The Effect of Poverty on Childhood Obesity

Madeleine Kadens

ECON 3161 Dr. Shatakshee Dhongde

Abstract

Over the last decade, childhood obesity in the United States has increased almost threefold as the national poverty rate has remained relatively constant. While governmental aid programs such as the Supplemental Nutrition Assistance Program (SNAP) have sought to support impoverished families by providing funds which can be spent at grocery stores, these programs are ineffective in preventing childhood obesity. This study will attempt to explain the relationship between poverty and obesity across the 50 U.S. states and District of Columbia by constructing several regression models. In addition to the primary explanatory variable, poverty, other control variables included in this model will be median household income, welfare recipients per capita, healthcare expenditure per capita, unemployment rate, rate of food insecurity, and education level. Because nutritious food tends to be more expensive, low-income households may resort to cheaper, yet unhealthier food options. For this reason, childhood obesity and poverty are hypothesized to have a positive relationship.

I. Introduction

The issue of obesity, and its associated health effects, has recently become more prevalent across the developing world, especially in the United States. Body Mass Index, (BMI), is the standard measurement used to determine if a person is obese. BMI estimates a person's body fat content based on their height and weight, and a BMI greater than 30 is considered to be in the obese range. While obesity is increasing amongst all age groups, child and adolescent obesity is increasing at a particularly alarming rate; it has more than tripled since the 1970s. According to the CDC, 1 in 5 people aged 6 to 19 years are considered obese by BMI, demonstrating just how widespread this issue has become amongst youths.

There are many uncontrollable factors that can contribute to obesity, such as genetics and underlying health conditions. However, a person's weight and physical health is also strongly dependent on their lifestyle, including their food choices and exercise habits. While lifestyle is generally a choice, impoverished individuals and families have more limited options when it comes to being healthy, and instead must do anything they can to survive. Many low-income communities are located within areas known as food deserts, where accessing nutritious and affordable food is difficult. For this reason, oftentimes these people resort to fast food, which is cheap and readily available, but unhealthy. This challenge imposed on people experiencing poverty implies a positive relationship between poverty and a person's likelihood to become obese. This paper will explore that link, while explicitly focusing on children experiencing poverty within the United States.

Low-income individuals are more likely to work multiple jobs with longer hours, and in turn are more likely to consume fast food for the low cost and convenience factor. Many federal aid programs are already in place to support these impoverished families, such as SNAP, which provides necessities at no cost to the recipient. SNAP, more commonly known as food stamps, operates similarly to a preloaded debit card. Eligibility and amount received is determined by income, but for many families, food stamps benefits alone are not enough to ensure a nutritious diet, especially for parents feeding multiple children. Additionally, in the case of a family living in a food desert with limited or no access to transportation, food stamps may not be enough. For these reasons, it is clear that the current nutritional aid programs in place in the U.S. are not sufficient. Unveiling an intrinsic relationship between poverty and obesity would help present the need for improved federal programs which provide low-income families with the means to adopt healthy eating habits, in turn combatting both childhood and adult obesity.

II. Literature Review

In 1997, the World Health Organization classified obesity as both a global epidemic and a public health crisis, while poverty has been a known a public crisis for centuries. Because both are such major issues that seemingly go hand in hand, there is extensive research examining the link between poverty and obesity. The National Health and Nutrition Examination Survey (NHANES) is a robust study which gathers data relating to all facets of public health in the United States. CDC researchers Ogden and Carroll (2018) performed a study utilizing data from the NHANES to discuss the prevalence of obesity among youths in the context of household income and education level of the head of household. The variables were cross-sectional as the study focused on differences in obesity within not only varying income brackets, but also race and levels of education. Within the age group of 2 to 19 years, prevalence of obesity was found to be 17% within the lowest income bracket, 19.9% within the middle-income bracket, and 10.9% within the highest income bracket. The stark contrast between obesity in the lowest and highest income brackets, a difference of 6.1%, confirms the hypothesis that obesity will increase as a family becomes more impoverished in relation to the federal poverty line. However, the rate of obesity in the middle-income bracket is surprisingly higher than the rate in the lowest income bracket, showing the most impoverished people may not experience the highest rate of obesity after all. The positive relationship between poverty and obesity still stands but may only remain true within a certain income bound.

Similarly, Hofferth and Curtin (2005) sought to disprove the paradox that having low income implies being underweight. Instead, they hypothesized that in developed countries, low income would be linked to in obesity in school-age children. This study cites food insecurity, the lack of reliable access to nutritious food sources, as a condition which many low-income households suffer from. It was also noted that in combination with food insecurity, low-income households are much more likely to experience other forms of hardship, such as being unable to afford adequate medical care. In general, Hofferth and Curtin utilize similar assumptions and variables in their analysis as this study, highlighting the impacts of food insecurity, governmental aid programs, and fast food consumption. However, the researchers hypothesized that the relationship between poverty and obesity will not be linear. Similar to the research performed by Ogden and Carroll, race and level of education were also included in this model as control variables. Although, this study goes a step further to include employment status and family structure, explaining that these variables contribute to the parents' ability to provide healthy options for their children. The results of this study did not find a significant *linear* relationship between poverty and obesity, supporting the hypothesis that the relationship would be positive, but nonlinear. Ultimately, Hofferth and Curtin arrived at a very similar result to Ogden and Carroll; children in families with income just above the poverty line (lower-middle income bracket), are more likely to experience obesity than children that fall below the poverty line. This makes sense, as those in the lowest income bracket may not have sufficient access to food in general, whether it is nutritious or not. Conversely, those in the lower middle-income bracket have more flexibility in terms of choices but are still limited by income restrictions.

Another 2015 study performed by Rogers and Eagle sought to correct bias in previous models showing the relationship between obesity and race which failed to account for socioeconomic status. Data from individual school districts within Massachusetts was examined in order to explain the intersectionality between obesity, income, and race. The data was separated by gender, and obesity was measured based on BMI, considering 85th percentile and above to be overweight, and 95th percentile and above to be obese. Unlike the previous two studies, Rogers and Eagle found a significant statistical relationship between obesity and children in low-income families, specifically in Massachusetts. This finding supports the hypothesis that lower income should lead to greater likelihood of obesity. However, this study found that when a multiple regression comparing obesity to both race and income was performed, the relationship between obesity and race almost disappeared. This finding indicates that the relationship between obesity and race may not be as strong as previous studies have claimed, and instead suggests that poverty is a more accurate explanatory variable for obesity.

This paper is unique from these other sources of literature because it will examine data on a state-to-state basis. Using such an aggregate data approach allows a broader analysis of macro trends across larger populations. This also allows for the opportunity to study individual performance of each state in the context of finding which policies are succeeding in keeping their residents healthy, and which are doing the opposite. Additionally, this study focuses on a wider population group as the data is not separated by gender or race to better address the issue of obesity amongst the entire population rather than within certain groups.

III. Data

In this model, the control variables are median household income, federal welfare per capita, healthcare expenditure per capita, unemployment rate, food insecurity, and education level. Additionally, *rural* is a dummy variable which indicates whether a state is predominantly rural or urban. First, it is important to examine median household income to get an idea of general wealth in each state. The income disparity between wealthier and poorer states is extremely large; for example, Massachusetts, the wealthiest state, has a median income that is $40,946 greater than Arkansas, the poorest state. Median income in

Massachusetts is almost double that in Arkansas, demonstrating a clear difference in quality of life in these states and suggesting that people in Arkansas are more likely to experience hardships such as food insecurity. While income is a very important variable, it is a secondary variable rather than the primary explanatory variable because it can be biased by cost of living. Thus, percentage of households experiencing poverty is a more accurate representation of the hypothesis this model attempts to explain. Next, welfare recipients per capita demonstrates the population's level of dependence on federal aid programs. As mentioned in the introduction, these programs are imperfect solutions to poverty as they do not always provide needy families with nutritious food options. As explained in the research performed by Hofferth and Curtin (2005), the presence of governmental assistance within a household is a strong indicator of a child's diet, and families dependent on this aid are more likely to consume more meals that are not prepared at home, such as fast food. Healthcare expenditure per capita measures the amount of money spent on privately and publicly funded healthcare services. Assuming states with greater healthcare expenditure provide more widespread and higher quality healthcare, residents of those states may be better informed about healthy living habits than those without reliable access to healthcare. This translates to healthier eating habits, meaning residents of states with greater healthcare spending may be less likely to experience obesity. Unemployment rate measures the percentage of individuals within the labor force which are currently unemployed. Because unemployment can be associated with reduced income, unemployed individuals may not be able to afford nutritious food. Similarly, households located within food deserts and therefore experiencing food insecurity do not have reliable access to healthy food options and are more likely to depend on fast food. Thus, states with higher rates of unemployment and food insecurity are predicted to have higher rates of childhood obesity. The model's dummy variable, *rural,* builds off the idea that households in rural areas are more likely to experience food insecurity than those in urban areas. Population density in rural areas is low and people live more spread apart, thus, in many cases, this means that a household's nearest grocery store is 10 or more miles away, posing an extreme challenge for those without access to transportation. Because of these restrictions, predominantly rural states will be expected to experience greater childhood obesity than urban states. Finally, previous studies have examined the relationship between education level and poverty and have concluded that greater education corresponds to lower poverty rates. Because more educated individuals tend to have higher income, they are able to purchase better food. For this reason, it is expected that states with a greater percentage of adults in the age range of 25-44 which hold a bachelor's degree or higher will experience lower childhood obesity rates. A summary of all variables as well as their descriptive statistics is provided in Tables 1 and 2 and Figure 1 below.

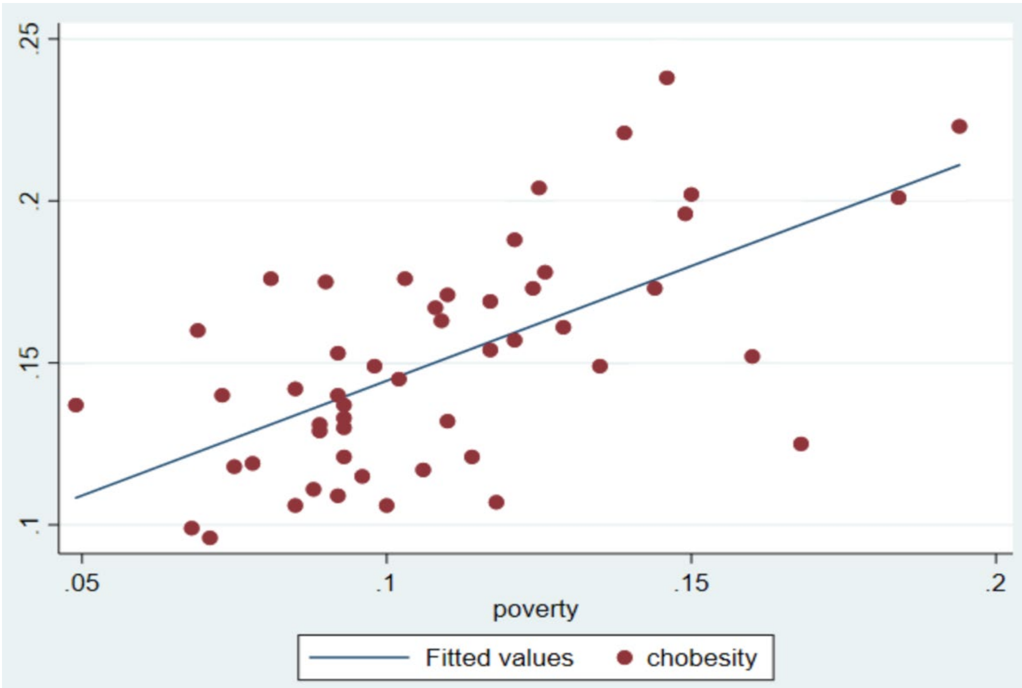
Table 1 - Variables

Variable Name	Description	Year	Units	Source
chobesity	Child obesity rate	2018-19	Percentage	Robert Wood Foundation
poverty	Population living below federal poverty line	2019	Percentage	US Census
logincome	Natural logarithm of median household income	2019	USD	US Census
logwelfare	Natural logarithm of welfare recipients per capita	2020	Households	US Census
loghealthcare	Natural logarithm of healthcare spending per capita	2014	USD	Centers for Medicare and Medicaid Services
unemployment	Unemployment rate	2020	Percentage	US Bureau of Labor Statistics
foodInsecurity	Prevalence of food insecurity	2019	Percentage	Center on Budget and Policy Priorities
educLevel	Adults 25-44 years old with a bachelor's degree or higher	2020	Percentage	National Science Foundation
rural	Indicates whether state is predominantly rural or urban	2010	Rural = 1 Urban = 0	US Census

Table 2 – Descriptive Statistics

Variable Name	Observations	Mean	Std. Deviation	Max	Min
chobesity	51	0.15	0.03	0.24	0.10
poverty	51	0.11	0.03	0.19	0.05
logincome	51	11.07	0.16	11.37	10.73
logwelfare	51	9.26	0.32	9.96	8.39
loghealthcare	51	9.02	0.15	9.39	8.70
unemployment	51	0.06	0.02	0.09	0.03
foodInsecurity	51	0.11	0.02	0.16	0.07
educLevel	51	0.36	0.08	0.70	0.23
rural	51	0.41	0.50	1	0

Figure 1 – Scatterplot of Poverty vs. Childhood Obesity



For this model to be reliable, it is important to evaluate whether it meets the criteria outlined in the CLM assumptions, which are as follows:

1. The first assumption states that the model must be linear in parameters. As shown by Figure 1, dependent variable, Y, and independent variable, X, do exhibit a positive linear relationship and do satisfy this assumption.

2. The second assumption is random sampling. This condition is satisfied as all of the data was obtained from sources that utilize random sampling, such as the U.S. Census.

3. The third assumption is no perfect collinearity between parameters. None of the explanatory variables exhibit a perfect linear relationship. Thus, this assumption is satisfied.

4. The fourth assumption is that the error term is zero. The constant term differs between the simple and multiple regression, indicating that this assumption may be violated. However, this condition is difficult to assume, and this violation may not stand.

5. The fifth assumption is homoskedasticity, which means that the error term must have a constant variance given any explanatory variable. This assumption is satisfied because the same controls are used across all of the parameters, meaning the error term should not change and its variance should not change.

6. The sixth assumption is normal distribution. Because the sample size is not large enough for this assumption to be dropped, the population error, u, must be independent of the explanatory variables and be normally distributed with zero mean and variance. The data is normally distributed and thus satisfies this assumption.

IV. Results

First, a simple linear regression was performed in order to test the relationship between the dependent variable, childhood obesity, and the primary explanatory variable, poverty. Subsequently, three multiple linear regression models were performed where different combinations of control variables were included in addition to poverty. The sample size of 51 was consistent across all four models as all data was sourced from nationwide studies.

Model 1

Equation 1: $chobesity = \beta_0 + \beta_1\ (poverty) + u$

After performing the simple regression, the estimated equation will be:

$$chobesity = 0.07 + 0.71(poverty)$$

In this model, *poverty* has a positive coefficient of 0.71, which can be interpreted as when poverty rate increases by 1 percentage point, the childhood obesity rate will also increase by 0.71 percentage points. This result supports the hypothesis that there is a positive relationship between poverty and childhood obesity. The R-squared value of this model is 0.39, indicating that the correlation between *chobesity* and *poverty* is mild. Additionally, *poverty* has a p-value of 0.00 and reasonably large t-stat of 5.61, indicating that this variable is statistically significant at the 1% level.

Model 2

Equation 2: $chobesity = \beta_0 + \delta_0(rural) + \beta_1(poverty) + \beta_2(logincome) + \beta_3(logwelfare) + \beta_4(loghealthcare) + \beta_5(unemployment) + \beta_6(foodInsecurity) + \beta_7(educLevel) + u$

After performing the multiple regression analysis, the estimated equation will be:

$$chobesity = -0.62 + 0.02(rural) + 0.38(poverty) + 0.04(logincome) + 0.03(logwelfare) + 0.01(loghealthcare) - 0.06(unemployment) + 0.04(foodInsecurity) - 0.15(educLevel)$$

Model 2 includes all secondary explanatory variables as well as a dummy variable to more accurately explain the relationship between *poverty* and *chobesity.* While *poverty* still has a positive coefficient of

0.38, the variable had a p-value of 0.121. While this p-value is not very high, since the variable is not statistically significant at 10% in this model, it cannot be concluded that the coefficient is statistically different than zero. In fact, all variables were found to be statistically insignificant except for *logwelfare* and *educLevel*, which had p-values of 0.055 and 0.051 respectively, and therefore were significant at the 10% level. Although the coefficient on *poverty* is inconsequential in this model, the significant variables *logwelfare* and *educLevel* had positive and negative coefficients respectively, which is consistent with this study's assumptions. The R-square value of this model is 0.55, but since several more variables were added to this model, this value is likely to be biased. For this reason, the adjusted R-square value of 0.46 is more accurate and suggests that there is still only a mild correlation between *chobesity* and *poverty.*

Model 3

Model 3: $chobesity = \beta_0 + \delta_0(rural) + \beta_1(poverty) + \beta_2(logwelfare) + \beta_3(educLevel) + u$

After performing the multiple regression analysis, the estimated equation will be:

$$chobesity = -0.15 + 0.01(rural) + 0.32(poverty) + 0.03(logwelfare) - 0.11(educLevel)$$

Model 3 is another multiple regression adjusted to include only the most significant variables from the previous model. This model still includes *poverty, logwelfare, educLevel,* and dummy variable *rural,* but the other four variables have been removed due to their high p-values. After this change, all variables were found to be significant at either the 5% or 10% level, and *poverty* still had a positive coefficient of 0.32. This can be interpreted as a 1 percentage point increase in the poverty rate leads to a 0.32 percentage point increase in the childhood obesity rate. The adjusted R-square value increased to 0.50 in this model despite the elimination of several variables, showing a slightly stronger correlation between *poverty* and *chobesity.*

Model 4

Model 4: $chobesity = \beta_0 + \beta_1(poverty) + \beta_2(logwelfare) + \beta_3(educLevel) + u$

After performing the multiple regression analysis, the estimated equation will be:

$$chobesity = -0.07 + 0.39(poverty) + 0.02(logwelfare) - 0.14(educLevel)$$

Like Model 3, Model 4 is a multiple regression including only the most significant variables, but *rural* has been removed. The coefficient on poverty is still positive and has increased from 0.32 to 0.39, meaning a 1 percentage point increase in poverty rate now causes a 0.39 percentage point increase in childhood obesity rate. Variable *logwelfare* was also statistically significant at 10% with a p-value of 0.095, while *poverty* and *educLevel* had p-values of 0.019 and 0.004. Of all the multiple regression models, *poverty* and *educLevel* were found to be significant at 2% only in Model 4, indicating that this model is the best representation of the relationship between *poverty* and *chobesity.*

Table 3 provides a summary of all variable coefficients, their significance level, and the standard error.

Table 3 – Regression Results Summary

Dependent Variable chobesity				
Independent Variables	Model 1	Model 2	Model 3	Model 4
poverty	0.71*** (0.13)	0.38 (0.24)	0.32* (0.16)	0.39*** (0.16)
logincome	-	0.04 (0.06)	-	-
logwelfare	-	0.03* (0.02)	0.03** (0.01)	0.02* (0.01)
loghealthcare	-	0.01 (0.03)	-	-
unemployment	-	-0.06 (0.35)	-	-
foodInsecurity	-	0.04 (0.33)	-	-
educLevel	-	-0.15* (0.07)	-0.11** (0.05)	-0.14*** (0.05)
rural	-	0.02 (0.01)	0.01* (0.01)	-
Intercept	0.07*** (0.01)	-0.62 (0.72)	-0.15 (0.13)	-0.07 (0.12)
No. of obs.	51	51	51	51
R-square	0.39	0.55	0.54	0.51
Adjusted R-square	0.37	0.46	0.50	0.48

Significant at *10%, **5%, ***2%

V. Extensions

Because many of the secondary explanatory variables were found to be statistically insignificant in the preceding models, robustness tests were performed to ensure there was not multicollinearity within the model. As seen in Table 4, none of the variables were perfectly correlated, but some do have reasonably large correlation coefficients. F-tests were performed for these highly correlated variables to see if some individually insignificant variables were jointly significant.

Table 4 – Correlation Coefficients

	poverty	*logincome*	*logwelfare*	*loghealthcare*	*unemployment*	*foodInsecurity*	*educLevel*	*rural*
poverty	1.00							
logincome	-0.65	1.00						
logwelfare	0.65	-0.37	1.00					
loghealthcare	0.04	0.20	0.10	1.00				
unemployment	0.23	0.35	0.47	0.20	1.00			
foodInsecurity	0.76	-0.74	0.50	0.07	0.08	1.00		
educLevel	-0.38	0.74	0.20	0.16	0.20	-0.61	1.00	
rural	0.18	-0.49	-0.12	-0.04	-0.51	0.17	-0.37	1.00

For the first F-test, Model 2 was used as the unrestricted model, and after dropping *logincome, loghealthcare, unemployment, and foodInsecurity* (all individually insignificant variables) the estimated equation of the restricted model will be:

$$chobesity = -0.15 + 0.01(rural) + 0.32(poverty) + 0.03(logwelfare) - 0.11(educLevel)$$

The null hypothesis for this model will be:

$$H_0 : \beta_2 = \beta_4 = \beta_5 = \beta_6 = 0$$

It should be noted that this model is the same as Model 3, so the following F-test will aim to confirm that these variables were insignificant to the model. At the 5% significance level, the critical value for $F_{4,42}$ is 2.18. The F-test produced an F-value of 0.16, which is smaller than the critical value. Therefore, we fail to reject the null hypothesis and it can be concluded that *logincome, loghealthcare, unemployment,* and *foodInsecurity* are both individually and jointly insignificant. Because these variables are insignificant in both cases, we can be confident that they do not make a meaningful contribution to the model and can be removed. This also indicates there is not multicollinearity and MLR3 is still satisfied.

The next F-test will focus on the relationship between *poverty* and *foodInsecurity.* Even though *foodInsecurity* has been deemed insignificant, the correlation coefficient between *poverty* and *foodInsecurity* is 0.76, indicating near multicollinearity. Because *foodInsecurity* was expected to be a meaningful variable, this F-test will reveal whether its insignificance can be attributed to multicollinearity.

For this test, the restricted model equation will be:

chobesity = 0.34 + 0.02(rural) – 0.03(logincome) + 0.04(logwelfare) + 0.01(loghealthcare) + 0.24(unemployment) – 0.11(educLevel)

The null hypothesis will be:

$$H_0 : \beta_1 = \beta_6 = 0$$

At the 5% significance level, the critical value for $F_{2,42}$ is 3.23. The F-test produced a value of 1.57, which is less than critical value 3.23. Once again, we fail to reject the null hypothesis and conclude that *poverty* and *foodInsecurity* are not jointly significant. For this reason, we can confidently say that the insignificance of f*oodInsecurity* is not due to multicollinearity. All other instances of high correlation coefficients between variables were tested and none were deemed jointly significant, meaning multicollinearity was not an issue in any of the models.

Another extension to the model was the addition of dummy variable *rural.* The purpose of this variable was to identify whether childhood obesity is more prevalent in predominantly rural states or urban states. Going off the assumption that poverty rates are greater in rural areas, it was expected that rural states would have higher rates of childhood obesity. To be considered rural, a state needed to have greater than 30% of its total population living in a rural area; a total of 21 states met this criterion. The base case was rural, and a state was assigned a value of 1if it was predominantly rural, or a value of 0 if it was predominantly urban.

The dummy variable was included in Model 2 and Model 3, in which it was statistically significant in only Model 3. For this reason, we cannot conclude that the coefficient on *rural* was statistically different from zero in Model 2. In model 3, *rural* had a p-value of 0.089, meaning it was significant at 10%, and had a positive coefficient of 0.01, which is extremely small. The coefficient can be interpreted as when all other variables are held constant, the childhood obesity rate will be 0.01 percentage points greater in rural states than in urban states. Because this coefficient is very small, this does not prove a meaningful relationship between childhood obesity and whether a state is rural or urban.

VI. Conclusions

Across all four models, primary explanatory variable *poverty* had a positive coefficient, supporting the hypothesis that childhood obesity and poverty will have a positive relationship. While many of the secondary control variables were found to be statistically insignificant, *poverty* was deemed significant in three out of the four models. Additionally, it should be noted that *educLevel* was found to be statistically significant in all four models and maintained a similar negative coefficient across all of them. This introduces an interesting relationship between childhood obesity and education level, which can likely be attributed to the proven positive relationship between education level and income. Other significant variables included *logwelfare* and dummy variable *rural*, which both exhibited a positive relationship with childhood obesity. The positive relationship between *chobesity* and *logwelfare* presents further evidence that households receiving governmental aid are more likely to consume less nutritious food that is not prepared at home, emphasizing the need for improved nutritional programs.

While the hypothesis was supported, the R-square value across all models indicated that the correlation between poverty and childhood obesity was relatively weak. This may be attributed to the fact that each U.S. state has a large population in which there is considerable variation in income, cost of living, etc. For example, the District of Columbia has one of the highest median household incomes in the nation, yet still has one of the highest poverty rates. For this reason, statewide average data may be skewed and not accurately representative of the entire population. If sufficient data becomes available, utilizing county level observations rather than state level observations would likely produce better results.

References

Hofferth, Sandra L., and Sally Curtin. “Poverty, Food Programs, and Childhood Obesity.” *Journal of Policy Analysis and Management*, vol. 24, no. 4, 2005, pp. 703–726. *JSTOR*, www.jstor.org/stable/30162676.

Ogden CL, Carroll MD, Fakhouri TH, et al. Prevalence of Obesity Among Youths by Household Income and Education Level of Head of Household — United States 2011–2014. MMWR Morb Mortal Wkly Rep 2018;67:186–189

Rogers, Robert et al. “The Relationship between Childhood Obesity, Low Socioeconomic Status, and Race/Ethnicity: Lessons from Massachusetts.” *Childhood obesity (Print)* vol. 11,6 (2015): 691-5. doi:10.1089/chi.2015.0029

Appendix: STATA Regression Model Outputs

Model 1

Source	SS	df	MS
Model	.022953269	1	.022953269
Residual	.035770025	49	.000730001
Total	.058723294	50	.001174466

Number of obs	=	51
F(1, 49)	=	31.44
Prob > F	=	0.0000
R-squared	=	0.3909
Adj R-squared	=	0.3784
Root MSE	=	.02702

chobesity	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
poverty	.7086259	.1263736	5.61	0.000	.4546687	.9625832
_cons	.0736143	.0142896	5.15	0.000	.0448983	.1023304

Model 2

Source	SS	df	MS
Model	.032219743	8	.004027468
Residual	.026503551	42	.000631037
Total	.058723294	50	.001174466

Number of obs	=	51
F(8, 42)	=	6.38
Prob > F	=	0.0000
R-squared	=	0.5487
Adj R-squared	=	0.4627
Root MSE	=	.02512

chobesity	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
poverty	.382807	.2416722	1.58	0.121	-.1049073	.8705214
logincome	.0357699	.0624295	0.57	0.570	-.0902179	.1617577
logwelfare	.0344788	.0175025	1.97	0.055	-.0008427	.0698004
loghealthcare	.0061464	.0271725	0.23	0.822	-.04869	.0609828
unemployment	-.0579711	.3486091	-0.17	0.869	-.7614929	.6455506
foodInsecurity	.0430631	.3339766	0.13	0.898	-.6309291	.7170552
educLevel	-.1457223	.0725528	-2.01	0.051	-.2921398	.0006952
rural	.0156436	.0096967	1.61	0.114	-.0039251	.0352122
_cons	-.616389	.7153572	-0.86	0.394	-2.060038	.8272603

Model 3

Source	SS	df	MS			
Model	.031826392	4	.007956598	Number of obs	=	51
Residual	.026896902	46	.000584715	F(4, 46)	=	13.61
				Prob > F	=	0.0000
Total	.058723294	50	.001174466	R-squared	=	0.5420
				Adj R-squared	=	0.5021
				Root MSE	=	.02418

chobesity	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
poverty	.3219895	.163219	1.97	0.055	-.0065533	.6505322
logwelfare	.0329131	.0149292	2.20	0.033	.0028622	.062964
educLevel	-.1147855	.0482659	-2.38	0.022	-.2119397	-.0176313
rural	.0136187	.0078385	1.74	0.089	-.0021593	.0293967
_cons	-.1527335	.131082	-1.17	0.250	-.4165878	.1111208

Model 4

```
. regress chobesity poverty educLevel logwelfare
```

Source	SS	df	MS			
Model	.030061356	3	.010020452	Number of obs	=	51
Residual	.028661938	47	.000609828	F(3, 47)	=	16.43
				Prob > F	=	0.0000
Total	.058723294	50	.001174466	R-squared	=	0.5119
				Adj R-squared	=	0.4808
				Root MSE	=	.02469

chobesity	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
poverty	.3923521	.1614747	2.43	0.019	.067507	.7171972
educLevel	-.1424554	.0465309	-3.06	0.004	-.2360635	-.0488473
logwelfare	.0246425	.0144506	1.71	0.095	-.0044283	.0537133
_cons	-.0681143	.1242839	-0.55	0.586	-.3181414	.1819127