Evaluation of a Community Based Food Program Support Project

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Abstract: The University of Kentucky Rural Child Poverty Nutrition Center piloted a program designed to provide local community organizations with both financial support and training resources to improve outreach programs in persistently poor communities. To evaluate the effectiveness of this program, data were collected using a survey on food security as well as participation rates in six USDA food programs: Supplemental Nutrition Assistance Program (SNAP), the National School Lunch Program (NSLP), the School Breakfast Program (SBP), the Summer Food Service Program (SFSP), the Special Supplemental Nutrition Program for Women, Infant and Child (WIC), the Child and Adult Care Food Program (CACFP). Survey results showed few differences between the participating counties and national trends. An analysis of participation rates indicated some evidence of a modest positive impact on SNAP, but also a decrease in use of WIC.

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Introduction

The USDA Food and Nutrition Service (FNS) administers a variety of programs designed to provide access to food for children who are in financial need. The Supplemental Nutrition Assistance Program (SNAP), the National School Lunch Program (NSLP), the School Breakfast Program (SBP), the Summer Food Service Program (SFSP), the Special Supplemental Nutrition Program for Women, Infant and Child (WIC), the Child and Adult Care Food Program (CACFP), and the Food Distribution Program on Indian Reservations (FDPIR) are all designed to provide nutrition to children. However, evidence suggests that these programs are often underutilized by eligible families. Coleman-Jenson et al. (2017) report that 59% of food insecure households reported receiving food assistance from one or more of the three largest Federal food assistance programs in 2016. Coleman- Jenson et al. (2018) report that participation amongst food insecure households dropped to 58% in 2017. This is a declining trend that can be observed over the last few years. Reasons for low take up rates include a lack of information about the programs, lack of physical access to the program, as well as stigma. Outreach to provide access to families, in particular in rural and high poverty areas, is challenging. Outreach is typically undertaken by local organizations, including school districts, religious organizations, and community action groups. These groups are often poorly funded and may lack training, experience and other resources which would improve their effectiveness in the outreach and education missions. This paper examines a quasi-experimental demonstration performed by the Rural Child Poverty Nutrition Center (RCPNC) at the University of Kentucky. The program was designed to provide support and training to improve the effectiveness of community based organizations promoting the use of safety net food programs.

Studies have shown that safety net food programs benefit the participants in various ways. Ratcliffe et al. (2011) find that SNAP participation reduces the likelihood of being food insecure. Kreider et al. (2012) also find supporting evidence that SNAP participation leads to reduced food insecurity. Kabbani and Kmeid (2005) find that participation in NSLP is associated with lower food insecurity for households with school-age children that experienced hunger during the year. Studies have also found similar outcomes for WIC participants (Kreider et al., 2012; Herman et al., 2004). Literature also shows positive externalities of these programs into other areas of well-being. Gunderson et al. (2012) find that receiving free or reduced-price lunches through NSLP leads to improved health outcomes amongst children. Change in caloric content of lunches provided through NSLP lead to improvements in standardized test scores (Figlio and Winicki, 2005). This suggests that food security can lead to better schooling outcomes as well. The positive spillover effects of food assistance programs is not limited to health and schooling outcomes. Hoynes and Schanzenbach (2009) show that participation in food stamp programs lead to a decrease in out-of-pocket food expenditures which potentially allows for reallocating the additional cash flow to other necessities. Blundell and Pistaferri (2003) find that food assistance programs reduce the effects of a permanent income shock to low-income families allowing for consumption smoothing. Considering the wide range of positive externalities imposed by food assistance programs, it is important to increase participation in these food assistance programs among eligible households.

With this in mind, the University of Kentucky Rural Child Poverty Nutrition Center (RCPNC) in conjunction with Altarum Institute and the Southern Rural Development Center, fielded a trial intervention program designed to provide local community organizations with both financial support and training resources to improve outreach programs in persistently poor communities. Community organizations serving the 322 persistently poor counties in the U.S. were eligible to apply to receive the support. As can be seen in Table 11, these counties have an average poverty rate of over 27%. Many have poverty rates approaching 50%.

The RCPNC developed a Request for Applications (RFA) released July 24, 2015. The RFA called for creative project proposals aimed at increasing coordination among child nutrition programs through a community-participatory approach. Eligibility was restricted to state or local government or nonprofit organizations for work conducted in one of the 322 targeted counties. A total of 50 organizations, representing 68 counties proposed projects. The RCPNC recruited 26 individuals who performed a review of the applications. Each application was reviewed and scored by three of the 26 individuals. Selection was based upon a variety of factors including county needs assessment, institutional organization and number of children potentially served. Seventeen projects representing 33 counties were initially selected and funded. Two projects exited the program prior to completion, reducing the number of counties which completed the program to 17. Our Analysis focus on three nested groups of counties: 322 eligible, 68 applicant counties, and 17 grantee counties.

To the best of our knowledge, no intervention with similar goals and approach to the one evaluated here has been piloted or evaluated. While many interventions – at both the national and regional level – have been developed to improve participation rates, these are typically designed around the benefits or application process. This intervention is therefore unique in that it provides development to local community organizations which in turn work with eligible families and children. Building local infrastructure may have longer lasting effects and may be more effective, since community organizations can tailor their efforts to specific local issues found in their community.

This intervention sought to develop and improve coordination efforts among USDA child nutrition programs through collaborative partnerships in order to increase participation of the programs. Grantees were provided training session through both face to face workshops and webinars. Additionally, the director of the project was available for technical assistance. Grantees were then guided in conducting a community needs assessment of their home community. This provided a basis to prioritize the needs of the community. Grantees then developed implementation strategies as well as communication and coordination plans that utilized available resources. By either developing or joining a community coalition, grantees sought to use multiple resources within their community. There were five major activities undertake by the grantees within their community coalition: Developing relationships and sharing knowledge and resources collectively; advancing and supporting the coalition's focus such as understanding how each of the programs overlapped and intersected; serving as advisors and collaborators on specific projects such as identifying new meal sites for a SFSP; promoting events and resources, such as disseminating information through diverse channels; and volunteering at events and activities.

While none of these projects directly impacts food program usage, the hypothesis was that better coordination and targeting of the myriad of programs and resources in the community would lead to higher program usage and reduced food insecurity. In order to evaluate the success of the intervention program two strategies were employed. First, the RCPNC fielded a survey of residents of the counties served by the intervention at three time points during the project: Fall of 2016 (shortly after counties were selected), Fall of 2017, and Fall of 2018, at the end of the project. The survey collected basic demographic information, information regarding access to and prior use of food programs, and the USDA Food Security Assessment (using a twelve-month window, and assessing both adult and child food security). The timing of the survey, late fall, was similar to the reference period for the December U.S. Current Population Survey, which also fields the USDA Food Security assessment, providing some comparison.

The second strategy was to use county level counts of participation in the targeted programs. Data were collected on participation rates in six programs: NSLP, SBP, SNAP, WIC, SFSP, or SSO. Of the fifteen participating grantees, all included SFSP in their target programs, and 10 included it as their primary program. The NSLP and SBP were next with nine counties including them in their target programs and two and three (respectively) including them in their target list. Seven projects listed SNAP as a target, while six listed WIC. Hence the evaluation focused on these programs for evaluation. County level control variables were also included in model tests. Data on some programs were difficult to obtain, resulting in some loss of sample size and power.

Findings provided evidence of some small impacts of the program on participation rates and perceived food insecurity. Study findings are limited due to a modest number of participating counties and due to the relatively brief evaluation period. We might expect longer term effects, since the project provided development and support which presumably would continue to provide benefits longterm. In section two, we describe the data, in section three, we present results from the survey, in section four, we present results from the analysis of participation data, and section five draws conclusions.

Data

As noted, two types of data were collected and analyzed. First, survey data were collected from a convenience sample of families residing in the counties served by the grant. Grantee organizations advertised the survey which was available online and through “pick up” printed surveys. Grantee organization personnel were not allowed to recruit, but simply provided announcements that a survey was being fielded. Survey respondents were anonymous volunteers.

The survey was conducted at three timepoints: October and November of 2016, October and November of 2017, and September and October of 2018. The timing was chosen for three reasons. First, this represented the beginning of the school year, and thus a period in time where contacting both families with existing relationships to the grantees, new families and families generally within the community was relatively simple. Many of the organizations were associated with school districts, and so advertising within schools was common.

Second, since many of the projects involved the summer food program, this made fielding the survey shortly after the summer particularly informative and made the summer food program more salient for respondents. Finally, this timing is similar to the reference period of the December Current Population Survey which also fields the USDA Food Security Assessment.

Sample sizes were modest, with 790 individuals responding in the first year, 723 responding in the second year, and 736 responding in the third year. It should also be noted that the survey is a convenience sample and may not be representative of the population as a whole. The survey instrument is included in the appendix. Details on response rates and missing data are discussed in the analysis section.

The source of data set obtained from administrative sources focused on participation rates in each of six programs: NSLP, SBP, SNAP, WIC, SFSP and SSO. Collecting these data required contacting administrative offices at the state and often county level. As such, some data were unavailable. Details of the collection are included in the appendix as are details on missing data and construction of participation rates. In addition to data on participation, data were collected on population, percent with a high school degree or more, percent African American, poverty rate, median household income, and the unemployment rate. These provided controls for differences in social and economic conditions across the counties.

Analysis

Food Security Measures

As with all survey data, item non-response impacted the quality of the data. We analyzed the impact on the sample sizes focusing on non-response in the key food security questions and in the income and demographic variables. Table 1 presents sample sizes by year using different response criteria for inclusion. The first column of table 1 presents the total number of surveys returned. For electronic surveys, this includes any survey started; for paper returns, this includes any survey returned with at least one answer (all returned surveys were entered). Since the main variable of interest is the Food Security (FS) measure, we consider two different approaches to missing data in the components of the measure. First, we take any case where at least one of the food security component questions was answered; this is the second column of table 1, labelled "Any FS." As can be seen by comparing column one and column two, nearly all respondents (at least 99% in each year) answered at least one of the food security questions. Second, we limit the cases to those where no more than one question was missing. Analysis of the missing data pattern demonstrated a concentration of complete or only one missing value, or many values missing. Comparing columns two and three, we note that the overwhelming majority of respondents who answered any of the food security questions, answered at least all but one of them (at least 94% in each year). Missing values in various demographic variables (age, gender, and race) further erode sample sizes. Column four presents the sample size of those who completed most of the food security questions and had complete demographic information. Again, over 90% of the column three respondents reported complete demographics. Those with complete food security and complete demographics exceeded 86% of the original returned surveys in each year. The highest rate of missing data occurred in the income questions. Overall, the sample with complete food security, demographic and income data represents 71% of the initial respondents, and 75% of those who completed the food security battery (no more than one missing).

All analysis conducted below was performed on various combinations of the four samples above (columns two through five). Qualitatively, the main results are quite robust across samples and are available upon request. We focus on the sample of complete responses to food security, demographics and income. Those with missing income were more likely to be food insecure than the group with income above 150% of the poverty line and the group between 133% and 150% of the poverty line. Missing income respondents were less likely to be food insecure than those either between the poverty line and 133% of the poverty line or those below the poverty line. However, including or not including that group in the analysis had little impact on coefficients on other variables.

We find that over the course of the program, food insecurity first fell and then returned to original levels. In table 2 we present the food security indicators for the analysis sample by year. We include the more detailed measures of food insecurity as well. We note the large drop in 2017. The difference is statistically significant in some models below. Concern arises that it appears to be different than both 2016 and 2018. We caution drawing strong conclusions based on this. The child indicator follows a similar pattern of dropping in 2017 and returning to similar levels in 2018.

Income is a significant determinant of food insecurity; in table 3, we present the food security indicators by income group. We include a row for those not reporting income (note that percentages in the first column do not include missing income group). The sample here is poor, as to be expected from the selection of persistently poor counties. Given the advertising for the survey, it likely reached families in contact with the grantees, who are likely disproportionately poor even for those counties. Overall, 35% of the households have income below the federal poverty threshold, 18% are between the poverty line and 133% of the poverty threshold, and slightly less than 18% are between 133% and 150% of the federal poverty threshold.

The pattern in table 3 is unsurprising: 67% of families living below the poverty threshold are food insecure and 58% of the families with children are child food insecure. The percentage of families who are food insecure falls as income rises. Only 9.8% of families with incomes over 150% of the federal poverty threshold are food insecure.

The typical (modal or average) respondent for our analysis sample was a 42-year-old African American woman with a high school degree (see table 4). While 36% of respondents were African

American, 33% were white (or European American) and 24% were of some other race. Only 0.2% of respondents were Asian while 7% of respondents were Native American. In regressions below we group Asian respondents with the base category of white. Over 31% of respondents reported a bachelor's degree or higher level of education. Only 15% of the respondents were male.

To provide context and some comparison, we compared data from the December Current Population Survey. The December CPS fields the Food Security measure. The CPS is a national survey, designed to be representative at both the national and regional level.

The results from the CPS are not strictly comparable to the counties in our survey: those counties are designated as persistently poor, and differ significantly in demographics from the states from which they are drawn. It is also because of the comparison and the lack of sampling weights available for our sample, that we did not use the CPS weights in our analysis.

Four samples from the CPS are presented: the full national sample, the sample of households from states which contained an eligible county, states which contained a county that applied, and states which contained a county that was funded. Overall, our survey is younger, has more African American and Native American respondents, and has a higher percentage of those with trade school or associates degrees. Our survey was frequently answered by women. The CPS demographics represent the "head of the household" as reported in the survey. This may explain certain differences like gender or education. The much higher response to "other" may indicate that our lack of options for race (no multi-race categories were allowed), led to respondents choosing other.

When comparing the demographics of the CPS samples and our samples, two things become immediately clear: our sample is significantly poorer than the overall sample and experiences much higher rates of household and child insecurity (see tables 5 and 6 and compare to tables 2 and 3). The overall rate of household food security in the CPS samples is between 19% and 23.3% (table 6), depending on year and sample. This is much lower than the 39% to 46% (depending on year) of the survey results in table 2. Across the four CPS samples, in table 5, poverty rates ranged between 15.7% and 18.5%. In contrast, table 3 shows that our survey had an overall 35% poverty rate. This is not surprising and consistent with the selection of persistently poor counties.

Similar to the ERS Annual Report on Food Security which finds a decline in food insecurity, using weights (Coleman-Jensen, et al., 2018) between 2016 and 2017, our analysis of the CPS data (using slightly different methodology) finds a small decline in food insecurity as well. Overall, food insecurity nationally fell from 19.6% to 19.3% (see table 6). This was a national decline and is mimicked in all four samples: our treated states too saw a decline from 22.8% in 2016 to 22.4% in 2017. This is a slightly larger decline than the national level, identical to the states in the applied group, and larger than the decline experienced by the overall eligible group. Unfortunately, at this writing, December 2018 food insecurity measures from the CPS are not available, hence we are unable to make comparisons.

One explanation for the trends in our survey may be changing demographics and income between the different samples. In order to test this, and to potentially isolate the source of change, we used linear regression models. We also tested alternative probit models which provided similar results, available upon request. We choose to present the linear probability models, as they are more simply interpreted. We present four specifications: only year dummies, year dummies with income group, year dummies with demographic controls, and a full model with year dummies, income groups, and demographic controls. In table 7 we note that the coefficient on year 2017, is relatively stable across all four specifications, varying between -.053 and -.057. This coefficient implies that the household food insecurity rate was between 5.3 and 5.7 percentage points lower in 2017 than the reference year of 2016. While not statistically significant in the baseline model (with no controls), the coefficient rose in magnitude slightly and became significant when either income group or demographics were included in the specifications (columns two and four).

In table 8, we present similar models for child food insecurity. In this case we note that while the coefficient on 2017 is not statistically significant in any specification, the magnitude – .039 to -.067 is economically significant. We also note that the inclusion of income does appear to mitigate the time differential (columns 2 and 4 have similar estimates at -.039 and -.046). While not significant, the pattern is similar to table 7, with a drop in 2017 and a return to baseline in 2018.

Column four in both tables demonstrates that income is clearly one of the most important determining factors of food insecurity. While in column three, race and education are statistically significant (in the household models, only education in the child models), only less than high school and bachelor’s and above remain significant when income is added. Even these fall substantially in magnitude.

In tables 9 and 10, we estimate the same models using the CPS data for eligible states. We choose eligible states as this group has the highest poverty rate of the four samples, although still significantly below the poverty rates of both the survey and the counties who were actually eligible. The models were estimated on all other subsamples with qualitatively similar results. We also note that in the survey, the bracketed income questions were designed to categorize household income into the four groups used in the analysis (the income categories were conditioned on the household size question and exactly match the categories). However, in the December CPS, the income categories are not so aligned, and thus poverty group is an estimate. This should reduce the importance of income and increase the importance of variables associated with actual income.

In table 9, the coefficient on year 2017 is negative and statistically significant when income categories are included in the specification (columns two and four). The magnitudes are smaller than those in table 7 with the full model showing a net decline of 2.1% between 2016 and 2017. Testing the difference between our result in the survey and the rise in the CPS reveals a statistically insignificant difference (this test assumes independent samples). It should be noted that the decline of 5.5% in our survey compared to the decline of only 2.1% in the eligible states is economically significant. However, given the fact that the eligible states also contain many more economically advantaged areas, this may explain the remaining difference. These results do not seem to indicate a strong impact of the program compared to national or eligible state trends.

In table 10, the models for child food security, the coefficient on year is negative but varies dramatically between nearly zero (base column) and -.064 (just income). When income was included in the controls, the magnitude was the largest. Tests between the full model coefficient across the two samples (assuming independence) failed to reject the null hypothesis that the coefficients were different. Thus the evidence suggests that, like the household measure, the observed drop in child food security is similar to overall trends.

County Level Participation Measures

To further test the impact of the program on participation, county level data were also analyzed. Our primary underlying model is a treatment effect model where we compared county level participation rates for the six programs between the counties which participated in the project and those that did not. Selection of a comparison group is crucially important, as is controlling for both differences in characteristics between those counties with participating organization ($Grant_{it}=1$) and those counties without participating organizations ($Grant_{it}=0$). Two comparisons groups were used in the analysis. The first group used all 322 counties (where data were available) that were in the list of persistently poor counties and thus eligible to submit grant proposals and participate in the project. The second comparison group included only those 68 counties (again with available data) which applied for a grant.

Concern arises that counties with an organization choosing to apply may systematically differ in important – but difficult to measure – ways from eligible counties with no such organization. Hence each analysis below was conducted using both the full sample as comparison and the applied group.

In estimating treatment effects from a project where assignment to treatment was clearly not random, it was important to control for any differences between the treatment and control groups. We operationalized the treatment effect estimation using two different, but complimentary, approaches. In the first approach, we estimated fixed effects linear regression models with controls for education, race, income, population, unemployment and poverty rates. The linear model was specified with a simple indicator for counties which received and participated in the grant program. We have data prior to the beginning of the program which allows the estimation of a fixed effects model. This model is best understood as isolating the change in participation before and after the program, while controlling for differences across counties. The estimation equation is given by:

$$Y_{it} = \beta_0 + \beta_1 X_{it} + \beta_2 Grant_{it} + \lambda_i + \varepsilon_{it}$$

Where, Y_{it} is the participation rate in NSLP, SBP, SNAP, WIC, SFSP, or SSO in county i at time t. X_{it} are the control variables – unemployment rate, population, percent of population with greater than high school education, and the count of the Black or African American population in the county. $Grant_{it}$ takes the value 1 when county i receives a grant and continues in the grant program throughout the period of the grant. We call these treated counties, grantees or the treatment group. In some of the models median household income and/or poverty rate are also included in the analysis. λ_i controls for county fixed effects and standard errors are clustered at the county level.

The main restriction with this model is that the impact of the program is assumed to be a simple shift in participation rate. Other models would include interactions with control variables which would allow for differential impacts across county types. However, given the small number in the treatment group, we focus on a simple model.

The second approach was to use propensity score matching to make average comparisons. The propensity score calculates the probability that a particular county would be included in the treatment group, conditional on the control variables. This probability provides a way to find "similar" counties in the control group (counties eligible for grants) to compare to the treated counties. It is essentially a weighted average of the difference in the outcome between treated

($Grant_{it}$ =1) counties and control counties. It relaxes the assumption of the linear model that the impact does not vary with other factors, but we are not able to use fixed effects to control for unobserved factors.

We estimated models of participation in six programs: National School Lunch Program (NSLP), School Breakfast Program (SBP), Supplemental Nutrition Assistance Program (SNAP), the Special Supplemental Nutrition Program for Women, Infants and Children (WIC), Seamless Summer Option (SSO), and Summer Food Service Program (SFSP). We expected that the SFSP would show the largest effect, since all grantees included this program in their target programs, and ten included it as a primary target. Additionally, we expected both NSLP and SBP to have large effects since these programs were targeted by nine of the original fifteen grantees. Outside of the two-major school-based programs, SNAP and WIC are the largest and most salient programs and were also targeted by many of the grantees.

Table 11 provides basic descriptive statistics for the six programs and the conditional variables (Table 12 provides sample sizes). Four samples were examined: the full sample includes (subject to missing data) 322 persistently poor counties who were eligible to apply for participation in the program; the applied sample contains the 68 counties covered in applications received, this group includes those counties selected, and those counties that continued through the grant program; the selected sample includes the 33 counties covered by organizations selected for participation in the grant; and the grantee sample includes the 17 counties which fully participated in the grant. It is worth noting that for the School Lunch, School Breakfast and SNAP programs, all groups exhibited a rise in participation between the before and after period. Additionally, participation rates in these three programs varied dramatically both across the four groups and within each group, as indicated by the standard deviations. Participation in WIC fell during the period for three of the four groups, rising only slightly for the full sample. We focus overall participation given the targets of the program.

With the exception of WIC, SSO, and SFSP, counties which applied to the project had slightly higher participation rates than the sample of eligible counties prior to the intervention. The counties selected for the grant had slightly lower School Lunch and SSO participation rates, negligibly lower SFSP participation rates and slightly higher school breakfast and SNAP participation rates prior to the program period. The WIC program, in contrast, saw declines in participation, with the most pronounced declines for the counties that applied and the counties that persisted in the program.

The table shows that poverty rates for each of the groups except the grantee group of counties is surprisingly higher following the intervention period. All the other conditional variables follow the expected increasing or decreasing patterns, both prior and following the intervention.

We first turn to the fixed effects regression analysis. table 13 presents regression results examining the effect of treatment on National School Breakfast program. As noted above, we used two different control groups: all persistently poor counties and those counties who applied. Columns one and two present basic regressions which include fixed effects for the counties but no other control variables. The results for these regressions are economically and statistically significant: the grantee counties show a slightly larger than 6 percentage point increase in participation. The remaining columns add additional control variables, and the estimated magnitudes declined between 2 and 4 percent points. It is interesting and important to note that throughout the specifications, the coefficient on treatment is positive, the program appears to have increased participation. As we knew from the outset, the small number of programs (15 grantees affecting just barely 30 counties) would provide very low statistical power. These results are quite encouraging in their robustness across specification, and provide evidence of positive effects. It is also noteworthy that in general, the effect when compared to the counties which applied, is largest across all but the first simple specification. Counties which did not apply to the program may have participated in other projects or may have had plans for other interventions, issues that are unknown and ones that we cannot address in model specifications.

Table 14 presents the same specifications for the NSBP. In this case, none of the coefficients on the treatment indicator were statistically significant, but all are positive. As with the School Lunch program, the effect measured against the other applicants is consistently the largest (although the difference is less marked), and all coefficients are positive. Overall, the estimated effect provides evidence of a 1.7 to 2.2 percent increase. While this is modest, and the results are not statistically significant, again we note the low power due to the modest sample size and argue that there may be some positive effects.

Table 15 examines the impact on the SNAP program. Since the interventions were nearly all primarily geared toward School Lunch or Breakfast type programs, we did not expect the SNAP program to have a large impact. While columns 1 and 2 show a 1.3 percent increase in participation (statistically significant), the remaining columns show less than ½ percent change. We do note that all specifications show a positive impact on participation, the impact itself is economically small, and did not reach statistical significance.

Table 16 presents results for participation in the WIC program. In all specifications, grantees appear to have reduced WIC program participation more than the control groups (noting that in general participation declined). The estimated effect is between -1.02 and -2.25 percent, depending on the sample and specification. The largest effects were found in columns one and two, where no control variables were included. In models where control variables were included, the effects are smaller and not statistically significant.

Tables 17 and 18 present the effects of the grant on SSO and SFSP programs, respectively. In the case of both programs, like the School Breakfast Program, the coefficients for the treatment indicator are not statistically significant, although positive for all the specification. The estimations for the SSO program range from 0.55 to 0.04 percent increases and for SFSP program, the changes range from 0.19 to 0.02 percent increases. While these results show a very small increase, that did not reach statistical significance, the low power due to small sample size combined with some limitations of the availability of data raises the possibility that there may be some positive effects by the intervention.

Table 19 presents all propensity score matching results. The results only include the equivalent of the coefficient on grant and thus are comparable to the first row of the previous regression tables. We caution that standard errors do not address covariance across time for the counties. Propensity score, unlike fixed effects, does not address unobserved heterogeneity. When using the full sample comparison, results are qualitatively similar to those found in the regression setting. The NSLP and SNAP programs showed positive impacts of the grant program, although only the impact on NSLP was statistically significant. As with the regression results the WIC program showed a statistically significant decline in participation rates for the grant recipients. In contrast, however, when using the applied counties, the impact on participation in the grant program was negative for all programs except SNAP, although none of the negative effects were statistically significant. The estimate for the SNAP program remained positive and was significant and slightly smaller. Possible explanations for this are that the selected counties were different in important but unobservable ways (hence the fixed effect estimates would be preferred) or that the program impact was highly variable depending on important controls; it is also possible that in simple regression models, one type of program was dominating (in which case the propensity score estimates are preferred). We believe that the most likely scenario is that the fixed effects estimates are more indicative of the impact of the program. Unobserved heterogeneity is likely to be crucially important in participation rates, especially given the relatively limited list of control variables used in the propensity score.

Conclusions

Overall, while the conclusions we can draw are limited; there appears to be only weak evidence that the program had an impact on the counties. We note that the survey data results do show an initial decline that is slightly larger than national trends. The differences between that decline and national trends may not be statistically significant and may be explained by differences in economic conditions. Given the subsequent rise in 2018, caution on interpretation is warranted.

Perhaps more convincing that there was an impact are some of the results from the county level analysis. The program had a modest positive impact on participation rates for the two school meal programs and SNAP, but a modestly negative impact on participation for WIC in these persistently poor counties. This does suggest that the program may, perhaps, reduce food insecurity as well. In conclusion, given the modest sample size, this effort provides some initial, albeit very weak, indication of programmatic effects.

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Table 1: Sample Sizes for Survey

Year	Returned Surveys	Any FS	Complete FS	Complete FS and Demographics	Complete FS, Demographics and Income*
2016	816	808	775	708	567
2017	733	729	708	665	554
2018	747	746	703	648	512
Total	2296	2283	2186	2021	1633

*Analysis sample used in all tables below except as noted.

Table 2: Food Insecurity Measures by Year for Survey

Measure	2016	2017	2018	Total
HH Indicator	44.3%	39.0%	45.7%	42.9%
Child Indicator	42.8%	36.1%	42.5%	40.5%
HH Detail				
Low	24.0%	22.0%	23.6%	23.2%
Very Low	20.3%	17.0%	22.1%	19.7%
Child Detail				
Low	29.5%	23.3%	21.5%	25.6%
Very Low	13.3%	12.8%	19.0%	14.9%

Table 3: Food Insecurity by Income Level for Survey

Income Group	Percent of Analysis Sample	HH Indicator	Child Indicator
Below Federal Poverty Line	35.3%	67.4%	58.6%
100% to 133% Poverty	18.2%	55.9%	47.6%
133% to 150% Poverty	17.8%	34.5%	27.4%
Over 150% of Poverty Line	28.7%	9.8%	7.1%
Missing Income*	NA	48.3%	38.0%

*This row is not part of the analysis sample.

Table 4: Demographic Characteristics Survey and Current Population Data

Variable	Survey Analysis Sample	CPS Full Sample	CPS States with Eligible Counties	CPS States with Applied Counties	CPS States with Treated Counties
Age	42.3	52.3	52.3	52.2	52.0
African American	.361	.112	.165	.185	.178
Native American	.071	.015	.016	.012	.013
White	.329	.813	.785	.767	.772
Asian	.002	.045	.021	.023	.024
Other race	.237	.015	.014	.013	.013
Less than High School	.088	.095	.121	.118	.119
High School Graduate	.336	.459	.484	.479	.475
Trade School	.126	.047	.051	.052	.051
Associates Degree	.132	.059	.055	.056	.054
Bachelor's Degree or Above	.317	.340	.289	.295	.301
Male	.149	.501	.495	.494	.496
Hispanic or Latino	.137	.106	.102	.089	.098
N	1633	104,951	32,929	28,626	25,015

Table 5: CPS income and food security

	Full Sample		States with Eligible Counties		States with Applied Counties		States with Treated Counties	
	Percent of Sample	Food Insecure	Percent of Sample	Food Insecure	Percent of Sample	Food Insecure	Percent of Sample	Food Insecure
All Households	100%	19.5%	100%	23.0%	100%	22.6%	100%	22.7%
Below Federal Poverty Line	15.7%	43.7%	18.5%	48.1%	18.1%	47.9%	16.3%	48.6%
100% to 133% Poverty	3.9%	44.2%	4.9%	45.1%	4.8%	45.2%	4.3%	45.6%
133% to 150% Poverty	3.9%	38.7%	4.5%	38.3%	4.4%	37.7%	4.0%	37.8%
Over 150% of Poverty Line	76.4%	12.2%	72.1%	14.1%	72.7%	14.0%	75.5%	14.1%

Table 6: CPS Food Insecurity by year

		Full Sample	Eligible	Applied	Treated
2016	Household	19.6%	23.3%	22.8%	22.8.%
	Child	26.6%	30.3%	29.5%	29.6%
2017	Household	19.3%	22.8%	22.4%	22.4%
	Child	25.9%	30.2%	29.8%	29.9%

Table 7: Linear Probability regressions on Household Food Insecurity Indicator Survey Analysis Sample

Food Insecure (HH)	Base	Income	Demographics	Full
Year 2017	-0.053	-0.054	-0.057	-0.055
	(1.79)	(2.05)*	(2.05)*	(2.08)*
Year 2018	0.014	0.031	0.015	0.030
	(0.47)	(1.19)	(0.53)	(1.17)
Below Federal Poverty		0.579		0.493
		(24.32)**		(14.76)**
100% to 133% Poverty		0.464		0.406
		(14.59)**		(11.27)**
133% to 150% Poverty		0.248		0.218
		(7.93)**		(6.72)**
Age/100			-0.173	0.008
			(1.96)	(0.10)
African American			0.068	0.008
			(2.32)*	(0.30)
Native American			0.118	0.070
			(2.39)*	(1.57)
Other Race			0.074	0.048
			(2.05)*	(1.42)
Less than High School			0.141	0.088
			(3.25)**	(2.02)*
Trade School			-0.102	-0.055
			(2.53)*	(1.43)
Associates Degree			-0.188	-0.042
			(4.81)**	(1.09)
Bachelors Degree plus			-0.346	-0.112
			(11.86)**	(3.35)**
Male			-0.035	-0.027
			(1.07)	(0.85)
Hispanic			0.045	0.028
			(1.09)	(0.72)
Intercept	0.443	0.105	0.601	0.169
	(21.20)**	(5.22)**	(11.66)**	(3.01)**
R^2	0.00	0.24	0.14	0.25

Notes: Dependent variable = 1 if food insecure; n=1,633, robust standard errors, significance * p<0.05; ** p<0.01.

Table 8: Linear Probability regressions on Child Food Insecurity Indicator Survey Analysis Sample

Food Insecure (Child)	Base	Income	Demographics	Full
Year 2017	-0.067	-0.039	-0.066	-0.046
	(1.86)	(1.16)	(1.88)	(1.35)
Year 2018	-0.003	0.029	0.009	0.030
	(0.09)	(0.87)	(0.27)	(0.91)
Below Federal Poverty		0.515		0.408
		(17.48)**		(10.07)**
100% to 133% Poverty		0.402		0.335
		(10.21)**		(7.75)**
133% to 150% Poverty		0.204		0.172
		(5.54)**		(4.49)**
Age/100			0.168	0.202
			(1.12)	(1.41)
African American			0.007	-0.033
			(0.18)	(0.94)
Native American			0.094	0.055
			(1.46)	(0.90)
Other Race			0.034	0.023
			(0.71)	(0.50)
Less than High School			0.190	0.166
			(3.64)**	(3.17)**
Trade School			-0.110	-0.080
			(2.29)*	(1.71)
Associates Degree			-0.209	-0.100
			(4.32)**	(2.07)*
Bachelor's Degree plus			-0.343	-0.165
			(9.35)**	(3.92)**
Male			0.000	0.011
			(0.00)	(0.28)
Hispanic			0.001	-0.013
			(0.01)	(0.26)
Intercept	0.428	0.075	0.460	0.121
	(16.76)**	(2.79)**	(6.37)**	(1.57)
R^2	0.00	0.17	0.13	0.20

Notes: Dependent variable = 1 if child food insecure; n=1,060, robust standard errors, significance * p<0.05; ** p<0.01.

Table 9: CPS Estimates of Household Food Insecurity Models

HH Food Insecure	Base	Income	Demographics	Full
Year 2017	-0.005	-0.028	-0.003	-0.021
	(0.98)	(5.61)**	(0.61)	(4.34)**
Below Federal Poverty		0.344		0.266
		(43.90)**		(32.78)**
100% to 133% Poverty		0.308		0.239
		(21.08)**		(16.26)**
133% to 150% Poverty		0.243		0.194
		(16.46)**		(13.17)**
Age/100			-0.298	-0.234
			(19.93)**	(15.83)**
African American			0.133	0.103
			(16.38)**	(13.11)**
Native American			0.175	0.129
			(7.44)**	(5.71)**
Other Race			0.140	0.120
			(5.58)**	(4.96)**
Less than High School			0.163	0.097
			(16.40)**	(9.92)**
Trade School			-0.044	-0.022
			(3.59)**	(1.91)
Associates Degree			-0.034	-0.013
			(2.84)**	(1.11)
Bachelors Degree plus			-0.165	-0.121
			(31.32)**	(23.40)**
Male			-0.069	-0.049
			(13.58)**	(9.90)**
Hispanic			0.052	0.033
			(5.22)**	(3.42)**
Intercept	0.233	0.154	0.424	0.320
	(62.27)**	(43.79)**	(40.65)**	(30.83)**
R^2	0.00	0.12	0.10	0.17
N	24,649	24,649	24,649	24,649

Notes: Dependent variable = 1 if household food insecure; robust standard errors, significance * p<0.05; ** p<0.01.

Table 10: CPS Estimates of Child Food Insecurity Models

Child Food Insecure	Base	Income	Demographics	Full
Year 2017	-0.000	-0.064	-0.002	-0.050
	(0.04)	(5.98)**	(0.18)	(4.81)**
Below Federal Poverty		0.304		0.232
		(24.39)**		(18.26)**
100% to 133% Poverty		0.303		0.223
		(12.42)**		(8.99)**
133% to 150% Poverty		0.315		0.218
		(8.48)**		(5.76)**
Age/100			-0.133	-0.097
			(2.82)**	(2.13)*
African American			0.130	0.101
			(8.23)**	(6.45)**
Native American			0.198	0.166
			(5.34)**	(4.78)**
Other Race			0.172	0.158
			(3.82)**	(3.60)**
Less than High School			0.116	0.069
			(5.91)**	(3.61)**
Trade School			-0.073	-0.048
			(3.21)**	(2.19)*
Associates Degree			-0.030	-0.011
			(1.31)	(0.50)
Bachelors Degree plus			-0.214	-0.169
			(19.37)**	(15.36)**
Male			-0.109	-0.091
			(10.49)**	(9.01)**
Hispanic			0.060	0.043
			(3.77)**	(2.81)**
Intercept	0.303	0.213	0.422	0.331
	(40.75)**	(29.58)**	(18.92)**	(15.08)**
R^2	0.00	0.10	0.11	0.16
N	7,230	7,230	7,230	7,230

Notes: Dependent variable = 1 if child food insecure; robust standard errors, significance * p<0.05; ** p<0.01.

Table 11: Summary Statistics for County Data Measures

	Full		Applied		Selected		Grantees	
	Before	After	Before	After	Before	After	Before	After
NSLP Participation Rate	76.05	80.32	78.42	82.40	74.81	79.61	70.37	74.67
	(24.27)	(18.49)	(17.29)	(18.46)	(20.35)	(20.88)	(25.01)	(23.81)
SBP Participation Rate	50.00	58.79	56.71	59.68	60.70	56.29	55.05	56.21
	(29.46)	(41.00)	(24.36)	(18.20)	(25.42)	(15.37)	(21.32)	(14.57)
SNAP Participation Rate	23.80	24.49	26.01	26.62	26.89	27.48	26.62	27.39
	(6.496)	(6.560)	(6.557)	(6.642)	(6.721)	(6.599)	(7.151)	(7.283)
WIC Participation Rate	16.49	15.49	11.57	9.646	11.08	9.112	13.78	11.41
	(19.36)	(17.79)	(17.46)	(15.01)	(18.83)	(16.10)	(22.04)	(19.24)
WIC Women	3.940	4.282	2.253	2.063	2.480	2.163	3.114	2.788
Participation Rate	(4.630)	(4.583)	(3.863)	(3.549)	(4.141)	(3.578)	(4.985)	(4.558)
WIC Children	7.895	7.418	6.053	5.100	7.365	6.409	8.491	7.725
Participation Rate	(11.87)	(11.27)	(11.37)	(10.12)	(14.07)	(12.99)	(15.83)	(15.13)
SSO Participation Rate	3.318	4.023	2.868	3.050	2.161	2.612	2.161	2.612
	(4.305)	(4.970)	(1.996)	(2.085)	(0.538)	(1.348)	(0.538)	(1.348)
SFSP Participation Rate	2.889	3.263	2.319	2.740	1.651	1.674	1.918	1.988
	(2.853)	(3.324)	(2.517)	(2.277)	(1.732)	(1.750)	(1.899)	(1.847)
Poverty Rate	27.55	27.62	29.42	29.60	30.95	30.77	28.96	29.02
	(5.579)	(6.258)	(5.630)	(5.998)	(6.630)	(6.930)	(5.973)	(6.251)
Median HH Income	31355.2	32552.8	29912.1	30511.7	30010.3	30254.3	31043.9	31576.2
	(4772.4)	(5310.3)	(4449.3)	(4848.9)	(4992.2)	(5691.9)	(5086.4)	(6197.5)
Unemployment Rate	12.20	11.48	13.90	12.89	14.98	13.62	12.58	11.48
	(4.331)	(4.255)	(4.769)	(4.585)	(4.784)	(4.798)	(3.441)	(3.179)
Population (1000 people)	31.86	32.25	45.05	45.79	62.04	63.60	91.82	95.23
	(73.47)	(77.30)	(104.3)	(110.6)	(144.3)	(153.6)	(189.7)	(202.9)
High school or more (%)	73.91	76.35	73.44	75.98	72.65	74.99	72.49	74.92
	(6.455)	(6.099)	(6.553)	(6.503)	(7.542)	(7.477)	(9.301)	(9.097)
African American	7854.0	7849.2	10990.0	10816.0	12112.5	11862.8	7908.5	7835.0
	(16678.0)	(17519.0)	(12231.4)	(12303.5)	(11985.6)	(11734.8)	(8398.3)	(8375.5)

Sample means with sample standard deviation in parenthesis.

Table 12: Sample Size for County Level Data

	Full		Applied		Selected		Grantees	
	Before	After	Before	After	Before	After	Before	After
NSLP Participation Rate	1384	568	299	110	142	50	82	32
	(319)	(310)	(67)	(61)	(32)	(30)	(18)	(16)
SBP Participation Rate	759	344	143	51	67	17	50	19
	(232)	(178)	(43)	(26)	(18)	(9)	(14)	(10)
SNAP Participation Rate	1610	322	340	68	165	33	90	18
	(322)	(322)	(68)	(68)	(33)	(33)	(18)	(18)
WIC Participation Rate	629	115	171	36	83	16	58	11
	(152)	(115)	(39)	(36)	(19)	(16)	(14)	(11)
WIC Women Participation Rate	531	84	139	26	74	13	49	8
	(121)	(84)	(29)	(26)	(16)	(13)	(11)	(8)
WIC Children Participation Rate	1001	173	207	40	89	15	69	11
	(210)	(173)	(43)	(40)	(18)	(15)	(14)	(11)
SSO Participation Rate	302	77	39	11	19	5	19	5
	(80)	(77)	(11)	(11)	(5)	(5)	(5)	(5)
SFSP Participation Rate	435	108	63	17	29	7	32	8
	(118)	(108)	(16)	(17)	(7)	(7)	(8)	(8)
Poverty Rate	1610	644	340	136	165	66	90	36
	(322)	(322)	(68)	(68)	(33)	(33)	(18)	(18)
Median HH Income	1610	644	340	136	165	66	90	36
	(322)	(322)	(68)	(68)	(33)	(33)	(18)	(18)
Unemployment Rate	1610	644	340	136	165	66	90	36
	(322)	(322)	(68)	(68)	(33)	(33)	(18)	(18)
Population (1000 people)	1610	644	340	136	165	66	90	36
	(322)	(322)	(68)	(68)	(33)	(33)	(18)	(18)
High school or more	1610	644	340	136	165	66	90	36
	(322)	(322)	(68)	(68)	(33)	(33)	(18)	(18)
African American	1610	644	340	136	165	66	90	36
	(322)	(322)	(68)	(68)	(33)	(33)	(18)	(18)

Overall number of county-year observations with number of counties in parenthesis.

Table 13: Fixed effects estimation for National School Lunch Program

	(1) All	(2) Applied	(3) All	(4) Applied	(5) All	(6) Applied	(7) All	(8) Applied
Grant	6.2189**	6.2189**	2.2971	4.2526	2.1758	3.7938	2.2953	4.2430
	(3.0387)	(3.0598)	(3.3442)	(3.1283)	(3.3418)	(2.9908)	(3.3409)	(3.1432)
Poverty(%)					-0.1528	-0.2547	-0.0677	0.0794
					(0.1483)	(0.3256)	(0.1598)	(0.3260)
Median HH Income			0.0002	0.0009			0.0002	0.0009
			(0.0002)	(0.0006)			(0.0002)	(0.0007)
Unemployment(%)			0.2908	0.0663	0.2998	0.0453	0.3019	0.0533
			(0.1884)	(0.2814)	(0.1944)	(0.2637)	(0.1944)	(0.2732)
Population			0.0004	0.0003***	0.0004	0.0004***	0.0004	0.0003***
			(0.0003)	(0.0001)	(0.0003)	(0.0001)	(0.0003)	(0.0001)
Greater than HS(%)			0.8034***	0.3153	0.8767***	0.5781*	0.8146***	0.3076
			(0.2092)	(0.4137)	(0.2000)	(0.3415)	(0.2100)	(0.4169)
Black population			-0.0111***	-0.0009	-0.0111***	-0.0008	-0.0111***	-0.0008
			(0.0017)	(0.0014)	(0.0017)	(0.0013)	(0.0017)	(0.0013)
_cons	77.1927***	78.9996***	82.7122***	22.9135	89.0920***	35.4412	84.8549***	19.7246
	(0.0498)	(0.2394)	(20.9936)	(31.3183)	(21.3351)	(33.6126)	(21.7071)	(34.4728)
N	1952	409	1952	409	1952	409	1952	409
Counties	320	67	320	67	320	67	320	67

Standard errors in parentheses. Standard errors clustered at county level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 14: Fixed effects estimation for National School Breakfast Program

	(1) All	(2) Applied	(3) All	(4) Applied	(5) All	(6) Applied	(7) All	(8) Applied
Grant	2.1584	2.1584	1.7664	2.1261	2.0896	2.2007	1.7660	2.0873
	(5.9752)	(6.0459)	(6.7404)	(6.8403)	(6.5457)	(6.4876)	(6.6504)	(6.6650)
Poverty(%)					0.5557^{**}	0.6577	0.3348	0.5763
					(0.2213)	(0.6113)	(0.2792)	(0.6452)
Median HH Income			-0.0007^{*}	-0.0006			-0.0005	-0.0002
			(0.0004)	(0.0008)			(0.0004)	(0.0009)
Unemployment(%)			-0.4183	0.3543	-0.4647	0.2471	-0.4711	0.2588
			(0.4193)	(0.9480)	(0.4274)	(0.9931)	(0.4249)	(1.0124)
Population			-0.0006^{**}	-0.0001	-0.0007^{**}	-0.0001	-0.0006^{**}	-0.0001
			(0.0003)	(0.0001)	(0.0003)	(0.0001)	(0.0003)	(0.0001)
Greater than HS(%)			1.4265^{***}	0.8142	1.2819^{***}	0.7463	1.3952^{***}	0.8042
			(0.3526)	(0.8799)	(0.3284)	(0.7315)	(0.3517)	(0.8690)
Black population			0.0136^{***}	0.0003	0.0137^{***}	0.0005	0.0136^{***}	0.0005
			(0.0009)	(0.0025)	(0.0009)	(0.0024)	(0.0009)	(0.0025)
_cons	52.7016^{***}	57.2826^{***}	-99.9885^{***}	16.2568	-125.0724^{***}	-15.8005	-112.3333^{***}	-12.2640
	(0.1029)	(0.5921)	(25.9633)	(66.3049)	(28.5668)	(70.7576)	(29.0210)	(67.9005)
N	1103	194	1103	194	1103	194	1103	194
Counties	233	43	233	43	233	43	233	43

Standard errors in parentheses. Standard errors are clustered at the county level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 15: Fixed effects estimation for SNAP

	(1) All	(2) Applied	(3) All	(4) Applied	(5) All	(6) Applied	(7) All	(8) Applied
Grant	1.3389***	1.3389***	0.3836	0.4114	0.3528	0.2843	0.3616	0.4064
	(0.4696)	(0.4728)	(0.4217)	(0.4386)	(0.3988)	(0.4044)	(0.4002)	(0.4320)
Poverty(%)					0.2176***	0.2181***	0.2247***	0.3027***
					(0.0415)	(0.0625)	(0.0489)	(0.0779)
Median HH Income			-0.0001**	0.0000			0.0000	0.0002*
			(0.0000)	(0.0001)			(0.0001)	(0.0001)
Unemployment(%)			0.2402***	0.2983***	0.1946***	0.2556***	0.1945***	0.2600***
			(0.0461)	(0.0755)	(0.0438)	(0.0683)	(0.0437)	(0.0642)
Population			0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
			(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Greater than HS(%)			0.2730***	0.2227*	0.2403***	0.2499**	0.2347***	0.1727
			(0.0421)	(0.1190)	(0.0389)	(0.1013)	(0.0428)	(0.1174)
Black population			-0.0000	-0.0010	-0.0000	-0.0009*	-0.0000	-0.0009*
			(0.0000)	(0.0006)	(0.0000)	(0.0006)	(0.0000)	(0.0005)
_cons	23.4846***	25.5187***	3.9902	14.6970	-2.5461	7.0320	-2.8903	3.3386
	(0.0038)	(0.0179)	(2.9586)	(11.6231)	(2.9999)	(11.1570)	(3.1931)	(10.4672)
N	2254	476	1932	408	1932	408	1932	408
Counties	322	68	322	68	322	68	322	68

Standard errors in parentheses. Standard errors clustered at the county level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 16: Fixed effects estimation for WIC – Total Participation

	(1) All	(2) Applied	(3) All	(4) Applied	(5) All	(6) Applied	(7) All	(8) Applied
Grant	-2.2524*	-2.2524*	-1.0434	-2.2391	-1.0171	-2.1432	-1.0421	-2.2096
	(1.2869)	(1.3017)	(1.5040)	(1.6787)	(1.4918)	(1.6180)	(1.4986)	(1.6236)
Poverty(%)					-0.0210	-0.0565	-0.0469	-0.1412
					(0.1315)	(0.1766)	(0.1972)	(0.1782)
Median HH Income			-0.0000	-0.0001			-0.0001	-0.0002*
			(0.0002)	(0.0001)			(0.0002)	(0.0001)
Unemployment(%)			-0.0996	-0.1159	-0.0902	-0.0945	-0.0888	-0.0738
			(0.1165)	(0.1687)	(0.1174)	(0.1167)	(0.1193)	(0.1172)
Population			-0.0000	-0.0001**	-0.0000	-0.0001**	-0.0000	-0.0001*
			(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Greater than HS(%)			-0.5420***	-0.0079	-0.5524***	-0.0475	-0.5318***	0.0231
			(0.1204)	(0.0769)	(0.1163)	(0.0948)	(0.1468)	(0.1050)
Black population			0.0001	0.0007	0.0001	0.0007	0.0001	0.0007
			(0.0001)	(0.0004)	(0.0001)	(0.0005)	(0.0001)	(0.0004)
_cons	16.3694***	11.3557***	59.4465***	11.4493	59.2198***	12.4144*	60.4902***	14.7389**
	(0.0190)	(0.0692)	(8.4915)	(7.4123)	(7.7278)	(6.2168)	(9.2149)	(5.7703)
N	744	207	744	207	744	207	744	207
Counties	152	39	152	39	152	39	152	39

Standard errors in parentheses. Standard errors clustered at the county level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 17: Fixed effects estimation for SSO

	(1) All	(2) Applied	(3) All	(4) Applied	(5) All	(6) Applied	(7) All	(8) Applied
Grant	0.3054	0.3054	0.2662	0.1750	0.0417	0.2193	0.3181	0.5517
	(0.3260)	(0.3416)	(0.6355)	(0.5788)	(0.5231)	(0.4699)	(0.6448)	(0.6562)
Poverty(%)					0.0160	0.1951	0.0981	0.3376
					(0.0676)	(0.1835)	(0.0901)	(0.2863)
Median HH Income			0.0002	0.0001			0.0002	0.0004
			(0.0001)	(0.0002)			(0.0002)	(0.0004)
Unemployment(%)			0.1562	-0.0481	0.1235	-0.0517	0.1427	-0.0729
			(0.1107)	(0.2261)	(0.1157)	(0.2650)	(0.1116)	(0.2677)
Population			-0.0000	-0.0000	-0.0000	0.0000	-0.0000	-0.0000
			(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Greater than HS(%)			0.2358^{**}	0.0585	0.3009^{**}	-0.0555	0.2307^{**}	-0.1127
			(0.1147)	(0.2280)	(0.1298)	(0.1910)	(0.1135)	(0.1959)
Black population			-0.0000	0.0003	-0.0001	0.0004^{*}	-0.0000	0.0009
			(0.0001)	(0.0004)	(0.0001)	(0.0002)	(0.0001)	(0.0007)
_cons	3.4573^{***}	2.8775^{***}	-20.6087^{**}	-6.9949	-20.0075^{**}	-3.6136	-24.4880^{**}	-16.0823
	(0.0043)	(0.0342)	(9.4538)	(19.0100)	(9.1166)	(13.7147)	(10.7674)	(22.7694)
N	379	50	379	50	379	50	379	50
Counties	86	12	86	12	86	12	86	12

Standard errors in parentheses. Standard errors clustered at the county level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 18: Fixed effects estimation for SFSP

	(1) All	(2) Applied	(3) All	(4) Applied	(5) All	(6) Applied	(7) All	(8) Applied
Grant	0.1040	0.1040	0.1976	0.0924	0.1873	0.0355	0.1831	0.0242
	(0.2492)	(0.2571)	(0.2339)	(0.1859)	(0.2510)	(0.2751)	(0.2448)	(0.2400)
Poverty(%)					0.0961^{***}	0.1997^{**}	0.0905^{**}	0.1654
					(0.0289)	(0.0906)	(0.0348)	(0.1059)
Median HH Income			-0.0001	-0.0001^{**}			-0.0000	-0.0001
			(0.0000)	(0.0001)			(0.0000)	(0.0001)
Unemployment(%)			0.0595	-0.0444	0.0377	-0.1385	0.0388	-0.1171
			(0.0402)	(0.0836)	(0.0375)	(0.1152)	(0.0378)	(0.1335)
Population			-0.0000^{*}	0.0000	-0.0000^{*}	0.0000	-0.0000	0.0000
			(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Greater than HS(%)			0.0379	0.0909	0.0186	0.0654	0.0235	0.1078
			(0.0471)	(0.1390)	(0.0453)	(0.0977)	(0.0464)	(0.1267)
Black population			0.0000	-0.0008	0.0000	-0.0006	0.0000	-0.0005
			(0.0000)	(0.0009)	(0.0000)	(0.0007)	(0.0000)	(0.0008)
_cons	2.9615^{***}	2.3985^{***}	1.7102	6.4797	-0.9823	-1.6392	-0.7533	-1.8289
	(0.0037)	(0.0257)	(3.3503)	(12.7466)	(3.2422)	(9.7565)	(3.4096)	(10.0562)
N	543	80	543	80	543	80	543	80
Counties	119	17	119	17	119	17	119	17

Standard errors in parentheses. Standard errors clustered at the county level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 19: Propensity Score Match Estimate (Controls, Income, and Poverty)

Program Participation	NSLP	NSBP	SNAP	WIC	SFSP	SSO
All Counties	4.9246**	-0.3502	2.4294	-8.1334***	-0.8745	-0.4684
	(2.3654)	(2.0293)	(2.1799)	(2.4170)	(0.5973)	(1.1982)
Applied Counties	-1.0932	-0.2587	3.4160**	-3.3228	-0.2479	-0.4139
	(4.1072)	(1.9674)	(1.5380)	(2.5003)	(0.2278)	(0.7911)
Matches	3	3	3	3	3	3

Standard errors in parentheses. Standard errors are clustered at the county level.
Propensity score matches made using lagged values of median household income, poverty, Unemployment rate, population, percent high school graduate or higher, total African American population, and time trend
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$