THE IMPACT OF ECONOMIC GROWTH ON ADULT OBESITY RATES IN RURAL AMERICA

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THE IMPACT OF ECONOMIC GROWTH ON ADULT

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Abstract: In the past several decades, obesity has become an increasingly severe problem in United States. From 2008 to 2018, the adult obesity rate rose from 33.8% to 42.4%. Obesity rates are notably higher in rural America when compared to their urban counterparts. Meanwhile, rural regions have experienced relatively slower employment growth and higher poverty rates during the recovery from the Great Recession. Social scientists are interested in determinants of – and potential solutions to – this rise in obesity rates. The existing literature has focused on the relationship between obesity and social / economic factors, such as the number of fast-food restaurants, limited physical activity, and unemployment rates. However, one unexplored question is whether the level of economic growth experienced by a rural area plays a role in the obesity problem. This paper assesses the impact of economic growth (measured by county-level GDP per capita) on obesity rates (measured by the county-level percentage of adults with BMI higher than 30) in rural America. Nationwide, data is collected on a host of demographic and economic characteristics for all non-metropolitan counties from 2012 to 2016, resulting in a county-level panel data set (n=1,948, t=5). Control variables include age, race and ethnicity, unemployment rates, rates of physical inactivity, and an index measuring healthy food availability. Two different econometric approaches were applied: (1) a fixed effects panel regression model and (2) a difference-in-difference model using propensity score matching (PSM). Under the PSM method, the outcome variable was the difference of obesity growth rates between 2014-2016 and 2012-2014, while the treatment was defined as growth rates in GDP per capita between 2012 and 2014. Different thresholds (such as 5% and 10% growth) were considered for the treatment. The results of both econometric models suggest that higher levels of economic growth in non-metro counties have a surprisingly *positive* impact on obesity rates in later years. This result is counter to the hypothesis and suggests that programs focused on rural economic growth may lead to undesirable outcomes in other quality-of-life metrics. The conclusion discusses these competing interests and how regional scientists can play a role in future research in this area.

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CHAPTER I

INTRODUCTION

1.1 Background

Obesity causes health problems, such as high blood pressure, strokes and diabetes (Courtemanche et al. 2016). Between 1961 and 2012, the adult obesity rate in the United States increased from 13% to 35% (Courtemanche et al. 2016), which means after 2012, over one third of Americans were obese. In 2005, the annual cost associated with obesity was estimated to be $190.2 billion (Cawley and Meyerhoefer 2012). Rural America is facing both the problem of obesity and slower economic growth. On one hand, the obesity rate in rural areas is higher than that in urban areas (shows in figure 1.1), which leads to higher morbidity and mortality of chronic diseases in rural locations (Hill, You and Zoellner 2014). On the other hand, compared with urban regions, rural regions have experienced relatively slower employment and personal income growth rates during the recovery from the Great Recession (Pender 2020).

However, the situation cannot be generalized. Hill, You and Zoellner (2014) found that severe obesity was more prevalent in urban rather than rural areas. In addition, there are also great differences in economic conditions of different rural locations. Pender (2020) discovered that employment rates had been growing (though at a lower rate compared to urban regions) in more urbanized rural counties since 2010 but declining in completely rural counties. Is the higher obesity rates in rural areas impacted by local poor economic conditions? The answer to this question needs further study.

1.2 Problem Statement

Obesity is related to several different social and economic factors, including the number of fast-food restaurants, limited physical activity, poverty, and income inequalities. Many articles have examined the relationship between obesity and these factors (Courtemanche et al. 2016; Congdon 2017; Cooksey-Stowers, Schwartz and Brownell 2017; Rummo et al. 2020). Some articles concluded that a positive relationship exists between economic factors – such as the unemployment rate – and obesity (Rummo et al. 2020). However, few studies have focused on whether economic growth is associated with reduced obesity rate, especially in rural areas. In particular, county level GDP, which works as a good indicator of a county's overall economic well-being, has never been used as a variable of main interest. Many of the previous studies in this area have used only one year's data rather than several consecutive years or have not focused explicitly on rural regions. Moreover, earlier researches also resulted in mixed findings, showing contradictory impacts of income level and employment status on obesity (Courtemanche et al. 2016; Rummo et al. 2020; Amarasinghe et al. 2009). What would be the difference in obesity rates between a rural region that experienced economic growth and an otherwise similar rural region that didn't? If economic growth leads to a reduction in regional obesity rates, then policy makers and researchers who work in the rural development field can argue more clearly that promoting regional economic development can not only bring economic benefits, but also help solve the problem of obesity.

1.3 Objectives

The general objective of this study is to increase the accuracy of knowledge that policy makers use to address the problem of obesity in rural America. Specific objectives include estimating the effect of specific social factors on obesity rates, and quantifying the effect of economic growth on obesity rates in rural America.

CHAPTER II

REVIEW OF LITERATURE

Persons with body mass index (BMI) higher than or equal to 30 kg/m^2 are considered as obese (WHO 2020). Research on the effect of economic factors on obesity is mixed. In addition to general economic indicators such as unemployment rates, poverty rates, and median household income, other economic variables such as the percentage of women employment, gasoline prices and fast-food prices also affect obesity rates (Courtemanche et al. 2016). Courtemanche et al.'s (2016) nationwide study observed that neither median household income nor unemployment rates exhibited statistically significant relationships with body BMI over a twenty-year time period (Courtemanche et al. 2016). Rummo et al.'s more recent (2020) research, however, find positive relationship between unemployment rate and BMI. Another study that focused on rural counties in West Virginia found that the relationship between the risk of obesity and household income is positive (Amarasinghe et al. 2009).

The studies mentioned above used BMI as a measure of obesity. Courtemanche et al. (2016)'s study used individual level BMI with state-level economic factors such as unemployment rates, median income, average work hours among employees, and alcohol prices and focused on the effect of those factors on obesity. Some individual level factors such as ethnic and marital status were also included. Courtemanche et al. (2016)'s study found that the number of restaurants and supercenters are the main factors that explained the rise of obesity, while the number of supermarkets had a negative relationship with obesity. There was a positive correlation between median household income (MHI) and BMI at the significant level of 5%. But MHI didn't affect whether an individual is obese or not. Amarasinghe et al. (2009)'s study collected data from rural counties in West Virginia. The author examined the impact of individual factors such as household income, employment status, education level, gender, age and ethnicity on obesity. In this study, obesity was a binary outcome variable that equaled to 1 when an individual's BMI was higher than or equal to 30 kg/m^2 and 0 when the BMI was less than 30 kg/m^2. Results showed that both age and income had positive relationship with obesity, while Hispanics and those with higher education level were less likely to be obese. In Rummo et al.'s (2020) study, the independent variables were collected at county level across the country; the research estimated the county-level factors' influence on the BMI of individual human beings. Rummo et al.'s (2020) study also found that unhealthy food environment (more convenience stores and limited service restaurant) contributed to higher BMI, while active commuting (walking, biking or public transportation) to work had negative relationship with BMI. Both Rummo et al.'s and Courtemanche et al.'s studies used cross-sectional and time series data, while Amarasinghe et al.'s study used only cross-sectional data (Courtemanche et al. 2016; Rummo et al. 2020; Amarasinghe et al. 2009). The differences mentioned above may be why the results of the previous studies are contradictory.

Most studies on obesity include both economic and social factors. So far, Courtemanche et al.'s (2016) research included the largest number of independent variables. But most of the economic factors used in Courtemanche et al.'s (2016) study may not reflect regional economic growth. For example, the increase in gasoline price reduces the opportunity cost of taking other means of transportation, such as bicycle and walking, and therefore may have a negative impact on obesity (Courtemanche et al. 2016). However, variables like changing gasoline prices may not be good indicators of economic development. But results from previous studies do provide clues that the relationship between economic factors and obesity is more than casual.

Social factors also affect obesity. An important social factor is the food environment. When estimating the food environment of a region, both the availability of healthy food and unhealthy food should be considered. The availability of healthy food includes the number of grocery stores, supermarkets, and farmer's markets. The availability of unhealthy food includes the number of fast-food restaurants, limited service establishments, and convenience stores (Cooksey-Stowers et al. 2017). Dunn et al.'s (2011) study focused on the impact of fast-food availability on obesity and found no evidence that the availability of fast-food restaurants can affect BMI level among white residents. The risk of obesity among non-white residents, however, is impacted by the availability of fast-food restaurants. This study used individual level data for both the dependent variable (BMI) and independent variables (race, gender, education level, distance to fast-food restaurant), and the data came from six to seven rural counties in central Texas. Another study found that a new measure called "food swamp" can work as a better predictor of obesity compared to the more traditional measure, "food desert" (Cooksey-Stowers et al. 2017). A "Food swamp" describes a region where fast food and junk food options overwhelmed opportunities for healthy food, while a "food desert" is used to describe a region with limited access to healthy food (Cooksey-Stowers et al. 2017).

Physical environment is another factor that affects obesity. Patterson et al. (2004) discovered that rural adults are less likely to participate in physical activities during their leisure time compared to urban residents. Rural adults were also more likely to be obese (Patterson et al. 2004). A more recent study combined food and exercise environments and analyzed their impact on obesity rates and found that limited access to physical activity is an important predictor of obesity (Congdon 2017). Congdon (2017)'s study used cross-sectional county-level data but did not assess changes over time. The studies mentioned above show that both activity and food environment have a significant impact on obesity.

Most of the previous studies on this topic either used state-level economic indicators

(Courtemanche et al. 2016; Finkelstein et al. 2012) or only cross-sectional data (Amarasinghe et al. 2009). To our knowledge, the study by Rummo et al. (2020) is so far the only one that both used county level social and economic factors and applied time-series data. However, although rural regions in America are both lagging in economic growth and facing more severe problems with obesity (Hill et al. 2014), none of the studies mentioned above specifically focused on the relationship between economic growth and obesity in rural America.

CHAPTER III

CONCEPTUAL FRAMEWORK AND METHODOLOGY

In this study, two different approaches will be used to quantify the impact of economic growth on obesity: panel analysis and propensity score matching (PSM). Using two different econometric approaches allows for testing the robustness of the findings. The panel nature of the data allows for the use of a fixed effects model to estimate the impact of economic growth on obesity. When using the panel data, unobserved measures, such as cultural factors can be controlled (Wooldridge 2012). PSM is an effective technique to estimate a potentially causal relationship (Caliendo and Kopeinig 2008). Moreover, by using PSM, different thresholds of GDP increases can be evaluated, which is a unique benefit of PSM over the fixed effects model.

3.1 Conceptual framework for panel analysis

There are two main aspects that affect obesity rates: economic factors and social demographic factors. Figure 3.1 describes the general relationship between the two aspects and obesity. Previous studies provide some information about which economic and social demographic factors are important indicators of obesity. Both Courtemanche et al.'s (2016) study and Rummo et al.'s (2020) study include the unemployment rate as an economic indicator associated with obesity. All of Courtemanche et al.'s (2016), Rummo et al.'s (2020) and Amarasinghe et al.'s (2009) studies also include household income as an economic indicator that may affect obesity. Outside of median household income and the unemployment rate, GDP is also an important variable that reflects county economic characteristics. However, no previous study has included GDP as an independent variable.

While most research to date has included income as a potential determinant of obesity, it is possible that an alternative measure might better capture a community's response to varying economic conditions. There usually exists positive correlation between personal income and GDP (Montana 2016). Personal income has components such as wages, benefits, rents, interests, and dividends. Personal income is an important part of GDP. Besides personal income, however, GDP also includes other important components of economy, including taxes on production and imports, social security contributions, corporate income taxes, and undistributed corporate benefits (Montana 2016). Social security contributions are payments to the government to enable payers to obtain future social welfare (which includes retirement pensions) (OECD 2021). Thus, social security contributions may be important for obesity among senior citizens. Corporate income taxes and undistributed corporate profits reflect the operation conditions of local companies. When in good condition, companies can provide more employment opportunities for the local area. Therefore, GDP is a more comprehensive indicator of the overall economic condition. Moreover, compared to urban areas, the "public sector" plays a larger role in the labor market in rural areas, which means the rural economy is more likely to depend on government income (Pender 2019). This paper argues that GDP is an important metric for capturing economic growth – particularly in rural counties – and uses GDP per capita as the primary independent variable of interest.

A general assumption is that improving overall economic conditions will lead those with higher incomes to consider unhealthy food (fast food or convenient food) as inferior goods. This will reduce the consumption of those goods, and lead to a reduction in the obesity rate in that region. Social factors, such as food environment and physical activities, are also associated with obesity rates. "Food swamps" – defined by areas that not only have less healthy food, but also have an excessive amount of fast or junk food – have been shown to be a significant predictor of obesity (Cooksey-Stowers et al. 2017). According to Cooksey-Stowers et al.'s (2017) study, junk food includes limited service establishments and convenience stores. Congdon (2017) discovered positive relationship between limited access to exercise and obesity rates. Obesity may also vary along social demographic groups. Fast food availability has a more significant impact on obesity rates among non-white rural residents (Dunn, Sharkey and Horel 2011). Control variables include in this study are population, race components, and age characteristics of the county.

In panel analysis, data from the same observations are collected across time (Wooldridge 2012). In this study, all the social and economic features mentioned above would not only be different across rural counties, but they would also change within a same county over time. Panel regression uses both aspects of the data variation within and between counties to explain the potential impact of economic growth on obesity rates.

3.2 Conceptual framework for propensity score matching

PSM is a method used to estimate treatment effects with non-experimental data. Different from an ideal experiment where treatment can be randomly assigned, in most social studies, it is unlikely to have the "treatment" as the only differentiating factor between the treated group and the control group. PSM, however, can help find observations in the control group that are "otherwise similar" to observations in the treated group (Caliendo and Kopeinig 2008).

The average treatment effect (ATE) measures the difference of outcomes between the treated group and the control group. In an ideal experiment, ATE measures can estimate the causal effect in both treated and control groups. For most social studies, however, only "outcomes with treatment" in the treated group and "outcomes without treatment" in the control group can be observed, since a single observation cannot be both treated and not treated at the same time.

Therefore, another evaluation parameter called average treatment effect on the treated (ATT) is introduced. The ATT equation is (Caliendo and Kopeinig 2008)

$$(1)\ ATT = E[Y(1)|D = 1] - E[Y(0)|D = 1]$$

Where Y (1) and Y (0) are outcomes for the treated and control group, respectively, and D stands for the treatment. In this study, the treatment is a threshold of economic growth, and the outcome is the obesity rate. The observations in the treated group are counties that experienced economic growth above the threshold while the control group contains counties that did not. D equals one for counties that experienced economic growth (at a certain rate) over the 2012 – 2014 period; and zero for counties that did not. However, this is the ideal situation. $[Y(0)|D = 1]$ would be an unobservable counterfactual term, since it is the expected value of the change of obesity rates for the control group if they had experienced economic growth. PSM is used to estimate this unobservable counterfactual term (Caliendo and Kopeinig 2008)

$$(2)\ ATT = E_{P(X)|D=1}\{E[Y(1)|D = 1, P(X)] - E[Y(0)|D = 0, P(X)]\}$$

where X is set of covariates that were used to estimate the propensity score. Propensity score is defined as the likelihood of being treated (which in this study would be the likelihood of experiencing economic growth).

Both panel analysis and PSM assume that social and economic factors can affect obesity rates. But PSM is more of a cross-sectional method, which means that the covariates won’t change across time. In the panel analysis, time-series data were collected to capture unobserved fixed effects. A main advantage of PSM is that it allows for explicit differentiation of rural counties that experienced high economic growth and “otherwise similar” rural counties that did not. Thus, PSM would serve as a good approach as a robustness check.

3.3 Hypotheses

The hypotheses of this research are:

(1) In rural America, counties that experienced recent economic growth will have lower obesity rates compared to otherwise similar counties that didn’t.

(2) As the food environment improves, obesity rates will decrease in rural America.

(3) As the proportion of residents who participate in physical activities increases, obesity rates will decrease.

3.4 Data

Data for this study is obtained from the U.S. Census Bureau, Bureau of Economic Analysis (BEA) and Robert Wood Johnson Foundation (RWJF). RWJF is a philanthropy that focuses on health care and provides annual data on health statistics. The RWJF health data was commonly used for analyzing and comparing counties in terms of health outcomes (Fitzpatrick et al. 2018, Kersh, Stroup and Taylor 2011, Thompson, Fernald and Mold 2012). Their dataset includes health information from a variety of sources (such as Behavioral Risk Factor Surveillance System and National Center for Chronic Disease Prevention and Health Promotion) and also includes demographic data from the U.S. Census. However, for some variables, RWJF may use the data from previous years in the current year’s report table (for example, 2009 data was used in 2012’s report). Therefore, some manual adjustments were made to the RWJF data so that the year corresponds to the actual year in which the data was collected (and not simply the year of the

RWJF report). Nationwide, county level data was collected from 2012 to 2016 (n=1,948, t=5). The 1,948 observations are all nonmetro counties (don't contain one or more urbanized areas of over 50,000 persons). Due to data availability, only counties in conterminous United States were included. To test the different influence of factors under different rural thresholds, non-metro counties were divided into micropolitan counties (contains urban clusters of 10,000-49,999 persons, n=638) and noncore counties (the rest of the counties, n=1,310). Data used for county classification was collected from USDA. The main independent variable, GDP, was adjusted by BEA as 2012's value. County level GDP data were not available from the BEA until 2019. This might be the reason why no relative previous studies had used GDP as an economic indicator. This study includes "food swamp index" and "percent of population that have access to exercise opportunities" as two independent variables that reflects the food and physical environment. The food swamp index is a continuous measure. Cooksey-Stowers et al. (2017)'s study shows that "food swamp" index works as a better indicator of obesity than the traditional "food desert" index. Based on the restaurant and store number data obtained from the U.S. Census Bureau, the food swamp index can be obtained by the equation below (Cooksey-Stowers et al. 2017)

$$\text{Food Swamp Index (FSI)} = \frac{\text{Fast Food/Limited Service Establishments + Convenience Stores}}{\text{Grocery Stores/Supermarkets}}$$

To obtain the amounts of these business establishments, relevant 6-digit obtained the North American Industry Classification System (NAICS) codes were acquired by searching on Census Bureau website. The NAICS codes for convenience store, gasoline station with convenience store, supermarket and limited service restaurant are respectively 445120, 447110, 445110 and 722513. As the data for convenience store in rural counties were very incomplete, "gasoline station with convenience store" were used instead of "convenience store". It is anticipated such substitution will not cause inaccurate results, because the number of convenience stores in rural areas is very small. Most of the convenience stores in nonmetro counties are "gasoline station with convenience store".

Initially, "percentage access to physical activity" (AE) was used to reflect the physical environment. However, the data provided by RWJF on this category is not robust. In 2012 and 2013, there are many missing values in the AE variable. Additionally, after 2014, RWJF changed the measuring method of AE, and the percentage increases significantly. Therefore, the measuring method of AE is inconsistent from 2012 to 2016. To solve this problem, I switched to another measurement called "physical inactivity rate" (PI), which measures the "percentage of adults that report no leisure-time physical activity" (RWJF, 2020). From 2014 to 2016, the correlations between PI and AE are all above 80 percent, which indicates that PI can be used as a good substitute of AE.

The dependent variable is the county level adult obesity rate. According to RWJF, this is measured by percent of population that are older than 20 years with BMI higher than or equal to 30 kg/m^2. The standard of obesity is set by the World Health Organization (WHO) (2020). Description of variables and descriptive statistics are listed in table 3.4.1 and 3.4.2.

3.5 Fixed effects model

The fixed effects model is

$$(3)\ y_{it} = \beta_0 + \beta_1 x_{it1} + \beta_2 x_{it2} + \ldots + \beta_k x_{itk} + \alpha_i + u_{it}$$

where y_{it} is the obesity rate for county i at time t, x_{itk} are the explanatory variables and β_k are the corresponding coefficients. α_i is an unobservable time-constant dummy variable (such as cultural factors) for each observation, and u_{it} is the time-varying error term that represents unobserved factors that change over time and affect y_{it}. It is assumed that $Cov(x_{itj}, u_{it}) = 0$, which means there is no correlation between the time-varying error term and independent variables. But α_i could be correlated with independent variables (Wooldridge 2012).

For each observation i, equation (3) was averaged over time t

(4) $\bar{y}_i = \beta_0 + \beta_1\bar{x}_{i1} + \beta_2\bar{x}_{i2} + \ldots + \beta_k\,\bar{x}_{ik} + \alpha_i + \bar{u}_i$

After applying the fixed effects method which is conducted by subtracting the average year equation (4) from the equation for different years in (3), the reformed balancing panel function is

(5) $\Delta y_{it} = \alpha_0 + \beta_1\Delta x_{it1} + \beta_2\Delta x_{it2} + \ldots + \beta_k\Delta x_{itk} + \Delta u_{it}$

The time-invariant dummy variable α_i is cancelled out. In this way, unobservable factors that do not change over time can be controlled (Wooldridge 2012).

In this study, the characteristics that could impact obesity but are difficult to observe and quantify may include political, cultural, and religious factors. These characteristics are time-constant and are likely to have impacts on independent variables such as real GDP and demographic characteristics. Therefore, a fixed effects model is appropriate for the situation.

The fixed effects model for this specific study is

$$(6)\ Ob = \beta_0 + \beta_1 ln\,(PC\_GDP_{it}) + \beta_2 PI_{it} + \beta_3 Unem_{it} + \beta_4 Age_{it} + \beta_5 African_{it} + \beta_6 Native_{it} + \beta_7 Asian_{it} + \beta_8 Hispanic_{it} + \beta_9 ln(Pop_{it}) + \beta_{10} Pov_{it} + \beta_{11} FSI_{it} + \delta_t + \alpha_i + u_{it}$$

where δ_t (t=1,2,3,4,5) is a dummy variable for different time period, α_i is the unobserved fixed effects term for each county, and u_{it} is the time-varying error term; all for time t for county i.

The main hypothesis of this study is that economic growth will have a negative impact on obesity rates in rural America. In the equation above, GDP is considered as the main variable of interest. Therefore, β_1 is expected to be less than zero. However, weight gain is an accumulative process that can take time (Courtemanche et al. 2016) and thus independent variables in time t may not have an impact until a later time period. Therefore, lag effects should be considered when exploring the influence of these factors on obesity. Rummo et al.'s (2020) study also used lagged independent variables. In this study, independent variables would be lagged for 1-2 years.

One concern with a panel approach is that of reverse causality (i.e. obesity rates impacting GDP). The impact of obesity on the economy is mainly reflected in medical spending (Cawley and Meyerhoefer 2012). However, medical spending only accounts for a small portion of GDP. To my knowledge, there is no evidence that obesity affects other components of GDP, such as household income and corporate income taxes. Lags of independent variables can also help minimize reverse causality concerns. Therefore, even if this study used the change in GDP to estimate obesity change over the same period, the problem of reverse causality is not likely to exist.

3.6 Difference-in-difference PSM model

In the PSM method, since both data before and after the treatment were available, a difference-in-difference model can be applied (Caliendo and Kopeinig 2008). Thus, the ATT equation became

$$(7)\ ATT = E\ (\Delta Y_{t1} \mid D = 1) - E\ (\Delta Y_{t0} \mid D = 1)$$

where the outcome variable ΔY_t (named Obesediff) is the difference between the percent change of adult obesity rates from 2012 to 2014 (named ΔObese1) and from 2014 to 2016 (named ΔObese2). The relationship can be mathematically expressed as

$$(8)\ \Delta Obese\ 1 = (2014\ obese\ rate\ -\ 2012\ obese\ rate)/2012\ obese\ rate$$

$$(9)\ \Delta Obese\ 2 = (2016\ obese\ rate\ -\ 2014\ obese\ rate)/2014\ obese\ rate$$

$$(10)\ Obesediff = \Delta Obese\ 2\ -\ \Delta Obese\ 1$$

Based on propensity scores, counties meeting the economic growth threshold (which can be varied) need to be matched to otherwise similar counties that did not see this level of economic growth. Propensity score is typically estimated through a probit regression model. The dependent variable is a binary variable equal to one when economic growth is above the defined threshold and zero when it is not. If a county experienced a percent increase in real GDP per capita greater than or equal to a certain threshold, then this county will be included in the treated group, otherwise it will be in the control group. This study measures the percent increase of real GDP per capita from 2012 through 2014 and will consider different thresholds of percent increase in real GDP per capita (5% and 10%). The independent variables were measured using data from 2012. The probit regression model is

$$(11)\ PC\_GDP_i = \beta_0 + \beta_1 Unem_i + \beta_2 Age_i + \beta_3 African_i + \beta_4 Native_i + \beta_5 Asian_i + \beta_6 Hispanic_i + \beta_7 ln(MHI_i) + \beta_8 ln(Pop_i) + \beta_9 Pov_i + \beta_{10} PI_i + \beta_{11} FSI_i + \beta_{12} Mining_i + u_i$$

Variable descriptions were listed in table 3.6.1. The reason that “Mining” was included was because the oil production boom after 2012 was showed to have very positive economic impacts in mining-dependent rural counties (Kassel 2020). Thus, counties with heavy mining activity may be more likely to have higher GDP growth during this time.

Then, counties in the treated and control groups with are matched based on their propensity scores. There are four different methods of matching: nearest neighbor, K - nearest neighbors, Kernel and Radius. The nearest neighbor method matches each treated county to the control county with the closest propensity score. The K - nearest neighbors method matches treated county to the average of its K - nearest neighbors (5 is often used in practice). In the Kernel method, all counties in the control group are matched to each county in the treated group. But the weights assigned to each county in the control group decreases as the propensity score is further away from that of the treated county. In the Radius method, counties in the control group with propensity scores within a certain threshold will be matched to each treated observation (Caliendo and Kopeinig 2008). This study will apply each of the last three methods to test the robustness of the results. After the observations are matched, difference in the change in obesity rates can be observed. A t-test will be conducted to estimate the difference of the means of the outcomes once the matching has been completed (Porter 2013).

CHAPTER IV

FINDINGS

4.1 Fixed effects estimation results

The results of independent variables lag for one to two years were largely consistent. However, when lagging for two years, the impact of GDP turned to be significant. In this section, we mainly discuss the results that lag for two years. A one-year lag results can be found in the appendix. Table 4.1.1 displays the estimation results. To relax the assumption of homoscedasticity, robust standard errors were applied. These values were presented in parentheses under the estimated coefficients. The overall R^2 of the regression under micropolitan classification is very low (0.0009), which indicates that the overall fit of this regression is not good. The overall R^2 of noncore counties, however, is relatively high (0.0853).

The results of noncore counties and whole non-metropolitan counties were similar. Both results showed that there existed a positive relationship between per capita GDP and obesity rates at 1% significant level. The corresponding coefficients implies that a county with a 1% higher per capita GDP had nearly 3% higher obesity rates two years later, holding other variables constant. This result was driven by noncore counties, as the coefficient for micropolitan counties was insignificant. The estimated coefficient of physical inactivity rates was only negatively significant at 10% level under the classification of micropolitan counties. This means micropolitan counties with higher physical inactivity rates has relatively lower obesity rates two years later, which is very counter-intuitive. The estimated coefficients of the food swamp index were insignificant under any classification. Under the classification of all non-metropolitan counties, the estimated coefficients of the percentage of African and native American were positively significant at 5% and 10% level, respectively. The estimated coefficient of the percentage of Asian American were positively significant at 5% level. This means that a county with higher percentage of these minorities also have higher obesity rates two years later. Under the classification of micropolitan counties, both the impacts of the percentage of African and native American lost significance, while in noncore counties, the influence of the percentage of Asian was not significant. The coefficient of the percentage of people that were older than 65 were positively significant under all classifications at 1% level. The impact of population was positively significant at 1% level in micropolitan counties and all non-metropolitan counties, but not for non-core locations.

When GDP per capita was replaced by median household income (MHI), the results showed that there was no relationship between MHI and obesity rates. The table of results was listed in the appendix. This scenario indicated that the positive relationship between GDP per capita and obesity rates may be driven by components of GDP other than MHI. As the results above showed that the coefficient of the percentage of senior citizens was highly positive, one assumption would be that social security contributions in GDP may be positively related to the percentage of obesity rates.

4.2 PSM results

The estimation results of the PSM method are displayed in Table 4.2.1 and 4.2.2. Overall, the result of PSM is consistent with that of the fixed effects model. Compared to otherwise similar counties, counties with 5% growth rate of per capita GDP from 2012 to 2014 are likely to experience 2-3% higher obesity growth rates from 2014 to 2016 over the 2012 to 2014 baseline. Under the non-metropolitan classification, the treatment effects were significant no matter which matching technique were applied, which showed the robustness of the results. Again, these results were mainly driven by noncore counties, as the treatment effects for micropolitan counties were insignificant.

When the per capita GDP growth threshold was raised to 10%, the treatment effects were generally 1% higher compared to those when the per capita GDP growth rate was at 5%, indicating that with counties with higher GDP growth rates had higher obesity growth rates as well. The treatment effects became significant in micropolitan counties while they lost significance in noncore counties. This is probably because compared to noncore counties, more urbanized rural counties had been recovering better from the great recession (Pender 2019), therefore making micropolitan counties more likely to experience substantial GDP growth.

The results of the probit regressions were listed in table 4.2.3 and 4.2.4 (in the appendix). Both micropolitan and noncore counties that are mining-dependent are more likely to experience 10% GDP growth (both at 1% significant level), which confirms that the oil production boom after 2012 had positive economic impacts in those counties. Generally, rural counties with higher MHI are more likely to experience economic growth, which matches the expectation. What is kind of counter intuitive is that counties with more population are less likely to have GDP growth. This result was mostly driven by noncore counties.

CHAPTER V

CONCLUSION

In conclusion, the results of this study are not consistent with the original hypotheses. The impact of GDP on obesity rates was expected to be negative, but the relationship turned out to be positive. Neither physical inactivity rates nor food environment (FSI) had significant impact on obesity rates. Other economic indicator, such as poverty rates and unemployment rates, didn’t show any influence on the obesity rates as well. Instead, counties’ obesity rates were showed to have closer relationship with demographic factors such as proportion of senior citizens and minorities.

These results may indicate that in rural counties with relatively good economic conditions, people will become more obese. However, it may also be caused by other reasons. A limitation of this study is that the situation of migration was not controlled. Since this study did not explore the relationship between individual economic status and obesity, but the relationship between the overall economic status and obesity rates of a county, migration is also an important factor of regional population composition. But migration is a non-fixed effect that is hard to capture. If the economic conditions of a county get better in a few years and attracted obese people from other regions with poor economic status, then such situations cannot be captured by this study. The higher the food swamp index is, the unhealthier the food environment is. But the result showed no impact of food swamp index on obesity rates, which is counter intuitive. According to an article published by USDA in September 2020, however, the impact of food environment on dietary health may not be as great as previous studies have shown. The article indicated that people's dietary health may depend more on the understanding of nutrient knowledge (Dong and Handbury 2020). In addition, Cooksey-Stowers et al.'s (2017) research used only cross-sectional data, this may cause them to overestimate the influence of food swamp index on obesity rates.

Results of this study showed that the problem of obesity in rural America could not be addressed by developing economic conditions. However, rural economies need to develop. Thus, "solving the problem of obesity while developing the rural economy" becomes a challenge for policy makers. As the results of the study showed a significant positive relationship between obesity rates and proportion of minorities, the obesity rate in a region may be more closely related to the diet habits of residents. People of different races have different eating habits, which leads to different obesity rates.

Policy makers may need to face the challenge from two perspectives. First, keep policies that help the development of rural economy. Second, local governments may put more efforts on promoting the knowledge of healthy diet in rural locations. Meanwhile departments like USDA may formulate programs that provide subsidies to enterprises in rural locations to supply their employees with healthy lunch. The program can be similar to the School Lunch Program but focuses more on providing healthy food to rural employees. Recipients of the program may need to provide qualifications that they would address the problem of obesity among their employees.

Further studies in this area can be improved from the following aspects. First, try to find out which components of GDP are the main driving forces that causes the positive relationship between GDP per capita and obesity rates. To achieve this, data about the percentage of each components needs to be collected. Second, more controlling variables that can be correlated with obesity may be included, such as the percentage of residents that participate in the food stamp program. Such control variables might be necessary because a study by USDA showed that participants in the food stamp programs had been spending more on unhealthy food (USDA 2016). Last, researchers may come up with methods that help control the migration situation (for example, by using instrumental variables).

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TABLES

Table 3.4.1. Variables description

	Description	Source
Dependent Variable		
Ob	Adult obesity rate	2012-2016 RWJF
Independent Variables		
GDP	Ln per capita GDP	2012-2016 BEA
PI	Physical inactivity rate	2012-2016 RWJF
Unem	Unemployment rate	2012-2016 RWJF
Age	Percentage of population above 65 years old	2012-2016 RWJF
African	Percentage of African American	2012-2016 RWJF
Asian	Percentage of Asian American	2012-2016 RWJF
Native	Percentage of Native American	2012-2016 RWJF
Hispanic	Percentage of Hispanic American	2012-2016 RWJF
Pop	Ln population of the county	2012-2016 RWJF
Pov	Poverty rates	2012-2016 Census
FSI	Food swamp index	2012-2016 Census

Table 3.4.2. Descriptive statistics

Variable	Mean	Std. Dev	Min	Max
Ob	32.1200	4.6525	10.7	57.7
PC GDP	51321.17	567553.1	6528.663	48700000
PI	27.4646	5.2353	8.1	49.9
Unem	6.4537	2.6858	0.8168	19.9747
Age	18.8745	4.2440	5.8148	38.1699
African	7.8142	14.7637	0	85.2325
Native	2.4596	7.6414	0	87.7696
Asian	0.7029	1.0963	0	31.7464
Hispanic	6.6380	14.1236	0	96.2540
Pop	23547.86	22072.7	71	198449
Pov	17.6705	6.7063	0	48.7
FSI	5.6817	3.9617	0	56

Table 3.6.1. Variables description for probit regression

	Description	Source
Dependent Variable		
Growth	Growth rate of PC GDP from 2012 to 2014	2012-2014 BEA
Independent Variables		
Pov	Poverty rates	2012 Census
MHI	Median household income	2012 RWJF
Unem	Unemployment rate	2012 RWJF
African	Percentage of African American	2012 RWJF
Asian	Percentage of Asian American	2012 RWJF
Native	Percentage of Native American	2012 RWJF
Hispanic	Percentage of Hispanic American	2012 RWJF
Pop	Ln population of the county	2012 RWJF
Age	Percentage of population above 65 years old	2012 RWJF
PI	Physical inactivity rate	2012-2016 RWJF
FSI	Food swamp index	2012-2016 Census
Mining	Dummy variable for economic dependence in mining industry	2013 USDA

Table 4.1.1. Results of the fixed effects model (lag2)

Variables	Non-Metro	Micropolitan	Non-Core
ln (PC GDP) (t-2)	2.8408*** (0.8130)	1.9512 (1.7519)	2.9445*** (0.9272)
PI (t-2)	-0.0304 (0.0362)	-0.1120* (0.0632)	0.0026 (0.0442)
Unem (t-2)	-0.1404 (0.0870)	-0.1484 (0.1545)	-0.1211 (0.1061)
Age (t-2)	0.9491*** (0.2096)	2.5207*** (0.5410)	0.6209*** (0.2256)
African (t-2)	0.6253** (0.3044)	-0.4689 (0.5729)	0.8668** (0.3510)
Native (t-2)	1.0069*** (0.2987)	-0.7979 (0.9613)	0.9385*** (0.3042)
Asian (t-2)	1.4127** (0.6060)	1.5640** (0.7094)	1.4477 (0.9060)
Hispanic (t-2)	-0.0429 (0.1736)	-0.4889 (0.3470)	0.1464 (0.1939)
ln (Pop) (t-2)	22.6283*** (6.7490)	77.4386*** (12.5542)	6.7829 (7.8642)
Pov (t-2)	-0.0209 (0.0481)	0.0879 (0.1015)	-0.0397 (0.0539)
FSI (t-2)	-0.0336 (0.0528)	-0.0053 (0.0806)	-0.0462 (0.0673)
2013	0.0534 (0.1425)	-0.4210 (0.3231)	0.1161 (0.1631)
2014	-0.2781 (0.2501)	-1.3621** (0.5604)	-0.1092 (0.2827)
Constant	-238.5798** (67.9640)	-828.1544*** (136.7122)	-81.9408 (76.1647)
Overall R^2	0.0231	0.0009	0.0853
Within R^2	0.0357	0.0802	0.0327
Between R^2	0.0556	0.0016	0.1185
Observation	1,948	638	1,310

* Statistical significance at the p=0.10 level.
** Statistical significance at the p=0.05 level.
*** Statistical significance at the p=0.01 level.

Table 4.2.1. Results of the difference-in-difference PSM model

ATT difference (GDP_Change>5% threshold)

	Nonmetro	Micro	Noncore
5-neighor	0.0210*	0.0101	0.0278**
	(0.0112)	(0.0210)	(0.0131)
kernel	0.0233***	0.0020	0.0329***
	(0.0082)	(0.0160)	(0.0096)
0.1 caliper	0.0204**	0.0119	0.0237**
	(0.0100)	(0.0190)	(0.0119)

* Statistical significance at the p=0.10level.
** Statistical significance at the p=0.05 level.
*** Statistical significance at the p=0.01level.

Table 4.2.2. Results of the difference-in-difference PSM model 2

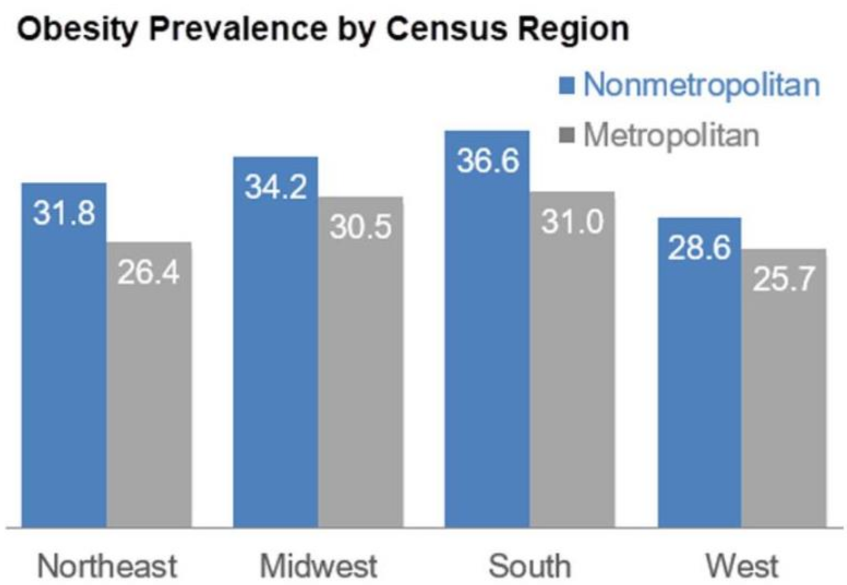
ATT difference (GDP_Change>10% threshold)

	Nonmetro	Micro	Noncore
5-neighor	0.0265** (0.0133)	0.0498* (0.0261)	0.0069 (0.0153)
kernel	0.0360*** (0.0109)	0.0318 (0.0223)	0.0373*** (0.0126)
0.1 caliper	0.0290** (0.0119)	0.0422* (0.0241)	0.0216 (0.0139)

* Statistical significance at the p=0.10level.
** Statistical significance at the p=0.05 level.
*** Statistical significance at the p=0.01level.

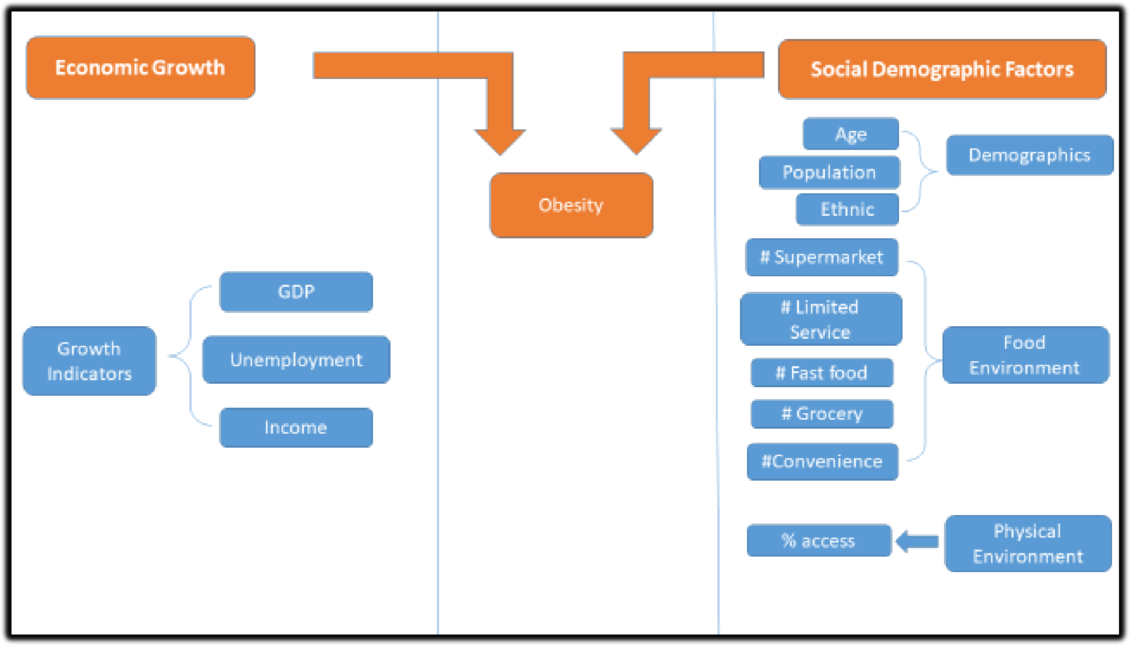
FIGURES

Figure 1.1. Obesity Prevalence by Census Region



(RHI hub 2020)

Figure 3.1. The Conceptual Model



APPENDICES

Table 4.1.2 Results of the fixed effects model (lag1)

Variables	Non-Metro	Micropolitan	Non-Core
ln (PC GDP) (t-1)	-0.0008 (0.3424)	-0.5864 (0.9821)	0.0101 (0.3657)
PI (t-1)	-0.0230 (0.0253)	-0.0052 (0.0429)	-0.0311 (0.0442)
Unem (t-1)	0.0153 (0.0547)	0.0116 (0.0961)	0.0227 (0.0664)
Age (t-1)	0.5624*** (0.1329)	1.3186*** (0.3182)	0.3771*** (0.1459)
African (t-1)	0.2533 (0.2133)	-0.4894 (0.4406)	0.4443* (0.2428)
Native (t-1)	0.8896*** (0.2514)	-0.7024 (0.6849)	0.9014*** (0.2498)
Asian (t-1)	1.0136** (0.4053)	1.3224*** (0.4878)	0.9482 (0.6284)
Hispanic (t-1)	0.0868 (0.1196)	-0.5688** (0.3470)	0.3281** (0.1359)
ln (Pop) (t-1)	15.6165*** (4.1930)	45.2640*** (7.9506)	6.4464 (4.8151)
Pov (t-1)	-0.0352 (0.0324)	-0.0324 (0.0743)	-0.0329 (0.0360)
FSI (t-1)	0.0276 (0.0528)	0.0365 (0.0527)	0.0247 (0.0471)
2013	0.0656 (0.1002)	0.0101 (0.2211)	0.0548 (0.1165)
2014	0.4110** (0.1621)	0.1928 (0.3674)	0.4148** (0.1827)
2015	0.3396 (0.2508)	-0.0379 (0.5392)	0.3822 (0.2887)
Constant	-133.9353*** (41.2854)	-447.5225*** (85.1939)	-42.7685 (45.7365)
Overall R^2	0.0231	0.0018	0.0431
Within R^2	0.0494	0.0764	0.0497
Between R^2	0.0315	0.0029	0.0585
Observation	1,948	638	1,310

* Statistical significance at the p=0.10 level.
** Statistical significance at the p=0.05 level.
*** Statistical significance at the p=0.01 level.

Table 4.1.3. Results of the fixed effects model with MHI as main variable (lag2)

Variables	Non-Metro	Micropolitan	Non-Core
ln (MHI) (t-2)	-0.2861 (1.5594)	-0.9093 (2.9125)	0.7183 (2.7700)
PI (t-2)	-0.0358 (0.0361)	-0.1262** (0.0624)	0.0029 (0.0441)
Unem (t-2)	-0.1443* (0.0860)	-0.1706 (0.1527)	-0.1427 (0.1050)
Age (t-2)	0.9031*** (0.2095)	2.4519*** (0.5403)	0.5791*** (0.2238)
African (t-2)	0.5920** (0.3038)	-0.4283 (0.5645)	0.7020** (0.3565)
Native (t-2)	1.0328*** (0.3002)	-0.6099 (0.9661)	0.9768*** (0.3079)
Asian (t-2)	1.2849** (0.6021)	1.4953** (0.7166)	1.8926*** (0.4884)
Hispanic (t-2)	-0.0255 (0.1752)	-0.5234 (0.3459)	0.1442 (0.2014)
ln (Pop) (t-2)	22.2511*** (6.6943)	76.1267*** (12.3940)	5.9510 (7.6219)
Pov (t-2)	-0.0337 (0.0484)	0.0755 (0.0999)	-0.0337 (0.0546)
FSI (t-2)	-0.0367 (0.0510)	-0.0041 (0.0780)	-0.0552 (0.0644)
2013	-0.0367 (0.1435)	-0.4825 (0.3262)	0.0065 (0.1582)
2014	-0.3148 (0.2593)	-1.3858** (0.5839)	-0.2547 (0.2837)
Constant	-201.0632*** (66.1451)	-782.8202*** (136.3274)	-49.977 (71.2390)
Overall R^2	0.00404	0.0005	0.0736
Within R^2	0.0322	0.0779	0.0307
Between R^2	0.0573	0.0008	0.1012
Observation	1,948	638	1,310

* Statistical significance at the p=0.10 level.
** Statistical significance at the p=0.05 level.
*** Statistical significance at the p=0.01 level.

Table 4.2.3. Probit regression results when PC_GDP growth rate at 5%

	Non-Metro	Micro	Noncore
Unem	-0.0172 (0.0144)	-0.0151 (0.0280)	-0.0208 (0.0175)
Age	0.0126 (0.0144)	0.0267 (0.0201)	0.0048 (0.0116)
African	-0.0006 (0.0027)	-0.0022 (0.0052)	-0.0029 (0.0032)
Native	-0.0095* (0.0050)	-0.0028 (0.0117)	-0.0120* (0.0056)
Asian	-0.2155*** (0.0663)	-0.2836*** (0.0963)	-0.1501 (0.1162)
Hispanic	0.0077*** (0.0024)	0.0062 (0.0041)	0.0090*** (0.0032)
Ln (MHI)	0.7467** (0.3267)	1.1005* (0.6629)	0.6343* (0.3871)
Ln (Pop)	-0.1280*** (0.0393)	-0.0240 (0.0770)	-0.1679*** (0.0541)
Pov	0.0074 (0.0099)	0.0114 (0.0211)	0.0068 (0.0114)
PI	0.0127* (0.0073	0.0186 (0.0125)	0.0120 (0.0093)
FSI	0.0078 (0.0085)	-0.0007 (0.0140)	0.0146 (0.0113)
Mining	0.2340** (0.1025)	0.4243** (0.1987)	0.1425 (0.1212)
cons	-7.5078 (3.7117)	-12.7352 (7.6531)	-5.8266 (4.3915)
R^2	0.0419	0.0499	0.0392
Observation	1,948	638	1,310

* Statistical significance at the p=0.10 level.
** Statistical significance at the p=0.05 level.
*** Statistical significance at the p=0.01 level.

Table 4.2.4. Probit regression results when PC_GDP growth rate at 10%

	Non-Metro	Micro	Noncore
Unem	0.0029	-0.0170	0.0127
	(0.0161)	(0.0341)	(0.0195)
Age	0.0184*	0.0153	0.0216*
	(0.0109)	(0.0239)	(0.0128)
African	-0.0007	-0.0084	0.0001
	(0.0031)	(0.0064)	(0.0037)
Native	-0.0085	-0.0382	-0.0035
	(0.0059)	(0.0272)	(0.0062)
Asian	-0.1448*	-0.1636	-0.2846**
	(0.0794)	(0.1097)	(0.1434)
Hispanic	0.0079***	0.0018	0.0131***
	(0.0031)	(0.0047)	(0.0033)
Ln (MHI)	0.7266**	0.3252	0.8840**
	(0.3605)	(0.7764)	(0.4229)
Ln (Pop)	-0.2504***	-0.1555*	-0.2909***
	(0.0446)	(0.0871)	(0.0606)
Pov	0.0098	0.0096	0.0060
	(0.0108)	(0.0249)	(0.0122)
PI	0.0150*	0.0091	0.0226**
	(0.0084)	(0.0148)	(0.0105)
FSI	0.0140	-0.0066	0.0241**
	(0.0095)	(0.0171)	(0.0123)
Mining	0.5060***	0.6773***	0.3217***
	(0.1226)	(0.2113)	(0.1257)
cons	-7.1719	-3.1907	-8.8240*
	(4.0980)	(8.9765)	(4.7967)
R^2	0.0672	0.0677	0.0701
Observation	1,948	638	1,310

* Statistical significance at the p=0.10 level.
** Statistical significance at the p=0.05 level.
*** Statistical significance at the p=0.01 level.

Table 4.2.5. PSM descriptive statistics (5% threshold)

Variable	Threshold	Nonmetro	Observation	Micro	Observation	Noncore	Observation
Obesediff	GDP_growth > 5%	0.0333 (0.0072)	777	0.0206 (0.0138)	221	0.0383 (0.0084)	556
	GDP_growth <= 5%	0.0101 (0.0063)	1,171	0.0195 (0.0113)	417	0.0049 (0.0074)	754
Δ Obese 1	GDP_growth > 5%	0.0093 (0.0027)	777	0.0172 (0.0054)	221	0.0062 (0.0031)	556
	GDP_growth <= 5%	0.0236 (0.0023)	1,171	0.0248 (0.0038)	417	0.0229 (0.0028)	754
Δ Obese 2	GDP_growth > 5%	0.0426 (0.0063)	777	0.0378 (0.0122)	221	0.0445 (0.0074)	556
	GDP_growth <= 5%	0.0337 (0.0055)	1,171	0.0442 (0.0100)	417	0.0278 (0.0064)	754

Table 4.2.5. PSM descriptive statistics (10% threshold)

Variable	Threshold	Nonmetro	Observation	Micro	Observation	Noncore	Observation
Obesediff	GDP_growth > 10%	0.0466 (0.0098)	417	0.0449 (0.0198)	104	0.0472 (0.0112)	313
	GDP_growth <= 10%	0.0119 (0.0054)	1,531	0.0150 (0.0098)	534	0.0102 (0.0064)	997
Δ Obese 1	GDP_growth > 10%	0.0038 (0.0037)	417	0.0140 (0.0070)	104	0.0003 (0.0043)	313
	GDP_growth <= 10%	0.0217 (0.0020)	1,531	0.0237 (0.0035)	534	0.0207 (0.0024)	997
Δ Obese 2	GDP_growth > 10%	0.0504 (0.0088)	417	0.0589 (0.0187)	104	0.0476 (0.0099)	313
	GDP_growth <= 10%	0.0336 (0.0047)	1,531	0.0387 (0.0086)	534	0.0309 (0.0056)	997

VITA

YANCHENG LI

Candidate for the Degree of

Master of Science

Thesis: THE IMPACT OF ECONOMIC GROWTH ON ADULT OBESITY RATES IN RURAL AMERICA

Major Field: AGRICULTURAL ECONOMICS

Biographical:

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