Food For The Hungry:

The Impact of Increased SNAP Payouts on Hunger

MPP Professional Paper

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ABSTRACT

In 2009, Congress passed the American Recovery and Reinvestment Act (ARRA). This legislation provided an increase in Supplemental Food Assistance Program (SNAP) payouts of 15%, on average. Employing the Linear Probability, Logit and Ordered Logit Difference-in-Difference models, I estimate the impact of this payout increase on reported hunger. I use data from the Food Security Supplement of the Current Population Survey. The results show that increases in SNAP payouts have reduced the probability of being hungry at all in the previous month. Furthermore, when estimating the impact on the frequency of hunger, I find that those who are likely to report being hungry more often experience larger reductions in their probability of being hungry due to increases in SNAP payouts. These findings support the effectiveness of increased SNAP payouts during harsh economic times and further help identify the level of reported hunger for which increasing payouts is more significant.

1. Introduction

In the years 2007-2009, the United States experienced what is commonly referred to as the Great Recession. This recession has had many negative effects on the socio-economic climate in America and the world, such as rising unemployment rates, increases in job losses and slow growth of new businesses (Bureau of Labor Statistics, 2012). Such a turn of events prompted the US government to pass the American Recovery and Reinvestment Act of 2009. This act allocated funds to numerous projects, which not only included infrastructure projects at the state level, but also a temporary increase in SNAP payouts to recipients. This amounted to an average increase of 15% in SNAP payouts (United States Department of Agriculture, 2012).

Since SNAP's primary goal is to provide additional support for families who have difficulty securing food, increasing SNAP payouts during a recession is meant to smooth out their consumption of food. It is thus necessary to understand whether this attempted consumption smoothing has affected the reported hunger of participants. The motivation behind this paper is based on understanding whether the high financial investment by the federal government has in fact helped poor families reduce their potential hunger in times of harsh economic climate.

This paper bears some similarities to Nord and Prell (2011) who looked at the impact of increased SNAP payouts on food security using Difference-in-Difference, among other methods, for the period 2008-2009. Though I employ the same dataset and Difference-in-Difference as well, I look at the impact of increased SNAP payouts on how frequently respondents report being hungry, a different food security indicator. I also employ data for years 2007 to 2010, which is a longer period than their data. The purpose of my paper is to investigate whether SNAP payout increases caused households to report less hunger in general, and to identify what effects this expansion had on the frequency of hunger.

I find that increased SNAP payouts have in fact reduced the probability of being hungry by 14%, on average and holding all else constant. This result is robust to the addition of other covariates and to sensitivity analysis. I also find that the probability of being hungry is reduced in greater magnitude for those who report being hungry more often. Those who reported being hungry 21-30 days experience a decrease of 35% in their probability to be hungry in that range again after SNAP increases.

The rest of this paper proceeds as follows: Section 2 gives some background information on SNAP participation during the great recession and reviews relevant recent literature. Section 3 explains the methods I employ including my model specification. Background information on the data used along with important notes regarding data manipulation is included in Section 4. Section 5 shows results and sensitivity analysis and Section 6 concludes with a discussion of my findings.

2. Background and Literature Review

2.1 Background on SNAP eligibility, participation and impact

According to the Congressional Budget Office (2012), 85% of households that were SNAP participants in 2010 were below the Federal Poverty Line (FPL). This follows from the fact that SNAP eligibility is largely dependent on household income. However, it is also dependent on the number of people in the household, among other factors. I employ those two factors as the main determinants of eligibility as they are good indicators for eligibility in SNAP. Households can also be deemed to be eligible or ineligible based on their participation in other social programs but are usually eligible due to the income threshold relative to the Federal Poverty Level Guidelines. About 72% of households eligible for SNAP participated in the program in 2009, with the likelihood of participating rising as household income went down. This implies that there are households eligible for SNAP that do not participate in the program (Congretional Budget Office, 2012).

SNAP participation usually increases in times of high unemployment (Congretional Budget Office, 2012). This implies that for a relatively high unemployment period such as the Great Recession (Bureau of Labor Statistics, 2012), there is a rise in SNAP participation.

2.2 Relevant Studies

The literature on SNAP is varied both in terms of the results and methods. Researchers have tried to evaluate SNAP's impact on food insecurity, food expenditure and how participants compare with non-participants in terms of food sufficiency.

Beatty and Tuttle (2012) find that as SNAP payouts increase, there is an increase in the share of household expenditures spent on food-at-home. This supports the consumption smoothing goal of increased SNAP payouts. Participating households are also seen to experience less food insecurity (Golla and Nord 2009, McKernan et al. 2011). Nord and Prell (2011) observe a similar trend during the

ARRA period. They find that increasing SNAP payouts reduces food insecurity by 2.2 percentage points. These studies point to SNAP participation effectively reducing food insecurity and stabilizing food consumption in times of recession. To supplement the literature, in this paper, I further estimate the impact of SNAP on the frequency of reported hunger.

3. Methods

One of the fundamental issues with statistical evaluations of social phenomena is that, unlike physical sciences, social experiments are not always practically, financially, or ethically feasible. For this reason, econometricians have developed numerous methods to go beyond the use of experimental methods. For this paper, I use Difference-in-Differences (DID) to measure the treatment impact. The passage of the ARRA acts as an exogenous policy shock, allowing SNAP to be evaluated as a natural experiment using DID. The treatment impact in this case is the Average Treatment Effect on the Treated (ATET).

3.1 Treatment and Comparison Groups

One of the fundamental issues with non-experimental methods of evaluation arises from self-selection. If program participants are allowed to self-select into the program (as is true with SNAP) they could be systematically different from those who do not self-select into the program. DID attempts to fix this issue by comparing the trends for the treatment group to those in the comparison group, before and after the treatment has occurred. For this method to work, it is important that the difference in trends between the groups is only due to the treatment. It is impossible to test this assumption. However, I select my treatment and comparison groups to minimize the potential differences in trends that take occur due to reasons other than the treatment.

Using traditional designs of DID, the treatment group should be SNAP participants while the comparison group should be people who qualify for SNAP but are not SNAP participants. However, this approach would prove problematic in this case. The people who are eligible for SNAP but do not participate are likely to have systematic differences compared to SNAP participants, making them an unsuitable comparison group. I thus employ an approach similar to Nord and Prell (2011) in defining my treatment and comparison groups. I identify those households that are eligible (less or equal to 130% of Federal Poverty Line) and participate in SNAP as my treatment group. My comparison group is then made up of those households that are barely eligible (150-250% of Federal Poverty Line) and do not participate in SNAP. The households in the 130-150% range of Federal Poverty Line are not used as their eligibility is not easily inferred. This assumes that these two groups, being close to that cut-off of eligibility, should be fairly similar allowing a more adequate comparison.

3.2 Assumptions

I need to make several assumptions to construct my treatment and comparison groups. First, I assume that those who are barely ineligible would enroll in SNAP were they eligible. Though untestable, this assumption relies on the potential that those in the comparison groups are rational actors. These households have limited resources, which restrict their consumption of a necessity (food). If given the opportunity, they would participate in order to increase their consumption of food, which is a basic necessity they have limited access to.

Further, I assume that people are not intentionally reducing their income in order to be SNAP eligible. This would produce an unnatural treatment group. Since income is a major determinant of selection into the treatment group, it is hard to imagine that households would purposefully restrict their income, as they are already not earning much.

Additionally, I assume that the treatment and comparison groups are subject to the same unobservable trends because they are close to each other on the eligibility discontinuity. Since these two groups are not far from each other in terms of socio-economic pressures, they are very likely to be subject to the same trends.

3.3 Model

$$Y = X_{it}\beta_1 + \beta_2 POST + \beta_3 TREATMENT + \beta_4 POSTTREAT + \beta_5 I_{[I=i]} + \epsilon$$

The model above looks at the impact of SNAP payout increases (given by β_4) on the frequency (days) the respondent reported being hungry due to not being able to afford enough food to eat in the past month. An alternate model will look at the impact of SNAP increases on being hungry at all. The two other variables in the model, given by β_2 and β_3, are dummy variables indicating being in the post treatment period and being in the treatment group, respectively. Covariates (X_{it}) employed are % of Federal Poverty Line, number of children, family size, employment status and race (6 categories, base: white). Though the data does not follow a panel structure, dummy variables for state and year attempt to make the time invariant portion of the error term the same across units of observation in each state.

My hypothesis is that the treatment impact will have a negative relationship to both versions of the variable of interest. I anticipate that increasing SNAP payouts has both reduced the probability of being hungry at all, and the probability of being hungry in all frequency categories discussed in Section 4.

4. Data

I use data from the Current Population Survey Food Security Supplement (CPS-FSS). This dataset is suitable for this paper due to its richness and the availability of information on households that participate in SNAP, their reported hunger, as well as baseline characteristics.

4.1 Background on CPS-FSS

The CPS-FSS is a supplement to the Current Population Survey administered in December of each year. It is a household-level questionnaire that inquires about the food security of respondents. The Food and Nutrition Service of the USDA uses an 18 item scale to assess food security based on the results of the CPS-FSS. Households that are eligible for the CPS-FSS are the same households that are eligible for the regular CPS. Respondents are identified based on where they stand relative to the Federal Poverty Guidelines and whether they are identified as potentially being "food insecure" (Data.gov, 2014).

An issue encountered as a result of using CPS-FSS data is the determination of household income. The CPS-FSS reports household income in ranges. Therefore, the identification of specific household income becomes problematic. I thus employ a technique similar to Prell and Nord (2011). I assign the nominal median income of each range to the corresponding households in the bracket. This method is appropriate for low-income households (which are the ones that make up my sample) as the range of each yearly income bracket is around $2500, which is rather small. The income assigned to the household is then a proxy for the actual household income.

4.2 Ordered Logit, Logit and Linear Probability Model

The variable of interest from the data identifies how often in the past 30 days the respondents went hungry because they could not afford more food. The responses of this variable are in numerical form from 1 to 30, while one category reports “at least once.” This particular category proved to be problematic for my purposes as these responses are necessary for analysis, but it would be hard to pinpoint which numerical value they represent. I thus modified the variable into a categorical variable assigning “none” for responses that were identified as 0, “few” for responses between 1 and 10 days (including “at least once “ responses since these responses are expected to represent a low frequency), "some" for responses between 11 and 20, and "many" for responses between 21 and 30. This categorization is arbitrary and was decided solely to ensure there is balance in the division of days. I modify these categories as part of sensitivity analysis in Section 5. The respondents who answered "at least once" were not found to have significant differences as compares to the rest of the sample using a T-test.

I employ an ordered logit (with base outcome "none") for the model. Furthermore, I generate another version of the variable to be a simple dummy variable which takes the value of "1" when respondents reported being hungry at all in the past month, and "0" for respondents who did not report being hungry. This variable is then used in both a logit model and a Linear Probability Model (LPM).

4.3 Final sample

After data manipulation, the sample is made up of 5,900 observations. I started with over 150,000 observations but once I limited the sample to the desired levels of FPL, by participation/non-participation in SNAP and by those who answered the question of interest, this number shrunk considerably.

The sample is separated between treatment and comparison group with a split very close to 50%. This implies that the separation using % of Federal Poverty Line created a balanced number of observations in the treatment and comparison groups. The average percentage of the FPL in our sample is 136%, which is around the cut off rate to get into the comparison group. On average, a household has 3 members and 0-1 children.

From Figure 1, a bigger proportion of responses tend to report few days of hunger, followed by no days of hunger. “Some” and “many” are the bottom two categories. Moving from 2008 to 2009, there is a reduction in the proportion of “few”, “many” and “some” while there is a drastic increase in “none.” This supports my hypothesis that as there are increased SNAP payouts in 2009, people are reporting being hungry less frequently, if at all.

The question inquiring about SNAP participation asks respondents whether they received SNAP during the past year. Since the responses to my independent variable is concerned with the past 30 days, I only keep SNAP participants that had SNAP 30 days prior to responding to the survey. Furthermore, I assume that treatment occurs at the start of 2009 when in fact the ARRA came into effect in

April of 2009. The data do not provide enough rich monthly information to allow for this distinction to be accounted for.

5. Results

5.1 Logit and Linear Probability Model

The predicted average predicted probability of being hungry at all for the sample is 66.8%. As seen in Table 3, the treatment impacts are highly statistically significant. When I add covariates, the coefficients and standard errors change only minimally. From the LPM models, the increase in SNAP payouts have reduced the probability of being hungry by 9.5-9.6 percentage points, on average, all else constant. The logit models produce very similar coefficients and standard errors. From the logit models, the increase in SNAP payouts cause a reduction in the probability of being hungry by 9.1-9.2 percentage points, on average, all else constant. Thus, the increase in SNAP payouts has reduced the probability of being hungry by 14%, on average and holding all else constant. The magnitude and direction of this change indicate that the increases in SNAP payouts have benefitted participants considerably.

5.2 Ordered Logit

From Table 4, all of the treatment impacts reach statistical significance and the coefficients do not change by much when covariates are added. The percentage change in the predicted probability of being hungry for the "few," "some," and "many" categories are 5.2%, 27.3%, and 35%, on average and all else constant. This shows a clear trend that those who are likely to report a higher frequency of hunger are the ones who experience a greater reduction in their probability of being hungry. This finding implies that increasing SNAP payouts does a good job at decreasing the likelihood of being hungry for those who are usually the most affected by hunger. It is however interesting to see that for the lower strata of "few" days of hunger, the reduction in the probability of being hungry is only 5%. This implies that getting more SNAP benefits does not necessarily do a good job at reducing the hunger of those who report fewer days of hunger.

5.3 Different Categories for Variable of Interest

To test whether my arbitrary categorization of the variable of interest into group of 10 days was adequate, I recode my variable of interest into different ranges. I now attribute "few" to 0-5 days, "some" to 6-15 days and many to "16-30" days. This will shrink the number of observations in the "few" category and increase the number of observation in the "many" category.

The treatment impacts once again are mostly statistically significant at the 5% level. The "many" category, once more has a greater percentage decrease in the probability of hunger. However, the coefficient on the "few" category in this case is statistically significant. This implies that increased SNAP payouts do not necessarily have a measurable impact on those who reported being hungry 1-5 days.

I further try to isolate the treatment impact to a range by rearranging the variable of interest into four categories based on the number of weeks. The strata employed are "1-7 days," "8-14 days," "15-21 days," and "22-30 days." The results show that the category "15-21 days" is highly significant. As the lowest category is expanded, it once again becomes statistically significant at the 5% level. The percentage decrease in the likelihood of being hungry "1-7 days," "8-14 days," "15-21 days," and "22-30 days" are 1.7%, 18.2%, 24.4% and 30.8%, on average and all else constant. Though the lowest category is significant, the magnitude of the decrease is the lowest compared to the other categories. As we go towards a higher frequency of hunger, there is a bigger magnitude in the reduction of the probability to be hungry, reinforcing the previous claim that increasing SNAP benefits has a bigger impact on those who report more frequent hunger than others.

6. Discussion and Conclusion

The results of my analyses suggest that increasing SNAP payouts reduces the probability of being hungry at various levels of hunger frequency. Increasing SNAP payouts during the Great Recession has reduced the probability of being hungry at all by 14%, on average, all else constant. As for the frequency of hunger, the treatment impact is strongest for those who report being hungry more frequently than others. Those who reported being hungry between 22-30 days in the previous month experienced a 35% decrease in their probability of being hungry, which is the largest treatment impact. Those who report being hungry less frequently either do not have an impact on their probability of being hungry or see a very small impact. I see similar trends when I employ a different categorizations of the dependent variable.

These findings are highly relevant to policies affecting food security and hunger. The goal of increasing payouts is to help people afford food, that is decrease the likelihood of hunger for households. By my results, it is clear that this has been accomplished by the increased payouts. These findings prove that in dire economic times, increasing food support does have positive impacts on poor families. There are limitations to my results however. The external validity of these results is potentially reduced if generalized to non-recession periods. In non-recession periods, there might be behavioral differences in participants, which are not captured here.

A potential future study would be to replicate my models but this time using the expiration of the SNAP payout reductions of 2013 as an exogenous shock. It would then be possible to analyze the reverse impact: what happens to hunger when benefits are reduced? This would help identify whether decreased payouts affect hunger as we get out of an economic downturn. Another idea for a future study would be to identify the reason behind the effectiveness of SNAP on households that report high frequency of hunger as opposed to households that report lower frequency of hunger. If the current dispensing of SNAP benefits is not helping certain groups as much as it intends to, it would imply that there is a need for a different kind of assistance for them.

Works Cited

Beatty, T. K., & Tuttle, C. (2012, May). Expenditure Response to Increases in In-Kind Transfers: Evidence from the Supplemental Nutrition Assistance Program. *AAEA/EAAE Food Environment Symposium* .

Bureau of Labor Statistics. (2012, February). *BLS Spotligh on Statistics: The Recession of 2007-2009*. Retrieved March 20, 2014, from Burea of Labor Statistics Spotlist: http://www.bls.gov/spotlight/2012/recession/pdf/recession_bls_spotlight.pdf

Congretional Budget Office. (2012, April). *The Supplemental Nutrition Assistance Program.* Retrieved March 21, 2014, from CBO Files: http://www.cbo.gov/sites/default/files/cbofiles/attachments/04-19-SNAP.pdf

Data.gov. (2014). *Data.gov - CPS FSS*. Retrieved March 22, 2014, from https://explore.data.gov/Income-Expenditures-Poverty-and-Wealth/Current-Population-Survey-Food-Security-Supplement/d6pf-n3qs

Golla, A., & Nord, M. (2009). Does SNAP Decrease Food Insecurity? Untangling the Self-Selection Effect. *Economic Research Report , 85*.

McKernan, S.-M., Ratcliffe , C., & Zhang, S. (2011). How much does the Supplemental Nutrition Assistance Program reduce food inseucirty? *American Journal of Agricultural Economics , 93* (4).

Minnesota Population Center. (n.d.). *IPUMS CPS-FSS*. Retrieved March 22, 2014, from IPUMS: https://cps.ipums.org/cps/food_security_sample_notes.shtml

Nord, M., & Prell, M. (2011, April). Food Security Improved Following the 2009 ARRA Increase in SNAP Benefits. *USDA Economic Research Service* .

United States Department of Agriculture. (2013, November 20). *A Short History of SNAP*. Retrieved March 20, 2014, from United States Department of Agriculture: Food and Nutrition Service: http://www.fns.usda.gov/snap/short-history-snap

United States Department of Agriculture. (2012, June 04). *USDA: Supplemental Nutrition Assistance Program*. Retrieved March 20, 2014, from ARRA: http://www.ers.usda.gov/topics/food-nutrition-assistance/supplemental-nutrition-assistance-program-(snap)/arra.aspx#.UytZCa1dW50

Tables and Figures

Table 1: Summary Statistics. CPS – FSS sample

	Proportion
Treatment Group	54.54%
Comparison Group	45.46%

	Treatment	Comparison	Total
Employed	13.19%	37.74%	52.18%
Unemployed	86.81%	62.26%	47.82%
Race:			
White	56.17%	48.10%	70.55%
Black	14.53%	23.28%	9.96%
Asian	1.43%	0.97%	4.33%
Hawaiian/Pacific Islander	0.13%	0.07%	0.37%
Hispanic	23.84%	22.53%	12.71%
More than 1 Race	3.90%	5.05%	2.08%

Mean (Standard Deviation)	Treatment	Comparison	Total	Min	Max
% of FPL	83.46 (28.89)	199.26 (29.50)	136.11 (64.57)	30.3	249.72
Family Size	3.67 (2.22)	3.02 (1.75)	3.38 (2.05	1	11
Number of Children	0.40 (0.93)	0.44 (0.93)	0.41 (0.93)	0	7

Table 2: Distribution of variable of interest into treatment and comparison group sorted by year. Sample of CPS-FSS.

	Frequency with which adults in the household was hungry due to the unavailability of food in the past month				
	None	Few	Some	Many	Total
2007					
Treatment Group	182 *28.88%*	306 *48.39%*	82 *12.95%*	62 *9.78%*	631 *100%*
Comparison Group	162 *29.16%*	286 *51.50%*	67 *11.96%*	41 *7.38%*	557 *100%*
Total	345 *29.01%*	592 *49.85%*	148 *12.48%*	103 *8.66%*	1,188 *100%*
2008					
Treatment Group	206 *29.73%*	356 *51.29%*	69 *10.00%*	63 *8.98%*	694 *100%*
Comparison Group	252 *28.21%*	447 *50.08%*	102 *11.46%*	91 *10.25%*	892 *100%*
Total	458 *28.87%*	803 *50.61%*	172 *10.82%*	154 *9.70%*	1,586 *100%*
2009					
Treatment Group	233 *32.28%*	346 *47.70%*	99 *13.68%*	46 *6.33%*	724 *100%*
Comparison Group	337 *39.81%*	385 *45.37%*	62 *7.33%*	109 *7.50%*	848 *100%*
Total	571 *36.34%*	730 *46.45%*	161 *10.25%*	19 *6.96%*	1,572 *100%*
2010					
Treatment Group	198 *31.33%*	297 *46.95%*	85 *13.42%*	53 *8.31%*	633 *100%*
Comparison Group	382 *41.51%*	395 *42.94%*	78 *8.50%*	65 *7.06%*	921 *100%*
Total	581 *37.36%*	693 *44.57%*	163 *10.50%*	118 *7.57%*	1,554 *100%*

Figure 1: Distribution of responses to the question "How many days in the past month have you been hungry because they could not afford more food?". Sample of CPS-FSS.

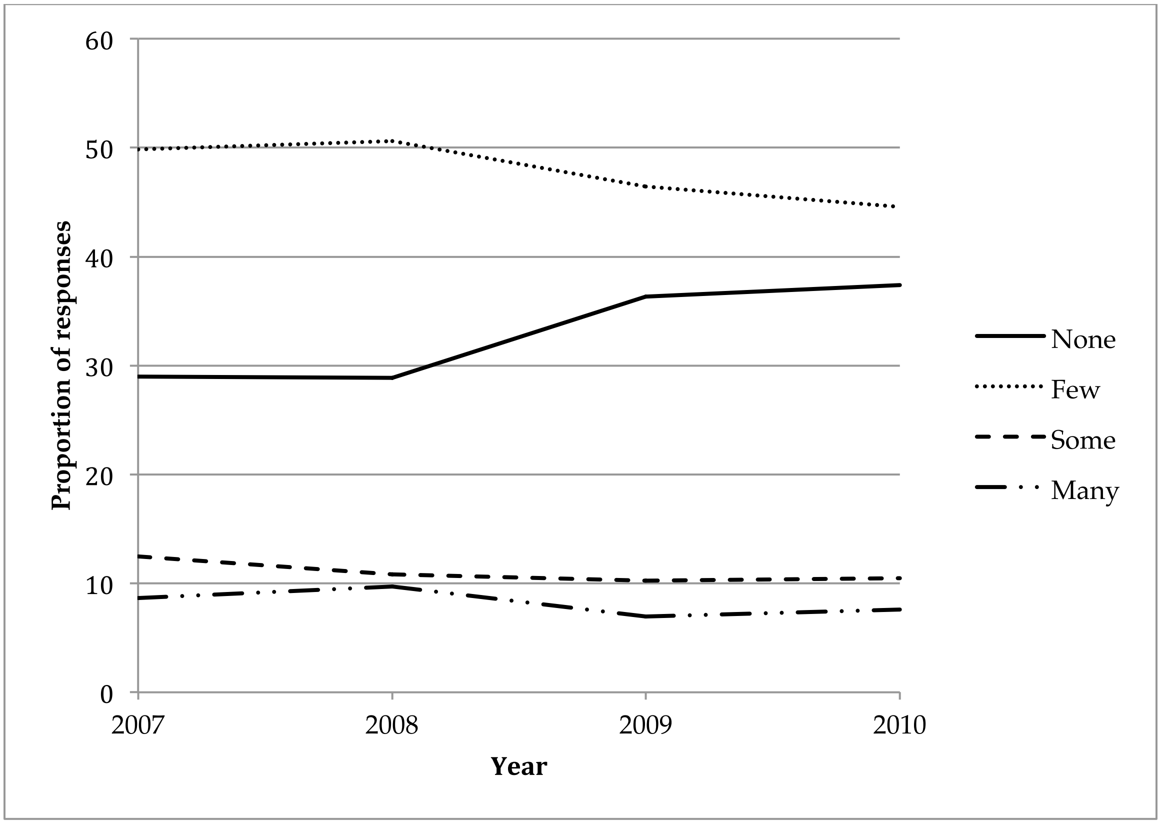

Table 3: Impact of increased SNAP payouts on the probability of being hungry at all.

	(1)	(2)	(3)	(4)
Change in probability of being hungry due to treatment	-0.0950***	-0.0961***	-0.092***	-0.091***
	(0.028)	(0.028)	(0.028)	(0.028)
Covariates	No	Yes	No	Yes
Fixed Effects	Yes	Yes	Yes	Yes
Number of Observations	5900	5813	5900	5813

Notes: Each column represents a different regression model. Columns (1) and (2) are Linear Probability Models while (3) and (4) are Logit Models, which coefficient shown being average marginal effects. Covariates are number of children, family size, employment status (0 for unemployed, 1 for employed), % of fpl and race (base: white, 6 categories). All models include dummy variables for state and year. Standard errors shown between parentheses are robust standard errors for column (1) and (2), and delta method standard errors for column (3) and (4). Weights used are IPUMS CPS household weights. Sample from CPS-FSS.

* p-value<0.1; ** p-value<0.05; *** p-value<0.01

Table 4: Impact of increased SNAP payouts on the probability of being hungry a few, some or many days, as compared to none.

Change in probability due to treatment:	(1)	(2)
A few days (1-10 days)	-0.025***	-0.025***
	(0.0075)	(0.0076)
Some days (11-20 days)	-0.031***	-0.030***
	(0.0090)	(0.0090)
Many days (21-30 days)	-0.030***	-0.029***
	(0.0086)	(0.0086)
Covariates	No	Yes
Fixed Effects	Yes	Yes
Number of Observations	5900	5813

Notes: Each column represents a different regression model. Base outcome of comparison is “none.” Coefficients shown are average marginal effects. Covariates are number of children, family size, employment status (0 for unemployed, 1 for employed), % of fpl and race (base: white, 6 categories). Both models include dummy variables for state and year. Standard errors shown between parentheses are delta method standard errors. Weights used are IPUMS CPS household weights. Sample from CPS-FSS.

* p-value<0.1; ** p-value<0.05; *** p-value<0.01

Table 5: Impact of increased SNAP payouts on the probability of being hungry a few, some or many days, as compared to none. Alternate categorization used for sensitivity.

Change in probability due to treatment:	(1)	(2)
A few days (1-5 days)	0.00094	0.00088
	(0.0013)	(0.0013)
Some days (6-15 days)	-0.042***	-0.040***
	(0.025)	(0.014)
Many days (16-30 days)	-0.033***	-0.0032***
	(0.011)	(0.014)
Covariates	No	Yes
Fixed Effects	Yes	Yes
Number of observation	5900	5813

Notes: Each column represents a different regression model. Base outcome of comparison is “none.” Coefficients shown are average marginal effects. Covariates are number of children, family size, employment status (0 for unemployed, 1 for employed), % of fpl and race (base: white, 6 categories). Both models include dummy variables for state and year.Standard errors shown between parentheses are delta method standard errors. Weights used are IPUMS CPS household weights. Sample from CPS-FSS.

* p-value<0.1; ** p-value<0.05; *** p-value<0.01

Table 6: Impact of increased SNAP payouts on the probability of being hungry 1-7 days, 8-14 days, 15-21 days, 22-30 days .

Change in probability due to treatment:	(1)	(2)
1-7 days	-0.0067**	-0.0065**
	(0.0027)	(0.0026)
8-14 days	-0.020***	-0.20***
	(0.0066)	(0.0067)
15-21 days	-0.022***	-0.022***
	(0.0074	(0.0075)
22-30 days	-0.024***	-0.024***
	(0.0080)	(0.080)
Covariates	No	Yes
Fixed Effects	Yes	Yes
Number of observation	5900	5813

Notes: Each column represents a different regression model. Base outcome of comparison is “0 days.” Coefficients shown are average marginal effects. Covariates are number of children, family size, employment status (0 for unemployed, 1 for employed), % of fpl and race (base: white, 6 categories). Both models include dummy variables for state and year. Standard errors shown between parentheses are delta method standard errors. Weights used are IPUMS CPS household weights. Sample from CPS-FSS.

* p-value<0.1; ** p-value<0.05; *** p-value<0.01

Appendices

Appendix A: Cross-tabulation of family income and reported hunger

Did adults in the household experience hunger in the past month?			
Family Income	No	Yes	Total
$5,000 to $7,499	105	174	279
	38%	62%	100%
$7,500 to $9,999	98	168	279
	38%	63%	100%
$10,000 to $12,499	99	244	343
	29%	71%	100%
$12,500 to $14,999	70	137	207
	34%	66%	100%
$15,000 to $19,999	95	137	337
	28%	72%	100%
$20,000 to $24,999	95	242	226
	28%	72%	100%
$25,000 to $29,999	68	119	187
	36%	64%	100%
$30,000 to $34,999	30	54	84
	36%	64%	100%
$35,000 to $39,999	30	54	84
	36%	64%	100%
$40,000 to $49,999	5	19	25
	22%	78%	100%
$50,000 to $59,999	8	13	21
	36%	63%	100%
$60,000 to $74,999	0	1	1
	0%	100%	100%
Total	709	1444	2154
	33%	67%	100%

Appendix B: Detailed regression outputs for models using LPM

	(1)	(2)
Treatment Group Dummy	0.0018	-0.16
	(0.20)	(0.028)
Post ARRA period Dummy	-0.026	-0.022
	(0.025)	(0.025)
Post ARRA*Treatment (ATET)	-0.096***	-0.96***
	(0.028)	(0.028)
Family Size		0.0037
		(0.0038)
% of FPL		0.00026
		(0.00024)
Number of Children		0.0056
		(0.0080)
Employment Dummy		-0.29*
		(0.017)
Race (Base: White)		
Black		-0.0093
		(0.021)
Asian		-0.22***
		(0.062)
Hawaiian/Pacific Islander		0.21**
		(0.89)
Hispanic		0.56***
		(0.021)
More than one race		0.036
		(0.033)
R-Squared	0.031	0.038
Adjusted R-Squared	0.022	0.027
F-Statistic	3.53	3.67
Number of Observations	5900	5813

Notes: Each column represents a different regression model. Employment Dummy takes a value of 1 if employed and 0 if unemployed. Both models include dummy variables for state and year. Standard errors shown between parentheses are robust standard errors. Sample from CPS-FSS.
* p-value<0.1; ** p-value<0.05; *** p-value<0.05

Appendix C: Detailed regression outputs for models using Logit

	(1)	(2)
Treatment Group Dummy	0.024	0.017
	(0.021)	(0.034)
Post ARRA period Dummy	-0.027	-0.22
	(0.025)	(0.025)
Post ARRA*Treatment (ATET)	-0.092***	-0.91***
	(0.028)	(0.028)
Family Size		0.0036
		(0.0038)
% of FPL		0.00026
		(0.00024)
Number of Children		0.058
		(0.0081)
Employment Dummy		-0.029*
		(0.018)
Race (Base: White)		
Black		-0.0090
		(0.021)
Asian		-0.22***
		(0.062)
Hawaiian/Pacific Islander		0.23***
		(0.089)
Hispanic		0.055***
		(0.020)
More than one race		0.035
		(0.032)
Pseudo R-Squared	0.0247	0.0301
Wald Chi-Squared	167.81	198.44
Number of Observations	5900	5813

Notes: Each column represents a different regression model. Coefficients shown are average marginal effects. Employment Dummy takes a value of 1 if employed and 0 if unemployed. Both models include dummy variables for state and year. Standard errors shown between parentheses are Delta Method Standard Errors. Sample from CPS-FSS.

* p-value<0.1; ** p-value<0.05; *** p-value<0.01

Appendix D: Detailed regression outputs for model using Ordered Logit without covariates

	(1)	(2)	(3)
Treatment Group Dummy	-0.000094	0.00011	-0.00011
	(0.0052)	(0.0063)	(0.0061)
Post ARRA period Dummy	-0.043	0.0052	-0.050
	(0.0067)	(0.0080)	(0.0078)
Post ARRA*Treatment (ATET)	-0.025***	-0.031***	-0.030***
	(0.0076)	(0.0090)	(0.030)
Pseudo R-Squared		0.014	
Wald Chi-Squared		197.03	
Number of Observations		5900	

Notes: Each column represents a different regression model. Column (1) is for "few" category, (2) is for "some" category and (3) is for "many" category. Base outcome of comparison is "none." Coefficients shown are average marginal effects. Employment Dummy takes a value of 1 if employed and 0 if unemployed. Model includes dummy variables for state and year. Standard errors shown between parentheses are Delta Method standard errors. Sample from CPS-FSS.

* p-value<0.1; ** p-value<0.05; *** p-value<0.01

Appendix E: Detailed regression outputs for Ordered Logit with covariates.

	(1)	(2)	(3)
Treatment Group Dummy	-0.019	-0.0023	-0.0022
	(0.0088)	(0.011)	(0.010)
Post ARRA period Dummy	-0.027	0.0033	-0.0032
	(0.0067)	(0.0081)	(0.0078)
Post ARRA*Treatment (ATET)	-0.025***	-0.030***	0.029***
	(0.0076)	(0.0090)	(0.0086)
Family Size	-0.000040	-0.000049	-0.000047
	(0.00099)	(0.0012)	(0.0012)
% of FPL	0.000013	-0.000016	-0.000015
	(0.000063)	(0.00077)	(0.000074)
Number of Children	0.0026	0.0032	0.0031
	(0.0021)	(0.0025)	(0.0024)
Employment Dummy	-0.0079*	-0.096*	-0.0092
	(0.0047)	(0.056)	(0.0054)
Race (Base: White)			
Black	-0.0057	-0.0061	-0.0057
	(0.0064)	(0.0065)	(0.0060)
Asian	-0.12***	-0.057***	-0.047
	(0.040)	(0.012)	(0.0088)
Hawaiian/Pacific Islander	-0.024	0.87	0.12
	(0.079)	(0.057)	(0.12)
Hispanic	0.0061	0.085	0.0083
	(0.047)	(0.069)	(0.0068)
More than one race	0.0040	0.0053	0.0051
	(0.0074)	(0.011)	(0.010)
Pseudo R-Squared		0.017	
Wald Chi-Squared		222.10	
Number of Observations		5813	

Notes: Each column represents a different regression model. Column (1) is for "few" category, (2) is for "some" category and (3) is for "many" category. Base outcome of comparison is "none." Coefficients shown are average marginal effects. Employment Dummy takes a value of 1 if employed and 0 if unemployed. Model includes dummy variables for state and year. Standard errors shown between parentheses are Delta Method standard errors. Sample from CPS-FSS.

* p-value<0.1; ** p-value<0.05; *** p-value<0.01