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Factors Explaining Obesity in the Midwest: Evidence from Data

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Abstract
This paper attempts to determine the factors explaining obesity in the Midwest by using standard OLS multiple regression analysis and cross-sectional data. We examine independent variables related to built environment and determine effects on obesity. This study finds that some factors influencing calories consumed, such as percent of restaurants that are fast food, are consistent with the prior literature. However, other factors, such as the number of fast food restaurants per 1000 people, yield surprising results. The results of this study suggest that obesity is a multifaceted issue that is not close to being fully explained.

Keywords
obesity, built environment, fast food, cross-sectional

Cover Page Footnote
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I. Introduction

What variables explain obesity rates in the Midwest? The goal of this study is to determine these variables and their relative importance in affecting obesity rates. Determining the causes of obesity is important because obesity is on the rise in the United States, obese people incur higher healthcare costs, and a growing number of these costs are absorbed by taxpayers. The incidence of obesity[1] has been growing across all developed countries, but the United States has experienced the largest increase with the percentage of U.S. adults who are obese more than doubling from 13.4% to 32.2% between the early 1960s and 2004 (Zhao and Kaestner 2009; Courtemanche and Carden 2011). With increasing obesity has come increasing health care costs since obese adults under the age of 65 in the United States incur annual medical expenses that are 36% to 37% higher than adults of normal weight (Rosin 2008). With roughly half of medical expenses brought about from being obese paid for by Medicare and Medicaid (Courtemanche and Carden 2011), taxpayers are footing a significant part of the bill from rising obesity rates. With obesity influencing large public programs, discussions surrounding government policies geared towards stemming the rise in obesity are becoming more serious. However, effective policies require an understanding of the root causes of the rise in obesity (Chou et al. 2004). Recent economic analysis has begun to discover these causes, but there is still plenty of debate.

II. Thesis Statement

At its most basic level, weight can be thought of in terms of calories consumed versus calories expended. If calories consumed are greater than calories expended, then weight is gained, while if calories expended are greater than calories consumed, then weight is lost. Thus, obesity can be thought of as an imbalance in this equation over time in favor of calories consumed. This simple model forms the foundation for the classic economic theory for increases in obesity: technological change has led to calories consumed increasing over time because the relative price of food has decreased and calories expended decreasing over time because of changes in the workplace (Philipson and Posner 1999; Lakdawalla and Philipson 2002; Cutler et al. 2003; Chou et al. 2004). The classic theory will act as a backdrop in the testing of our variables as we will seek to understand the factors influencing calories consumed and calories expended. Our hypothesis is that factors influencing calories consumed will have a bigger effect on obesity than factors influencing calories expended, and substitutes for workplace caloric expenditure, such as the availability of recreational facilities, will have little effect.

[1] Obesity is defined as having a Body Mass Index (BMI) greater than 30. BMI is defined as weight in kilograms divided by height in meters squared (kg/m^2).

III. Literature Review

Although only a recent area of economic study with most research published in the last decade, there is a growing body of literature examining the causes and consequences of obesity. Obesity is a subject studied across several disciplines; however, economic analysis is unique because unlike genetic studies or general health studies focused on explaining why a given person is obese, the goal with economics is to explain the growth in obesity rather than why a given person is obese (Chou et al. 2004). Genetic factors can explain why some people are more prone to becoming obese, but genetic factors cannot explain the rapid rise in obesity rates since changes in the gene pool would take longer than a few decades to take effect. Thus, economic studies have searched for causes that disturbed the balance between calories consumed and calories expended since these factors could change in a relatively short period of time. Studies have found evidence for both increased consumption and decreased expenditure, but each study seems to give varying degrees of significance to each component influencing obesity.

Early research focused on the effects of technological change on both consumption and expenditure. Philipson and Posner (1999) theorize that technological change led to a more sedentary workplace environment, and labor saving appliances at home also led to a decrease in calories expended. According to these authors, decreased workplace exercise was not fully offset by the jogging and gym “revolution” because in the workplace people were essentially paid to exercise while people have to pay to exercise outside of work, mostly in the form of forgone leisure activities. Lakdawalla and Philipson (2002) attempt to empirically test the theoretical reasoning of the prior research. They use individual level data from the National Longitudinal Survey of Youth (NLSY) and examine the effects on a person’s weight based on their job strenuousness. One problem faced is whether occupational choice is endogenous with respect to weight; do people who weigh more choose more sedentary jobs? Rather than looking at potentially misleading cross-sectional data, Lakdawalla and Philipson (2002) analyzed weight both before and after each person changed jobs. They determine that occupational choice is mostly exogenous with respect to weight, and 60% of the recent increase in weight within the United States is from technological change causing more sedentary workplace and home environments. However, these results may not be replicable since the authors only looked at female workers, perhaps not a representative sample for the entire U.S. population.

Cutler et al. (2003) also criticize Lakdawalla and Philipson (2002) by arguing that changes in workplace environment mostly occurred in the earliest part of the 20th century and that in the time period Lakdawalla and Philipson

(2002) considered, workplace environment changed only modestly. Cutler et al. (2003), along with more recent research (Bleich et al. 2007) also contend that the importance of workplace-related exercise to weight gain is weakened by the fact that, although children and the elderly largely do not work, they experienced weight gain in tandem with working adults. Rather than changes in energy expenditure, Cutler et al. (2003) point to increases in calorie consumption as the primary cause of rising obesity. According to Cutler et al. (2003), greater technology for producers of food led to a decrease in the price of food, while even more importantly, improved technology for consumers such as the microwave reduced the time costs of preparation. The effects of reduced time costs of consumption are more pronounced in calories consumed outside of mealtimes (snacks) than during mealtimes, since calories consumed during mealtimes remained roughly the same during the time period Cutler et al. (2003) analyzed. Thus, they conclude that larger portion sizes at restaurants and the greater availability of fast food are not to blame for the recent rise in obesity.

Subsequent research (Chou et al. 2004; Dunn, Sharkey, and Horel 2011) however, finds a relationship between fast food availability, full-service restaurant availability, and obesity. Chou et al. (2004) find that decreases in the real cost of food account for only a small part of the rise in obesity rates, while increases in the per-capita number of restaurants accounts for 68% of the rise in obesity.[2] To put this in perspective, a 10% increase in the number of restaurants equates to an increase in the number of obese people by 9%. Contrary to Chou et al., (2004), Anderson and Matsa (2011) find almost no causal relationship between either fast food or full service restaurants on obesity. They point to two reasons why restaurant consumption does not cause obesity. People who naturally eat more, eat at restaurants. Thus, they would overeat at home as well. Additionally, people offset a larger restaurant or fast food meal by consuming less at home. Anderson and Matsa (2011) find that although people consume roughly 339 calories more in a restaurant meal than a normal meal at home, there is at most a 35 calorie difference over the course of a day. Thus, restaurants affect calories consumed for a single meal but not for an entire day.

Dunn et al. (2012) criticize Anderson and Matsa (2011) for attempting to piece together data from different sources across different geographical regions and times. According to Dunn et al. (2012), Anderson and Matsa's (2011) samples are not representative and thus not generalizable. Dunn et al. (2012) studies a more diverse area in central Texas and concludes that whites and non-

[2] Chou et al. (2004) also find that the increase in the real price of cigarettes brought about by higher taxes and more restrictive smoking laws accounts for 23% of the increase in obesity. They find that smokers have higher metabolic rates than non-smokers and smokers also consume fewer calories. Their results are supported by Ewing et al. (2003) and Chen et al. (2009) who find that smokers tend to have lower BMI's than non-smokers.

whites are affected differently by the availability of fast food. According to Dunn et al. (2012), this difference in response to fast food availability could explain between 2% and 8% of the difference in BMI between whites and non-whites.[3] However, Dunn et al. (2012) falls short in the same areas as Anderson and Matsa (2011); both make use of relatively small sample sizes covering small geographic regions.

Studying the effects of full service restaurant and fast food availability is part of a broader trend in the literature towards understanding how built environment affects obesity. However, much like with restaurant availability, there is not yet a consensus on the effect, if any, built environment has on obesity. Another component of built environment being studied is with chain grocers. Chen et al. (2009) find that adding one chain grocery store to a person's food landscape (defined as a one mile radius from a person's home) in a poor neighborhood decreases his or her BMI by .3; however, there is an opposite effect with wealthier neighborhoods. This study is lacking, however, because its sample includes only people in one county that is predominantly educated, female, and white. In a geographically broader and more representative study, Courtemanche and Carden (2011) conclude that the spread of Walmart Supercenters explains 10.5% of the rise in obesity since the late 1980s because Walmart Supercenters supply cheap food. Similar to Chen et al. (2009), however, the effect was not uniformly distributed across all subsets of the population; the effect was strongest in rural areas.

Specific aspects of built environment such as restaurant and grocer availability have unclear effects on obesity; however, a broader component of built environment, urban sprawl, has perhaps an even less clear impact on obesity. Ewing et al. (2003) theorize that residents of more sprawling neighborhoods are likely to walk less and be heavier since travel on foot is more difficult than in more compact neighborhoods. Their empirical analysis shows that greater sprawl is correlated with higher BMI and obesity but that the effects are small. Eid et al. (2007) criticize Ewing et al. (2003) for failing to take into account that people predisposed to being obese self-select into more sprawling neighborhoods.[4] Eid et al. (2007) reason that heavier people do not like to walk, so they move to sprawling neighborhoods where they can get around more easily by car. When accounting for self-selection, Eid et al. (2007) find no evidence that urban sprawl

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[3] Several studies have shown that there are large disparities among races for both BMI and obesity (Eid et al. (2007); Chen et al. 2009). Whites typical have lower BMIs and are less obese than African Americans or Hispanics.

[4] This is a similar type of problem to obese people choosing more sedentary jobs that was faced by Lakdawalla and Philipson (2002). Much like with how Lakdawalla and Philipson (2002) track people's weight before and after changing jobs, Eid et al. (2007) track people's weight before and after changing neighborhoods.

causes obesity. Contrary to Eid et al. (2007), Zhao and Kaestner (2009) find that roughly 13% of the increase in the obesity rate from 1976 to 2001 is attributable to urban sprawl. The impact of urban sprawl and other built environment factors on obesity are still unclear.

We contribute to the literature by focusing on explaining the effects of built environment on obesity rather than the role of relative food prices since the impact of built environment on obesity is more uncertain than the impact of food prices. We use more recent data, a larger geographic area, and a more representative sample than previous studies. We also are able to control for more factors than past studies.

IV. Methodology

The county is our unit of analysis as we examine the 737 counties that comprise the Midwestern states of Indiana, Iowa, Illinois, Michigan, Minnesota, Missouri, Ohio, and Wisconsin. The primary data source is County Health Rankings and Roadmaps (http://www.countyhealthrankings.org). Data for occupational categories and percent of the population age 25 and over with a bachelor's degree or higher were obtained from American Community Survey five year (2007-2011) estimates.

Table 1, listed below, includes the dependent variable and all of the independent variables used in both models, along with their means and standard deviations.

Table 1

Variable	Mean	Standard Deviation
Percent of the adult population classified as obese	30.463	2.621
Percent of restaurants that are fast food	41.654	13.822
Number of fast food restaurants per 1000 people	.540	.204
Percent of zip codes with a healthy food outlet	51.891	22.029
Recreational facilities per 100,000 people	9.311	6.8081
Percent rural	59.125	27.458
PM days (number of days that air quality was unhealthy due to fine particulate matter)	1.260	1.788
Percent blue collar	11.442	2.733
Percent physically inactive	27.238	4.182
Population	82,439.36	250,517.547
Percent African American	2.996	5.098
Percent Hispanic	3.050	3.4461
Percent Asian	.871	1.149
Percent female	50.212	1.527
Percent unemployed	9.597	2.653
Median household income	$44,647.83	$8,433.314
Percent of population 25+ with bachelor's degree or higher	18.552	7.448

We restrict our analysis to the adult population by using adult obesity rates (percent of the adult population having a BMI greater than 30). The obesity data are compiled by the County Health Rankings from the Behavioral Risk Factor Surveillance System (BRFSS). Thus, since the data is derived from a survey item asking for height and weight and since people tend to underreport weight and exaggerate their height, reported obesity rates are less than actual obesity rates (Rosin 2008). However, past research indicates that there is a strong correlation between actual and self-reported BMI (Courtemanche and Carden 2011). Thus, we do not try to correct for the underreporting of BMI in this study.

Independent variables focusing on access to food sources and recreational facilities are compiled by the County Health Rankings from the 2009 County Business Patterns. The literature suggests that these factors may have some causal influence on obesity. The Recreational facilities rate (Rec Fac Rate) is calculated as the number of recreational facilities per 100,000 people. It is suggested that people will exercise more if they have suitable areas to exercise. Thus, as the Rec Fac Rate increases, we expected the obesity rate to decrease. However, there is a limitation to this data. While the data do a reasonable job of determining the quantity of recreational facilities in a county, it fails to take into account the quality of the recreational facilities. Another factor related with the Rec Fac Rate yet previously unexplored by the literature is pollution. Pollution may be positively associated with obesity since greater pollution may discourage people from exercising outside and using recreational facilities such as parks. The metric used in this study is the number of PM days (number of days that air quality was unhealthy due to fine particulate matter). Thus, the higher the PM days, the greater the air pollution.

Percent healthy foods is defined by the percent of zip codes in a county with healthy food outlets. Healthy food outlets include supermarkets and grocery stores but exclude convenience and corner stores since supermarkets and grocery stores traditionally stock healthier foods than convenience and corner stores. Since healthy foods contain fewer calories, it is theorized that greater availability of healthy food options leads to a decrease in obesity (Chen et al. 2009). On the opposite side of consumption, we include two variables related to fast food availability. Percent fast food is simply a proportion of restaurants that are fast food and is defined by the number of fast food outlets divided by the total number of restaurants in a county. The variable for number of fast food restaurants per 1000 people was computed by dividing the total number of fast food restaurants (taken from the 2009 Census County Business Patterns) by the county population (taken from the 2009 Census) and then multiplying by 1000. Both the proportion of fast food restaurants relative to other restaurants and the proportion of fast food restaurants relative to population are thought to be positively correlated with obesity.

Percent blue collar is theorized to be negatively correlated with obesity since blue collar workers typically have relative active workplace environments and caloric expenditure in the workplace can decrease obesity (Philipson and Posner 1999; Lakdawalla and Philipson 2002). Since no data exist at the county level for blue collar workers, we operationally defined blue collar workers as the civilian employed population 16 years and over who have natural resource, construction, or maintenance occupations. While these data do a good job of focusing in on occupations that typically require physical activity, they fail to take into account that some blue collar workers may have a sedentary workplace environment while some white collar workers may have more active workplace environments.

We were able to control for a wide variety of factors from race to economic factors. Since whites typically have lower BMIs and are less obese than African Americans and Hispanics (Eid et al. 2007; Chen et al. 2009), we use 2009 census data to control for percent Hispanics and African Americans in a county. We also include percent Asian and theorize that percent Asian will be negatively correlated with obesity rates. Education level and income are two factors that conventional wisdom presumes are negatively associated with obesity; therefore, we control for median household income and percent of the population above age 25 with a bachelor's degree or higher. We also control for percent physically inactive (defined by the percent of the adult population that during the past month, except in the workplace, did not engage in any physical activity) because physical inactivity is hypothesized to be positively associated with obesity. Gender is also controlled for since men are less likely than women to be obese (Zhao and Kaestner 2009).

The study employs standard OLS multiple regression analysis expressed in the following equation:

(1) $$Y_i = bX_i + e$$

where Y_i is the predicted obesity rate for county i, b is a partial slope measuring the impact that X_i has on Y_i, X_i is a matrix of factors theorized to influence obesity, and e is an error term accounting for omitted variable bias. From this theoretical model we developed two regression equations with r^2 values of .331 and .329. The first model includes all the variables while the second model drops the statistically insignificant variables.

V. Findings

Table 2, listed below, details the results of the two different regression models. Two separate models are included, with the first reporting all independent variables and the second dropping all variables that fail to achieve the 90% confidence level. We report unstandardized and standardized coefficients (in parenthesis), significance levels, and, in the bottom row, r^2 values.

The unstandardized coefficient[5] is the partial slope of the regression plane. It gives the amount of change in the dependent variable from a one-unit change in the independent variable, all else constant. The standardized coefficients make use of a conversion to standard units, z-scores, and thus reflect the number of standard deviations the dependent variable will change from a standard deviation change in the independent variable. The r^2 value in each model is the percentage of variation in the dependent variable that can be explained by the variance in all the independent variables found in each model.

Table 2: Models 1 and 2

Variable	Model 1	Model 2
Percent of restaurants that are fast food	.027*** (.141)	.028*** (.147)
Number of fast food restaurants per 1000 people	-1.488** (-.116)	-1.331** (-.103)
Percent of zip codes with a healthy food outlet	.011** (.089)	.011*** (.093)
Recreational facilities per 100,000 people	.000 (.001)	
Percent rural	.000 (-.005)	
PM days (number of days that air quality was unhealthy due to fine particulate matter)	.149*** (.101)	.155*** (.106)
Percent blue collar	-.050 (-.052)	
Percent physically inactive	.146*** (.233)	.150*** (.240)
Population	.000* (-.070)	.000* (-.069)
Percent African American	.049** (.096)	.054*** (.106)
Percent Hispanic	.006 (.008)	

[5] For example, in Model 1 an increase in the percent of restaurants that are fast food by one percentage point leads to an increase of .027 percentage points in the adult obesity rate in a county, all else equal.

Percent Asian	-.250** (-.110)	-.225** (-.099)
Percent female	.045 (.026)	
Percent unemployed	.110*** (.111)	.109*** (.111)
Median household income	.000* (-.086)	.000* (-.087)
Percent of population 25+ with bachelor's degree or higher	-.070*** (-.199)	-.060*** (-.171)
R Square	**.331**	**.329**

Significance Measures:

- *p < .10 (90% confidence level)
- **p < .05 (95% confidence level)
- ***p < .01 (99% confidence level)

Standardized partial coefficients are in parentheses

Most of the relationships between the independent variables and the dependent variable are consistent with the prior literature; however, the number of fast food restaurants per 1000 people is negatively associated with obesity. In both models, as the number of fast food restaurants per 1000 people increases, the obesity rate decreases. Although the literature is inconclusive with some research suggesting that fast food restaurants have no causal effect on obesity (Anderson and Matsa 2011) and other research suggesting that there is a causal link between growing obesity rates and an increase in fast food (Chou et al. 2004), no research suggests that fast food restaurants actually decrease obesity. One explanation for this contradictory finding comes from fast food restaurants situating in areas where consumers have relatively high time values (Chou et al. 2004). Consumers typically have higher time values in more urban areas, and these areas are typically comprised of a higher Asian population, higher education levels, and higher incomes- all factors that are negatively correlated with obesity. Thus, areas with greater density of fast food restaurants per 1000 people have lower obesity rates than areas with a lower density of fast food restaurants.

Another surprising finding from the models is that percent healthy foods is positively associated with the adult obesity rate. The effect is small yet statistically significant at the 95% confidence level in model 1 and statistically significant at the 99% confidence level in model 2. One explanation for these findings might be from healthy food options (grocery stores) locating in wealthier neighborhoods since adding a chain grocery store to a wealthier neighborhood increases BMI in the neighborhood (Chen et al. 2009). Running contrary to this line of reasoning, however, is that income is negatively associated with adult obesity. However, in both models median household income has only a small effect on adult obesity, and it is only statistically significant at the 90% confidence level.

Perhaps the most surprising finding from this study is that the model only accounts for roughly 1/3 of the variation in adult obesity across Midwestern counties. Even with 16 independent variables, the variation in all 16 independent variables is only able to account for roughly 1/3 of the variation in the dependent variable. With 2/3 of the variation in adult obesity left unexplained even with 16 different explanatory factors, it seems evident that obesity is a multifaceted issue with many diverse explanatory factors. Thus, the model suffers from omitted variable bias. There are three types of omitted variables in our model: variables that are theorized to influence obesity yet suffer from data limitations, variables that are theorized to influence obesity and have reliable data yet cannot be analyzed using OLS multiple regression analysis, and variables that influence obesity yet we did not think to include. One variable that could be analyzed in the model but that does not have reliable data is the adult smoking rate. The decrease in smoking rates accounts for roughly 23% of the increase in obesity (Chou et al. 2004); however, adult smoking rates were not included in the model since the data was available in only 562 of the 737 counties in the sample. An example of a variable that has reliable data yet cannot be analyzed using cross-sectional data in an OLS multiple regression analysis is the decrease in the price of food over time. Omitted variable bias results in the model explaining only a small portion of the variation in adult obesity rates across counties in the Midwest.

VI. Conclusions

Using standard OLS multiple regression analysis, this study finds that some factors influencing calories consumed, such as percent of restaurants that are fast food, are consistent with the prior literature while other factors, such as the number of fast food restaurants per 1000 people and percent healthy foods, yield surprising results. Additionally, factors influencing caloric expenditure have little effect, with percent blue collar and the recreational facilities rate failing to achieve statistical significance at the 90% confidence level. This study also adds to the literature by introducing a new variable that may partially explain adult obesity, pollution level. While the effects of pollution on health have been studied (Pope et al. 2002), no research to date has looked at how pollution may impact the exercise choices that people make. Pollution is likely to be positively correlated with obesity since greater pollution may cause people to spend less time outside engaging in leisure activities. Both models give a positive association between pollution and adult obesity at the 99% confidence level.

This study, however, has many weaknesses. Given cross-sectional data this study seeks correlation rather than causation. With cross-sectional data, there is no way of dealing with endogeneity problems. This is especially problematic given that previous research addressed endogeneity with urban sprawl and workplace environment. As mentioned above, the study is also plagued with omitted variable bias since our models only account for roughly 1/3 of the variation in adult obesity rates. Given that the county is the unit of analysis we are unable to distinguish between workplace, neighborhood, and driving routes between work and home, which could be important for a number of built environment factors. For example, someone could live in a county that has no fast food restaurants yet work in a county that has several fast food restaurants. Although there are a number of weaknesses to this study, the findings are consistent with prior theory and literature and can thus serve as a preliminary guide to policy making.

When making policy recommendations related to obesity, it is important to distinguish between a person's ideal weight in economic terms and ideal weight according to health professionals. It is possible for someone to be obese yet be at his economically ideal weight. For example, a business professional may be obese because he values his time highly and thus frequents fast food restaurants on a daily basis. This individual faces a trade-off between health and time and rationally chooses to economize on time while experiencing weight gain. Although weight may be above an ideal weight determined by a health professional, the individual is still maximizing total utility. Although there has been a substantial increase in weight in the United States, most people are better off despite being heavier (Philipson and Posner 1999; Cutler et al. 2003). Additionally, government intervention in an attempt to "cure" the obesity epidemic would likely make consumers worse off (Cortemanche and Carden 2011; Dunn et al. 2012).

Thus, rather than more government intervention in the marketplace, policies might look at reversing government policies that contribute to rising obesity. Farm subsidies in the United States are concentrated on large agribusinesses that produce a disproportionately high amount of corn relative to smaller farms (Finkelstein and Strombotne 2010). Government intervention makes corn products, such as high fructose corn syrup, relatively cheaper than healthier farm products such as fruits. Government intervention also helps to conceal the full cost of being obese since roughly half of obesity related healthcare spending is paid for by government (Courtemanche and Carden 2011). If people paid for a greater portion of the costs of being obese, then there would be a greater incentive for weight loss. Given that increases in obesity have largely been the result of the market functioning to make people better off by making food cheaper and the strenuousness of work and home life easier (Finkelstein and

Strombotne 2010), it is surprising that the market is not seen as a phenomenon that could help stem the rising tide of obesity. The market already has developed ways of coping with being obese through drugs such as cholesterol medication. The market has even found a way to reverse some of the effects of being obese through bariatric surgeries. The market provides goods and services at continually decreasing prices and increasing quality that help combat obesity.

Given that obesity is a complicated and multifaceted issue, there are many avenues for future research. Future research may examine the same factors as our study but with more useful data or statistical techniques. For example, future research might utilize more micro level data to distinguish between built environment effects such as fast food restaurants on people's home, workplace, and commuting environments. Given that both models account for only 1/3 of the variation in adult obesity, there is plenty of room for future studies to examine the omitted variables in this study. One example that has only seen limited study is the effect of religion on obesity. Since many religions have teachings related to gluttony as sin, religious people might have lower obesity rates, but the few empirical studies suggest otherwise (Cline and Ferraro 2006). In general, the best future studies will likely make use of more micro level data yet use a wide geographic range so that the results are fully generalizable to the population as a whole.

This study finds that some factors influencing calories consumed such as percent of restaurants that are fast food are consistent with the prior literature. However, other factors such as the number of fast food restaurants per 1000 people and percent healthy foods yield surprising results. Additionally, factors influencing caloric expenditure such as percent blue collar and the recreational facilities rate have little effect. This study finds that a number of factors are associated with obesity. However, given that the models only account for roughly 1/3 of the variation in adult obesity, there are many factors left unexplained. The results of this study suggest that obesity is a multifaceted issue that is not close to being fully explained.

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