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Economic Growth and Adult Obesity Rates in Rural America*

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Abstract: Obesity has become an increasingly severe problem in the United States. From 2008 to 2018, the adult obesity rate rose from 33.8% to 42.4%, with rates that are notably higher in rural areas 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, food assistance program participation, 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). The results of both econometric models suggest there is no relationship between economic growth and future obesity rates. This suggests that programs focused on rural economic growth may not affect 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.

Keywords: obesity, rural America, economic development, propensity score matching
JEL Codes: O1, R11, R23

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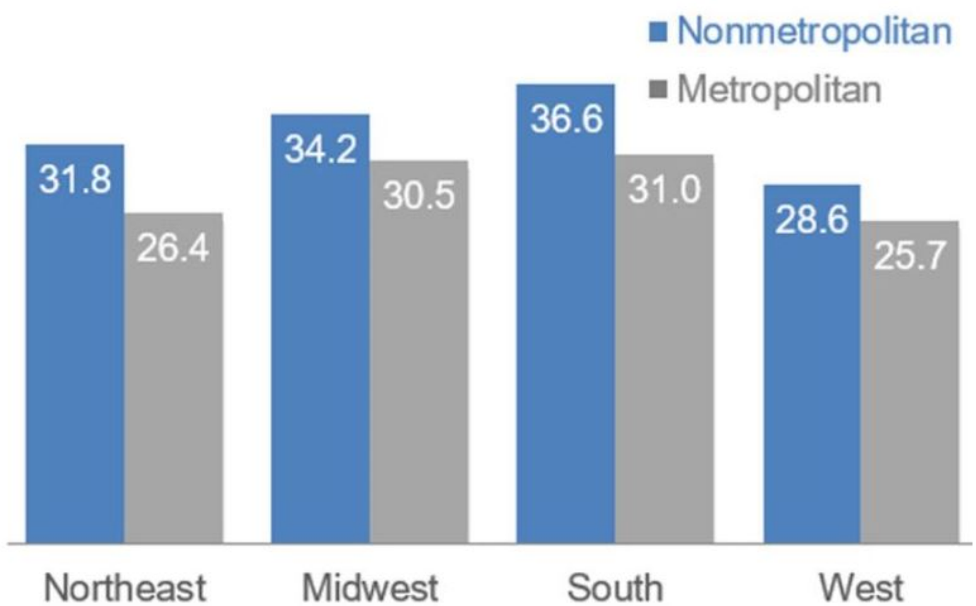
1. INTRODUCTION

1.1. Background

Obesity causes health problems, such as high blood pressure, strokes, and diabetes (Kissebah et al., 1989; Long et al., 2006). Between 1961 and 2012, the adult obesity rate in the United States increased from 13% to 35% (Courtemanche et al., 2016); the rate has risen to over 42% as of 2018 (Hales et al., 2020). 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 the one hand, obesity rates in rural areas are higher than those in their urban counterparts (Figure 1), which leads to higher morbidity and mortality of chronic diseases in rural locations (Hill et al., 2014).[1] 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, 2019).

Figure 1: Obesity Prevalence by Census Region (2016)



Source: Lundeen et al. (2018)

However, the situation cannot be generalized. Hill et al. (2014) found that severe obesity was more prevalent in urban rather than rural areas. In addition, there are also great differences in the economic conditions of different rural locations. Pender (2020) shows 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. Are higher obesity rates in rural areas influenced by poor local economic conditions? Can rural

[1]This paper uses the terms "rural" and "non-metropolitan" interchangeably; however our data is at the county level so "non-metropolitan" is more appropriate

areas improve their obesity rates by focusing on economic development? The answer to these questions needs further study.

1.2. Problem Statement

Obesity is related to several social and economic factors, including the number of fast-food restaurants, limited physical activity, poverty, and income inequality. Many articles have examined the relationship between obesity and these factors (Courtemanche et al., 2016; Fan et al., 2016; Congdon, 2017; Cooksey-Stowers et al., 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, no studies we are aware of have focused on whether economic growth over time is associated with reduced obesity rates, especially in rural areas. In particular, county-level Gross Domestic Product (GDP), which can be used as an indicator of a county's overall economic well-being, has never been used as the primary variable of interest when considering obesity trends. Additionally, many previous studies in this area have used only a single year of data or have not focused explicitly on rural regions. The evidence to date has resulted in mixed findings, showing contradictory impacts of income and employment status on obesity (Amarasinghe et al., 2009; Courtemanche et al., 2016; Rummo et al., 2020). Are there meaningful differences in obesity rates between a rural region that experienced economic growth and an otherwise similar one that did not? If economic growth leads to a reduction in regional obesity rates, then policymakers 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.

2. LITERATURE REVIEW

The official definition of obesity is provided by the World Health Organization: individuals with body mass index (BMI) higher than or equal to 30 kg/m^2 are considered obese (WHO, 2021). A significant amount of research has explored the effect of economic factors on obesity, both for individuals and for aggregate rates by city or county. 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 employed, gasoline prices, and fast-food prices have been shown to impact obesity rates (Courtemanche et al., 2016). The nationwide study in Courtemanche et al. (2016) observed that neither median household income nor unemployment rates exhibited statistically significant relationships with BMI over a twenty-year time period. More recent research in Rummo et al. (2020), however, finds a positive relationship between the local unemployment rate and BMI. Another study focused on West Virginia rural counties found that the relationship between obesity risk and household income is positive – suggesting that more income may lead to undesirable health outcomes (Amarasinghe et al., 2009).

The studies mentioned above used BMI as a measure of obesity. Courtemanche et al. (2016) used individual-level BMI with state-level economic factors such as unemployment rates, median income, average work hours among employees, and alcohol prices to examine the effect of those factors on obesity. Some individual-level factors, such as ethnicity and marital status, were also included. Courtemanche et al. (2016) found that the number of restaurants and supercenters were 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 5% significance level; however, MHI did not affect whether an individual is obese (i.e., BMI over 30). Amarasinghe et al. (2009) collected data from rural counties in West Virginia, but only for 2003. The authors 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 1 when an individual's BMI was higher than or equal to 30 kg/m^2 and 0 otherwise. Results showed that age and income positively correlated with obesity, while Hispanics and those with higher education levels were less likely to be obese. In Rummo et al. (2020), the independent variables were collected at the county level across the country for the years 2003-2012; the research estimated the influence of county-level factors on the BMI of individuals. Rummo et al. (2020) found that an unhealthy food environment (more convenience stores and limited service restaurants) contributed to higher BMI scores, while active commuting (walking, biking, or public transportation) to work had negative relationships with BMI.

Most studies on obesity include both economic and social factors. Courtemanche et al. (2016) included the largest number of independent variables, with 27 state- and individual-level variables related to general economic factors or personal characteristics. But, most of the economic factors used in Courtemanche et al. (2016) do not necessarily reflect regional economic growth. For example, an increase in gasoline price reduces the opportunity cost of taking other means of transportation, such as bicycling or walking, which can negatively impact obesity (Courtemanche et al., 2016). However, variables like changing gasoline prices are not necessarily good indicators of local economic development. Regardless, the results from these previous studies provide clues that the relationship between economic factors and obesity is more than casual.

Social factors also affect obesity. An important social factor in this realm is the local food environment. When observing the food environment of a region, the availability of both healthy and unhealthy food should be considered. The availability of healthy food typically 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. (2012) focused on the impact of fast-food availability on obesity and found that the availability of fast-food restaurants affected BMI levels among non-white residents only. This study used individual-level data for both the dependent variable (BMI) and independent variables (race, gender, education level, and distance to fast-food restaurants). The data came from six to seven rural counties in central Texas. However, recent research has found that a new measure called "food swamps" can work as a better predictor of obesity compared to the more traditional "food desert" measure (Cooksey-Stowers et al., 2017).[2]

[2]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).

The local 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 – and were more likely to be obese. A recent study combined food and exercise environments to examine their impact on obesity rates. It found that limited access to physical activity is an important predictor of obesity (Congdon, 2017). Congdon (2017) used cross-sectional county-level data but did not assess changes over time. These studies generally 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 (Finkelstein et al., 2012; Courtemanche et al., 2016) or only cross-sectional data (Amarasinghe et al., 2009). To our knowledge, the study by Rummo et al. (2020) is the only one that used county-level social and economic factors and also applied time-series data. Further, although rural regions in America are both lagging in economic growth and facing more severe problems with obesity (Hill et al., 2014), no previous studies we are aware of specifically focused on the relationship between economic growth and obesity in rural America.

3. CONCEPTUAL FRAMEWORK AND METHODOLOGY

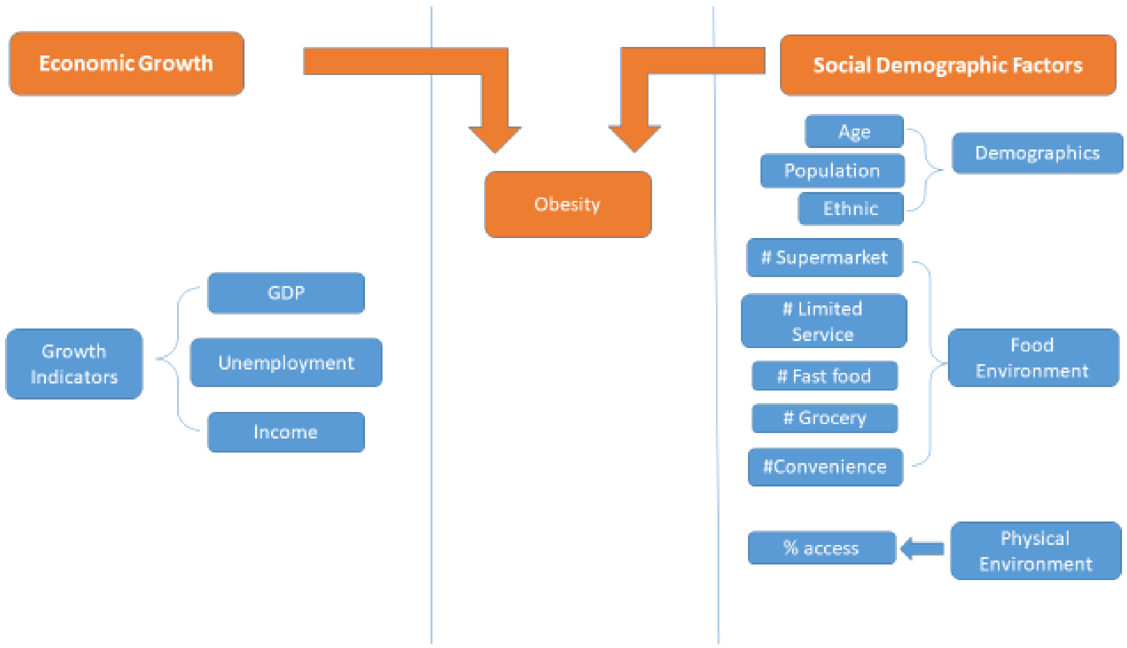
This study uses two distinct econometric approaches to quantify the relationship between economic growth and obesity: panel regression and propensity score matching (PSM). Using two different statistical techniques helps test the robustness of the findings. The panel nature of the data (1,948 non-metro counties followed for five years) allows for the use of a fixed-effects model to estimate the relationship. An advantage of the panel data approach is that unobserved measures, such as cultural factors, can be controlled (Wooldridge, 2015). Alternatively, PSM is an effective technique to estimate a potentially causal relationship (Caliendo and Kopeinig, 2008). PSM allows for the evaluation of different thresholds of GDP increases (i.e. 5% vs. 10% growth), which is a unique benefit of PSM over the fixed-effects model.

3.1. Conceptual Framework for Panel Analysis

Two main components affect obesity rates in our conceptual model: economic factors and social demographic factors. Figure 2 describes the general relationship between the two components and obesity. Previous studies provide some information about which economic and social demographic factors are important indicators of obesity. Both Courtemanche et al. (2016) and Rummo et al. (2020) include the unemployment rate as an economic indicator associated with obesity. Each of Amarasinghe et al. (2009), Courtemanche et al. (2016), Rummo et al. (2020) 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, alternative measures might better capture how a community is faring economically. A positive correlation typically exists between personal income and GDP (Diacon and Maha, 2015).

Figure 2: The Conceptual Model



Personal income includes wages, benefits, rents, interests, and dividends – an important part of GDP. Besides personal income, however, GDP also includes other important components of an economy, including a business operating surplus, taxes on production and imports, social security contributions, corporate income taxes, and undistributed corporate benefits (Pritzker et al., 2015). Social security contributions are payments to the government to enable payers to obtain future social welfare (which includes retirement pensions) (OECD, 2021). Corporate income taxes and undistributed corporate profits reflect the operating conditions of local companies. When in good condition, companies can provide more employment opportunities for the local area – or even invest in the local physical environment (such as subsidizing gym memberships for employees or constructing walking trails). Therefore, GDP is a more comprehensive indicator of the overall economic condition of a county. 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 governmental contributions (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 for our conceptual framework is that improving overall economic conditions will lead people living in those locations 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. Increases in local economic productivity could also encourage investment in local infrastructures such as gyms or parks. 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)[3]. Congdon (2017) discovered a positive relationship between limited access to exercise and obesity rates. Obesity may also vary along social demographic groups. Control variables included in this study are county-level population, race, and age characteristics.

Other variables that have been shown to potentially impact obesity rates are (1) participation in the Supplemental Nutrition Assistance Program (SNAP) (Baum, 2011; Almada and Tchernis, 2018), and (2) local levels of education (Amarasinghe et al., 2009; Cooksey-Stowers et al., 2017). Leaving out these potentially influential variables could lead to omitted variable bias. As such, we include the percentage of households in a county that participated in SNAP, and the percentage of adults aged 25 to 44 with some post-secondary education.

In panel analysis, data from the same observations are collected across time (Wooldridge, 2015). In this study, the social and economic features included would not only be different across rural counties but would also change within the same county over time. Panel regression uses both aspects of the data variation (within and between counties) to isolate 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. Unlike 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 and the control groups. 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 in 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:

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

where Y(1) and Y(0) are outcomes for the treated and control group, respectively, and D stands for the treatment (Caliendo and Kopeinig, 2008). 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 a specific threshold, while the control group contains counties that did not. D equals one for counties that experienced economic growth (at this pre-specified rate) over the 2012 – 2014 period; and zero for counties that did not. However, the second term in equation (1) $E[Y(0)|D = 1]$ is an unobservable counterfactual term. This is because it represents the expected value of the change in obesity rates for the control group (by definition, one that did not grow above the threshold rate) if they had in fact experienced this level of economic growth. PSM is used

[3]Cooksey-Stowers et al. (2017) define junk food as limited service establishments and convenience stores.

to estimate this unobservable counterfactual term

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

where X is a set of covariates that were used to estimate the propensity score (Caliendo and Kopeinig, 2008). Thus, the propensity score is defined as the likelihood of being treated (i.e., 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 in that the covariates from a single time period are used to estimate the likelihood of economic growth. The panel analysis uses time-series data to capture unobserved fixed effects for each county, and for this reason, we argue the panel specification is preferred. However, a unique 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 serves as a robustness check on the findings of the panel model.

Our main hypothesis is that rural counties experiencing recent economic growth will have lower obesity rates compared to otherwise similar counties that did not. We also hypothesize that improvements in the food environment will be associated with declines in obesity rates.

3.3. 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, county-level data on health statistics. The RWJF health data has been commonly used for analyzing and comparing counties in terms of health outcomes (Kersh et al., 2011; Thompson et al., 2012; Fitzpatrick et al., 2018). Their dataset includes health information from a variety of sources (such as the Behavioral Risk Factor Surveillance System and the National Center for Chronic Disease Prevention and Health Promotion). Also, it 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 non-metro counties as defined by the Office of Management and Budget. Due to data availability, only counties in the conterminous United States were included. To test the different influence of factors under different rural thresholds, non-metro counties were divided into micropolitan counties (containing urban clusters of 10,000-49,999 persons, n=638) and noncore counties (the remaining counties, n=1,310) based on 2013 USDA classifications.[4] The main independent variable, GDP, was adjusted by BEA as 2012's value and converted into a per-capita measure. County-level GDP data were not available from the BEA until 2019, which could be a reason why no prior studies have used GDP as an economic indicator in the obesity literature.

[4]Some counties lack data in specific years and so the number of observations reported in the results is slightly lower than these totals.

Table 1: Variable Descriptions

	Description	Source
Dependent Variable		
Obese	Adult obesity rate	2012-2016 RWJF
Independent Variables		
PC GDP*	Per capita GDP	2012-2016 BEA
PI	Physical Inactivity Rate	2012-2016 RWJF
Unem	Unemployment rate	2012-2016 RWJF
Elderly	Percentage of population above 65 years old	2012-2016 RWJF
African American	Percentage of African American	2012-2016 RWJF
Native American	Percentage of Native American	2012-2016 RWJF
Asian American	Percentage of Asian American	2012-2016 RWJF
Hispanic	Percentage of Hispanic American	2012-2016 RWJF
Pop*	Population of the county	2012-2016 RWJF
College	Percentage of adults (25-44) with some post-secondary education	2012-2016 RWJF
Pov	Poverty rates	2012-2016 Census
SNAP Rate	Supplemental Nutrition Assistance Program Participation (% of Households)	2012-2016 Census
FSI	Food swamp index	2012-2016 Census

Notes: * denotes that the natural logarithm (ln) transformation is used in specifications. RWJF denotes Robert Wood Johnson Foundation County Health Rankings. BEA denotes Bureau of Economic Analysis.

Table 2: Descriptive Statistics

Variable	Mean	Std.Dev	Min	Max
Obese	32.12	4.65	10.70	57.70
PC GDP	49,100	352,167	6,620	954,316
PI	27.46	5.24	8.10	49.90
Unem	6.45	2.69	0.82	19.97
Elderly	18.87	4.24	5.81	38.17
African American	7.81	14.76	0	85.23
Native American	2.46	7.64	0	87.77
Asian American	0.70	1.10	0	31.74
Hispanic	6.64	14.12	0	96.25
Pop	23,548	22,0723	71	198,449
College	53.64	11.26	2.56	94.44
Pov	17.67	6.71	0	48.70
SNAP Rate	14.52	7.11	0	56.69
FSI	5.68	3.96	0	56.14

Note: Means are across all 5 years of data (2012-2016).

This study includes the "food swamp index" and "physical inactivity rate" as two independent variables that reflect the food and physical environment. The food swamp index is a continuous measure and has been shown to work as a better indicator of obesity than the traditional "food desert" index (Cooksey-Stowers et al., 2017). Based on the restaurant and store number data obtained annually from the U.S. Census Bureau, the food swamp index can be obtained by the equation below (Cooksey-Stowers et al., 2017):

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

To obtain the amounts of these business establishments, relevant 6-digit North American Industry Classification System (NAICS) codes were acquired by searching on the Census Bureau website. The NAICS codes for convenience stores, gasoline stations with convenience stores, supermarkets, and limited service restaurants are 445120, 447110, 445110, and 722513, respectively.[5]

Initially, the "percentage of residents with access to physical activity" (AE) was used to reflect the physical environment. However, the data provided by RWJF on this category is not robust across our period of analysis. 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 dramatically. Therefore, the measuring method of AE is inconsistent from 2012 to 2016. To solve this problem, we switch to another measurement called the "physical inactivity rate" (PI). This variable 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 above 80 percent, indicating that PI can be considered a reasonable substitute for AE.

The dependent variable is the county-level adult obesity rate. According to RWJF, this is measured by the percentage of the population that is older than 20 years with BMI higher than or equal to 30 kg/m^2.[6] Tables 1 and 2 provide a description of the variables included in the analysis, and their descriptive statistics.

3.4. Fixed-effects Model

The fixed-effects panel regression is

$$y_{it} = \beta_0 + \beta_k x_{itk} + \alpha_i + \delta_t + u_{it} \tag{3}$$

where y_{it} is the obesity rate for county i at time t; x_{itk} are a series of explanatory variables for characteristic k with β_k the corresponding coefficient; α_i is an unobservable time-constant

[5] Because the data for a convenience store in rural counties were incomplete, "gasoline stations with convenience stores" were used instead of "convenience stores." It is anticipated that such substitution will not cause inaccurate results, because the number of convenience stores in rural areas is very small. Most convenience stores in nonmetro counties are "gasoline stations with convenience stores."

[6] Unfortunately, RWJF does not report any underlying individual or average county-level BMI values, only the percentage with BMI over 30. This prevents us from estimating an average increase in BMI at the county level.

dummy variable (such as cultural factors) for each observation; δ_t are time fixed-effects, and u_{it} is the time-varying error term that represents unobserved factors that change over time and affect y_{it}. This specification assumes that $cov(x_{it}, u_{it}) = 0$, which means there is no correlation between the time-varying error term and each of the independent variables. But α_i could be correlated with the independent variables (Wooldridge, 2015). Note that x_{itk} includes our primary variable of interest, the per-capita GDP of county i.

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 likely impact independent variables such as real GDP and demographic characteristics. Therefore, a fixed-effects model is appropriate for the situation. Other variables, such as weather or public health campaigns, do potentially vary over time – but likely exhibit limited variation over the 5 years in our data. Thus, counties with "better" weather, resources, or public health employees will have impacts that are captured by the inclusion of county fixed effects.

The main hypothesis is that economic growth will have a negative impact on obesity rates in rural America. Therefore, β_{GDP} 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. (2020) also used lagged independent variables. The decision of which variables to lag requires careful consideration. We argue, following Courtemanche et al. (2016), that the potential impacts of economic factors (GDP, unemployment, poverty, and SNAP participation) are more likely to accrue over time – and thus we include them with a 2-year lag. There is less reason to believe that social factors (age, race, population, college) will have a delayed influence. Therefore, we initially lag the independent economic variables by two years (consistent with several recent studies) while including contemporaneous versions of the social variables. An exception is the food swamp index, which is a social variable. We include it with a 2-year lag with the argument that the food environment takes time to potentially influence local obesity rates.

An important point is how long to lag the variable of interest. Our working hypothesis is that prior-year GDP is associated with future obesity, but how many years prior is less clear. We explore a variety of years (including a future-year GDP as a falsification test) to test the robustness of our results. The county-level GDP data from BEA begins in 2001, so we are able to test lags from 10 years to 1 year in the future.

One concern with a panel approach is reverse causality (i.e. obesity rates influencing 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 our knowledge, there is no evidence that obesity affects other components of GDP, such as household income or corporate income taxes. Using lags of several independent variables, as we do here, can also help minimize reverse causality concerns. Therefore, the problem of reverse causality is not likely to be particularly problematic.

3.5. Difference-in-difference PSM Model

The PSM approach here is essentially a difference-in-differences model that considers time periods both before and after economic growth (Caliendo and Kopeinig, 2008). First, we look at economic growth during time period 1 (2012-2014) and consider counties above a specified threshold as "treated." Then, we observe the changes in obesity during the later period (2014-2016), and compare the obesity rate differences across treated / control groups. Thus, the ATT expressed in equation (1) becomes:

$$ATT = E[\Delta Y_{t1}|D = 1] - E[\Delta Y_{t0}|D = 1] \tag{4}$$

where the outcome variable ΔY_t (named Obesediff) is the difference between the percent change of adult obesity rates from 2012 to 2014 (named $\Delta Obese_1$) and from 2014 to 2016 (named $\Delta Obese_2$). The relationship can be mathematically expressed as:

$$\Delta Obese_1 = (2014obese - 2012obese)/2012obese \tag{5}$$

$$\Delta Obese_2 = (2016obese - 2014obese)/2014obese \tag{6}$$

$$Obesediff = \Delta Obese_2 - \Delta Obese_1 \tag{7}$$

Counties exceeding the 2012-2014 economic growth threshold (which can be varied) can be matched to otherwise similar counties that did not see this level of economic growth via propensity scores, which are 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. This study measures the percent increase of real GDP per capita from 2012 through 2014 and will consider two different thresholds of the percent increase in real GDP per capita over that time (5% and 10%). The independent variables in this regression are from 2012. Appendix A specifies the probit model and associated variables. We are also able to assess Obesediff over a different period (i.e. $\Delta Obese_1$ = changes between 2012-2015; $\Delta Obese_2$ = changes between 2015-2016) with our existing dataset. We call this a 3-year lag model since it uses GDP growth over the initial 3 years.

Next, counties in the treated and control groups are matched based on their propensity scores. There are four different commonly-used 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 (i.e. a 1-to-1 match). The K-nearest neighbors method matches the 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 considered "matches" for each county in the treated group; however, the weights assigned to each control-group county decrease as the propensity score moves further away. In the radius method, counties in the control group with propensity scores within a certain threshold are matched to each treated observation (Caliendo and Kopeinig, 2008). This study applies each of the last three methods to test the robustness of the results. After the observations are matched, the difference in the change in obesity rates can be observed. A t-test is conducted to estimate the difference between the outcome means once the matching has been completed (Porter, 2013).

4. FINDINGS

4.1. Fixed-effects Estimation Results

Our initial panel model specification in equation (3) is run with two-year lags on the independent economic variables and contemporaneous versions of the social variables. Robust standard errors (clustered at the county level) are used to relax the assumption of homoscedasticity. Table 3 displays the baseline estimation results (i.e without GDP).

The baseline results are similar across both categories of non-metropolitan counties. Higher levels of physical inactivity are highly associated with higher obesity rates, as expected. Having an older, and larger, county population is also associated with higher obesity rates, although the elderly coefficient is only significant for micropolitan counties. Several contemporaneous demographic characteristics display statistical significance, although they are somewhat counter to expectations: African-American and Native American percentages are negatively associated with obesity, while Asian-American percentage is positively associated (although only in micropolitan counties). Counties with higher levels of poverty and SNAP participation are marginally and positively associated with higher rates of obesity in non-core counties. The interaction term – included due to strong correlation (above 0.8) between poverty rates and SNAP participation rates – was negatively associated with obesity. This suggests that for a given level of poverty, higher SNAP participation relates to lower obesity in the future – but again, only in non-core counties. Several variables with a priori expectations did not show up as significant, namely the food swamp index and percentage with some college education.

The crux of our findings is displayed in Table 4, which shows the coefficients on lagged (and future) values of GDP per capita. Each of these variables is added to the baseline model one at a time, to explore whether different lags are associated with future obesity rates after controlling for the variables in Table 3. As Table 4 makes clear, lagged values of GDP per capita are largely insignificant beginning from 10 years prior to the current value. An exception is lagged GDP from 2 years prior, when there is a positive association with obesity that is driven by non-core counties. The associated coefficient implies that a county with a 1% higher per-capita GDP had obesity rates that were 2.7 – 2.8 percentage points higher 2 years later. However, this appears to be a spurious result as nearly all other years were not significant. There are similar spurious results in 10- and 9- year lags – one positive, one negative – but overall the results are not supportive of a meaningful relationship between GDP and future obesity levels. A falsification test for future values of GDP (forward 1 year) returns the expected non-significant coefficient.

4.2. PSM Results

The estimation results from the PSM method are displayed in Tables 5 (for 5% growth in per-capita GDP) and 6 (for 10% growth).[7] Overall, the results of PSM generally agree with

[7] There were 771 non-metro counties experiencing greater than 5% per-capita GDP growth from 2012-2014 (221 micropolitan, 556 non-core), but only 417 that experienced greater than 10% growth over that period (104 micropolitan, 313 non-core).

Table 3: Baseline Results of the Fixed-Effects Model

Variable	Non-metro	Micropolitan	Non-Core
PI	0.4155***	0.4888***	0.3788***
	(0.0194)	(0.0333)	0.0237)
Unem(t-2)	-0.0558	-0.1471	-0.0456
	(0.0777)	(0.1300)	(0.0972)
Elderly	0.4926**	1.2038***	0.3144
	(0.2057)	(0.4485)	(0.2325)
African American	-0.7996**	-0.8979*	-0.7215*
	(0.3138)	(0.5015)	(0.3929)
Native American	-0.9200**	-1.3122**	-1.0229**
	(0.4361)	(0.7103)	(0.5082)
Asian American	1.2873***	2.3542***	0.6296
	(0.4760)	(0.6009)	(0.6204)
Hispanic	-0.2311	-0.7397*	-0.0055
	(0.2116)	(0.4331)	(0.2367)
ln (Pop)	20.3110***	35.9475**	16.3737**
	(5.7984)	(9.5059)	(7.2038)
College	-0.0358	0.0045	-0.0368
	(0.2197)	(0.0498)	(0.0242)
Pov (t-2)	0.1182*	-0.0005	0.1342*
	(0.0671)	(0.1418)	(0.0755)
SNAP(t-2)	0.1626*	-0.1112	0.2137**
	(0.0869)	(0.1876)	(0.0983)
Pov*SNAP(t-2)	-0.0089***	0.0052	-0.0111***
	(0.0033)	(0.0077)	(0.0038)
FSI (t-2)	-0.0375	0.0196	-0.0558
	(0.4325)	(0.0644)	(0.0554)
Constant	-175.0011***	-362.0303***	-128.5389***
	(56.837)	(99.7877)	(67.9353)
Year Fixed Effects	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes
Within R2	0.2072	0.3065	0.1707
Observations	1,900	628	1,272

Notes: The 1%, 5%, and 10% levels of significance are given as ***, **, and *, respectively.

Table 4: Lagged GDP Results of the Fixed-Effects Model (t-10 through t+1)

Variable	Non-metro	Micropolitan	Non-Core
ln(PC GDP) (t-10)	1.1718	0.2394	1.4530*
	(0.7733)	(1.935)	(0.8399)
ln(PC GDP) (t-9)	-0.7703	-2.8547**	-0.1280
	(06577)	(1.4466)	(0.7206)
ln(PC GDP) (t-8)	0.0555	-0.4394	0.0905
	(0.5635)	(1.2796)	(0.6334)
ln(PC GDP) (t-7)	0.2957	0.3329	-0.0390
	(0.5635)	(1.2340)	(0.6251)
ln(PC GDP) (t-6)	-0.1645	0.0071	-0.4198
	(0.5845)	(1.2703)	(0.6539)
ln(PC GDP) (t-5)	0.5209	-1.7201	0.7939
	(0.6055)	(1.2227)	(0.6694)
ln(PC GDP) (t-4)	-0.0187	0.8539	0.0471
	(0.3968)	(0.9478)	(0.4379)
ln(PC GDP) (t-3)	0.1840	0.4707	0.25103
	(0.2242)	(0.7458)	(0.2394)
ln(PC GDP) (t-2)	2.8501***	2.4759*	2.7073***
	(0.7472	(1.4329)	(0.8881)
ln(PC GDP) (t-1)	-0.0593	-1.0158	-0.0984
	(0.3192)	(0.7802)	(0.3584)
ln(PC GDP) (t)	-0.1659	-0.3101	-0.2978
	(0.1793)	(0.5060)	(0.1976)
ln(PC GDP) (t+1)	0.4149	0.5077	0.2838
	(0.4614)	(0.9947)	(0.5233)
Observations	1,900	628	1,272

Notes: Each version of GDP is added to the baseline controls in Table 3. Twelve distinct models are shown. The 1%, 5%, and 10% levels of significance are given as ***, **, and *, respectively.

those under the panel regression reported in Table 4 for lags (t-2) and (t-3) – but shed additional skepticism on the 2-year lag results. Several matching techniques show a positive relationship between two-year GDP growth and future obesity rates, with treatment effects suggesting that those counties with 5% or 10% GDP growth between 2012-2014 experienced obesity rates that were 2.4-3.7 percentage points higher during 2014-2016. However, only five of the 15 reported treatment effects are statistically significant for the 2-year lag. The 3-year lag results are more similar to those from the panel regression, with 13 out of 15 treatment effects indicating no evidence of a relationship.

Table 5: Results of the Difference-in-Difference PSM Model for 5% GDP Growth

	2-year lag			3-year lag		
	Nonmetro	Micro	Noncore	Nonmetro	Micro	Noncore
5-neighbor	0.0181	0.0151	N.B.	N.B.	0.0267	-0.0212
	(0.0109)	(0.0211)			(0.0452)	(0.0207)
Kernel	0.0236***	0.0023	N.B.	N.B.	0.0037	0.0396**
	(0.0081)	(0.0157)			(0.0399)	(0.0170)
0.1 caliper	0.0249*	0.0191	N.B.	N.B.	0.0112	-0.0089
	(0.0099)	(0.0188)			(0.0423)	(0.1940)

Notes: N.B. denotes that the propensity score model is not balanced. The 1%, 5%, and 10% levels of significance are given as ***, **, and *, respectively.

Table 6: Results of the Difference-in-Difference PSM Model for 10% GDP Growth

	2-year lag			3-year lag		
	Nonmetro	Micro	Noncrore	Nonmetro	Micro	Noncore
5-neighbor	0.0181	0.0463	0.0262	-0.0019	0.0858	-0.0146
	(0.0129)	(0.0248)	(0.0148)	(0.0278)	(0.0698)	(0.0172)
Kernel	0.0348***	0.0258	0.0366***	0.0401	0.0348	0.0138**
	(0.0106)	(0.0211)	(0.0122)	(0.0245)	(0.0572)	(0.0067)
0.1 caliper	0.0298***	0.0391	0.0255	0.0144	0.1026	0.0059
	(0.0116)	(0.0226)	(0.0134)	(0.0256)	(0.0704)	(0.0154)

Notes: The 1%, 5%, and 10% levels of significance are given as ***, **, and *, respectively.

A discussion of the probit regression model underlying the PSM technique is provided in Appendix A, with results for the 5% and 10% per-capita GDP growth specifications in Appendices B and C, respectively. Both micropolitan and noncore counties that are mining-dependent are more likely to experience 5% and 10% GDP growth, 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 expectations. A somewhat counter-intuitive result is that counties with positive population growth are less likely to have per-capita GDP growth exceeding the 5% or 10% thresholds; however, this was mostly driven by noncore counties and could reflect the smaller population bases in these locations.

5. CONCLUSION

The results of this study do not support the original hypotheses that increases in GDP are associated with declines in future obesity rates in non-metro counties. Instead, the basic finding is that there is no association between increases in per-capita GDP and future obesity rates in rural locations. The fixed-effect panel regressions produced the expected results for several control variables, as physical inactivity rates, percentage of elderly, and SNAP participation was positively associated with obesity rates. This suggests that our model behaves according to economic theory. The fact that propensity score matching resulted in qualitatively similar outcomes offers some degree of robustness to our primary finding. Further, while prior research has emphasized the potential impact of the food environment on obesity, this relationship did not hold under the specification here. According to a recent article published by USDA, people's dietary health may depend more on the understanding of nutrient knowledge than on the local food environment (Dong and Handbury, 2020) – an argument that finds support from our models. While our results are not necessarily causal, they add to the limited body of evidence on the relationship between rural economic growth and obesity.

An important takeaway from this study is that the problem of obesity in rural America is not likely to be addressed by focusing on economic development. This is not to say that rural economic development is no longer an important goal. However, assuming that improved economic growth will also lead to an improvement in local obesity rates does not seem to be a valid conjecture. Thus, "solving the problem of obesity while developing the rural economy" becomes a more challenging proposition for policymakers.

An important limitation of our analysis is how migration may impact the data. Because we measure *county-level* productivity and obesity but are unable to capture the number of individuals moving into/out of a specific county over time, the results may be influenced by the attraction/loss of obese individuals from outside the country. We explored this by examining whether GDP growth impacted future population change within our data and found only a very small correlation ($r < 0.05$).[8] This suggests that economic growth is not driving migration; however, our model is currently unable to differentiate obesity changes due to migration versus those occurring in the pre-existing (non-migrant) population.

Policymakers can address this challenge from two perspectives. First, they should keep policies in place that focus on the development of rural economies but understand that such policies are unlikely to impact local obesity rates. These economic development policies could actively include components that seek to directly address the obesity issue, such as requiring employee health checkups for companies receiving rural business-related grants or loans or even providing options for healthy lunches to employees. Another option would be to fund program evaluations that specifically include looking at local obesity rates prior to and following implementation. Second, local governments may put more effort into promoting the knowledge of healthy diets in rural locations. Cooperative extension educators and county health departments are important contributors to this work, and expanding their funding with explicit expectations for improving obesity outcomes is one option for local leaders to

[8]We looked at the correlation between per-capita GDP change over a specific period (for example, 2012-2014) and county population change in future years (2014-2016), and found that the correlations were all < 0.05.

consider.

Future studies in this area may benefit from several specific avenues of research. First, additional measures of economic growth should be explored. We focus on productivity growth as measured by GDP, but other measures such as purchasing power, income inequality, or wealth accumulation may be more important. It may also be possible that one or more specific components of GDP are associated with obesity. We believe that data on the percentage of the underlying GDP components needs to be collected and made public – something that is not currently done with the BEA data.[9] Second, developing a modeling approach that can control for the migration problem (for example, by using instrumental variables or focusing on years/counties where the migration situation is explicitly known) would allow for more appropriate comparisons to be run. We also note that our statistical approach did not control for regional "hot spots" of obesity, such as the rural South or Appalachia. Studies focusing on these locations or recognizing them within the analysis (perhaps by including group-mean fixed effects) would be a useful extension of this work. Finally, regional scientists should continue to research linkages between rural economic development and other potentially undesirable quality-of-life metrics (such as those related to personal health, income/wealth inequality, social relationships, or housing affordability). Documenting these negative linkages could help policymakers and local leaders develop appropriate responses to concerns about detrimental spillover effects.

[9]For example, the BEA's state-level GDP estimates contain data on employee compensation, business gross operating surplus, taxes on production and imports, and subsidies (each of which contributes to GDP by state). Such lower-level breakouts are not available for county-level data. In 2019, roughly 53% of U.S. GDP was from compensation, 40% was from gross operating surplus, and 7% was from taxes on production and imports; however, there was significant state-level variation in these numbers.

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APPENDIX A PROBIT REGRESSION SPECIFICATION

The probit regression model used for the Propensity Score Matching is:

$$PCGDP_i = \beta_0 + \beta_1 Unem_i + \beta_2 Elderly_i + \beta_3 Native_i + \beta_4 Asian_i + \beta_5 Hispanic_i + \\ \beta_6 ln(MHI)_i + \beta_7 PopChange + \beta_8 Mining_i + u_i$$

Variable descriptions mostly follow from Table 1, with the exceptions of the independent variable and $Mining$. The dependent variable $PCGDP_i$ equals the percentage change in per-capita GDP for county i between 2012 and 2014 (in the initial specification) and is represented as a dummy variable taking value 1 when it exceeds the thresholds of 5% and 10%. $PopChange$ is a binary variable taking value 1 if the county had positive population change during the 2012-2014 period. $Mining$ is a dummy variable taken from the USDA Economic Research Service that indicates if the county is mining-dependent, and takes a value of 1 if the mining industry either accounts for 13% or more of total county earnings or 8% or more of total county employment during 2010 – 2012 (Pender, 2019). It is included because the oil production boom after 2012 has been shown to have significant positive economic impacts in mining-dependent rural counties (Kassel, 2020; Whitacre et al., 2020). Thus, counties with heavy mining activity may be more likely to have higher GDP growth during this time.

The results of these regressions are displayed in Appendices B (for 5% GDP growth) and C (for 10% GDP growth). We also run these models for GDP growth between 2012 and 2015 (not shown). The 3-year lag results in Tables 5 and 6 reflect this model.

APPENDIX B PROBIT RESULTS FOR PC GDP GROWTH $\geqslant 5\%$

	Non-metro	Micropolitan	Non-Core
Unem	-0.0369***	-0.0294	-0.0437***
	(0.0126)	(0.0248)	0.0153)
Elderly	0.0185**	0.0273	0.0150
	(0.0081)	(0.0173)	(0.0096)
Asian-American	-0.2588***	-0.2836***	-0.1531
	(0.0654)	(0.0919)	(0.1104)
Hispanic	0.0092***	0.0073**	0.0108***
	(0.0023)	(0.0038)	(0.0029)
ln (MHI)	0.6462***	0.7330*	0.4917*
	(0.2242)	(0.3971)	(0.2721)
Pop Change	-0.0494***	-0.2567**	-0.2474***
	(0.0140)	(0.1112)	(0.0802)
Mining	0.3117***	0.5185**	0.1974*
	(0.1005)	(0.1939)	(0.1175)
Constant	-7.5035***	-8.5210*	-5.6105*
	(2.5672)	(4.5452)	(3.1149)
R^2	0.0400	0.0593	0.0348
Observations	1,948	638	1,310

Notes: PC GDP Growth is measured between 2012 and 2014. The 1%, 5%, and 10% levels of significance are given as ***, **, and *, respectively.

APPENDIX C PROBIT RESULTS FOR PC GDP GROWTH $\geqslant 10\%$

	Non-metro	Micropolitan	Non-Core
Unem	0.0029	-0.0901*	0.0127
	(0.0161)	(0.0541)	0.0195)
Elderly	0.0184*	0.0667*	0.0216*
	(0.0109)	(0.0342)	(0.0128)
Asian-American	-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)
Pop Change	-0.2504***	-0.1555*	-0.2909***
	(0.446)	(0.0871)	(0.0606)
Mining	0.5060***	0.6773***	0.3217***
	(0.1226)	(0.2113)	(0.1257)
Constant	-7.1719***	-3.1907	-8.8240*
	(4.0980)	(8.9765)	(4.7967)
R^2	0.0672	0.0677	0.0701
Observations	1,948	638	1,310

Notes: PC GDP Growth is measured between 2012 and 2014. The 1%, 5%, and 10% levels of significance are given as ***, **, and *, respectively.