Senior Project

Department of Economics

The Effectiveness of the 'High Obesity Program' in the U.S.: County-Level Analysis of 11 States

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Abstract

The growing obesity rate and its burden on national health care costs have been a significant problem in the U.S. This paper evaluates the effectiveness of obesity intervention policies, especially the “High Obesity Program (HOP)” that was implemented in 11 states of the U.S. between 2014 and 2018. The program included better nutrition, physical activity, and education initiatives in counties with over 40% obesity rate. Using county-level data and a difference-in-differences model augmented with county and year-fixed effects, this paper finds that HOP reduces the adult obesity rate by 1.56 percentage points. When the analysis is focused only on counties with obesity levels of 30%-50% before HOP roll out, the results are robust with HOP reducing the obesity rate by 1.47 percentage points.

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I. Introduction

For the past few decades, obesity has become a global ‘epidemic’, making it one of the major health issues that nations need to face. According to the Centers for Disease Control and Prevention (CDC), the U.S. adult obesity rate has reached 42.4 percent in 2017-2018 up from 30.5 percent in 1999-2000. Much research has been done linking obesity with various negative health outcomes including heart disease, diabetes, some types of cancer, and stroke. However, this is not the only cost of obesity; nations must bear the burden of economic costs that are rising due to obesity. In the U.S., obesity-related medical care costs are estimated at 147 billion US dollars a year (Finkelstein et al., 2009). This is in addition to the loss of productivity and early exit from the labor market that are caused by the poor health condition of obese individuals.

The U.S. has implemented programs that promote a healthy diet, increased physical activity, and educational content; one such program is the “High Obesity Program”. High Obesity Program funded land-grant universities in 52 counties of 11 states with at least one county in which the prevalence of obesity among adults was more than 40% (CDC, 2020). These universities partnered with community organizations, public health agencies, and stakeholders to implement policy, systems, and environmental (PSE) strategies to prevent obesity, focusing on 1) education and promotion; 2) nutrition; and 3) physical activity from 2014 to 2018 (Murriel et al., 2020).

In my paper, I examine the effectiveness of the High Obesity Program (HOP) on obesity rates in the target counties from 2011 to 2017, comparing them with the control counties in all 11 states[1] in the U.S. where HOP where implemented. This paper adds to the current literature as it

[1] Alabama, Arkansas, Georgia, Indiana, Kentucky, Louisiana, North Carolina, South Dakota, Tennessee, Texas, West Virginia

is the first comprehensive county-level analysis of the effectiveness of the “High Obesity Program” in reducing obesity in all 11 participating states, using the fixed effects and difference-in-differences model. This enables us to see the true effects of the program on the population’s obesity rate. Analyzing the effects of such a program helps policymakers decide on increasing the funding to the current recipients and expanding the program in wider scope across the country. The rest of the paper is organized as follows: section II provides a brief overview of the literature, section III the theoretical discussion on the main variable of issue – obesity, section IV the data overview, section V the methodology, and section VI and VII provide results and the conclusion respectively.

II. Literature Review

In addition to the medical experts who research obesity to identify its negative impact on the overall health of the individuals, economists also analyze this problem to determine its economic harms and how to devise effective policies to battle it. Although biological factors, such as genes, do play a role, they cannot solely explain the rise in obesity since it has happened too quickly to be explained in evolutionary terms; thus, obesity is primarily a product of choice and a result of the difference between energy consumed and energy spent (Philipson and Posner, 2008). Specifically, the neoclassical theory of obesity indicates that a less physically demanding lifestyle due to technological changes along with increased consumption of food that has gotten cheaper are the main factors that led to the obesity epidemic (Philipson and Posner, 2008). Furthermore, some studies examine the link between income, race, and obesity. Non-Hispanic Black adults (49.6%) had the highest age-adjusted prevalence of obesity, followed by Hispanic adults (44.8%) (Hales et al., 2020). The Healthy People 2010 report acknowledges that obesity rates are higher among adolescents from poor households relative to middle- and high-income households; among African American women relative to white women, and among low-income relative to the more affluent groups. This can be explained by the energy-dense foods that cost less than the healthy perishable foods and therefore encourage low-income families to save money with unhealthy purchases (Drewnowski and Darmon, 2005).

U.S. healthcare spending on obesity and related diseases has reached an all-time high and many studies have been estimating the costs of obesity on national healthcare spending (Specchia et al., 2015; Biener et al., 2020). Biener et al. (2020) use the instrumental variables method to estimate the impact of obesity in youth on U.S. medical care costs. Specifically, they use the BMI of the child's biological mother as their instrument for the child's BMI. They conclude that for boys and girls pooled, an additional unit of BMI raises annual medical care costs by $76 and obesity raises annual medical care costs by $907, a 92% increase relative to average expenditures among healthy weight children (Biener et al., 2020). Thus, it is crucial to stop the ongoing increase in the obese population using different types of interventions.

Several papers analyze different interventions taken through the High Obesity Program in each area. Powers et al. (2019) analyze the Live Well Faith Communities, a 9-week faith-based health promotion initiative, which promotes healthy meals and educational training at churches in the 14 high obese counties in Alabama. They conduct a 1-group pretest-posttest survey to determine differences in faith community policies and environments, interpersonal support, and individual behavior before and after the initiative. Findings suggest that the program is effective in changing individual behavior, for example, 31.6% of pretest respondents indicate they often or always purchase foods with lower added sugar, whereas 48.8% indicate this at post-test (Powers et al., 2019). Wallace et al. (2019) find increased healthy meal consumption through direct education opportunities through HOP such as in-store food demonstrations, cooking classes, gardening workshops, nutrition programs, and exercise classes. Out of the 1,844 adults, children, and adolescents who participated, 61% (248 of 405) reported being more physically active as a result of participating in the programs, 59% (117 of 199) reported eating more fruit, and 66% (131 out of 199) reported eating more vegetables.

Furthermore, Kendall et al. (2019) analyze the food store implementation in five food stores in the treatment counties in Louisiana. The intervention consists of healthy food demonstrations, in-store marketing, and encouraging store owners to stock healthy items. In-store marketing includes green signals “Go,” indicating the healthiest foods; yellow signals “Caution,” indicating somewhat healthy foods; and red signals “Stop and Think,” indicating the least healthy foods (Kendall et al., 2019). Using survey analysis, the authors find that although the intervention was not effective in shifting purchasing or dietary habits of customers, positive changes in some food store environments persisted.

Two papers specifically describe the physical activity interventions of HOP in rural Alabama and Texas. 101 interventions took place in 14 counties in Alabama directed towards physical activity, such as installing or repairing playground equipment at community parks. The authors suggest researchers use the community participatory model when planning for community-level physical activity intervention to increase effectiveness (Wallace et al., 2019). Castillo et al. (2019) describe how Hidalgo County in Texas promotes physical activity through the bicycle infrastructure from HOP funding, such as building a 50-mile bike road. In total, HOP increased access to healthier foods for more than 1.5 million people, increased access to physical activity for nearly 1.6 million people, and the recipients leveraged resources totaling more than $7.5 million during 2017 and 2018, the final 2 years of HOP (Murriel et al., 2020). Overall, the majority of the papers done on HOP present positive behavioral effects on the population.

Theoretical Discussion

The neoclassical theory of obesity by Philipson and Cutler claims technological progress as one of the main causes of obesity growth, due to the consequent decreased physical activity and the increased caloric intake (Specchia et al., 2015). This theory extends on the assumption that obesity is the result of energy consumed far exceeding the energy spent by an individual. Furthermore, highly processed foods are loaded with extra calories while giving less satiety, leading to overconsumption and weight gain. These theories emphasize the role of lifestyle factors in the increased prevalence of obesity.

The High Obesity Program /HOP/ was implemented among the counties with high obesity rates where they implemented nutrition and physical activity initiatives. Directed in improving people's lifestyles, HOP is expected to affect the community's food and activity choices positively, leading to obesity rates decreasing due to less calorie intake and more calorie expenditure among the treatment population. Thus, this study tests the hypothesis that HOP participating counties experience lower obesity rates.

Hypothesis: HOP participating counties experience lower obesity rates.

Questions can arise about whether changing only the food and physical environment is enough to change people's choices in the long run. However, the rational choice theory assumes that people make prudent and logical decisions in the case of environmental and policy changes. Thus, empirical analysis of the effectiveness of obesity prevention programs is necessary because it can reduce the nation's expenditure on obesity-related diseases by spending less in total by conducting prevention programs today.

III. Data

The adult obesity rate is the main dependent variable of this study which is available from the "County Health Rankings and Roadmaps" database from the University of Wisconsin Population Health Institute and the Robert Wood Johnson Foundation. This county-level database includes the percentage of obese adults, those with a BMI (Body Mass Index[2]) equal to or more than 30, in every county in the United States. The focus of this analysis is on 11 states that have at least one county participating in the HOP program. The data is from 2011 to 2017 which is three years before the HOP start year of 2014. The main variable of interest is an indicator variable, HOP, that is equal to "1" if a county participates in the High Obesity Program, and "0" otherwise. The regression model includes two sets of fixed effects. First, county-fixed effects to control for any variable that is constant for each county over time, and second, year-fixed effects that control for any variable that is constant for all counties in a given year. The regression includes control variables[3]: % of the population of ages 65 and over, % some college, unemployment rate, children in single-parent households, income ratio[4], median household income, percentage of the population that are white, black, asian, hispanic, american indian, pacific islander, % female, % not proficient in English. Figure 1 shows the percentage of participating counties in each state. Alabama has the most counties participating in HOP compared to its non-participating counties and it is supported with their average adult obesity rate before HOP which was 41%, the highest average among all the states. Georgia and Texas have the lowest percentage of participating counties with 1.26% and 0.39% respectively. They also have one of the lowest average obesity

[2] Body Max Index (BMI) is a person's weight in kilograms (or pounds) divided by the square of height in meters (or feet). A high BMI can indicate high body fatness. BMI screens for weight categories that may lead to health problems, but it does not diagnose the body fatness or health of an individual (CDC).
[3] Description of each control variable is in Section IX, Appendix.
[4] Measures the ratio of household income at the 80th percentile to income at the 20th percentile.

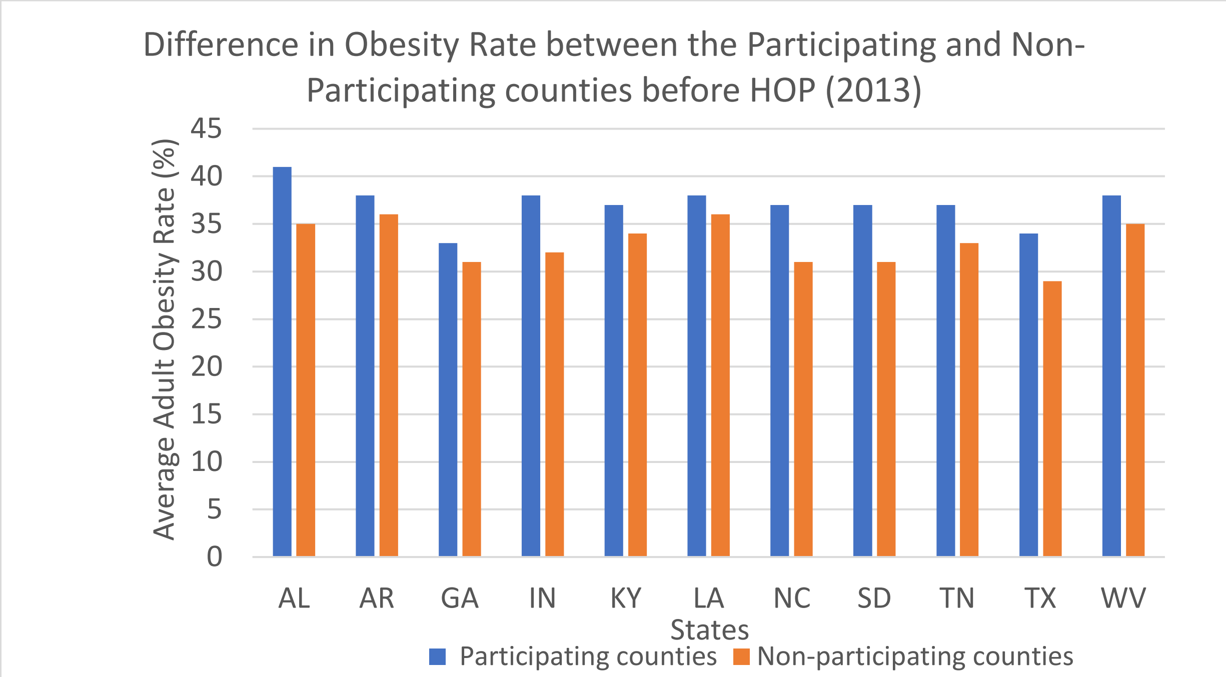
rates in 2013 with Georgia at 33% and Texas at 34% average obesity rates among HOP participating counties.

Figure 1. HOP participating counties in each state by percentage

States	Total counties	Percentage participating
Alabama	67	20.90%
Arkansas	75	8.00%
Georgia	159	1.26%
Indiana	92	2.17%
Kentucky	120	5.00%
Louisiana	64	6.25%
North Carolina	100	4.00%
South Dakota	66	9.09%
Tennessee	95	4.21%
Texas	254	0.39%
West Virginia	55	5.46%

Source: The University of Wisconsin Population Health Institute

Figure 2. Comparison of the participating and non-participating counties by average adult obesity rate in each state in 2013

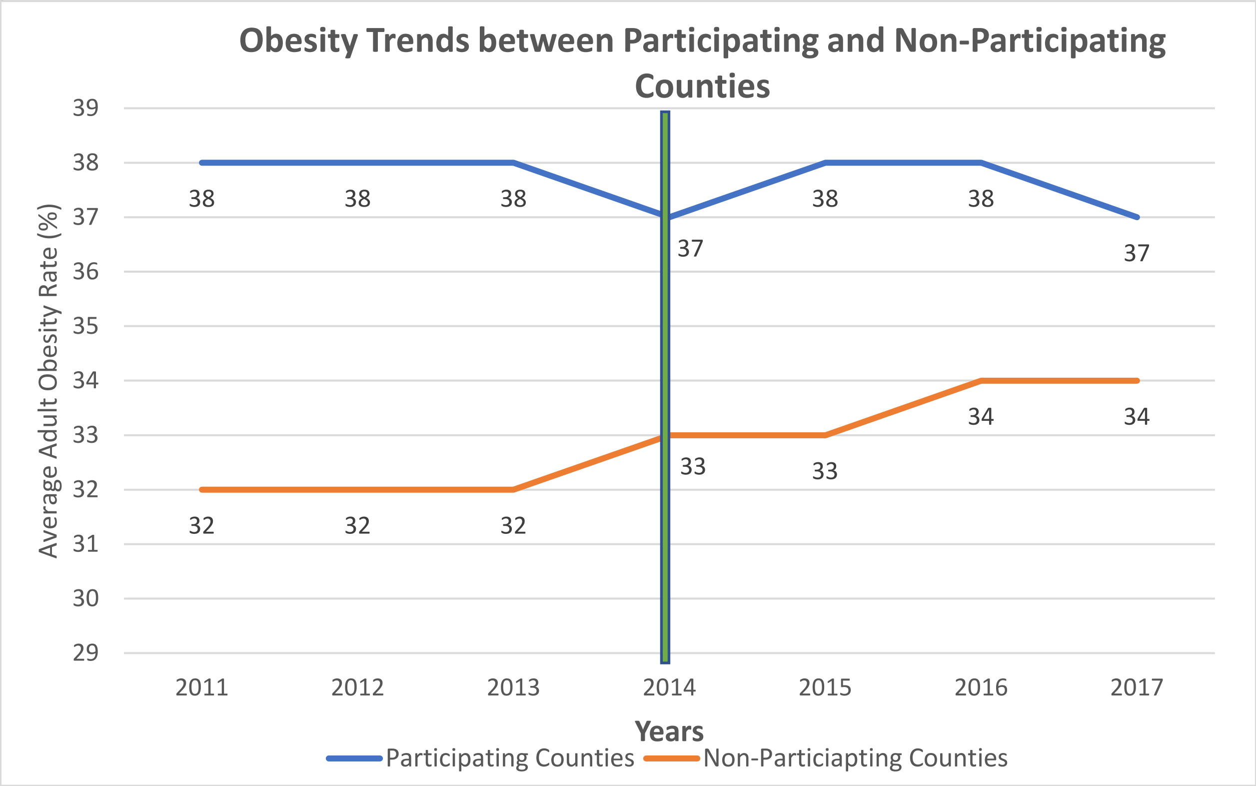


Source: The University of Wisconsin Population Health Institute

Figure 2 provides a comparison between the participating and non-participating counties by average adult obesity rate before the HOP implementation by each state. We can see that the participating counties (in blue) had higher obesity rates in every state than the non-participating counties which justifies the HOP's target counties that have high obesity levels. From figure 3, we can see how the average obesity rates in two groups, participating and non-participating, have changed over time. The initial average obesity rate of counties that have participated was significantly higher at 38% compared to the non-participating counties with a 32% average obesity rate. As the time passes, especially after the HOP implementation (green bar in the graph), participating counties that received the HOP funding have stable obesity rates in most years and decreasing rates in some years. Meanwhile, the non-participating counties are experiencing increasing obesity rates since 2013 and onward. This difference in trends between the two groups gives an incentive to analyze the impact of HOP on the obesity rates in these counties and its significance.

To see if the participating and non-participating groups are comparable before the intervention takes place, a T-test is done using the data from 2013 which was before the HOP intervention. However, a very low p-value suggests that there was a difference between the two groups before the intervention took place which may be a problem for the analysis. Figure 4 shows that the two groups have differences in their variables where there is a significant difference in all of the variables, except the percentage of the population over age 65, female, and pacific islander. The control variables, county and year-fixed effects, and marginal analysis used in the main regression in this paper help account for this difference.

Figure 3. Average adult obesity trends between the participating and non-participating counties from 2011 to 2017



Source: The University of Wisconsin Population Health Institute
Note: The green bar indicates the start of HOP implementation.

Figure 4. Summary statistics for the variables in the model by participation status before HOP intervention (2013)

Variables	Participating	Non-participating	Difference
Adult Obesity Rate	38.21	32.06	6.15***
% Age over 65	16.01	16.56	-0.55
% Female	49.44	50.14	-0.70
% Some College	44.66	50.55	-5.89***
Unemployment Rate	9.33	7.68	1.65***
Income Ratio	5.17	4.71	0.46***
Median Household Income	34293.50	42425.82	-8132.32***
% Not Proficient in English	1.14	2.12	-0.97**
% Single-Parent Households	45.27	34.11	11.16***
% White	57.75	73.87	-16.12***
% Black	30.48	11.98	18.50***
% Asian	0.46	0.93	-0.48***
% Hispanic	4.62	10.90	-6.29***
%American Indian	5.82	1.35	4.47*
% Pacific Islander	0.08	0.08	0.01

Source: The University of Wisconsin Population Health Institute
Note: "*" indicates 10% significance level, "**" indicates 5% significance level, "***" indicates 1% significance level.

IV. Methodology

This paper examines the effect of HOP on participating counties' obesity rates using the difference-in-differences method augmented with county and year-fixed effects. The difference-in-differences method compares the post-HOP-implementation difference between the treatment and control groups (i.e., participating and non-participating counties) in obesity rate to their pre-treatment difference to determine whether the HOP has any impact on the participating counties. The first year of the HOP implementation varies across states with six states beginning in 2014, two more states in 2015, and three more states in 2016[5]. Separate regressions are run for each sub-samples of HOP to see if the program was effective for each cohort.

The main model used in this analysis is as follows:

(1)

$$\text{Obesity Rate}_{ct} = B_0 + \delta\,\text{HOP}_{ct} + X_{ct} + \text{County}_c + \text{Year}_t + u_{ct}$$

where the obesity rate is the main dependent variable and measured for county c in year t. HOP is the main variable of interest (the DID variable) and equal to 1 if it is a year in which HOP is implemented in a given county (0, otherwise) and X represents all the control variables[6]. A two-way fixed effects model (County-fixed effects and Year-fixed effects) is used to control for any variables that are constant within counties across time and variables that are constant across counties in any given year and u represents the error term.

[5] See Figure 7 in the Appendix that has the names of these states and counties.
[6] Complete introduction of these variables can be found in the Appendix, figure 8.

For the difference-in-differences method to be able to identify the causal effect of interest, we need to assume that the treatment and control group would have had a similar trend in the post-treatment period if there was no treatment, i.e., the parallel trend assumption. One way to test the validity of this assumption is to analyze whether the two groups have a similar trend prior to the treatment assignment. In other words, if it can be established that the participating and non-participating counties have a similar trend in obesity rate prior to HOP implementation, then it is reasonable to expect they would have continued to have a similar trend in the absence of the HOP intervention.

To test the parallel trend assumption, the following model is used with data prior to 2014:

(2)

$$\text{Obesity Rate}_{ct} = B_0 + B_1\text{Treatment}_c + B_2\text{Year}_t + \sigma(\text{Treatment}_c \text{ x } \text{Year}_t) + \text{County}_c + X_{ct} + u_{ct}$$

Treatment, in this second regression equation, is equal to "1" if the county ever participated in HOP and "0", if otherwise. The main variable of interest is the interaction term between treatment at a given county and year fixed effect where its coefficient σ is expected to be zero. The treatment and year interaction term (treatment*year) is included in the model to see how the treatment group changes as the years pass. Figure 5 shows the results of the parallel trends test ran on regression 2 and the coefficient on the treatment and year interaction term (treatment*year) is not statistically significant which means the obesity rate in the two groups was moving in a parallel trend before the HOP implementation. This result also helps address the t-test results from figure 4.

Figure 5. Parallel Trends Test before the HOP Intervention

Variables	Parameter Estimate
Treatment	-225.66 (275.69)
Year	0.28*** (0.08)
Treatment*Year	0.11 (0.14)
Control Variables?	yes
County and Year Fixed Effects Included?	yes
Observations	3439
Adjusted R-Squared	0.8655
F-Statistics	413.05***

Note: Heteroscedasticity-Robust Standard errors are in parenthesis under parameter estimates. "*" indicates 10% significance level, "**" indicates 5% significance level, "***" indicates 1% significance level. Control variables include: % of population of ages 65 and over, % some college, unemployment rate, children in single-parent households, income ratio, median household income, percentage of population that are white, black, asian, hispanic, american indian, pacific islander, % female, % not proficient in English.

Source: The University of Wisconsin Population Health Institute

V. Results

The results in figure 6 include all four models that are used in the analysis: model one includes only the states that were receiving HOP funding in 2014; model two includes two more states that were added to the program in 2015, and model three has all 11 states from 2016. The marginal analysis model focuses only on the counties that have 30%-50% adults with obesity in 2016 to show randomness in the selection of counties. Models one to three have roughly the same parameter estimates on HOP and are statistically significant. Thus, the marginal analysis is based on the model that has all the states, which is model 3. The models have adjusted R-Squared values ranging from 52% to 65%, indicating the proportion of variation in the adult obesity rate that is explained by these models.

Figure 6. Regression Results on Adult Obesity Rate

Regression Results				
Variables	**Model 1**	**Model 2**	**Model 3**	**Marginal Analysis**
Intercept	123.17**	138.18**	113.86**	116.03
	(66.03)	(63.12)	(60.89)	(88.94)
HOP	-1.21***	-1.41***	-1.56***	-1.47***
	(0.47)	(0.42)	(0.45)	(0.46)
% Age over 65	0.14	0.17	0.17	0.35
	(0.19)	(0.18)	(0.16)	(0.25)
% Female	0.08	0.04	0.16	0.33
	(0.18)	(0.17)	(0.17)	(0.24)
% Some College	0.005	-0.01	-0.01	-0.02
	(0.02)	(0.02)	(0.01)	(0.02)
Unemployment Rate	-0.43***	-0.32***	-0.37***	-0.33***
	(0.07)	(0.06)	(0.06)	(0.07)
Income Ratio	0.18	0.18	0.27	0.08
	(0.2)	(0.19)	(0.17)	(0.23)
Median Household Income	0.00006**	0.00006**	0.00004	0.000008
	(0.00003)	(0.00003)	(0.00003)	(0.00003)
% Not Profficient in English	0.004	0.01	-0.005	0.09
	(0.09)	(0.09)	(0.09)	(0.22)
% Single-Parent Households	-0.02	-0.02	-0.03**	-0.02
	(0.02)	(0.02)	(0.01)	(0.02)
Race				
% White	-0.92	-1.06**	-0.86	-0.98
	(0.67)	(0.64)	(0.61)	(0.88)
% Black	-1.65**	-1.57**	-0.89	-0.89
	(0.73)	(0.68)	(0.64)	(0.91)
% Asian	-1.24	-1.46**	-1.1	-2.29**
	(0.88)	(0.85)	(0.74)	(1.14)
% Hispanic	-0.31	-0.48	-0.32	-0.52
	(0.68)	(0.64)	(0.62)	(0.87)
% American Indian	-0.77	-0.92	-0.73	-0.81
	(0.66)	(0.63)	(0.6)	(0.88)
% Pacific Islander	2.33	-2.52	-1.26	-1.39
	(3.62)	(2.49)	(1.33)	(1.36)
County and Year Fixed Effects Included?	yes	yes	yes	yes

Observations	3284	3979	5733	4080
Adjusted R-Squared	0.6435	0.6539	0.6273	0.5203
F-Statistics	40.11***	39.13***	35.22***	20.08***

Note: Heteroscedasticity-Robust Standard errors are in parenthesis under parameter estimates. "*" indicates 10% significance level, "**" indicates 5% significance level, "***" indicates 1% significance level. Model 1 includes the states which were receiving HOP intervention in 2014: Alabama, Kentucky, South Dakota, Tennessee, Texas, West Virginia. Model 2 includes the states which were receiving HOP intervention in 2015: Alabama, Kentucky, South Dakota, Tennessee, Texas, West Virginia, Arkansas, Louisiana. Model 3 includes all 11 states which were receiving HOP intervention in 2016. Model 4 includes the counties that have average adult obesity rate of 30%-50%.

Source: The University of Wisconsin Population Health Institute

The regression of the main model /3/ tells us that being a HOP intervention county reduces the adult obesity rate by 1.56 percentage points. When the analysis is focused only on counties with obesity levels of 30%-50% before HOP roll out /marginal analysis/, the results are robust with HOP reducing the obesity rate by 1.47 percentage points at a statistically significant level. The unemployment rate is statistically significant in all four models, the percentage of the white, black, and Asian populations are also significant in one or two models each. These significant results in HOP support the results from the previous studies done on HOP participating counties mentioned in section II where Alabama had 48.8% of post-test respondents indicating they often or always purchase foods with lower added sugar compared to the 31.6% of respondents in pretest before the healthy meals and educational training at churches (Powers et al., 2019). In Tennessee, 61% (248 of 405) of participants of HOP education opportunities such as in-store food demonstrations, cooking classes, gardening workshops, nutrition programs, and exercise classes reported being more physically active as a result of participating in the programs, 59% (117 of 199) reported eating more fruit, and 66% (131 out of 199) reported eating more vegetables (Wallace et al., 2019). The results from these previous studies supports the findings in this paper.

VI. Conclusion

Using county-level data and a difference-in-differences model augmented with county and year-fixed effects, this paper finds that HOP reduces the adult obesity rate by 1.56 percentage points. When the analysis is focused only on counties with obesity levels of 30%-50% before HOP roll out, the results are robust with HOP reducing the obesity rate by 1.47 percentage points at a statistically significant level.

Knowing the true effects of obesity intervention programs is crucial in improving public health. Increasing the funding to the current recipients and expanding the program in wider scope would reduce obesity across the country. However, due to limited data availability, this paper does not closely look into the amount of fundings each state received each year; thus, further research is needed to be done on how much funding should be a reasonable amount that balances the costs and benefits to the society.

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VIII. Appendix

Figure 7. HOP implementation start years by states and counties

No.	Start year	University	State	Counties
1	2014	Auburn University	Alabama	Barbour, Bibb, Bullock, Chambers, Coosa, Crenshaw, Cullman, Escambia, Greene, Lowndes, Macon, Pickens, Sumter, and Wilcox.
2	2015	University of Arkansas	Arkansas	Chicot, Craighead, Jefferson, Monroe, Ouachita, and Woodruff.
3	2016	University of Georgia	Georgia	Calhoun, Taliaferro
4	2016	Purdue University	Indiana	Jackson and Lawrence
5	2014	University of Kentucky	Kentucky	Clinton, Elliott, Letcher, Lewis, Logan, and Martin.
6	2015	Louisiana State University	Louisiana	Madison, St.Helena, Tensas, and West Feliciana
7	2016	North Carolina State University	North Carolina	Edgecombe, Halifax, Lee, and Northampton
8	2014	South Dakota State University	South Dakota	Bennett,Buffalo, Campbell, Corson, Union, and Ziebach
9	2014	University of Tennessee	Tennessee	Haywood, Humphreys, Lake, and Lauderdale.
10	2014	Texas A&M University	Texas	Hidalgo
11	2014	West Virginia University	West Virginia	Barbour, Gilmer, and Pleasants.
				Total 52 counties

Source: Centers for Disease Control and Prevention. (2020, April 9). *High obesity program (2014 – 2018)*

Figure 8. Control variables and their description

Control Variables	Description
% Age over 65	Percentage of population that are 65 and older
% Female	Percentage of female population
% Some College	Percentage of adults age 25-44 with some post-secondary education
Unemployment Rate	Percentage of population ages 16+ unemployed and looking for work
Income Ratio	Ratio of household income at the 80th percentile to income at the 20th percentile
Median Household Income	Median Household Annual Income in U.S. Dollars
% Not Proficient in English	Percentage of population that are not proficient in English
% Single-Parent Households	Percentage of children that live in single-parent households
% White	Percentage of Non-Hispanic white population
% Black	Percentage of Non-Hispanic African American population

% Asian	Percentage of Asian population
% Hispanic	Percentage of Hispanic population
% American Indian	Percentage of American Indian and Alaskan Native population
% Pacific Islander	Percentage of Native Hawaiian/Other Pacific Islander population

Source: The University of Wisconsin Population Health Institute

SAS Codes

```
libname AEData "~/my_shared_file_links/u47408605/Data"
        access=readonly;
run;

PROC IMPORT
DATAFILE="/home/u53660747/MySAS/HOPdata22.xlsx"
OUT=work.hop
DBMS=xlsx
  REPLACE;
  Sheet="HOP";
  GETNAMES=Yes;
RUN; quit;

proc means data=work.hop;
var Obesity ;
by State;
where everparticipated=1 and Year=2013;
run;

proc means data=work.hop;
var Obesity ;
by State;
```

```
where everparticipated=0 and Year=2013;
run;

/*creating the marginal analysis data*/
data marginallist;
set work.hop;
  where Obesity>=30 and Obesity<=50 and year= 2013;
marginal=1;
keep FIPS marginal State;
run;

proc sort data=marginallist;
    by FIPS;
run;

proc sort data=work.hop;
    by FIPS;
run;

data marginaldb;
merge work.hop marginallist;
by FIPS ;
run;

data marginaldb2;
set marginaldb;
where marginal=1;
run;

/*main regression analysis*/
```

```
ods output ParameterEstimates=Model1;

proc surveyreg data=work.hop;

class FIPS Year;

model Obesity=HOP Somecollege Unemp Incomeratio singleparent over65 black
americanindian asian pacificislander hispanic White noneng female medianhouseholdinc FIPS
Year /solution adjrsq ;

where state in ("Alabama" "Kentucky" "South Dakota" "Tennessee" "Texas" "West Virginia");

run;

quit;


ods output ParameterEstimates=Model2;

proc surveyreg data=work.hop;

class FIPS Year;

model Obesity=HOP Somecollege Unemp Incomeratio singleparent over65 black
americanindian asian pacificislander hispanic White noneng female medianhouseholdinc FIPS
Year /solution adjrsq ;

where state in ("Alabama" "Kentucky" "South Dakota" "Tennessee" "Texas" "West Virginia"

"Arkansas" "Louisiana") ;

run;

quit;


ods output ParameterEstimates=Model3;

proc surveyreg data=work.hop;

class FIPS Year;

model Obesity=HOP Somecollege Unemp Incomeratio singleparent over65 black
americanindian asian pacificislander hispanic White noneng female medianhouseholdinc FIPS
Year /solution adjrsq ;

run;

quit;


/*marginal analysis model*/

ods output ParameterEstimates=Model4;
```

```
proc surveyreg data=marginaldb2;

class FIPS Year;

model Obesity=HOP Somecollege Unemp Incomeratio singleparent over65 black
americanindian asian pacificislander hispanic White noneng female medianhouseholdinc FIPS
Year /solution adjrsq ;

run;

quit;


Data Table_Long;

   length Parameter $20;

   Set Model1 Model2 Model3 Model4 indsname=Database /*temporary variable*/;

   keep Model Variable value;

   Model=scan(Database, -1, ".");/*-1: the first word from right handside*/

   Parameter=compress(Parameter);

   Variable=catt(parameter,"_1");

   Estimate_Rounded=round(estimate,0.01);

   if Probt>0.1 then Star="   ";

      else if Probt>0.5 then Star="*";

        else if Probt>0.01 then Star="**";

          else Star="***";

   Value=catt(Estimate_Rounded,star);

   Output;

   Variable=catt(parameter,"_2");

   StdErr_Rounded=round(stderr,0.01);    /*rounding the stderr value to 2 decimals*/

   Value=catt("(",StdErr_Rounded,")");  /*to put the stderr in paranthesis*/

   Output;

   Where estimate ne 0;

Run;


proc sort data=Table_Long;
```

```
   by Model Variable;
run;

data Model1Reg Model2Reg Model3Reg Model4Reg;
   set Table_Long;
   if model="MODEL1" then output Model1Reg;
   if model="MODEL2" then output Model2Reg;
   if model="MODEL3" then output Model3Reg;
   if model="MODEL4" then output Model4Reg;
run;

data Table_Wide(drop=Model);
   merge Model1Reg(rename=(Value=Model1)) Model2Reg(rename=(Value=Model2))
Model3Reg(rename=(Value=Model3)) Model4Reg(rename=(Value=Model4));
   by Variable;
run;

ods excel file="/home/u53660747/MySAS/RegTable.xlsx";
proc print data=Table_Wide noobs;
run;
ods excel close;

/*t-test*/
proc means data=work.hop;
var Obesity Somecollege Unemp Incomeratio singleparent over65
black americanindian asian pacificislander hispanic White
noneng female medianhouseholdinc;
where everparticipated=1 and Year=2013;
run;
```

```
proc means data=work.hop;
var Obesity Somecollege Unemp Incomeratio singleparent over65
black americanindian asian pacificislander hispanic White
noneng female medianhouseholdinc;
where everparticipated=0 and Year=2013;
run;

proc ttest data=work.hop plots=none;
class everparticipated;
var Obesity Somecollege Unemp Incomeratio singleparent over65
black americanindian asian pacificislander hispanic White
noneng female medianhouseholdinc;
where Year=2013 /*and Obesity<=50 and Obesity>=30*/;
run; quit;

/*parallel trends test*/
Data parallel;
SET work.hop;
treatment=everparticipated;
where Year>=2011 and Year<=2013;
RUN;

proc surveyreg data=work.parallel;
class FIPS;
model Obesity=treatment Year treatment*Year Somecollege FIPS
Unemp singleparent over65 black americanindian
asian pacificislander hispanic White noneng female medianhouseholdinc /*FIPS*/  /solution
adjrsq ;
run;
quit;
```