error.

We find substantial under-reporting of food stamp receipt, with a quarter to half of true recipient households not recorded as such. As well as these false negatives, we also examine the rate of false positives. We find that a substantial, but much smaller share of nonrecipients are recorded as receiving food stamps. Since most households are nonrecipients, these false positives can have a substantial effect on net reporting. A large share of these false positives, but never a majority, are imputed observations. Both false negatives and false positives are associated with a variety of household and interview characteristics. We also find large differences across the three surveys in false negative and false positive rates.

Our results on the determinants of errors allow the partial testing of theories of misreporting. We are able to provide evidence on the role of stigma, salience, complicated patterns of receipt, and other explanations that have been suggested in the literature. The results presented in this paper also provide an informative assessment of survey quality and should guide the improvement of household surveys. There are very few variables in household surveys for which we can obtain independent and accurate measures to evaluate survey quality, but program receipt is one such variable.

In their review, Bound et al. (2001) note that little work has examined the consequences of program receipt reporting errors for substantive analyses.[3] Since we find high error rates that are correlated with covariates, many types of analyses should be affected, i.e. biased by program misreporting. Conceptually, program receipt is both an important dependent and explanatory variable. Program receipt is also important in the analysis of distributions such as income. Substantively, erroneous program receipt will affect studies of who receives benefits and why they do, and studies of program effects on labor supply, health, consumption and other outcomes. The role programs play in reducing poverty and otherwise altering the income distribution will also be biased. In our empirical application, we focus on showing the nature and extent of bias for a dependent variable, program takeup.

The use of government programs is examined in a large literature that relies on potentially error-ridden self-reports of program receipt.[4] For example, the survey data we show to suffer from substantial error was used in several recent studies that examined the likelihood that those eligible for food stamps participated in the program (Blank and Ruggles, 1996; Gundersen and Oliveira, 2001; Wu, 2010).

Takeup studies typically show that participation rates among eligibles are well below one. However, given the extent of underreporting, a major part of what appears to be non-participation may actually be recipients whose receipt is not recorded in the household survey. A better understanding of underreporting and how it may bias takeup estimates has important implications for both policy makers and researchers. Accurate estimates of program receipt are needed to know who is benefiting from programs, why families choose not to participate in certain programs, and how individual characteristics affect participation. Such information can be used to increase takeup and better target programs to the most needy an issue that has long concerned policy makers (see U.S. GAO, 2004 for efforts to raise food stamp participation). However, we find that misreporting leads to biased estimates of the determinants of program receipt and

[3] Notable exceptions include Bollinger and David (1997, 2001).
[4] For excellent reviews of research on takeup of food stamps and other programs see Remler and Glied (2003) and Currie (2006).

policies based on the findings from survey data may therefore be misguided. Our linked data indicate…

Our results also suggest biases in studies of other program effects such as those where program receipt is used as an explanatory variable in a regression. The bias due to an explanatory variable with classical measurement errors (that are uncorrelated with truth and with other explanatory variables) is a well-known standard result. However, here we show that the errors of measurement are correlated with the true values as well as with a range of explanatory variables. This non-classical form of the errors means that the bias will take a complicated form. In addition, instrumental variable methods will not provide consistent estimates.[5]

Misreporting will also bias studies of the distributional consequences of transfer programs. Studies that examine the extent to which food stamps increase the resources of poor families will understate the impact of the FSP when there is underreporting. In addition, correcting for underreporting bias will yield better measures of the well-being of the disadvantaged. There is a very large literature examining the distributional consequences of welfare and social insurance programs, yet very few studies attempt to account for misreporting.[6] We also examine the related problem of item non-response and whether the imputations provided by the Census Bureau improve analyses with the data. We find that non-response is related to both observed covariates and true values given covariates, which rejects the common assumption that values are missing (conditionally) at random. Furthermore, the distribution of imputed values is far from the true distribution. In terms of their effects on estimates of the determinants of program participation, the imputations in the ACS reduce the bias from non-random non-response, while the imputations in the CPS and SIPP have almost no effect on the estimates.

In the following section, we briefly summarize the main theories of misreporting in surveys, focusing on ideas applicable to program receipt. We then summarize past work on the misreporting of government transfers, emphasizing food stamp misreporting. In Section IV, we describe our data sources and matching. Section V provides our main evidence on misreporting while Section VI analyzes how misreporting varies with

[5] Bound et al. (2001) discuss a version of this argument.

[6] For example, Wheaton (2007), Scholz, Moffitt and Cowan (2008), and Meyer (2010) employ rough adjustments to account for program misreporting.

household characteristics. Section VII shows that misreporting affects our understanding of program receipt. In Section VIII we analyze imputation and the use of imputed data, and conclusions are offered in Section IX.

II. Theories of Misreporting

In this section, we briefly review the main theories of misreporting. In their review of the literature, Sudman and Bradburn (1974) point out the lack of a general theory of reasons for misreporting in surveys. Along the same lines, Bound, Brown and Mathiowetz (2001) note that few fundamental principles have been established in the literature. With this backdrop, we follow the Bound et al. (2001) framework which divides reasons for misreporting into three areas: cognitive processes, social desirability and essential survey conditions.

The cognitive process of answering a question is typically broken into four steps: comprehension of the question, retrieval of the information from memory, comparison of the retrieved and requested information, and communicating the result. Issues that may lead to misreporting include difficulty understanding questions, difficulty encoding information in memory or retrieving it, and lack of salience of information (see Sudman, Bradburn and Schwarz, 1996, for a review). If problems of understanding are an important factor causing misreporting, we would expect misreporting to be less common among the more educated and more prevalent among respondents with limited English proficiency.

Much of the empirical measurement error literature has focused on recall and retrieval problems. One of the central precepts in this literature is that a longer recall period leads to more errors. Though we should note that some recent studies have found no effect of the length of the recall period on the degree of response errors (e.g. Marquis and Moore, 1990, who analyse the receipt of food stamps and other programs) and other evidence on this relationship is far from conclusive. Bound, Brown and Mathiowetz (2001) suggest that rather than the mere passage of time, the complexity of the experience over time is related to misreporting. Thus, households with irregular or infrequent receipt should be more likely to fail to report. Since the frequency of receipt differs across households, this hypothesis is potentially testable. Another precept in this literature is that more salient events are more easily remembered. Sometimes though it has been found that high salience can lead to overreporting.

The length of the recall period also tends to affect whether has an impact on the way in which respondents fail to accurately recall when an event happened. According to the some early studiesempirical evidence, a short recall periods leads respondents to report events that have occurred before the reference period and thus leads to overreporting. On the other hand, a long recall periods isare associated with underreporting, because respondents tend to report events as having occurred earlier than they trulyreally occurred.

The second class of reasons for misreporting is the influence of social desirability. Social desirability refers to a tendency of respondents to report socially desirable answers whether or not they are true. The economic literature has mainly focused on the failure to report receipt of government programs due to the social stigma of dependence on government programs. This idea suggests underreporting among those with high income and education for whom welfare receipt seems more out of place, and we would also expect underreporting due to stigma to be more prevalent among the elderly, the employed, two-parent families, and the childless, all of whom may seem less needy. The accuracy of survey data is also affected by features of the survey design such as the survey mode and method (see Groves 1989 for a review). Characteristics of the interviewer and the emphasis of the survey may matter. Different surveys have different foci, and it would be surprising if the topics stressed by a particular survey were not done with greater care (and thus greater accuracy) than other elements. Some respondents may be more cooperative than others, as Bollinger and David (2001) have emphasized in their analysis of misreporting and attrition. If respondent cooperativeness is an important factor, we might expect respondents who are unwilling to answer certain questions to provide less accurate answers to the questions they do answer. Proxy respondents may also be less accurate .The survey design may also affect the accuracy of the data in mechanical ways through the coding and editing process. Given the high rates of item non-response in some household surveys, the imputation methods employed by the survey can be another important source of error.

We might add a more economic theory of the interview. Both interviewer and respondent face a time constraint. Often surveys are so long that complete answers would be very costly for both parties to produce. This situation may lead portions of the interview to be done in a cursory way or skipped after screening questions are answered in a way to avoid further questions. Similarly, to save time, the interviewer may pursue questions about certain sources of income more for some respondents than others based on their perceived likelihood of receipt.

III. Previous Evidence on the Extent and Nature of Misreporting

Several studies have documented significant misreporting of transfer program income in survey data. Bound, Brown and Mathiowetz (2001) as well as Moore, Stinson and Welniak (2000) provide reviews of the literature up to 2001, so this summary will focus on their main conclusions and newer studies. We are concerned with the reporting of whether a program was received rather than the amount reported. While the evidence on the reporting of amounts is scant, there is some evidence that the main determinant of the degree of underreporting is whether receipt is reported at all (Moore, Marquis and Bogen, 1996, Moore, Stinson and Welniak 2000, Meyer, Mok and Sullivan 2009).

There are three main approaches to assess the validity of survey reports: comparisons of survey aggregates to administrative totals, partial validation studies and full validation studies. Comparisons of aggregate survey reports to administrative totals show that the survey reports generally fall substantially short of actual program spending, (see Meyer, Mok and Sullivan, 2009 and the many earlier studies that they cite). The rate of net underreporting found tends to differ sharply across programs and surveys and has tended to rise over time. However, these results are potentially biased if weighting does not correct for any problems of undercoverage or non-response. Probably more importantly, these studies cannot provide information on the extent to which false negatives are counterbalanced by false positive reports. In addition, the literature on the causes of misreporting suggests that the propensity to misreport depends on household and interview characteristics that cannot usually be examined with aggregate data. Thus, comparisons to aggregates can only provide very limited information about the factors that are associated with misreporting. Aggregate data cannot be used to assess bias in applications using multivariate data or to devise sophisticated corrections for the bias in such analyses. Consequently, while these studies provide an important indicator of survey problems, more information is needed to examine the causes and consequences of misreporting.

Validation studies, which most commonly link survey and administrative data, can provide this additional information. Most early validation studies were partial design studies, since they only examined the survey response of known program recipients. While these studies can provide evidence on the false negative rates and the characteristics associated with failure to report receipt, they cannot examine false positive reporting. Consequently, they only allow inference about net reporting rates under the assumption that the effect of false positives is negligible. Marquis et al. (1981) as well as Moore, Stinson and Welniak (2000) review the findings of this literature. They show substantial false negative rates that differ considerably across programs and studies. Both reviews argue that the literature has overemphasized the social undesirability of program receipt as the main problem in the reporting of government programs in part because the partial design studies emphasize under-reporting because that is what they are able to capture.

This line of argument leads both Moore, Stinson and Welniak (2000) and Bound, Brown and Mathiowetz (2001) to call for further complete design studies that validate the reports of both recipients and non-recipients so that both types of error can be examined. The main hurdle to direct matching of survey and administrative microdata at the individual or household level is the rarity of such matches. When matched data are available, they are typically only for a short time period and for a small subset of the survey respondents, such as those from a single state. However, such studies have provided important additional insights about misreporting and have challenged the notion that the net effect of misreporting of transfer programs is negative. Past food stamp validation studies have found substantial rates of false negative reports, for example, 20 percent of true recipients are not recorded as such in the 1984 SIPP (Marquis and Moore 1990) and 40 percent are not in the Maryland sample of the 2001 predecessor of the American Community Survey (Taeuber et al. 2004). There are large differences in the false negative rates across these studies and the fact that they tend to focus on a single survey and often one state leaves open the question whether the differences in these rates are due state or survey.

As to false positive reports or receipt by true nonrecipientsAcross programs besides food stamps, these complete validation studies also agree on the finding that false positive rates are much lower than false negative rates, but the range of false positive rates they find is large. For the Food Stamp Program, false positive rates range from 0.3 percent in Bollinger and David (1997) to 2-3 percent in Moore, Marquis and Bogen (1996). As there are far more non-recipients than recipients even such low rates of false positives lead to high error counts. The early complete design studies reviewed by Marquis et al. (1981) have challenged the notion that the net effect of misreporting is to understate total program receipt. Rather, they point towards substantial reporting errors in both directions leading to slight net overreporting. More recent validation studies (Marquis and Moore 1990, Marquis, Moore and Bogen 1996, Taeuber et al. 2004) provide evidence of net underreporting of food stamp recipiency. Consequently, the question whether the net bias is positive or negative remains open. Due to the limitations mentioned in the previous paragraph, it is also unclear whether there is a general direction of the bias or whether its direction depends on the survey as well as the population and time period covered.

Even in the most favorable case of a small or zero net under-reporting, the substantial error rates these studies find are likely to bias analyses of sub-populations and bias multivariate models if errors are correlated with individual and household characteristics. The assumption that the errors are independent of other variables is commonly invoked in order to come up with a simple summary measure of the degree of misreporting (e.g. Moore, Stinson and Welniak 2000) and to analyze or correct the bias due to misreporting (e.g. Hausman, Abrevaya and Scott-Morten 1999). In light of the importance of this assumption and the fact that the theories of misreporting discussed above strongly suggest a relation to both demographic and economic characteristics, it is surprising that few of these studies have examined whether misreporting is indeed random. Notable exceptions are Bollinger and David (1997, 2001, 2005), who reject this assumption by showing that reporting of food stamp receipt is related to income, gender, education, household structure as well as survey non-response.Bollinger and David (1997, 2001) are also the only authors we know that use validation data to analyze the impact of misreporting on multivariate models that include a program receipt variable. Misreporting has been discussed as a potential explanation for empirical findings such as the low take-up of government programs among the elderly (Haider, Jacknowitz, Schoeni 2003) as well as the surprisingly low take-up among households in extreme poverty (Tiehen, Jolliffe and Gundersen 2012). However, a thorough analysis of these biases requires more information on the nature and correlates of misreporting as well as more analytic results on the consequences of non-classical measurement error. In the absence of the latter, complete design validation studies offer a unique opportunity to analyze these biases in specific cases by comparing models relying on a validated variable to those using a survey variable.

IV. Data

We examine three large and frequently used household datasets: the 2001 American Community Survey (ACS)[7], the 2002-2005 Current Population Survey Annual Social and Economic Supplement (ASEC), formerly the Annual Demographic File or March CPS and data from January 2001 – April 2005 from the 2001 and 2004 panels of the Survey of Income and Program Participation (SIPP). These data from these surveys are matched at the individual level to administrative data on food stamp and TANF receipt in Illinois and Maryland and then aggregated to the household level. Due to the smaller SIPP sample, we pool the data from Illinois and Maryland. In all three surveys the sample for our analyses is households with a household head at least age 16.

The administrative data provide information on food stamp and TANF receipt for Illinois and Maryland. The monthly records report program receipt, amounts (for some years), as well as Social Security Number (SSN). From these monthly records we are able to construct the start and end dates of receipt spells. The source of the Maryland data is the Client Automated Resource and Eligibility System (CARES) provided by the Maryland Department of Human Resources to the Census Bureau Data Integrated Division. The data provided to the Census Bureau cover the period 1998 through 2003

[7] Strictly speaking we used the 2001 Supplementary Survey or SS01 which differs slightly from the ACS.

and include monthly information on all Maryland residents receiving food stamps and TANF benefits during that period. The source of Illinois data is the Illinois Department of Human Services (DHS) client database, a subsystem of the Client Information System. Each extract contains mainly cross-sectional data, with some limited historical information. From these extracts, Chapin Hall has created the Illinois Longitudinal Public Assistance Research Database (ILPARD), a longitudinal database of public assistance cases (including FSP and AFDC/TANF receiptThe ILPARD is updated monthly with new cases from the IDHS system and records that IDHS has changed in the past month. The Food Stamp Program data of the Illinois DHS Client Database contain information on all members of the household and their monthly utilization of the program. The data supplied to the Census Bureau cover 1998 through 2004.

Definitions

Food stamp receipt in the ACS comes from the question "At any time DURING THE PAST 12 MONTHS, did anyone in this household receive Food Stamps?" To match this definition we create a binary variable using the administrative data that indicates whether food stamps were received in the survey month or the previous 12 months by anyone in the household. Food stamp receipt in the CPS refers to receipt in the previous calendar year which we mimic in the administrative data. Because seam bias is known to be an issue in the SIPP (Moore 2008), we combine the four monthly reports of food stamp receipt from each interview to create an indicator for receipt during the four month period which we also do in the administrative data.

The food stamp household is notoriously difficult to define, but this complication does not impinge on our analyses. We examine whether a household in the ACS, CPS or SIPP that reports (or does not report) receipt of food stamps, has any member that is a recipient in the administrative data. This reliance on the survey household definition greatly simplifies the analysis. Note that a survey household may contain more than one FSP assistance unit or may include some individuals who are in an assistance unit, as well as others who are not.[8] Since not all individuals in a household are necessarily

[8] To be clear, we are able to accurately determine what share of true recipient survey households report receipt, but we cannot determine what share of true recipient assistance units report receipt.

successfully matched to the administrative data, there is a bias in our estimates that leads the raw results to understate our main conclusions, as we discuss below.

Linking

Linking the survey and administrative data is accomplished using a variable called the Protected Identification Key or PIK. In order to receive food stamps, an individual must have a validated SSN (their name, gender, and date of birth must match SSA records). The FSP data are subject to regular audits by the USDA. The validated SSN is converted to a PIK by the Census Bureau. The Census Bureau uses name, address and date of birth from the ACS records to create a PIK for survey individuals. A PIK is obtained for 96.4 percent of the Illinois TANF and food stamp records over the entire period and 97.8 percent of the Maryland records. In the survey data, a PIK is successfully obtained for at least one member of 92.7 percent of ACS households in Illinois and 94.9 percent of ACS households in Maryland. The rates are considerably lower for CPS households. Prior to 2005, respondents were asked to supply their SSN in the CPS to allow linking, and a PIK was not determined for those who did not supply an SSN, reducing the share of households that can be linked. We have a PIK for at least one member of 68 percent of Illinois CPS households and 81 percent of Maryland CPS households. The PIK rate is similar in the SIPP, in which 71 percent of all households have a PIK. However, the rates are slightly lower for those who are likely food stamp recipients in all three surveys. For example, in the ACS the rates are 89 percent in Illinois and 92 percent in Maryland for households with income below twice the federal poverty line. The main sample for our analyses is households with at least one household member who has been assigned a PIK. We examine what household characteristics are associated with it being unable to be linked to a PIK. The results of probit equations for whether a household is PIKed are reported in Appendix Table 1-3 for the ACS, CPS and SIPP respectively. We find that in each survey, several observable characteristics predict that a household is PIKed, so we can reject that a PIK is missing at random. However, few of the variables matter consistently across surveys. An exception is that smaller households are less likely to be PIKed in all surveys. As this means that observations are not missing completely at random, we multiply survey weights by the inverse of the predicted probability of a household having a PIK (see e.g. Wooldridge 2007) in our analysis, where the covariates used in that prediction can be seen in Appendix Tables 1-3.

Potential Biases due the Matching Process

The matching process may lead to errors in the linked data for reasons such as missing or mis-matched PIKs, households moving into one of the two states during the reference period and differences in the length of the reference period. In this section, we discuss the extent of these problems and the likely biases they may cause in our analyses. We conclude that they will tend to bias downward false negative reporting rates and bias upward false positive rates. Consequently, our main findings are likely to somewhat understate the difference between truth and survey reports.

First, we include households in our samples if anyone in the household has a PIK. Someone in the household may receive food stamps, but if they do not have a PIK we do not treat the household as a recipient household unless someone else in the household who has a PIK is a recipient in the administrative data. This issue would have the effect of understating true food stamp receipt. We might reasonably assume that affected households, those that are partially PIKed leading their administrative food stamp status to indicate non-receipt when they are recipients, have reporting rates higher than nonrecipients, but lower than recipient households with all members PIKed and who are likely to have only recipient members. Then, as shown in the Appendix, the false positive rate is biased upward and the false negative rate is biased downward. About 14 percent of ACS households with at least one PIK have members without a PIK, while 24 of CPS households in Illinois (15 percent in Maryland) have this situation. Thus, this bias could be substantial.

Second, a household that moved into the current state over the last year may have received food stamps in their previous state even if they did not in their current state of residence. The administrative data from their current state of residence would not report that receipt. Thus, mobility across state lines will lead to an understatement of true food stamp receipt. Under the assumption that such households that received in a previous state but not the current state have a reporting rate higher than those who received in neither the previous nor current state, but lower than those who received in the current state, the false positive rate will have been biased upward and the false negative rate biased downward (again see the Appendix for a proof). Since only about two percent of individuals move across state lines in a year, the likely bias is small.

Third, a small fraction of the administrative records do not have a PIK. As in the last two cases, this type of error will lead some true recipient households to not appear as recipients in the administrative data. Again, if such households have reporting rates higher than true nonrecipients, but lower than other true recipients, the false positive rate would be overstated and the false negative rate understated.

Fourth, a PIK may be incorrectly assigned to a survey household. If the household is a true administrative recipient household, then the situation is analogous to the third case above. The situation is different, however, if the household is a true nonrecipient household, a likely more common case since the vast majority of households do not receive food stamps. In this case, false negatives may be overstated since the incorrectly assigned PIK may be for a member of a household that is a recipient household in the administrative data. Given that most households do not receive food stamps, this last possibility should be uncommon. Thus, the incorrect false negatives require the joint occurrence of two low probability events: an incorrectly assigned PIK and administrative food stamp receipt for that PIK.

Finally, in the ACS we consider a household to be a recipient household if food stamps are received anytime during a 13 month period rather than the 12 month period that is asked about in the ACS. The additional month added in the 13 month definition is the oldest of the 13 months. This convention leads more households to be classified as true recipient households than might be warranted. In principle, this convention could lead to either higher or lower false negative and false positive rates. A reasonable assumption, though, is that the households affected by this convention have reporting rates between those of the households that are either participants or non-participants under either definition. In this case, the false positive rate will be biased downward and the false negative rate biased upward. We examined the magnitude of this potential bias by only defining administrative receipt based on the 12 months preceding the current month and find that false negative and false positive reports are only negligibly different under the two assumptions.

Overall, the first three cases likely lead to understatement of the false negative rate and overstatement of the false positive rate. The fourth case is hard to evaluate since the frequency or incorrectly assigned PIKs is not known, but the likely bias seems small and the final possible bias can be directly examined and is found to be very small. Consequently, it seems likely that false negatives are understated and false positives are overstated, so that the linked data understates the difference between true and reported food stamp receipt.

V. Agreement between Survey and Administrative Reports

In this section we examine the differences in food stamp receipt between the administrative data and the survey data. We find substantial under-reporting by true recipients and low rates, but sizable numbers, of false positives in all surveys. However, the rates differ considerably between the three surveys, which leads the ACS and CPS to understate net food stamp receipt, while it is slightly overstated by the SIPP. Besides misreporting, non-response and the subsequent imputations are an important source of survey error. Examining only non-respondents, we find that the probability of non-response depends on true program receipt. The imputations in all three surveys cause substantial error at the household level, but differ in their effect on overall rates: while the CPS imputations understate rates of food stamp receipt of non-respondents by almost 50 percent, the ACS and SIPP imputations overstate it. All population estimates and percentages are weighted by household weights adjusted for a missing PIK.[9]

Table 1 reports a cross tabulation of administrative receipt of food stamps and ACS survey reports of food stamps in the top panel for Illinois and in the bottom panel for Maryland. Overall, in the administrative data 7.5 percent of households in Illinois and Maryland receive food stamps over the 2000-2001 period to which the survey refers. However, reporting errors are common: the false negative rate is 33 percent, as shown by the row percentage of the center cell of the first column. These are very high rates of failing to report receipt when a household is truly a recipient household: One-third of those households that receive food stamps are not recorded as receiving in the survey.

[9] While we report weighted statistics throughout the paper, the weights tend to be unimportant.

The share of true nonrecipients who are reported as recipients is 0.73 percent (see the row percentage of the first cell of the second column). However, most households do not receive food stamps, so the relatively low rate of false positives still implies that a substantial number of non-recipient households are misclassified as recipients by the survey. Overall, the high rate of false negatives leads to a net understatement of food stamp receipt of 24 percent in the ACS survey data. This can be seen by comparing the column total for reported receipt to the row total for administrative receipt.

Using CPS data, we repeat these cross-tabulations, reporting the results in Table 2. 8.8 percent of the households in the CPS receive food stamps according to the administrative data. The share of administrative food stamp recipient households that do not report receipt in the CPS is even higher than in the ACS. 48 percent or almost half of the recipients in the two states do not report receipt.This share of false negatives has increased over the 3 (MD) or 4 years (IL) for which the administrative data is available. This increase is pronounced in Maryland, where by 2004 over 60 percent of recipient households are not recorded as recipients. As in the ACS, the share of non-recipients that report receipt remains low, 0.84 percent. The net effect of false positives and false negatives is that the CPS understates food stamp receipt by a substantial 41 percent. This accords quite closely with the net understatement by 39 percent for the Illinois time period and 38 percent for the Maryland time period reported in Meyer, Mok and Sullivan (2009) based on national aggregate data for months of participation.

Table 3 presents the same cross-tabulations using SIPP data. 6 percent of the households in the SIPP receive food stamps according to the administrative data, 23 percent of which fail to report food stamp receipt. Thus the false negative rate in the SIPP is substantially lower than in the CPS and quite a bit lower than in the ACS. On the other hand, 1.5 percent of non-recipient households report food stamp receipt in one of the four reference months, so the false positive rate is roughly twice as high as in the other two surveys. However, at least part of the difference is due to the fact that we consider a household to report food stamps if they reported receipt in any of the four reference months in the SIPP. This will almost inevitably drive down the rate of false negatives and is likely to increase the rate of false positives, because mistakenly reporting receipt in any of the four months results in a false positive.[10]On the other hand, note that neither the false positive nor the false negative rate is affected by a factor of 4, so there must be additional factors that make households more likely to report food stamp receipt in the SIPP than in the ACS and CPS. The combination of the lower false negative and the higher false positive rate results in slight overreporting (by 3 percent) of food stamp receipt in the SIPP. Our findings seem to confirm the belief that the SIPP is the most accurate of the three data sets in measuring program receipt: It has the lowest false negative rate and the most accurate net reporting rate. Slight overreporting may well be preferable to the substantial underreporting in the ACS and CPS, particularly if one is only concerned with univariate statistics on food stamp receipt. However, roughly half of this improvement stems from the higher false positives rate, i.e. from introducing additional error, which may well aggravate the consequences of misreporting in multivariate analyses such as the take-up models we analyze in section 0.

In summary, we find low rates of false positives in all three surveys, but substantial rates of false negatives. The false negative rates exceed 50 percent in some cases, so all three surveys need to induce more accurate reporting by true program recipients in order to accurately analyze government programs and the recipient population. However, we also find large differences in the rates of false positives and false negatives and hence net reporting across surveys. This is in line with the fact that previous studies have found a wide range of rates of misreporting. Contrary to these studies, however, we were able to link the same administrative data to multiple surveys using the same matching procedure. Hence, the differences we find between surveys have to be due to survey-specific characteristics such as the focus of the survey, its length or its target population. For example, one factor that could contribute to the lower false negative rate in the SIPP is the shorter reference period, which should mitigate recall error. The fact that we still find substantial differences between the ACS and the CPS, which are samples from the same population, reinforces the idea that the differences in misreporting are at least partly caused by differences in the survey design. We will

[10] Contrary to the case of false negatives, it could also reduce the false positive rate if false positives mainly stem from reporting receipt in the wrong months, but we consider this unlikely.

examine the determinants of misreporting at the household level and thereby potential causes of misreporting in the next section.

More generally, the differences between the surveys provide further justification to the pessimism both Bound, Brown and Mathiowetz (2001) and Moore, Stinson and Welniak (2000) express regarding a general theory of misreporting. Both the extent and nature of misreporting does not only depend on the item in question, but also depends heavily on the implementation of the survey. Consequently, conclusions regarding important issues such as net underreporting or whether the errors are related to observable characteristics may have survey and program specific answers, but cannot be dealt with in general.

The discrepancy between the administrative and the survey data is the combination of multiple sources of error. Besides misreporting, the most important origin of error probably is non-response. Our linked data provides the true recipiency status of non-respondents and thereby allows us to examine two important questions that arise when dealing with non-response: Whether the probability of obtaining an answer depends on the true value of the answer, i.e. whether non-response is conditionally random and whether the imputed values provided by the surveys improve the quality of the data.

Tables 4-6 repeat the cross tabulations of Tables 1-3, but only for those observations for which household food stamp recepit is imputed.[11] Several patterns are evident in these tables. First, only a small share of households are imputed in the ACS (1.6 percent) and non-response is low, but a little more frequent in the CPS (3.6 percent) . The imputation rate in the SIPP is substantially higher at 7.7 percent, but it is not directly comparable to the ACS and CPS, since we consider an observation to be imputed if any of the four reports was imputed. It is not four times as high though, but twice as high in the CPS and almost four times as high as the ACS. So unless there is very little serial correlation in non-response, this indicates that individuals are less likely to respond to the food stamp question in the SIPP, which could be due to the longer survey.However, non-response is an important factor in analyses of households that receive food stamp, because a large share of true food stamp households is imputed: 13.6 percent of the population estimate in the ACS, 9.3 percent in the CPS and 13.6 percent in the SIPP. An

[11] Imputation methods in the three surveys are described in Section VIII.

even larger share of reported food stamp households are imputed in the ACS and SIPP, while the shares are similar in the CPS.

Second, the share of true food stamp recipients is higher among those who are imputed than among respondents. This is particularly pronounced in the ACS, where 53.4 percent of the imputed households are actual recipients, compared to 6.6 percent among non-imputed observations. There are substantial differences in the other two surveys, but the share of true recipients among imputed and non-imputed observations is closer aligned in the CPS (22.5 compared to 8.2 percent) and the SIPP (11 compared to 5.6 percent). Thus, non-response is not random in all three surveys, because the probability of obtaining a response is lower among true recipients in all three surveys. It also underlines that the selectiveness of non-response is survey specific, since the households that choose not to answer differ in their probability of receiving food stamps across the three surveys. Just as misreporting, non-response appears to be significantly influenced by factors related to the survey design. The finding that the likelihood of non-response depends on the true value poses a problem for common imputation methods and other corrections for missing values. If this relation differs substantially between surveys as our data suggests, it will be even harder to assess and correct its impact. However, most methods rely on the weaker assumption that values are missing conditionally at random, which we explore further in section 0.

Third, comparing imputed receipt to administrative receipt reveals that imputations lead to substantial error at the household level. In particular, a substantial share of the false positives is due to imputation. These observations account for 41 percent of false positives in Illinois and 26 percent of false positives in Maryland, despite being no more than 2.1 percent of the total sample. Because of these imputed false positives, the overall false positive rate (0.83 percent in Illinois and 0.51 percent in Maryland) is not a good indicator of households' tendency to report receipt when they are not recipients (0.49 percent in Illinois and 0.38 percent in Maryland).

The goal of imputations, however, is usually not to provide accurate predictions at the individual or household level, but to reproduce the distribution of the missing variable among the non-respondents. Comparing the rates of food stamp receipt among non-respondents according to the survey imputations to the true share according to the administrative data reveals that the imputations fail to capture even the marginal distribution of food stamp receipt: While 22.5 percent of non-respondents in the CPS are true food stamp recipients, the CPS imputations only assign receipt to 12 percent of them, thereby understating the rate of receipt by 46 percent. On the other hand, the imputations overstate true food stamp receipt among non-respondents in the ACS by 21.6 percent and in the SIPP by 29 percent. Another criterion to evaluate imputations is whether they make the distribution in the entire sample align better with the true distribution. According to this, the overimputation in the ACS may be regarded beneficial, because there is net underreporting in the ACS. However, the imputations in the other two surveys affect make net misreporting worse, by leading to more overreporting in the SIPP and adding to the underreporting in the CPS. As in the case of false positives, it also involves introducing additional error as an improvement, which may have negative effects on the joint distribution of food stamp receipt with other variables in the survey. While it is difficult to assess whether the imputations improve the joint distribution overall, we will examine whether they improve the relation between program take-up and demographic and economic characteristics in section 0.

VI. What Affects the Agreement between the Survey Reports and the Administrative Records?

We next examine how misreporting of food stamp receipt differs across households. If misreporting does not depend on household characteristics, then it is fairly straightforward to correct estimates of takeup and the distributional effects of programs (examples of such corrections can be found in Meyer, Mok and Sullivan 2009, and Meyer 2009). However, if misreporting is correlated with household characteristics, we can use estimates of the relationships to adjust statistical analyses. We first look at variables that determine false negatives, in all three surveys and then examine variables that predict false positives. In the analyses of the determinants of misreporting, we examine those with income less than twice the poverty line, to focus on a group for whom food stamp receipt is especially relevant.

In the first two columns of Table 7-8 and the first column of table 9 we report probit equations for the determinants of false negative reporting in the ACS, the CPS and the SIPP. Here the subsample is those who, according to the administrative data, are recipients of food stamps (true recipients). We report average derivatives of the probability of being a false negative reporter rather than coefficients to aid the interpretation of the magnitudes. The explanatory variables differ slightly due to availability in the three surveys, but all models include family type, number of adults and children, number of members that had a PIK, age categories, gender, education, ethnicity and employment status of the head, whether the household is in a rural area, income relative to the poverty line for a household of the given composition, reported receipt of other programs, receipt of TANF and length of food stamp receipt from administrative data as well as whether food stamp receipt was imputed. In the ACS and SIPP, we also examine whether the head of the household is disabled, is a U.S. citizen and the role of language, in the CPS and the SIPP we control for the time period. In the SIPP, we also include time in months since last food stamp receipt, a dummy if the household is in Maryland and several variables that are related to the quality of the interview.

Despite a fairly small sample for this analysis, there are some noticeable differences across households in false negative reporting and in all surveys we can easily reject the hypothesis that misreporting is unrelated to household characteristics. Even though the marginal effects of many of the variables are imprecisely estimated, some common themes emerge. While the household composition variables are imprecisely estimated, the coefficients on the number of adults and single households with children are negative in 4 out of 5 models. The same is true for households in rural areas, which are less likely to fail to report in the ACS and CPS. The difference in the probability of reporting is large (0.1) and significant in the ACS, but insignificant and small in the CPS and SIPP. Households headed by a white person are less likely to fail to report in all samples. The difference is sizeable (0.05-0.11) and significant in the ACS (at the 5 percent level) and the SIPP (at the 10 percent level). There is some evidence that households headed by a more educated person are more likely to underreport, but the estimates are imprecise. Households headed by a person 50 or older are quite a bit more likely to be false negatives (by 0.12-0.15), with the exception of the CPS Maryland sample, where the effect is large and positive. Misreporting seems to be related to the gender of the householder, but the signs of the marginal effects differ across surveys. Non-U.S. citizens are surprisingly less likely to fail to report, and the difference is significant in the SIPP and the ACS Illinois sample. However, households where a language other than English is spoken (ACS, significant in Maryland) or where the head speaks poor or no English (SIPP) are much more likely to fail to report food stamp receipt. Higher income increases the likelihood that a recipient will not report receipt, but there is no clear evidence of an impact of disability and employment status.

We also examine the association of not reporting with reported receipt of other transfer programs. Quite uniformly, true recipients who report receipt of other programs (public assistance, housing assistance) are more likely to report food stamp receipt. The difference is large, for example in the ACS it is nearly twenty percentage points for reported public assistance receipt in both states. On the contrary, administrative TANF receipt increases the probability of false negatives in all samples, but the effect is insignificant in three of them. Agreeing with the idea that regularity of receipt is important, those who received food stamps in more months in the reference period, are more likely to report receipt. This difference is very pronounced, an additional month of food stamp receipt is estimated to decrease the non-reporting probability by 0.02-0.05. This is consistent with recall error being one of the reasons for false negatives. Further evidence of recall error is provided by the SIPP, where we included the number of months since the last food stamp receipt in the reference period. As expected, this increases the probability of false negatives, by 0.04 per month.

Finally, we examine several variables that are related to the quality of the data, the interview and the matching process. As the analysis of the imputed observations suggested, the imputation dummy is significant in all samples. Interestingly, it shows that in the ACS and the SIPP imputations are more accurate than reports by true recipients (all else equal, an imputed observation is less likely to be a false negative), while the CPS does worse. We find little evidence of an effect of the other data quality variables. The number of household members that were PIKed has no impact on false negatives, which is reassuring about the quality of the match. In the SIPP, we include how many members of the household were interviewed, whether an interview with the household head was conducted and whether anyone without a PIK was interviewed, none of which has a significant effect. We also include a variable that measures the fraction of other program receipt and income variables that were imputed, one for the entire household and one for the household head. This can be seen as a measure of how well the interview went and how cooperative the respondents were on other questions. While the responsiveness of the household head does not matter, the overall responsiveness of the household members decreases false negatives. This makes some sense considering that it only requires one cooperative household member to avert a false negative.

We also examine the frequency of reporting receipt by those who are truly non-recipients in columns 3 and 4 of Tables 7 and 8 and column 2 of table 9. The sample for this false positive analysis, those who are truly nonrecipients, is much larger than that used for the false negative analysis. However, the false positive rate is so low that the number of false positives is much smaller than the number of false negatives. Given the small number of "ones" in this probit analysis, there are fewer significant determinants of reporting in these equations, but we can still easily reject the hypothesis that overreporting is unrelated to household characteristics. The number of household members under 18 seems to decrease the likelihood of a false positive (significant and positive in the ACS for Illinois and the SIPP), while the number of adults matters but goes in different directions in the surveys. There is some evidence that households headed by a white person report more accurately, although this evidence is weaker than among true recipients. Households headed by a person 50 or older are less likely to misreport if they do not receive food stamps, contrary to their counterparts that receive food stamps. This may indicate that stigma plays a larger role for these households. Similarly, income relative to the poverty line decreases the probability of false positives, even though it leads to less accurate reporting of food stamp receipt. While this may be additional evidence of stigma, it could also be explained by the fact that these households are less likely to receive food stamps and thus are less likely to make mistakes about their recipiency status. Besides weak evidence that disability may be related to lower rates of false positives, we find no further systematic evidence of demographic characteristics. Reporting receipt of other programs increases the probability of false positives, particularly report of public assistance. This supports the hypothesis that misreporting is partly due to respondents confusing government programs (Nicholas and Wiseman 2009). However, the effect is much smaller than in the false negatives probits, so additional factors may be at work there, such as some people being more truthful reporters than others. The marginal effects of the imputation dummy confirm the finding of the last section that many false positives are due to imputation and that imputations are worse than reports by true non-recipients in all surveys. The number of members PIKed variable underlines that some false positives are likely due to missing PIKs, but the impact is modest. We do not find evidence of an effect of the other data quality variables.

In conclusion, we have found that both false positives and false negatives are systematically related to household characteristics, which renders many of the commonly used corrections for misreporting invalid. However, while misreporting is related to household characteristics in all surveys, we find few consistent patterns. This may be due to the small sample sizes or because misreporting is mainly survey-specific. The variables that consistently matter in our results support several of the common explanations for misreporting, such as stigma, confusing government programs and a latent "cooperativeness" that causes truthful reporting.

VII. The Effect of Misreporting on Estimates of Program Receipt

The previous sections have shown that there is substantial misreporting of food stamp receipt and that it is systematically related to household characteristics. It is well known that such non-classical measurement error will bias coefficients in econometric models, but little is known about how inference will be affected. Having true food stamp receipt matched to survey data gives us the opportunity to directly examine in how far the use of administrative data provides a different understanding of the determinants of food stamp receipt than we obtain from survey data alone. We first estimate the determinants of receipt using only survey data. We then re-estimate the determinants of receipt, combining the survey data with the administrative data on food stamp receipt, using the administrative measure of receipt as the dependent variable. This approach combines the accurate dependent variable with the rich explanatory variables from the surveys. We then compare the two equations for the use of food stamps. Throughout this section, we restrict our sample to households with income below twice the poverty line to have a sample for which food stamp receipt is a likely possibility. We include observations with an imputed dependent variable, the next section considers the effect of excluding these observations. Appendix tables 4-6 provide summary statistics for the estimation sample.

The determinants of food stamp receipt using only ACS survey data can be seen in Table 10 column 1 for Illinois and column 4 for Maryland. The survey estimates suggest that, controlling for household income, a household headed by a single parent is about ten percentage points more likely to be a recipient than a married couple household in both states. Those 50 or older are much less likely to be participants than those ages 40-49 in Illinois, while in Maryland the effect is only evident for those 60 or older. The differences in receipt for these older groups are large: 10 percentage points in Illinois and 9 percentage points in Maryland compared to those 40-49. The marginal effects of education and income have the expected signs, with high school dropouts 6 percentage points more likely to participate in Illinois and 7 percentage points more likely in Maryland than those with some college. Income is a strong predictor of food stamp receipt. In Illinois, households with income equal to half the poverty line are 7 percentage points more likely to receive food stamps than households with income 1.5 times the poverty line. In Maryland, the difference is 10 percentage points. The estimates also suggest that households with a non-employed or disabled head are much more likely to receive food stamps. In Illinois, non-whites are more likely to participate, while there is little difference by race in Maryland. The strongest relationship is found for an indicator of reported receipt of public assistance or housing assistance. Those reporting housing assistance receipt are more than 1.5 times as likely to be recipients than an average individual, while those reporting public assistance receipt are more than twice as likely to be recipients.

Replacing the mis-measured ACS survey receipt variable with the administrative measure of receipt gives us a different picture of determinants of food stamp participation. Column 2 and 5 of Table 10 repeat the participation analysis substituting an administrative dependent variable for the poorly reported survey measure of receipt.[12] Columns 3 and 6 of Table 10 report p-values for tests of equality of the derivatives based on the survey data alone and those based on the survey and administrative combined data. Households headed by a single individual or parent are much more likely to be recipient households in the combined data. In Illinois the difference is 4-5 percentage points while in Maryland it is 6-9 percentage points, and these differences are at least marginally statistically significant in most cases. The average derivative for race is also significantly different, with the specifications with the administrative dependent variable indicating that participation is four percentage points greater for non-whites than the survey data only specifications in both states. The derivatives for reported receipt of public assistance or housing benefits are significantly different in most cases, as are those for having more family members with a PIK. In Illinois, the marginal effect of age, particularly for age 50-59, is quite different in the combined data, and the difference is statistically significant. The association with speaking English only is also significantly different. For Maryland, the association with income is quite different in the combined data, indicating substantially larger differences in participation by income. Overall, one can reject that the combined data yield the same estimates as the ACS survey data alone at a level below 0.0001 in Illinois and at 0.0004 in Maryland.

We report the determinants of food stamp participation using the CPS data in Table 11. Again, columns 1 and 4 of this table provide the average derivatives for the models that use only survey data. There are quite a few similarities with the ACS survey data results. Again, all else equal, single parent households are more likely to be recipients, though the relationship is not significant in Maryland. Households with many children are more likely to receive food stamps, and this difference is significant in both states. Households headed by a person 70 or older are less likely to receive food stamps, while those that have very low income, a non-employed head, who report receipt of public assistance or housing benefits, are significantly more likely to receive food stamps in both states according to the CPS data. In Illinois, those without a high school degree are more likely, and those with a college degree less likely to receive than those with

[12]We have also examined the coefficients (as opposed to the average derivatives) for each of the specifications. The overall results are very similar for the coefficients, though the differences between the combined and survey data estimates are smaller in some cases, but not uniformly so.

some college. There is some tendency toward higher receipt in rural areas, though the evidence is fairly weak. The survey data alone do not suggest that food stamp receipt has been rising over time in either of the states.

When we substitute the administrative measure of receipt for the poorly reported survey measure, the determinants of reporting change in important ways. These estimates are reported in columns 2 and 5 of Table 11, a chi-square test that the marginal effects are jointly the same with the administrative and the survey variable rejects this hypothesis in both states. The difference in participation between single parents and a married parent changes from 5 percentage points to 13 in Illinois and from 1 percentage point to 8 in Maryland with the administrative data measure. In Illinois the change is statistically significant while it is not in Maryland, but in Maryland there is some evidence of an increased marginal effect of the number of children in a household. Participation is also much higher among non-whites and lower income households than it is in the survey data alone in Illinois. Contrary to the survey data, which showed no time trend, in the combined data there is significant evidence of increasing receipt in Illinois, and strong and significant evidence in Maryland.

The results from the SIPP that use only survey data are reported in column 1 of Table 12 and are similar to the results from the other two surveys. Single parents are again more likely to receive food stamps, but in the SIPP this also applies to single individuals. There is weak evidence of a negative age gradient and households with a non-white head are more likely to be participants. As before, income relative to the poverty line has a negative impact on program take-up, while households in rural areas and with a head reporting a disability or poor English skills are more likely to receive benefits. There is a strong positive association between reporting food stamps and receipt of other programs (housing assistance and TANF). Contrary to the CPS, there is a time trend in the survey data, but it is flat until 2003 and then increases sharply.

Column 2 of Table 12 reports the results that use the administrative dependent variable. Again, a joint test rejects that the results from the two dependent variables are the same and a number of marginal effects are significantly different: The number of adults has a pronounced negative effect in the administrative data, but the number of members PIKed now increases the probability of food stamp receipt. As in the other two surveys, the effects of ethnicity and income are more pronounced when using administrative food stamp receipt, while the association with reporting other programs is weaker. The marginal effects of two age categories (30-39 and 50-59) change significantly. While the survey data suggests that participation declines over the life-cycle, the relation is U-shaped with the administrative data, increasing rapidly after age 50. However, the evidence is weak since the marginal effects are not estimated very precisely. Households in Maryland are almost 5 percentage points less likely to report food stamps, despite not being less likely to receive food stamps. The time trend is clearly different with the administrative dependent variable, showing more rapid growth in the first half of the time period and a less drastic increase in the second half.

Overall, misreporting clearly changes inference regarding program take-up as the joint tests show, but the small sample sizes make it hard to discern problems that are common to all three surveys. One of the differences between the combined administrative and survey data and the survey data alone that is worth emphasizing is the differences in participation by age. Haider et al. (2003) and Wu (2010) emphasize lower food stamp takeup by older households in survey data. Gunderson and Ziliak (2008) find a more complicated pattern by age. In some cases, the sharp differences in misreporting by age carry over to imply that the combined data show much less of a difference between the aged and the non-aged, thus explaining a significant part of the puzzle in past work. We see this pattern in our largest sample, that for Illinois using ACS data. This pattern is not evident in the CPS data though. Another noteworthy difference is the impact of income relative to the poverty line. Food stamp receipt declines more rapidly with income in the administrative data, so analyses using survey data only are likely to understate the distributional consequences of the food stamp program. Finally, mis-reporting has a pronounced impact on the time trend in food stamp receipt. In the CPS, the survey reports conceal the time trend, while in the SIPP they suggest a flat profile followed by a steep increase instead of a more steady increase.

We should also emphasize that while the survey data alone would lead one to make incorrect inferences in some cases, the overall picture obtained from the survey data is fairly accurate. Most of the significant derivatives remain significant and changes in the sign of derivatives in the participation equations are rare when one goes from the survey data alone to the combined data. Overall, only 21 out of 115 derivatives change sign, this pattern holds even in the CPS where half of true food stamp recipients fail to report. A high priority for future research should be to explore through analytical models and simulations the generality of this result.

VIII. Evaluating Food Stamp Imputation

Section V has shown that non-response is an important problem for analyses of food stamp receipt because a substantial share of true food stamp recipients are non-respondents. When responses regarding receipt or amounts are missing in surveys, components of income are often predicted using other information. This section will provide further evidence that non-response is non-random, even conditional important covariates, and discuss how respondents and non-respondents differ. If non-response is not conditionally random, the researcher faces the dilemma that both omitting the imputed observations and including them will lead to bias. In a review of recent issues of leading social science journals, we found that authors were about equally split between including and excluding observations with imputed values. We use the unique data we have to evaluate the quality of food stamp imputations in the ACS, CPS and the SIPP. While it is easy to assess whether including the imputations changes parameter estimates, it is usually impossible to know whether the change is an improvement or leads to greater bias. The linked data allows us to examine whether including the imputed observations improves parameter estimates in models of food stamp take up and therebyprovide guidance for researchers who appear to be uncertain about the choice of whether or not to rely on imputed data.

Food stamp receipt in the ACS, CPS and SIPP is, as in other Census data sets, imputed using hot deck methods. In the ACS, households (not in group quarters) are classified by state into one of twenty cells, defined by full interactions of family type, presence of children, poverty status, and the race of the reference person. The data go through what is called a “geosort” before the imputation process. The most recent nonmissing response from a given cell at the smallest level of geography available is substituted for a missing response. The CPS hot deck procedure differs from that in the

ACS in some important ways. Households are classified into a much larger number of cells based on non-geographic characteristics, but at the national level. The cells are defined by full interactions of number of people in the household (6 categories), household income (9 categories), household type (3 categories), age of head (2 categories) and receipt of public assistance (2 categories) for a total of 648 cells. Finally, the SIPP also employs a hot-deck procedure at the national level and only uses donors from the current wave. It applies a geosort to the data, but with much less geographic detail than the ACS. Food stamp receipt is then imputed within cells formed by age (6 categories), race (2 categories), sex (2 categories), marital status (4 categories), number of children (3 categories) and work experience (3 categories), a total of 864 cells. By relying on reported values only, all three surveys assume that non-response is random within each cell, i.e. that non-response is random conditional on the variables that form the hot deck cells.

The linked administrative data provides us with true recipiency status, so it makes this assumption testable. We test whether non-response is conditionally random by running the model of food stamp receipt with the administrative dependent variable separately on the respondent and non-respondent sample with income less than twice the poverty line in the SIPP[13]. Despite the small sample of imputed observations, an F-test clearly rejects the hypothesis that the coefficients are the same for respondents and non-respondents with a p-value of 0.00001. Consequently, we can reject the hypothesis that the values are missing conditionally at random. To assess the difference between respondents and non-respondents further, we use the parameter estimates from the respondents to predict the probability of food stamp receipt for the non-respondents. We then run a non-parametric regression of administrative food stamp receipt on the predicted probabilities using only the non-respondents. If non-response were conditionally random, these probabilities stem from a correctly specified model, so we should obtain a 45-degree line. However, figure 3 shows that the regression line is significantly different from a 45-degree line: It crosses it from above at a predicted receipt slightly above 0.1 and remains below it for the remaining range. This means that

[13] By the time we performed this analysis, our access to the ACS and CPS data had expired, so we are only using the SIPP.

most non-respondents are less likely to receive food stamps than respondents with the same characteristics. However, non-respondents with a low predicted probability of food stamp receipt are more likely to receive food stamps.

The analysis above shows that neither including nor excluding the imputed observations will lead to unbiased inference. Thus, the relevant question when deciding whether to use or omit imputed observations is whether they improve parameter estimates. On the benefit side, imputations allow researchers to use all observations, which may mitigate sample selection bias if the imputation procedure reproduces the joint distribution of the missing values well. On the other hand, imputations cause bias because the joint distribution of the missing values differs from that of the imputed values. Additionally, they can cause bias that is similar to the bias from measurement error or omitted variables if the variables that are used to predict imputed values are not well chosen for the outcome model. These arguments are discussed in more detail in Mittag (2013). The overall impact on the estimated coefficients depends on the model at stake, but our data allows us to test it for any given model. We can do so by testing whether adding the imputed observations moves the survey based estimates closer to estimates based on the administrative data, which we consider "truth". We first focus on the effect of including the imputed observations in the models of food stamp take up from section 0I and then discuss whether our findings are likely to generalize to other models.

In Tables 13 to 15 we directly compare the derivatives from food stamp receipt equations with and without observations with imputed values for food stamp receipt. We compare the derivatives for both survey based participation equations with one based on the administrative measure of food stamp receipt. Table 13 indicates that in the ACS in Illinois there is not a great advantage to using the imputed values. In nine of twenty-three cases, the specification with imputed values is closer to the one relying on administrative data. In fourteen cases the reverse is true. Maryland, however, provides fairly strong evidence in favor of including the imputed values, with twenty of twenty-three derivatives from the specification including imputed values being closer to the administrative data specification. Chi-square statistics for the difference in the full set of derivatives indicate that a variance weighted average of the derivatives is considerably closer to the administrative data estimates when the imputed values are included[14]. In both states, the statistics are about 20 points smaller with the imputed values, with 23 degrees of freedom. Thus, we find that including the ACS imputed observations leads to estimates that are closer to those based on the combined data with an administrative dependent variable.

The results from the same analysis for the CPS in Table 14 show some differences between the two surveys. In Illinois there is little advantage to including the imputed values. In ten of twenty-one cases, the specification including the imputed values is closer to the administrative one, while in the other eleven cases the reverse is true. In Maryland, the derivatives from the specification with the imputed values are closer for five variables, but further away for the other sixteen variables. Thus, the specification excluding the imputed values seems to perform slightly better. However, the chi-square statistics for the joint test on all of the derivatives show that there is little difference between the specifications with and without the imputed values: in the CPS, the survey estimates with the imputed values and without the imputed values are about equally far from the combined data estimates. The difference is even smaller in the SIPP, where 14 out of 27 derivatives are closer to the combined data estimates when including the imputed observations and the chi-square statistics are almost identical. Thus, the imputed observations in the CPS and SIPP do not help to reduce the bias from non-random missing data, but the ACS imputations lead to an improvement.

Two important open questions are why the ACS imputations perform better than the CPS and SIPP imputations and whether this is likely to apply to other models. The findings of Bollinger and Hirsh (XXXX), who study the effect of imputing the dependent variable in a linear model, provide a potential explanation. The imputed values only contain information from the variables used in the hot deck, so after conditioning on these variables the imputed values are white noise. In the CPS and SIPP, only variables that are also used in our model of food stamp receipt are used in the imputation process. Thus, the only systematic variation in the imputed values that is not already captured by the non-imputed observations arises from the less restrictive functional form and the

[14] However, chi-square statistics are increasing in the sample size, so even if the imputations make no difference at all, we would expect a slight increase in the chi-square statistic due to the increased sample size.

omission of some variables in the imputation model. This can explain why we find no impact in the CPS and SIPP. If the imputed observations are indeed close to white noise after conditioning on the hot deck variables, it suggests that we should expect little benefit from including them in other models as well. On the contrary, they may cause biases similar to those found in Bollinger and Hirsh (XXXX) and Mittag (2013). While these biases are negligible in our case, our findings point towards excluding the CPS and SIPP food stamp imputations. On the other hand, the ACS imputations are based on much fewer variables, but also on very detailed geographic information that is not included in our model of take-up, so that the imputations contain information beyond our covariates. This can explain why including the imputed observations has a greater impact on the estimates in the ACS than in the CPS and SIPP. However, additional conditioning variables can also cause bias or the improvement may be due to the imputation bias partially canceling the bias due to measurement error. Consequently, this provides some evidence in favor of including the ACS imputations in other models, but the evidence is far from conclusive.

Our assessment of the imputations only constitutes a case study, but several conclusions may be informative to the researcher trying to decide whether to use imputed values or not. First, our analysis of non-response adds to the growing evidence (e.g. Bollinger and Hirsch forthcoming) that the assumption of values missing conditionally at random is unlikely to hold in survey data. Second, it confirms that imputations only matter if they are based on information that is not already included in the model. While such information could also make estimates worse, we find that the imputations in the ACS are better than in the SIPP and CPS. Further evidence of this is provided by the effect of imputation status in the misreporting models, but whether this is due to the geosort and whether it will improve estimates in other models remains an open question. Taken together, these findings imply that when trying to decide whether to use imputed observations, one of the key questions is whether the variables that were used to create the imputations help to explain the difference between respondents and non-respondents in the imputed variable.

IX. Conclusions and Possible Extensions

Benefit receipt in major household surveys is often underreported. This misreporting has important implications for our understanding of the economic circumstances of disadvantaged populations, program takeup, the distributional effects of government programs, and studies of other program effects. We use administrative data on Food Stamp Program participation matched to American Community Survey, Current Population Survey and Survey of Income and Program Participation household data. We show that over thirty percent of true recipient households do not report receipt in the ACS, approximately fifty percent do not report receipt in the CPS and 23 percent in the SIPP. Misreporting, both false negatives and false positives, varies with individual characteristics. We examine the determinants of program receipt using our combined administrative and survey data, which allows us to examine accurate participation using individual characteristics missing in administrative data. Our food stamp participation results differ from conventional estimates using only survey data, in several important ways. Food stamp participation is higher among single parents, non-whites, and those with lower income than the survey data alone suggest. Participation by age and the patterns of multiple program participation are also different using the administrative data. The results indicate that under-reporting is part of the explanation for the low receipt rate among the elderly. Misreporting is affects the income profile of food stamp receipt, so it will bias analyses of targeting and distributional consequences. Lastly, using only the CPS survey data, one would miss much of the rise in food stamp participation in the first half of this decade. It is also possible to think of the glass as half full, rather than half empty. It is striking that the signs and significance of most determinants of food stamp receipt in the survey data alone match those in the combined administrative and survey data. This result is found even in the CPS where half of true food stamp recipients are not recorded as recipients.

We find that non-response is related to both observable and unobservable characteristics and thus not ignorable. To evaluate the use of imputations, we examine whether our estimates of the determinants of participation using survey data alone are closer to those using the accurate combined data when imputed survey observations are excluded. Interestingly, excluding the imputed observations leads to worse estimates in the ACS, but estimates that are a similar distance from the combined estimates in the CPS and SIPP. We speculate that the difference is due to the fine geographic detail that is used in the ACS imputations.

There are many possible extensions to this work. It is likely that the under-reporting of food stamps has large effects on estimates of the distribution of resources at or below the poverty line. This issue is particularly important as poverty calculations that incorporate food stamps are increasingly reported. For example, the ACS is currently being used to calculate state level poverty rates that incorporate in-kind transfers such as food stamps (Levitan et al. 2010, Smeeding et al. 2010, Zedlewski et al. 2010). The national Supplemental Poverty Measure that the Census Bureau has started to release in 2011 relies on food stamp reporting in the CPS (Interagency Technical Working Group 2010). The data described here along with extensions of these methods can be used to design appropriate imputations to account for the pronounced and increasing under-reporting of food stamps that we have found. Other useful extensions of our results would include analyzing the extent and implications of misreporting of other government programs, in other survey datasets, and time periods.

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Appendix

Bias in Error Rates with Partial PIKed Data and Migration

Let the 2x2 matrix of potentially biased but observed response probabilities conditional on administrative receipt be

	Survey Data	
Administrative Data	p_{00}	p_{01}
	p_{10}	p_{11}

where p_{ij} is the probability of j being reported in the survey given that i is recorded in the administrative data. Thus, the row probabilities sum to 1. A subscript of 1 means food stamp receipt for a household, while 0 means no food stamp receipt for a household.

Now some households that are true food stamp recipient households will not be recorded as recipient households in the administrative data. Such errors will occur because in some cases not all household members have a PIK and those members may receive food stamps even when others in the household do not. These households will appear in the first row of the above matrix, but should be in the second row. Thus, the number of recipient households will be understated in the administrative data. Let p_1 be the probability that a household reports receipt in the survey when it is one of these true recipient households that is misclassified in the administrative data as a nonrecipient household.

Let the matrix for households that are not subject to this misclassification be

	Survey Data	
Administrative Data	$\tilde{p}_{00}$	$\tilde{p}_{01}$
	$\tilde{p}_{10}$	$\tilde{p}_{11}$

The observations subject to the misclassification in the administrative data are those where some, but not all household members received food stamps and some but not all household members have a PIK. It seems reasonable to assume that such households are more likely to report food stamp receipt than households where no-one receives food stamps, given that they are true recipient households. However, such households seem less likely to report receipt than households where everyone is PIKed and at least one household member receives food stamps. In these latter households, the dominant case will be that everyone receives food stamps. Thus, it seems very likely that the former households where some members do and some do not receive food stamps are less likely to report receipt than households not subject to administrative misclassification.

In inequalities, these assumptions mean that $\tilde{p}_{01} < p_1 < \tilde{p}_{11}$.

Under these conditions, it is easy to show that the true false positive rate $p_{01}^* = \tilde{p}_{01}$ will be lower than the observed rate p_{01}, and the true false negative rate p_{10}^* will be higher than the observed rate $p_{10} = \tilde{p}_{10}$. These conclusions follow because the observed false positive rate p_{01} is a weighted average of the true rate $p_{01}^* = \tilde{p}_{01}$ and p_1 which is larger than $\tilde{p}_{01}$. Similarly, the true false negative rate p_{10}^* is a weighted average of $p_{10} = \tilde{p}_{10}$ and 1-p_1 which is larger than $\tilde{p}_{10}$ since $p_1 < \tilde{p}_{11}$ and $\tilde{p}_{10} = 1 - \tilde{p}_{11}$.