THE IMPACT OF THE COMPLETE FOOD ENVIRONMENT ON COUNTY-LEVEL OBESITY RATES

A THESIS

Presented to

The Faculty of the Department of Economics and Business

The Colorado College

In Partial Fulfillment of the Requirements for the Degree

Bachelor of Arts

By

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April 2015

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Mathematical Economics

Abstract

Obesity rates in the United States have risen dramatically in the last several decades. In an attempt to explain this trend, much of current literature looks for correlation between community demographic characteristics and independent food-environment components. Few studies analyze the direct relationship between obesity rates and the food-environment, however. This paper explores this relationship at a county-level across the United States in order to fill the problematic gap in the literature. To provide a complete representation of the food-environment, county-level data for the prevalence of fast-food restaurants, full-service restaurants, grocery stores, convenience stores, and supercenters are analyzed for their relationship to obesity rates at the county-level while controlling for a multitude of demographic and community characteristics. This study concludes that fast-food restaurants and convenience stores are positively correlated with obesity rates, while full-service restaurants and grocery stores are negatively correlated with obesity rates. Though intuitive, these conclusions provide representative insight to policy-makers on the true dynamic between the food-environment and obesity rate such that effective strategies may be implemented to better fight the obesity epidemic.

KEYWORDS: (obesity, food environment, fast-food, grocery stores, food)
JEL CODES: (I140, J10, L66)

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Introduction

United States obesity continues to rise at an alarming rate, reaching an estimated 34.9% of adults in 2012 (Ogden, Caroll, Kit, & Flegal, 2014).[1] With mounting evidence of serious medical repercussions including increased risk of cardiovascular disease, stroke, high blood pressure, diabetes and cancer, obesity promises major economic and health implications across the United States and the globe (Mayo Clinic, 2014).[2] In the U.S., eating-out expenditures more than doubled between 1970 and 2012 (United States Department of Agriculture, Report on Food Consumption and Demand, 2014).[3] Simultaneously, obesity was estimated to account for 9.1% of total health expenditures and 300,000 deaths in 1998, while a more recent study estimates obesity accounted for nearly 21% of total health expenditures in 2012 (Finkelstein, Fiebelkorn, & Wang, 2003; Cawley & Meyerhoefer, 2012). Further, more than 60% of American adults do not obtain regular physical activity, and 25% do not obtain any at all (United States Department of Health and Human Services, Physical Activity and Health: A Report of the Surgeon General, 1996). Collectively, these statistics are indicative of a growing sedentary and obesogenic American lifestyle.[4] Currently, it is widely accepted that the rising prevalence of obesity is the result of eating too many calories, maintaining an unhealthy diet, and not

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[1] Figure 6.1 in Appendix A demonstrates increasing United States obesity rates by state over time.

[2] Complete extent of health risks associated with obesity are concisely noted at http://www.mayoclinic.org/diseases-conditions/obesity/basics/complications/con-20014834.

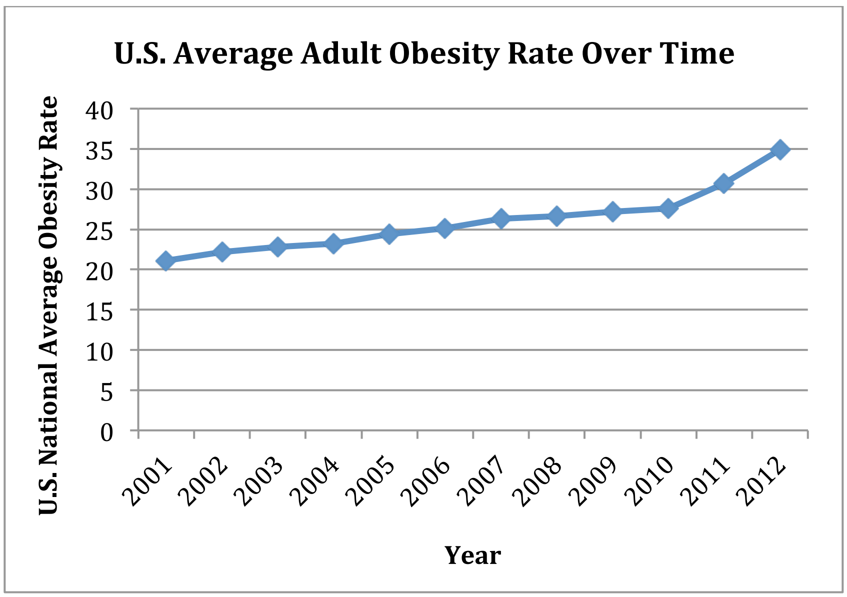
[3] Figure 6.2 in Appendix B demonstrates the trends for eating-out expenditure in the United States.

[4] The term "obesogenic" originated in 1996 and is an adjective which refers to environmental causes of increased weight gain (Weidenhofer, 1996).

obtaining adequate physical activity (Center for Disease Control, Obesity and Overweight, 2013).[5]

Food accessibility and availability significantly influence consumption choices and are the factors primarily utilized in explaining the rising obesity levels depicted in Figure 1.

Figure 1. Line graph illustrating the increasing United States average adult obesity rate over time.



Source: author's calculations.

With the rise in meals eaten away from home and the rapidly expanding full-service and fast-food restaurant industries, disparities in the nutritional provision of these food-consumption options are concerning. On one hand, the availability of grocery stores and

[5] A more extensive explanation of this widely-accepted relationship may be found at http://www.cdc.gov/obesity/adult/defining.html

supermarkets is associated with more fruit and vegetable intake, healthier diets, lower rates of obesity, and lower food costs. This association supports the well-established negative relationship between food costs and diet quality: as price of a healthy food item increases, demand decreases (French et al., 2001; Morland, Wing, & Diez Roux, 2002). On the other hand, several studies demonstrate that full-service and fast-food restaurants tend to serve high-calorie, fatty, and carbohydrate-dense foods relative to foods prepared in the home (Lin, Frazao, & Guthrie, 1999; Zenk et al. 2005). Despite these worrying qualities, eating-out expenditures as a percent of food budget have more than doubled since 1970 (Report on Food Consumption and Demand, 2014). Together, these trends imply that the American population is spending more money on the consumption of less-healthy food.

Although obesity and food environment characteristics are seemingly correlated, many food-accessibility studies instead examine the dynamic between the food environment components and community demographic characteristics. Food environment components, or the different kinds of restaurants and grocery stores, have not been comprehensively evaluated for their role on obesity levels across the country. This lack of analysis is problematic, however, as governments are currently attempting to mitigate the obesity epidemic without a strong body of evidence on strategy efficiency. According to a survey operated by the Organization for Economic Cooperation and Development in 2008 (OECD), the majority of OECD government initiatives for reducing obesity are currently targeting improvements to diets through existing infrastructure such as schools, healthcare systems and community centers. Without understanding the dynamic between food environment and obesity levels, however, these initiatives may be very ineffective at lowering obesity. Other strategies such as increasing physical activity or altering the available food environment components may be a more cost-effective approach. This study aims to provide evidence on the role of the food environment in obesity rates, and help in the development of economic and public health policies attempting to address the obesity epidemic, such that more informed and efficient strategies may be implemented.

Because few studies have evaluated the comprehensive effects of the complete food environment on obesity rates, this study seeks to fill this gap by analyzing the relationship between obesity rates and the availability of grocery stores, convenience stores, fast-food and full-service restaurants at a county-level across the United States. Understanding these effects is necessary in the development of economic and public health policies to address the domestic and global obesity issue. Positive relationships are predicted between county-level obesity rates and the presence of convenience stores as well as fast-food restaurants. A negative relationship is predicted between obesity rates and the prevalence of grocery stores and full-service restaurants.

The next section reviews current relevant literature. This is followed by a description of the necessary theory and model utilized in Section 2. Data and methodology are discussed in Section 3. Section 4 presents the results of analysis, followed by a discussion of the findings and the model's limitations. Finally, the study concludes with a summary of the results and a description of the implications on health and economic policy in Section 5.

Literature Review

Obesity, classified as a Body Mass Index (BMI) over 30.0 units, is significantly impacted by individual demographics and genetics as well as external environmental, societal and economic factors.[6] Because these components all interact, a complex dynamic exists between demographics, food environment and obesity. Current literature attempts to explain these relationships individually, the majority of which focus on community demographics or food environment characteristics such as food-store proximity, food-store type or restaurant prevalence. Though seemingly dissimilar from this study, a thorough understanding of these associated relationships is essential to designing a predictive model of obesity rates.

Role of Demographics on Obesity Rates

Several demographic characteristics are significant predictors of food-shopping behaviors and obesity rates. While it is apparent that the relationships exist, it is important to note that their roles are difficult to isolate due to interaction between factors. In addition, causal direction is not usually clear.

First, gender is believed to be an interacting correlate of obesity. Though males have higher BMIs, a sample of the American population showed males are less likely to be obese (Chou, Grossman, & Saffer, 2004; Inagami, Cohen, Finch, & Asch, 2006; Mehta & Chang, 2008). Worldwide, obesity rates tend to be higher in women than men, all other things being equal. Some evidence implies that male obesity rates are growing at

[6] According to the Center for Disease Control, the obesity threshold is a Body Mass Index of 30.0 units. Values of the Body Mass Index are calculated by dividing weight in kilograms by height in meters.

a faster rate, however, especially in developed countries (Fairburn & Brownell, 2002, pg. 390). Reasons behind this trend remain unclear.

Racial disparities in obesity prevalence are relatively conclusive. Both Blacks and Hispanics are more likely to be obese and overweight than Whites and Asians (Inagami et al., 2006; Mehta & Chang, 2008). While Blacks are more likely to be obese, Whites, Asians and Hispanics are more likely to be obese at a younger age (Chou et al., 2004; Maddock, 2004). In addition to environmentally introduced correlates, cultural norms are also hypothesized to play a role in racial obesity patterns. Such norms may appropriate unhealthy eating habits such as consuming high-fat or fried foods, overeating, fasting and binging.

Many studies conclude that a community's food environment is molded by the socioeconomic status of the population. Inagami et al. (2006) conclude that being employed is positively associated with BMI. Beyond employment, real household income has a decreasingly negative effect on the probability of being obese (Chou et al., 2004; Mehta & Chang, 2008). Causal direction is again problematic in understanding this dynamic. Obese individuals may be less likely to obtain high paying jobs, or unemployed individuals may gain weight from stress-induced overeating. Regardless of direction and correlation, both employment and income are considered indicators of obesity levels.

Education level is also significantly negatively correlated with obesity levels. A study of twins found that an additional year of formal education might decrease the probability of being overweight by 2-4% (Webbinck, Martin, & Visscher, 2008). Likewise, Chou et al. (2004) found that college graduates are 9% less likely to be obese than a demographically similar individual who only completed some high school. They also conclude that graduation from college maximizes the probability that BMI is in the range that minimizes mortality and morbidity risks. Other studies similarly found that college graduation was significantly negatively correlated with BMI (Inagami et al., 2006; Mehta & Chang, 2008). Finally, women demonstrate stronger positive relationships between obesity rates and education levels than men in OECD countries (Fairburn & Brownell, 2002).

Marital status and family size are also significantly correlated with obesity levels. Married and widowed individuals are 19% and 26% more likely to be overweight, respectively, than single, never married individuals (Chou et al., 2004). Other research finds similar significant positive correlations between probability of obesity and being married (Inagami et al., 2006). Having any children is significantly positively correlated with eating at fast-food restaurants, as is number of children (Mehta & Chang, 2008). Further, Fairburn and Brownell (2002) conclude that childhood obesity is most prevalent in families with parents who are obese.

Age has a slightly more complex role in probability of being obese, following a concave bell-shaped curve. For Americans, while each additional year of age increases average BMI, probability of being obese is highest around the age of 57 (Chou et al., 2004; Mehta & Chang, 2008). Several studies show that the percent of the adult population over 55 years old is significantly positively correlated with obesity rates, (Inagami et al., 2006; Maddock, 2004). The relationship between age and obesity is hard to capture, however, as rationale, preferences for food, and shopping behaviors change significantly throughout a lifetime.

Regardless of accessibility of restaurants and food stores, transportation has been evaluated as both a promoter of unhealthy eating habits and as an opportunity for accessing healthier foods. Examined as an indicator of the impacts of a sedentary lifestyle, several studies find that owning a car is significantly positively correlated with BMI (Inagami et al., 2006; Mehta & Chang, 2008). Relatedly, the transition to a more sedentary lifestyle is illustrated in the exercise habits of Americans. The Surgeon General's Report on Physical Activity and Health (1996) shows that more than 60% of American adults do not obtain regular physical activity and 25% do not obtain any at all. Further, the report concludes that more than 50% of young Americans (age 12-21) do not obtain regular physical activity and that participation in physical education classes has dropped by nearly 20%. Without considering diet, these statistics alone highlight an obesity-promoting lifestyle shift towards unhealthy habits. Further, these statistics are outdated and assumingly have increased since this data was analyzed. On the other hand, studies show that inaccessibility of healthy food stores does not negatively impact diet quality, but instead motivates residents to travel farther to access their primary healthy food store (Burdette & Whitaker, 2004; Garasky, Morton, & Greder, 2004). In this scenario, access to transportation could be considered obesity reducing.

Genetics are also believed to play a large role in the probability of being obese. Obesity is proven to run in families, even if family members do not live together or share similar lifestyle habits such as eating and exercising (Allison, Faith, & Nelson, 1996). This is supported by heritability estimates for obesity, which are typically high, greater than .70 (Kopelman, 2004; Walley, Blakemore, & Froguel, 2006).[7] According to a review by Rankinen et al. (2006), there are 22 genes that have five or more positive associations of variants with obesity. This alludes to the complexity in genetic predisposition to obesity, in that each gene likely contributes very little to body weight, but the combined impact is significant. It is the collective function of the inherited obesity-promoting genes that determine how the individual responds to their environment. Because this relationship is not well defined, it is hard to represent and account for in obesity studies.

Chou et al. (2004) also hypothesize that several macroeconomic lifestyle-altering changes caused dramatic changes in the American food environment. Growth in the labor-force participation of women has led to less time spent in the home and less time available for active leisure. Additionally, labor market developments since 1970 demonstrate only slow growth and even reductions in real income. Amongst other factors, these shifts in the labor market decrease time and money available for preparing nutritious meals in the home. As a result, demand for inexpensive convenience and fast-food rose, increasing caloric intake. In turn, the supply and availability of food changed significantly in order to meet demand.

Demographics summary. Overall, numerous demographic factors impact the likelihood of obesity. The roles of gender, race, socioeconomic status, education level, and marital status are conclusive. The roles of age and accessibility of transportation on obesity rates are less conclusive. The majority of these characteristics are exacerbated given an individual's environment. Therefore, it is important to recognize the role of and

[7] Heritability estimates are generally considered the probability of offspring inheriting specific characteristics or genetic traits. In the case of obesity, geneticists estimate offspring of obese parents will be obese with approximately 70% probability.

identify the methods successful in improving the American food environment in order to combat the obesity epidemic.

Role of Food Environment on Obesity Rates

Food-store proximity. Proximity to healthy versus unhealthy food-providing firms is perhaps the most inconclusive of determinants of the impacts of food environment on obesity levels. Some research suggests individuals are minimally impacted by the proximity of healthy food-providing firms, perhaps due to the accessibility and affordability of modern transportation (Burdette & Whitaker, 2004; Garasky et al., 2004; Sohi, Bell, Liu, Ballersby, & Liese, 1999). Other research suggests the proximity of healthy and unhealthy food stores is indeed predictive of diet habits (Inagami et al., 2006; Jeffery, Baxter, McGuire, & Linde, 2006). Studies analyze these effects in both low-access areas and low-quality areas.[8] Evaluation of the complete food environment may be more indicative of the true effects of these relationships.

Like many health issues, there are proposed discrepancies in food availability between rural and urban areas. Despite evidence from Morris, Neuhauser, & Campbell (1992) that rural areas have more supermarkets per county than urban areas, Morris & Bellinger (1990) found that rural food outlets of any type are more likely to contain poorly stocked shelves and lack healthy nutritious foods. Further, Kaufman (1990) found that relative to residents in urban areas, poor residents in rural areas depend on smaller convenience stores, which Glanz, Sallis, Saelens, & Frank (2007) found to provide dramatically fewer healthy food options than grocery stores.

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[8] Low access areas are generally defined as those with physically fewer healthy food-providing stores. Low-quality areas are generally defined as those that provide healthy food but at poor quality.

Despite these arguments, several studies conclude that residents in low food-access areas are aware of a limited availability to healthy foods, but agree that the limited availability does not impact diet. Instead, residents simply travel farther to their primary food store (Burdette & Whitaker, 2004; Garasky et al., 2004; Sohi et al., 1999). Likewise, another study surveyed 26 advanced economies and failed to find any correlation between proximity to fast-food restaurants and obesity levels (de Vogli, Kouvonen & Gimeno, 2011). Though analysis only examines one fast-food restaurant chain, the study's multi-national scale validates the results as representative. Collectively, these results imply that proximity to food-providing firms appears irrelevant to consumption decisions, and instead suggest that it simply encourages residents to travel farther for access to healthy foods.

On the other hand, Inagami et al. (2006) find distance to food store locations to be significantly positively correlated to BMI: the farther the grocery store from a household, the more likely the residents to have a higher BMI. Additionally, a study by Jeffery et al. (2006) evaluates obesity rates relative to proximity to both fast-food restaurants as well as the restaurant environment as a whole. The authors found obesity was significantly positively correlated to proximity to fast-food restaurants, but not correlated with proximity to all restaurants. These contradictory results illustrate the need for more research into potential disparities in the effects of fast-food and full-service restaurants.

Demographic-specific investigations have found that disparities exist in accessibility between races. Studies suggest, for example, that impoverished Black neighborhoods are 1.1 miles farther from the nearest supermarket compared to impoverished White neighborhoods, and that Blacks travel greater distances to any type of grocery store (Zenk et al., 2005; Mari Gallagher Research & Consulting Group, 2006). Even if stores are accessible, in predominantly Black neighborhoods a lower proportion of stores carry fresh, quality produce. This disparity is only partially explained by differences in types of food stores available (Morland, Diez Roux, & Wing, 2006; Zenk et al., 2006). Further, predominantly Black and Hispanic neighborhoods have six times more fast-food restaurants and fewer supermarkets and grocery stores than predominantly White neighborhoods (Block & Kouba, 2006; Block, Scribner, & Desalvo, 2004; Galvez et al., 2007).

Income and proximity to food environment components are also correlated. Research shows that low-income residents have fewer and smaller healthy food outlets, and must travel farther for the same amount of access as “non-poor” residents (Alwitt & Donley, 1997; Chung & Myers, 1999; Kaufman, MacDonald, Lutz, & Smallwood, 1997). In addition to limited healthy food availability, studies find that fast-food restaurant proximity is inversely related to neighborhood income (Simon, Kwan, Angelescu, Shih, & Fielding, 2008; Wang, Kim, Gonzalez, MacLeod, & Winkleby, 2007). Further, Cotterill and Franklin (1995) show that more low-income residents lack adequate transportation, further limiting accessibility of food outlets. Collectively, these results imply that low-income residents are more likely to depend on fast-food restaurants and a limited number of more expensive food outlets (Chung & Myers, 1999; Morris & Bellinger, 1990).

Food-store proximity summary. In summary, there is no consensus on the relationship between food store proximity and obesity levels. Several studies demonstrate a negative correlation between median household income and distance to nearest quality grocery store, while others find a relationship between distance to nearest quality grocery store and the racial makeup of the neighborhood. Confounding results exist, however, in the relationship between distance to nearest quality grocery store and obesity rates. Existing studies fail to capture the effects of the entire food environment, however, limiting the legitimacy of their conclusions. A more complete evaluation, including the incorporation of full-service restaurants, convenience stores, and more specific characteristics of the county is necessary to better understand the dynamic between proximity of restaurants and obesity rates.

Restaurant prevalence. Community availability of restaurants and restaurant food prices are directly related to dietary intake. For this reason, many studies examine the relationship between prevalence of types of restaurants and obesity levels. Though prevalence is extremely dependent on community characteristics, the effects of restaurant availability are not necessarily uniform.

Evaluation of fast-food restaurant prevalence is relatively conclusive: many studies find significant positive correlations between fast-food restaurants per capita and obesity levels (Chou et al., 2004; Maddock, 2004; Mehta & Chang, 2008). One global study finds density of a representative fast-food chain to be significantly correlated with prevalence of obesity in both genders across 26 affluent nations (de Vogli, Kouvonen, & Gimeno, 2011). Maddock's study (2004) is most comparable to the focus of this study, analyzing the relationship between obesity levels and the prevalence of fast-food restaurants at the state level. Though the analysis would be more informative at a county-level, the dataset Maddock utilizes does not provide enough data for county-level analysis. This study expands on this limitation by using a more elaborate model and analyzing at a county level using a more thorough dataset.

Data is less conclusive on the relationship between obesity levels and full-service restaurants. In an attempt to capture the effects of the complete restaurant environment, Mehta and Chang (2008) conclude that while the ratio of fast-food to full-service restaurants is a significant positive correlate of weight status, density of full-service restaurants is independently negatively correlated with obesity levels. Similarly, a study of 75,000 American adolescents concludes that higher prevalence of full-service restaurants is related to a greater likelihood of fruit and vegetable consumption, indicative of healthier diets (Powell, Auld, Chaloupka, O'Malley, & Johnston, 2007). Contradictory research argues instead that higher densities of full-service restaurants are positively correlated to increases in weight (Chou et al., 2008; Jeffery et al., 2006).

Restaurant prevalence is shown to be dependent on community income. Studies show that poorer neighborhoods have fewer healthy food options available than non-poor neighborhoods (Glanz et al., 2007; Lewis et al., 2005; Moore & Diez-Roux, 2006). More specifically, fast-food and full-service restaurants are more prevalent in low- and medium-income census tracts, while supermarkets are significantly less prevalent (Morland, Wing, Diez Roux, & Poole, 2002; Powell et al., 2007; Shaffer, 2003). Block et al. (2004) found a 10% increase in fast-food restaurant density to be directly correlated to a 5% decrease in median household income.

The demographic characteristics of communities are also implicated in impacting community restaurant environments. Block et al. (2004) found that neighborhoods with 80% Black residents had 2.4 fast-food restaurants per square mile as compared to 1.5

fast-food restaurants per square mile in neighborhoods with only 20% Black residents. Similarly, full-service restaurants are more prevalent in White neighborhoods than in racially mixed or predominantly Black neighborhoods (Morland, Wing, Diez Roux, & Poole, 2002; Lewis et al., 2005).

Though the existence of the relationship is definitive, the literature is inconclusive on the direction of causation between obesity and restaurant-type availability. Several studies alternatively suggest that weight-status of residents affect preferences and demand for restaurants (Mehta & Chang, 2008). Similarly, Morland et al. (2006) propose that the local food environment may influence community characteristics: for example, they suggest that obese individuals may select communities that have a higher prevalence of fast-food restaurants. Further, Walker et al. (2010) argue that restaurant-type availability is influenced by the competition within the market: the growth of chain stores on the outskirts of inner-cities that offer consumers better quality, variety and price in turn force the small, urban grocery stores to close. With limited accessibility to affordable food in the cities, fast-food restaurants open in their place, offering poor-quality foods at attractive prices. These possibilities are very difficult to capture in an empirical study but add valuable insight to understanding the relationship between obesity and restaurant prevalence.

Restaurant prevalence summary. Regardless of causation direction, the evident correlation between obesity and restaurant prevalence is concerning. Significant evidence supports the strong positive relationship between fast-food restaurants and obesity levels. The relationship between full-service restaurants and obesity levels is much less obvious, with several studies concluding both significance and insignificance. Nevertheless, the impacts of income and race on county fast-food and full-service restaurant prevalence are well understood: income displays a negative correlation with fast-food and full-service restaurant prevalence, while the percentage of the population that is Black is positively correlated with fast-food restaurant prevalence. More concrete evidence on the individual roles of restaurant types on obesity levels may help the isolation and elimination of obesity-promoting food environments. Using restaurant prevalence as one predictor of obesity levels across the country will shed light on the role of this food environment component in United States obesity.

Food-store type. While many studies broadly evaluate the role of all grocery stores, many have found that several categories of grocery stores have different prevalence trends and impacts in a community. Most commonly, stores are divided into categories of supermarkets, chain and non-chain grocery stores, and convenience stores for more specific analysis.

Generally, it is well accepted that supermarkets are more likely than grocery stores and convenience stores to stock healthful foods and to offer foods at a lower cost (Kaufman et al., 1997; Powell, Slater, Mirtcheva, Bao, & Chaloupka, 2006; Liese, Weis, Pluto, Smith, & Lawson, 2007; Glanz et al., 2007). Larson, Story, & Nelson (2009) state that supermarkets offer the greatest variety of high-quality products at the lowest costs. Next, chain stores frequently provide food items at prices 10-40% lower than prices in non-chain stores, but are not readily located in areas with high poverty rates, such as inner-cities (Chung & Myers, 1999). The supermarkets and grocery stores that are available in inner-cities have higher prices than comparable stores in less densely populated areas (Kaufman, 1997).

In analyzing the impacts of different kinds of grocery stores, several studies find that increased availability of chain supermarkets is statistically associated with lower prevalence of obesity, while greater availability of convenience stores is significantly associated with higher prevalence of obesity (Powell et al., 2007; Morland et al., 2006). Likewise, another study found that residents in an area with high supermarket density were 25% more likely to have a healthy diet than those with low supermarket density (Moore, Diez Roux, Nettleton, & Jacobs, 2008). Morland, Wing, & Diez Roux (2002) found that the presence of one supermarket increases fruit and vegetable consumption among Blacks and Whites by 32% and 11% respectively. In a study conducted in areas with low access to food stores, residents successfully identified the lack of affordable healthy food options within their community. This lack of accessibility, however, significantly diminished the ability to obtain foods necessary to maintain a healthy diet (Hendrickson, Smith, & Eikenberry, 2006). Research shows that neighborhood residents with better access to supermarkets and other grocery stores providing healthy food products tend to sustain healthier diets (Larson et al., 2009).

Neighborhood income also impacts the categories of grocery stores available. Residents of low-income neighborhoods are proximate to fewer chain supermarkets, smaller grocery stores and live closer to convenience stores (Cotterill & Franklin, 1995; Powell et al., 2007; Wang et al., 2007; Morland, Wing, Diez Roux, & Poole, 2002). Research also shows that the nearest supermarket is markedly farther away and posts higher food prices in more impoverished census tracts (Moore & Diez-Roux, 2006; Powell et al. 2007, Zenk et al., 2005). This could be due to the prevalence of low-income neighborhoods in urban areas where there are fewer supermarkets available, unavailable or limited transportation, and racial disparities (Powell et al., 2007).

Grocery store prevalence is also impacted by the ethnic composition of the neighborhood. Though availability of chain supermarkets is significantly correlated with lower obesity rates for all races, the association between supermarket availability and obesity rates for Blacks is larger than other races (Powell et al., 2007). This is concerning however, because numerous studies show that predominantly Black neighborhoods are much less likely than racially mixed neighborhoods to have either supermarkets or grocery stores, and are more likely to have smaller grocery stores and convenience stores (Galvez et al., 2007; Moore & Diez Roux, 2006; Morland, Wing, & Diez Roux, 2002; Morland, Wing, Diez Roux & Poole, 2002; Morland et al., 2006; Powell et al., 2007; Raja, Ma, & Yadav, 2008; Shaffer, 2002).

Food store type summary. In summary, availability of food stores seems to have a definitive impact on obtainability of healthy foods. Prevalence of categories of food stores seems to depend on community characteristics, however. This is an unfortunate trend, as the demographic in most need has the least accessibility to healthy foods necessary for the maintenance of a healthy diet.

Summary

Demographics are conclusively shown to influence elements of the food environment such as food-store availability, proximity of food-stores, and the frequency of restaurants. The relationship between the food environment and obesity is less defined, however. Complete understanding of this relationship requires evaluation of the total food environment across the United States. Current literature implements limited, regionally focused analysis or small sample-based representations. Though their findings provide insight, a more extensive analysis will illuminate the true dynamic between food environment and obesity.

Theory

While there is consensus throughout the literature that changes in the food environment play a role in the rising obesity levels, there is considerable variation in the results. Further, current literature tends to only analyze small, regionalized study samples. Most acknowledge these shortcomings, and recommend caution in applying their conclusions on larger scales. In order to accurately represent and understand the relationship between obesity and food environment in the United States, many call for a national analysis. Aiming to fill this gap in the literature, this study models United States obesity rates relative to the prevalence of various food environment components using county-level analysis.

Base Model

This study builds upon the work of Maddock (2004) who uses Ordinary Least Squares regression analysis to examine the relationship between obesity and the prevalence of fast-food restaurants at the state-level, a question similar to that proposed in this study. Though the research examines only one component of the food environment and at a less specific level of analysis, Maddock's model accounts for many correlates of obesity identified in the existing food-environment literature. Maddock incorporates many demographic factors as determinants of obesity. These variables include median household income, population density, race, gender, and age distribution. Variables accounting for physical inactivity and nutritional quality are also incorporated. Residents per fast-food restaurant and square miles per restaurant are variables used as representations of fast-food restaurant prevalence.

Maddock uses the following model:

$$\mathrm{OR} = \alpha_0 + \beta_1\mathrm{FFR} + \sum_1^n \delta_i X_i + \varepsilon_i \quad (3.1)$$

which reflects obesity rate, OR, as a function of a constant term, α_0 ; the element β_1FFR capturing fast-food restaurant prevalence and the associated coefficient; the sum of a vector of the independent demographic variables mentioned above and their associated coefficients, $\sum_1^n \delta_i X_i$; and an error term, ε_i.

Modifications

For this study, some variables are added to better represent available food options. In addition to fast-food restaurant prevalence, independent variables are added that account for other components of a community's food environment. Representative variables for grocery stores, convenience stores, supercenters and full-service restaurants per 1000 residents as well as the pure count provide a complete picture of the food environment in the model. Further, adding variables representing number of available farmers' markets and recreation facilities per capita is predicted to account for more variation between communities.

Beyond the food environment, this study adds several demographic factors that impact obesity levels in a community. As discussed in the literature review, education, owning a car, employment, and marital status are all shown to be significant demographic predictors of obesity rates. Adding these variables gives a better representation of community demographics, further specifies the model and therefore more accurately predicts obesity rates.

Despite strong evidence that some genetic traits are believed to predispose individuals to obesity, this relationship is not yet well understood. For this reason, studies fail to accurately represent this component in their models. Therefore, a variable accounting for genetic predisposition will not be included in this study. Instead, the effect of genetics on obesity rates will be captured in other demographic variables and the error term.

Other correlates of obesity are excluded from this study. Variables such as density of alcohol outlets, specific types of grocery stores available, cigarette-smoking trends, genetic predisposition and parent's education are excluded due to data unavailability. Other community traits such as proximity to food-stores, neighborhood violence and population receiving food-assistance program benefits are excluded due to weak evidence of significance.

The first study to do so, county-level analysis provides more specific insight into the dynamic between food environment and obesity rates. Simultaneously, accounting for several components of the food environment provides a more complete understanding of the dynamic between obesity rates and food-environment components. Because Maddock finds significant correlation even at the state level, significant results are expected for county-level analysis despite the small limitations.

Empirical Model

The empirical model used in this study is as follows:

$$\begin{aligned} OR = {} & \beta_0 + \beta_1 FFRper1000 + \beta_2 FSRper1000 + \beta_3 GSper1000 + \beta_4 CSper1000 + \beta_5 Sper1000 \\ & + \beta_6 FRMKTper1000 + \beta_7 FFR + \beta_8 FSR + \beta_9 GS + \beta_{10} CS + \beta_{11} S + \beta_{12} FFperFS + \\ & \delta_1 ExpendpcFFR + \delta_2 ExpendpcR + \delta_3 PctLA + \delta_4 PctLIA + \delta_5 PctLIANC + \\ & \delta_6 PIMtoS + \delta_7 PctHSPA + \delta_8 RecFacper1000 + \delta_9 DR + \delta_{10} PctWhite + \delta_{11} PctBlack \\ & + \delta_{12} PctHisp + \delta_{13} PctAsian + \delta_{14} Pct65 + \delta_{15} Pct18 + \delta_{16} MedHI + \delta_{17} PovertyRate \\ & + \delta_{18} Urban + \delta_{19} UnempRate + \delta_{20} PctCollegeGrad + \delta_{21} PctMarried + \varepsilon_i \qquad (3.2) \end{aligned}$$

where OR is the county-level obesity rate in 2012 as predicted by county-level data of:

- **β_0**, representing a constant term,
- **FFRper1000**, representing fast-food restaurants per 1,000 population in 2011,
- **FSRper1000**, representing full-service restaurants per 1,000 population in 2011,
- **GSper1000**, representing grocery stores per 1,000 population in 2011,
- **CSper1000**, representing convenience stores per 1,000 population in 2011,
- **Sper1000**, representing wholesale retail centers per 1,000 population in 2011,
- **FRMKTper1000**, representing farmers' markets per 1,000 population in 2011,
- **FFR**, representing the number of fast-food restaurants in 2011,
- **FSR**, representing the number of full-service restaurants in 2011,
- **GS**, representing the number of grocery stores in 2011,
- **CS**, representing the number of convenience stores in 2011,
- **S**, representing the number of wholesale retail centers in 2011,
- **FFperFS**, representing the ratio of fast-food to full-service restaurants in 2011,
- **ExpendpcFFR**, representing expenditures per capita at fast-food restaurants in 2010,
- **ExpendpcR**, representing expenditures per capita at full-service restaurants in 2010,
- **PctLA**, representing percent of households with low food access in 2010,
- **PctLIA**, representing percent of households with low income and low food access in 2010,
- **PctLIANC**, representing percent of households with low income, low food access and no car in 2010,

- **PIMtoS**, representing a price index of healthy to unhealthy foods in 2010,
- **PctHSPA**, representing percent of high schoolers who are physically active in 2009,
- **RecFacper1000**, representing recreation and fitness facilities per 1,000 population in 2011,
- **DR**, representing percent of adult population with diabetes in 2010,
- **PctWhite**, representing percent of population that is White in 2010,
- **PctBlack**, representing percent of population that is Black in 2010,
- **PctHisp**, representing percent of population that is Hispanic in 2010,
- **PctAsian**, representing percent of population that is Asian in 2010,
- **Pct65**, representing percent of population that is 65 years or older in 2010,
- **Pct18**, representing percent of population that is 18 years or younger in 2010,
- **MedHI**, representing median household income in 2010,
- **PovertyRate**, representing percent of population below poverty threshold in 2010,
- **Urban**, representing county status as either urban or non-urban (rural) in 2010,
- **UnempRate**, representing unemployment rate in 2010,
- **PctCollegeGrad**, representing percent of adults over 25 that attained bachelor's degree or higher in 2009,
- **PctMarried**, representing percent of residents who are married in 2000, and
- **ε**, representing an error term for the model.

This section outlines the construction of a model primarily based on the model proposed by Maddock (2004). By adding several food environment variables and accounting for additional demographic correlates, the model provides a more complete reflection of the dynamic between food environment and obesity rates. Additionally, using county-level data adds legitimacy to the application of these results across the country.

Data

This section discusses the data sources and their use in the model, followed by the model's advantages and limitations. This study uses data from the Economic Research Services division of the United States Department of Agriculture (USDA ERS), the United States Department of Labor's Bureau of Labor Statistics (BLS) and the National Research Center for Family and Marriage.

Dataset

Variable choices were made based on previously identified predictors of obesity rates, as summarized in the literature review. The Food Environment Atlas dataset acquired from the USDA ERS provides data on food environment factors for 3177 counties in the United States across all 50 states, with the objective of stimulating research on the effects of food environment on food choices and diet quality.[9] Of the 210 in the original dataset, 27 variables were chosen for analysis in this study.[10] Though the report was published in February of 2014, the data is from 2009, 2010, or 2011 depending on the variable.

County-level employment data was retrieved from the Local Area Unemployment Statistics program within the BLS (LAUS). While the LAUS publishes data annually, statistics for 2010 were used to more accurately match the data from the Food Environment Atlas. On several occasions, the BLS left out counties that were included in

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[9] See http://www.ers.usda.gov/data-products/food-environment-atlas.aspx for the complete statement of objectives and goals of the Food Environment Atlas dataset.

[10] A complete list of documentation for all data included in the Food Environment Atlas is located at http://ers.usda.gov/datafiles/Food_Environment_Atlas/Data_Access_and_Documentation_Downloads/Current_Version/documentation.pdf.

the Food Environment Atlas. Missing values were recorded for this variable for these counties in the dataset.

Data on marital status at the county level was obtained from the National Center for Family and Marriage Research at Bowling Green State University. This data is from 2000, their most recent publication of this material. Again, where county-specific data was not provided, missing values were recorded in the dataset.

Several eliminations reduced the sample size to 3148 counties. 5 counties were eliminated because they were missing data for more than 2/3 of the variables.[11] Additionally, the Food Environment Atlas dataset included both the Virginia counties and the state regions. The 24 state regions had no reported data, however, and were therefore removed from the dataset. Even if data were reported, the regions would be removed to avoid double-counting results in Virginia, potentially skewing the analysis. Despite the eliminated data, the sample size is still sufficiently large enough for the analysis to be considered representative.

Dependent Variable

The dependent variable in this study is the adult obesity rate in a United States county (OR). Because it is already in percent form, variable data is comparable between counties. As discussed in the literature review, many studies have modeled obesity rates using only one or two components of the food environment. This study seeks to expand on the literature by using a more complete model to predict the dependent variable:

- **OR:** the percent of county residents over 20 years of age classified as obese, or having a Body Mass Index over 30.0.

[11] For example, Yellowstone National Park, WY was included as a county but yielded no data.

These county-level health estimates were provided to the USDA ERS by the Center for Disease Control and Prevention through their Behavioral Risk Factor Surveillance System (BRFSS). Data is available from these sources for 2009 and 2010.

Independent Variables

Food environment components. The model uses a more complete representation of the food environment to model obesity rates in each county. Five different food environment components, or food stores, are analyzed in this study: fast-food restaurants, full-service restaurants, grocery stores, supercenters, and convenience stores. The variables and their definitions are as follows:

- **FFR:** the number of limited-service, or "fast-food", restaurants in the county.[12]
- **FSR:** the number of full-service restaurants in the county.[13]
- **GS:** the number of supermarkets and grocery stores in the county.[14]
- **S:** the number of supercenters and warehouse club stores in the county.[15]

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[12] According to the North American Industry Classification System, limited-service restaurants are classified as establishments primarily providing food services where patrons generally order or select items and pay before eating (except snack and nonalcoholic beverage bars). Food and drink may be consumed on the premises, taken out, or delivered to the customer.

[13] According to the North American Industry Classification System, full-service restaurants are classified as establishments primarily providing food services to patrons who order and are served while seated and pay after eating.

[14] According to the North American Industry Classification System, grocery stores are classified as establishments primarily engaged in retailing a general line of food, such as canned and frozen foods; fresh fruits and vegetables; and fresh and prepared meats, fish and poultry. While delicatessen-type establishments are included, convenience stores and large general merchandise stores such as supercenters and warehouse club stores are excluded.

[15] According to the North American Industry Classification System, warehouse clubs and supercenters are primarily engaged in retailing a general line of groceries in combination with general lines of new merchandise, such as apparel furniture, and appliances. This category excludes grocery stores and supermarkets.

- **CS:** the number of convenience stores, sometimes referred to as food marts, in the county.[16]

- **FFperFS:** the ratio of fast-food restaurants to full-service restaurants in the county.[17]

- **FFRper1000:** the number of limited-service restaurants in the county per 1000 county residents; restaurant data is from the U.S. Census Bureau, County Business Patterns.

- **FSRper1000:** the number of full-service restaurants in the county per 1000 county residents.

- **GSper1000:** the number of supermarkets and grocery stores in the county per 1000 county residents.

- **Sper1000:** the number of supercenters and warehouse club stores in the county per 1000 county residents.

- **CSper1000:** the number of convenience stores in the county per 1000 county residents.

- **FRMKTper1000:** the number of farmers' markets in the county per 1000 county residents.[18]

Together, the above variables assumingly reflect the total food environment in a county. By including all five components, the model provides a more accurate representation of the individual roles in obesity rates. In addition to the number of each food store, variables representing food store per 1000 population are used in the regression. This measure accounts for variation in the number of food stores between counties due to

[16] According to the North American Industry Classification System, convenience stores or food marts are primarily engaged in retailing a limited line of goods that generally includes milk, bread, soda, snacks and sometimes gasoline.
[17] For counties in which there are zero full-service restaurants, no value was recorded in this variable for that county. Counties with zero fast-food restaurants recorded a value of 0 for that variable.
[18] A farmer's market is unofficially defined as a market in which two or more vendors sell agricultural products directly to customers through a common marketing channel. At least 51% of retail sales are direct to customers.

population differences. Farmers' markets are included to account for counties where more residents depend on food that is locally grown and sold.

With the exception of farmers' markets, restaurant and store data for the above variables are provided to the Food Environment Atlas by the County Business Patterns program of the U.S. Census Bureau. The Marketing Services Division of the USDA Agricultural Marketing Service provided farmers' market data to the Food Environment Atlas. The data collected is for food stores established and operational in 2011.

County characteristics. Qualities of each individual county will also influence obesity prevalence. The variable data are all percentages, ratios or averages such that comparisons can be made between counties without encountering bias from population size. Nine variables in this model account for obesogenic or health-benefitting factors that impact obesity:

- **PctLA:** percentage of people in an urban county living more than 1 mile from a supermarket or large grocery store, or more than 10 miles in a rural county.

- **PctLIA:** percentage of people in a with low income and living more than 1 mile from a supermarket or large grocery store in an urban county, or more than 10 miles in a rural county.

- **PctLIANC:** percentage of housing units in a county without a car and more than 1 mile from a supermarket or large grocery store.

- **ExpendpcFFR:** average expenditures (in current dollars) on food purchased at limited-service restaurants by county residents.

- **ExpendpcR:** average expenditures (in current dollars) on food purchased at full-service restaurants by county residents.

- **PIMtoS:** a ratio of the regional average price of low-fat milk to the regional average price of sodas relative to the national average price ratio.[19]

[19] Low-fat milk includes nonfat and 1% milk. Sodas include carbonated diet and caloric-sweetened beverages. This data is regionally reported, and is therefore not a county-specific indicator.

- **RecFacper1000:** the number of fitness and recreation centers in a county per 1000 county residents.[20]

- **PctHSPA:** percentage of high school students who self-report doing any kind of physical activity that increased their heart rate and made them breathe hard for a total of 60 minutes per day on each of the 7 days before the survey.

- **Urban:** a dummy variable carrying a value of 1 if the county is urban, and the value 0 otherwise.[21]

The wide variety of controls should account for a significant amount of the variation between obesogenic factors at the county level. The first three variables in this category are intended to account for individuals with limited accessibility to healthy food, who then may be more prone to consuming unhealthily at establishments such as fast-food restaurants or convenience stores. The expenditure variables reflect the reliance on food away from the home across counties. Despite reflecting regional price differences, the price index of milk to soda accounts for relative price mark-ups of healthy food across counties. The next two variables, recreational facilities and percent of high schoolers that are physically active, capture variance in fitness qualities between counties. Finally, the urban variable accounts for the generally lower accessibility of healthy foods in urban counties relative to rural counties.

Store access data are from a 2012 report, Access to Affordable and Nutritious Food: Updated Estimates of Distances to Supermarkets Using 2010 Data. The

[20] According to the North American Industry Classification System, fitness and recreation centers are establishments primarily engaged in operating fitness and recreational sports facilities featuring exercise and other active physical fitness conditioning or recreational sports activities.

[21] Urban areas include all counties containing one or more high-density urban area containing 50,000 people or more. Urban counties also included those outlying counties that are economically tied to the central counties, as measured by the share of workers commuting on a daily basis to the central counties. Non-urban, or rural counties have no cities with 50,000 residents or more.

Accommodation and Food Services: Geographic Area Series study by The Economic Census provided restaurant expenditure data. The low-fat milk and soda price index is generated using the Quarterly Food-at-Home Price Database. Recreation and fitness facility data for 2011 was provided to the Food Environment Atlas by the County Business Patterns program of the U.S. Census Bureau. Data on physical activity of high schoolers is from the 2009 Youth Risk Behavior Surveillance System. The dummy variable classifying counties as urban or rural uses the USDA ERS's Rural Classification system using 2010 data.

Demographic characteristics. The final twelve variables account for variation in population demographics between counties. Data for the variables are in percentage form, such that comparisons can be made between counties without bias from population size. Twelve variables account for the impacts of demographics on obesity levels:

- **PctWhite:** percentage of county resident population that is non-Hispanic White.
- **PctBlack:** percentage of county resident population that is non-Hispanic Black or African American.
- **PctHisp:** percentage of county resident population that is of Hispanic origin.
- **PctAsian:** percentage of county resident population that is Asian.
- **Pct65:** percentage of county population 65 years old or older.
- **Pct18:** percentage of county population under the age of 18 years.
- **DR:** the percent of county residents over 20 years of age that are diabetic (excluding gestational diabetes).
- **MedHI:** median income by household in 2010.[22]
- **PovertyRate:** percentage of county residents with household income below the poverty threshold.

[22] This data includes income of all household members 15 years old or older.

- **PctMarried:** percentage of county residents that are legally married.
- **PctCollegeGrad:** percentage of county residents with a college degree or higher.[23]
- **UnempRate:** percentage of county residents that are unemployed and actively seeking employment.

The first four variables capture racial differences in obesity rates, while the next two capture difference in obesity rates by age. Median household income, unemployment and poverty rates account for the impacts of income on obesity. Adult diabetes rate is primarily used as an independent variable, but is also tested as the dependent variable of this model for result comparison. Obesity is considered a possible complication for diabetics, due to the inability to process glucose (Mayo Clinic, 2014). Finally, marital status and educational achievements control for the impact of lifestyle on obesity rates.

Race, age, and poverty rate data are from the 2010 Census provided to the Food Environment Atlas by the U.S. Census Bureau. The Small Area Income and Poverty Estimates - 2010 Data study by the U.S. Census Bureau provided income data to the Food Environment Atlas. Educational statistics are from data collected by the U.S. Census Bureau's American Community Survey, and published by the USDA. These statistics are county averages between 2009 and 2013. Data for percentage of population with at least a college degree in any given year is not readily available. The marital status variable uses 2011 data retrieved from the NCFMR, while the unemployment rate data is from 2010, and was retrieved from the BLS.

[23] This data is an average of the data from 2009 and 2013, to more accurately match the majority of the dataset.

Summary Statistics

Summary statistics for the dependent variables and a selection of independent variables are displayed in Table 3.1. Obesity rates at a county-level range from a minimum of 13.1% of the population to a maximum of 47.9%. The number of fast-food restaurants in a single county ranges from 0 to 7,211, a range similar to that of full-service restaurants. Counties range in population size from the smallest with 82 people, to the largest with nearly 10 million.

Table 6.1 in Appendix C is a complete table of summary statistics for all dependent and independent variables. A correlation matrix for all independent and dependent variables can be found in Appendix D as Table 6.2.

TABLE 3.1

SUMMARY STATISTICS

Variable	Count	Mean	Standard Deviation	Minimum	Maximum
OR	3138	30.55395	4.242072	13.1	47.9
DR	3138	10.71138	2.252997	3.3	19.4
CS	3138	39.1638	91.36109	0	2030
FFR	3138	68.90695	237.2122	0	7211
FSR	3138	72.38432	239.9401	0	7125
GS	3138	20.50701	84.81212	0	2117
S	3138	1.461759	3.4437	0	85
RecFacper1000	3141	0.0713382	0.0737543	0	0.62513
PctWhite	3143	78.2947	19.88815	2.667918	99.16318
PctBlack	3143	8.748643	14.42144	0	85.43878
Pct65	3143	15.88254	4.19021	3.470599	43.38472
MedHI	3142	43144.87	10742.29	20577	119075
Population	3143	98232.77	312901.2	82	9818605

Source: author's calculations.

Advantages and Limitations

This study has several key advantages. First, very few studies execute their analysis at the county level. In fact, many actually suggest analysis at the county level as the next avenue in establishing the relationship between obesity rates and various food environment characteristics. In Maddock's study (2004), for example, the use of state-level analysis makes for a very small sample size, and also provides a less accurate representation of the impacts of the food environment on obesity rates after accounting for demographic variables. Maddock suggests completing his analysis at the county level to better understand the dynamic. This suggestion for research development is relatively similar to the analysis conducted in this study.

In contrast to other studies, this work accounts for all fast-food restaurants. Most studies use limited samples of restaurant chains as assumed representations of the entire industry. For example, Maddock uses the prevalence of only two fast-food chains as proxies for all other fast-food establishments. Though Maddock acknowledges this limitation, it is concerning that these two chains are assumed to accurately represent the entire fast-food environment. The multinational study by deVogli et al. (2011) uses only one fast-food restaurant chain in the analysis. By accounting for all fast-food establishments available, this study provides more accurate insight.

Though a significant limitation of many current studies is potential self-report bias, this study cannot improve on this limitation. For example, bodyweight, physical inactivity, and fruit and vegetable consumption data are self-reported in Maddock's dataset, allowing the possibility of report bias. Accounting for these variables without self-reported data is relatively difficult, however. By using a larger dataset and better representative variables, this study assumingly minimizes the effects.

Other data limitations of Maddock's model persist through this model and analysis. For example, shopping preferences cannot possibly be captured and represented by using state or county-level analysis. In turn, demand-side variations will not completely be accounted for. That is, if obesity rates are higher in areas with higher accessibility of fast-food restaurants, it is unclear if this is result of supply or demand. This causal direction should not be interpreted from results. Next, data outliers may impact the model in unpredictable and undetectable ways. Zoning laws in counties inhibiting the establishment of fast-food restaurants are difficult to control for, impacting results. Finally, harsh climates, amongst other things, likely impact shopping behaviors and consumption tendencies in ways difficult to control for with quantitative data.

Results

This section presents the results of the Ordinary Least Squares regression analysis of United States obesity rates at the county level. This section also discusses the processes and modifications to the model that were implemented to achieve the final model and results. Overall, the models are able to capture the impact of the food environment components on obesity rates. Though they do not play as strong of a role as anticipated in predicting obesity rates, many of these components are statistically significant.

The main focus of this study is understanding the role of various food environment components in predicting obesity rates. Several hypotheses are tested. First, the coefficients for fast-food restaurants and convenience stores are expected to be statistically significant and positive. This would indicate that a county with one more fast-food restaurant or convenience store would have a higher obesity rate than an otherwise identical county. This is the expected relationship given evidence of the poor nutritional quality provided by and the rate at which Americans are consuming meals at such establishments.

Second, the coefficient for grocery stores is expected to be statistically significant and negative. This would indicate that the obesity rate in a county with one more grocery store would be lower than the obesity rate in an otherwise identical county. This is the expected relationship because grocery stores offer healthier food for reasonable prices.

Finally, there is no definitive hypothesis for coefficient sign for supercenters or full-service restaurants. Previous literature offers mixed results, thus making predictions of their impact on obesity rates more difficult. Some evidence indicates that full-service restaurants offer poor nutritional-quality food, therefore implying a positive correlation with obesity rates. Other evidence indicates that full-service restaurants offer better quality food than fast-food restaurants, and could be considered "healthy" and obesity-reducing.

With a wide variety of control variables, this model isolates the role of food environment components on obesity rates. Additionally, this model expands on current research with county-level analysis. In this way, the results fill a gap in the literature, where there is no county-level analysis of the comprehensive role of the food environment on obesity rates. The model more accurately captures the interaction between the food environment components and obesity rates, producing more representative results than earlier studies.

Regression Analysis

Diagnostic testing of the initial regression of the original full model indicated the need for corrective measures. In addition to mild multicollinearity amongst a few variables (PovertyRate, PctAsian, Pct65, PctLIANC), an initial skewness and kurtosis test of normality on the model residuals indicates that they do not exhibit normal variance.[24] At first glance, this is problematic to the analysis, as normality is an essential assumption of Ordinary Least Squares regression analysis. The residuals fail to meet the normality threshold Chi^2 value (adjusted Chi^2 value of 12.92, well above the threshold level of 7). However, graphical representations of the model residuals demonstrate that the residuals appear to have normal distribution. Though the model's residuals do not fall under the normality threshold, they do very much resemble normal results. Given the use of county-level analysis, it seems unlikely for slight abnormality to arise from sample bias,

[24] For a full correlation matrix of all variables, see Table 6.2 in Appendix D.

which might suggest the non-normality is due to outliers.

In an attempt to rectify the non-normality of the model residuals, a newly specified model adjusts and tests the functional form. Though the majority of the variables are already represented as a percent, generating variables that reflect the food environment component variables in logarithmic (log) form allows for the coefficients to also be interpreted as percentages. The new model replaces all food environment component variables with the log form of that variable (ten in total), and maintains all other independent variables in their original, non-log form. Results of this regression with the food environment variables in log form are presented as Model 1 in table 5.1. The variables “logfsr”, “loggper1000”, and “logffrper1000” were omitted due to multicollinearity.

Model 2 restores the model’s sample size to over 2000 counties by eliminating “logs” and “logsper1000” variables representing prevalence of superstores in each county. The variables “logcper1000”, “loggper1000” and “logffrper1000” were omitted due to multicollienarity. After mild normality concerns with Model 2, a new Model 3 reintroduces food environment component prevalence variables in non-log form: “gs”, “cs”, “fsr”, and “ffr”. Model 3 retains variables reflecting food environment per capita in log form (i.e. logcper1000), while continuing to exclude variables reflecting superstore prevalence in order to maintain sample size. The following section provides a more in-depth discussion of these modifications.

TABLE 4.1

RESULTS FOR IMPACT ON OBESITY RATES

VARIABLE	Model 1	Model 2	Model 3
dr	0.918***	0.951***	0.807***
	(0.0592)	(0.0439)	(0.0415)
pctlowa	-0.00430	0.0273***	0.00472
	(0.0159)	(0.00980)	(0.00346)
pctlowia	0.0419	-0.0428*	
	(0.0410)	(0.0253)	
pctlowianc	-0.0535	-0.0981***	-0.0693**
	(0.0599)	(0.0339)	(0.0328)
frmktper1000	2.666	1.215	1.349
	(2.693)	(1.005)	(1.008)
expendpcff	-0.00372***	-0.00488***	-0.00456***
	(0.000985)	(0.000732)	(0.000734)
expendpcr	-0.00448***	-0.00519***	-0.00551***
	(0.000688)	(0.000529)	(0.000534)
pimtos	0.0587	0.135	0.865*
	(0.617)	(0.485)	(0.484)
pcthspa	0.108***	0.0928***	0.0802***
	(0.0281)	(0.0215)	(0.0217)
recfacper1000	-1.049	-1.406	-1.604*
	(1.663)	(0.860)	(0.865)
pctwhite	-0.00505	-0.0168*	-0.0134
	(0.0145)	(0.00916)	(0.00872)
pctblack	0.0324**	0.0211**	0.0240***
	(0.0142)	(0.00862)	(0.00849)
pcthisp	-0.0379***	-0.0413***	-0.0406***
	(0.0146)	(0.00925)	(0.00927)
pctasian	-0.0924*	-0.121**	
	(0.0526)	(0.0476)	
pct65	-0.248***	-0.227***	
	(0.0319)	(0.0229)	
pct18	0.0543	0.0570**	0.199***
	(0.0436)	(0.0269)	(0.0227)
medhi	2.16e-05	4.17e-06	3.62e-05***
	(1.75e-05)	(1.30e-05)	(9.24e-06)
povertyrate	-0.0286	-0.0114	
	(0.0290)	(0.0198)	
urban	-0.0879	-0.00991	0.115
	(0.187)	(0.136)	(0.130)
unemprate	-0.0470	-0.0882***	-0.0703***

TABLE 4.1 Continued			
	(0.0320)	(0.0225)	(0.0216)
pctcollegegrad	-0.178***	-0.178***	-0.187***
	(0.0167)	(0.0116)	(0.0114)
pctmarried	-11.68***	-7.219***	-14.99***
	(3.003)	(2.071)	(1.927)
population	-5.38e-07*	-6.10e-07**	-6.14e-06***
	(3.00e-07)	(2.66e-07)	(1.55e-06)
FFperFS	-1.293***	-0.223	-0.247
	(0.404)	(0.162)	(0.163)
loggs	-0.338*	-0.247**	
	(0.175)	(0.116)	
logs	0.253		
	(0.163)		
logcs	-0.734	0.266*	
	(0.576)	(0.149)	
logffr	0.876*	0.138	
	(0.497)	(0.194)	
logcper1000	1.297**		0.107
	(0.615)		(0.154)
logfsrper1000	-1.843***	-0.361*	-0.653***
	(0.506)	(0.205)	(0.222)
logfsr		-0.120	
		(0.266)	
gs			-0.00126
			(0.00135)
cs			0.00681***
			(0.00204)
ffr			0.00964***
			(0.00222)
fsr			-0.00550***
			(0.00108)
loggper1000			-0.402***
			(0.109)
logffrper1000			0.107
			(0.191)
logsper1000			
Constant	39.33***	37.24***	34.71***
	(2.890)	(1.942)	(1.683)
Observations	1,257	2,194	2,194
R-squared	0.750	0.741	0.734

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Source: author's calculations

Model 1

In addition to explaining approximately 75% of the variance in obesity rates at the county level, many of the variables in Model 1 are statistically significant with 95% or 99% confidence.[25] However, the results of Model 1 in Table 5.1 illustrate that the coefficient signs do not consistently match the anticipated results hypothesized from the review of relevant literature.

Results matching hypotheses. Variables that both match the expected coefficient sign and are statistically significant with at least 95% confidence are: adult diabetes rate, percentage of population that is Black, percentage of population with at least a college degree, full-service restaurants per 1000 people, and convenience stores per 1000 population. With the exception of full-service restaurants per 1000 people and population with at least a college degree, all of the aforementioned variables have a positive correlation to obesity rate. That is, unit increases for these variables are correlated with an increase in the obesity rate. In addition to statistical significance, the coefficients for these variables are also relatively large, indicating a strong relationship to obesity rate. The other two variables (full-service restaurants per 1000 population and percent of population with a college degree) are negatively correlated with obesity rates. This relationship implies that an increase in these variables would lead to a decrease in the obesity rate. For example, the model suggests the obesity rate in a county with 1% more full-service restaurants per 1000 population is approximately .35% lower than an

[25] Model 1 encompasses the original full model with slight functional form changes: the ten food environment component variables are in log form.

otherwise identical county. Again, these coefficients are large enough to assume the variables play an important role in obesity rates.

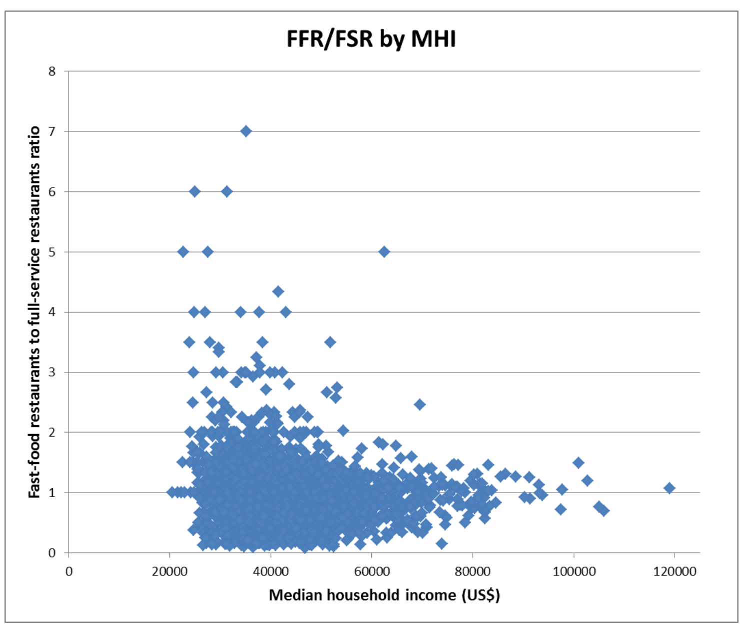
Results not matching hypotheses. The results of the model indicate that several variables are statistically significant, but carry coefficients with signs opposite of the anticipated results. These are: percent of high schoolers physically active, the ratio of fast-food restaurants to full-service restaurants, percent of population 65 years old or older, and the variables reflecting expenditures per capita at both fast-food and full-service restaurants.

Unanticipated results could be the result of report bias for percent of high schoolers physically active and expenditures per capita at fast-food and full-service restaurants. Due to stigmatization of obesity, individuals may feel inclined to report overestimates of time spent exercising, or underestimates of expenditures at restaurants on the surveys providing this data to the Food Environment Atlas dataset. Doing so could lead to regression results that do not accurately reflect the true relationship. Regardless, coefficients for the expenditure per capita variables are very close to zero despite being statistically significant. This suggests that while there is a relationship, the correlation is very small.

The coefficient signs for the other two variables, percent of population 65 years or older and the ratio of fast-food to full-service restaurants, are counterintuitive. While older age has often been considered a positive indicator of obesity, the negative coefficient on Pct65 might suggest that obesity is now more prevalent in the population younger than 65 years. For example, a county with a large population older than 65 years has a smaller population younger than 65 years, where perhaps obesity is more prevalent.

This could lead to a relatively low obesity rate and cause the negative coefficient on Pct65. Similarly, the unexpected large negative coefficient on the ratio of fast-food to full-service restaurants implies that where this ratio is higher, obesity rates are lower. This might be the result of fast-food restaurants being disproportionately more prominent than full-service restaurants in low-income areas, where obesity is low. Several studies have shown that fast-food and full-service restaurants are more prevalent in low- and medium-income census tracts (Morland, Wing, Diez Roux, & Poole, 2002; Powell et al., 2007; Shaffer, 2003). In areas of all other income levels, the ratios are likely similar to each and obesity rates are likely higher. Figure 4.1 demonstrates this hypothesized trend in the dataset: as median household income increases, the ratio of fast-food to full-service restaurants decreases.

Figure 4.1. Scatterplot illustrating the ratio of fast-food to full-service restaurants by county-level median household income.



Source: author's calculations.

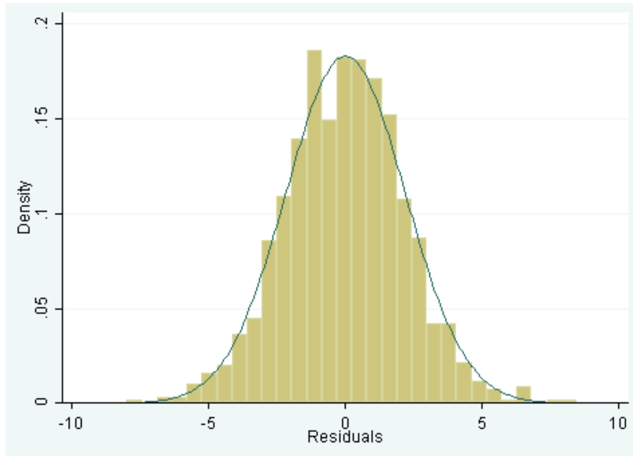
This relationship partially explains the negative coefficient on the ratio of fast-food to full-service restaurants.

Results for variables with uncertain hypotheses. Finally, two variables are statistically significant for which existing literature offers mixed results, making the coefficient sign difficult to predict: percent of population that is married, and percent of the population that is Hispanic. Perhaps the most shocking result of this analysis, the large negative coefficient on percent of population that is married is opposite of the anticipated and established relationship between married population and obesity rates. However, one study proposes a “social sorting” mechanism in marriage markets, in which individuals prefer thinner spouses, with higher incomes and wealth (Chiaporri, Oreffice, & Quintana-Domeque, 2012). This argument supports the findings of Model 1, in that counties with larger married populations would assumingly have fewer obese people and a negative relationship between the two variables.

Model qualities. After regressing this newly specified model, a normality test of the residual variance illustrates that the residuals now fall below the threshold for normal variance.[26] A normality histogram and a normality plot further establish the normality of the residuals (Figure 4.2 and Figure 4.3 respectively). Model 1 accounts for approximately 75% of the variance in county-level obesity rates across the United States. A Breusch-Pagan test failed to reject homoscedasticity of the residuals, upholding an essential assumption of OLS regression analysis.[27]

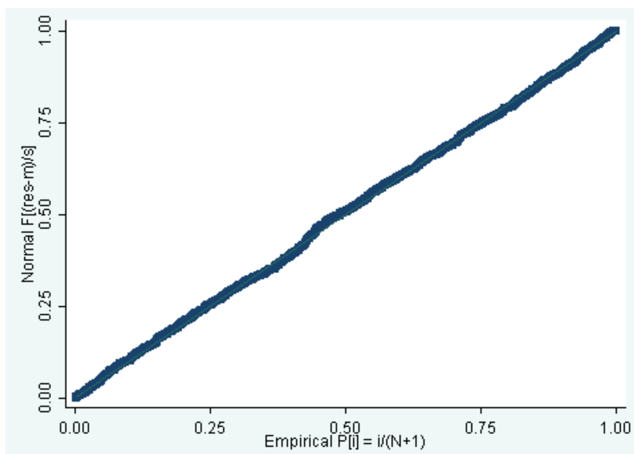
[26] Adjusted Chi^2 value for Model 1 is 5.02, which is under the normality threshold of 7.0.
[27] Breush-Pagan test Chi^2 value is .25, and therefore we cannot reject the null hypothesis of homoscedasticity of the model residuals.

Figure 4.2. Normality histogram of Model 1 residuals.



Source: author's calculations.

Figure 4.3. Normality plot of Model 1 residuals.



Source: author's calculations.

Like the normality histogram and plot for the full model, these figures demonstrate proximity to normal variance. The normality histogram of Model 1 does not appear to have the right-skew present in the normality histogram of the original full model, but there does appear to be a small inconsistency around the top of the bell-curve, where the distribution differs slightly from the normal curve. The normality plot also appears comparably proximate to the 45-degree line. There appear to be small deviations from the diagonal, however.

Though minor, the differences in the normality figures between Model 1 and the original full model could be due to the much smaller sample size for Model 1. In converting food environment component variables to the log form, a significant number of data points were lost. Data points that carried the value zero prior to conversion to log form are now undefined, and reported as missing data. A significant number of these data points were counties that had zero supercenters. Relatively few counties have the resources to sustain demand for a supercenter, and therefore with the transformation of these variables to log form, counties with a zero in any of the food environment component variables were excluded from analysis. In order to determine the impacts of the reduced the sample size resulting from excluding this significant portion of the data, an additional model is analyzed that removed the variables logs and logsper1000 (Model 2), restoring the sample size to over 2000 counties.

Model 2

The results of Model 2 are relatively comparable to the results of Model 1, as illustrated in Table 4.1. Variables that maintain approximate coefficient size and significance are:

- **DR**: adult diabetes rate,
- **ExpendpcFFR**: expenditures per capita at fast-food restaurants,
- **ExpendpcFSR**: expenditures per capita at full-service restaurants
- **PctHSPA**: percent of high schoolers physically active,
- **PctBlack**: percent of population that is Black,

- **PctHisp**: percent of population that is Hispanic,
- **Pct65**: percent of population that is 65 years or older,
- **PctCollegeGrad**: percent of population with at least a college degree, and
- **PctMarried**: percent of population that is married.[28]

Results differing from Model 1. Several variables are not statistically significant in Model 1, but are significant in Model 2. Though the coefficient is relatively small, percent of the population with low access (PctLA) is statistically significant and positively correlated with obesity rates as anticipated. Further, percent of population with low income, low access and no car (PctLIANC) is statistically significant and considerably negatively correlated with obesity rates. Together, these results suggest that while a larger population of low-access residents may increase obesity rates, a larger proportion of this population that is low income and without a car will have the opposite impact.

Next, the percent of the population that is Asian is statistically significant and negative, with a large coefficient indicating that the impact of this indicator is much stronger than that of the other races. Percent of the population 18 years or younger is statistically significant and positive in this model, potentially suggesting that the prevalence of obesity is in fact higher in the younger population, all else being equal. Population and the unemployment rate are significant and negatively correlated with obesity rates. While the coefficient on the population variable is very small, the model predicts a county with 500,000 more people will have obesity rates .3% lower than an

[28] The variable percent of population that is married (PctMarried) remains statistically significant and negative, but does decrease from -11.24 in Model 1 to -7.15 in Model 2, indicating a weaker impact on obesity rates.

otherwise identical county, a substantial difference. The statistically significant negative coefficient on unemployment rate might suggest that areas with higher unemployment rates have a larger population who can afford or access food, but may not be able to maintain an obesogenic lifestyle. This coefficient is relatively small, however, indicating that its role in obesity rates is not as strong as many other indicators such as percent of the population 65 years or older or population with a college degree.

Finally, the food environment component variable "loggs" representing grocery store prevalence is statistically significant and negative. Though interpretation of the coefficient units are not necessarily straightforward, these results are as hypothesized. For example, the results indicate that in a county with ten grocery stores, an additional grocery store will result in obesity rates approximately 2.5% lower than an otherwise identical county.[29]

Model qualities. While Model 1 explains approximately 75%, Model 2 explains approximately 74% of the variance in obesity rates at the county level across the United States. This implies that removing the variables reflecting supercenters did not detract much from the credibility and predictive abilities of the model. Further, this model is more comprehensive than Model 1 because of the significantly larger sample size. With nearly double the observations, the model is assumed to be much more reflective of obesity rate trends across United States counties.[30]

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[29] A 1 percent increase in grocery stores in a given county will lower obesity rates by .25% percent. Adding "one percent of a grocery store" is difficult to conceptualize, however, and is therefore more easily interpreted in terms of whole grocery stores having an effect on obesity rates by a scalar of the coefficient.

[30] Like the original full model, heteroskedasticity was ruled out using a Breusch-Pagan Test (P=.65).

There are a couple limitations of Model 2. First, a skewness and kurtosis test implies the residuals of this model are not normally distributed.[31] However, the residuals do appear normal in normality plots despite failing to meet the threshold for normality. Additionally, several food environment component variables are eliminated in Model 2 due to multicollinearity. Multicollinearity is to be expected between these variables, however, as demand for each is driven by population. For example, more convenience stores and grocery stores are demanded in larger counties and fewer are demanded in smaller counties. Thus, the data for the food environment components fluctuate in similar ways between counties of different sizes. Regardless, eliminating these variables from the analysis is counterproductive to understanding their dynamic in impacting county-level obesity rates. Ignoring multicollinearity, Model 3 reintroduces in their non-logged form the food environment component variables eliminated from Model 2.

Model 3

Results of analysis of Model 3 are not dramatically different from the results of either Model 1 or Model 2, as illustrated in Table 5.1. Median household income is now significant. The positive coefficient for median household income might suggest that as individuals have more financial flexibility, they can afford to consume and spend more on food, all else being equal, which could lead to higher obesity rates. Though the coefficient is very small, the obesity rate in a county with a median household income $1,000 higher would be .3% higher than an otherwise identical county. In addition, the variables representing full-service restaurant prevalence and full-service restaurants per

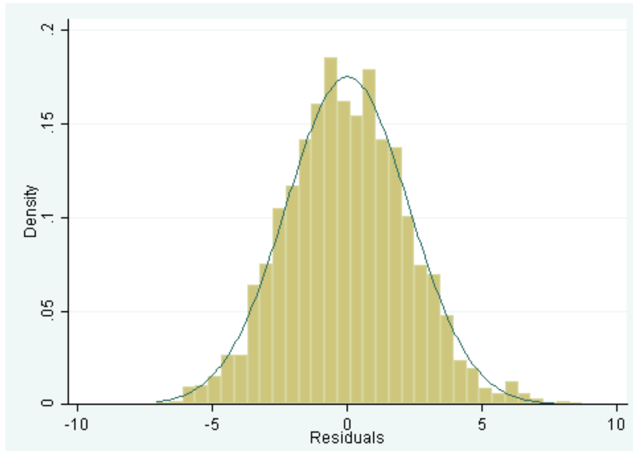
[31] The normality test Chi^2 value for Model 2 residuals is 7.43, which narrowly misses the normality threshold value of 7.0.

1000 population are significant.[32] Model 3 suggests that a county with 1% higher ratio of full-service restaurants per 1000 population has an obesity rate .65% lower than an otherwise identical county. Finally, variables representing convenience store and fast-food restaurant prevalence are both statistically significant and positive, while prevalence of full-service restaurants and the variable representing grocery stores per 1000 population are statistically significant and negative.

These results match the anticipated coefficient signs for these variables and support the hypotheses for the impacts of the various food environment components on obesity rates. A normality test of Model 3 results in Chi^2 value of 8.43, very close to but still above the threshold for residual normality. A normality histogram and plot indicate that the residuals very closely resemble a normal distribution, again suggesting that the non-normality may be the result of outliers as opposed to sample-bias (Figure 4.4 and Figure 4.5 respectively). A Breusch-Pagan test for heteroskedasticity fails to reject homoskedasticity in the error terms, preserving an essential assumption necessary for Ordinary Least Squares regression analysis.

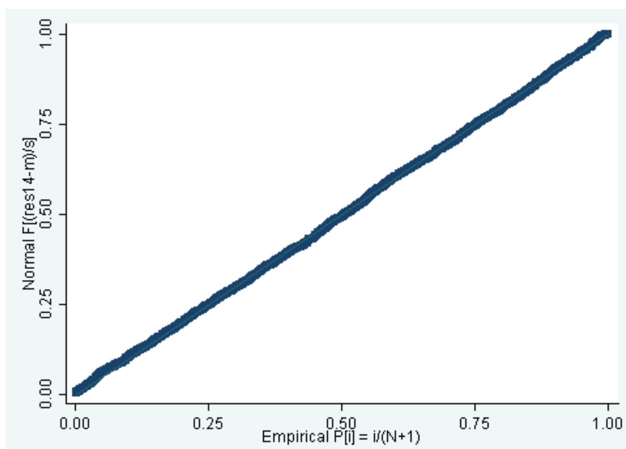
[32] Full-service restaurants per 1000 population was significant in Model 1, insignificant in Model 2 and significant again in Model 3. Coefficients for this variable are very similar between Model 1 and Model 3.

Figure 4.4. Normality histogram of Model 3 residuals.



Source: author's calculations.

Figure 4.5. Normality plot of Model 3 residuals.



Source: author's calculations.

Summary

Overall, the various food environment component variables are significant across the models. When they are significant, the coefficients reflect the anticipated relationships. Additionally, the coefficients are similar in magnitude between models, indicating that the coefficients accurately reflect their impact given our dataset. Finally, though the variables are significant, the relative sizes of the coefficients are relatively small. For example, the obesity rate in a county with one more convenience store or fast-food restaurant is predicted to be approximately .007% or .01% higher, respectively, than an otherwise identical county. The obesity rate in a county with 1% more full-service restaurants per 1000 people or with one more full-service restaurant is predicted to be .653% or .006% lower, respectively, than an otherwise identical county. This suggests other identifiers, such as percent of population with diabetes, with a college degree, married, or 18 years or younger, are stronger predictors of obesity than food environment components. Still, the establishment of the significance of food environment components on obesity is important.

Conclusion

According to the World Health Organization, the increasing prevalence of obesity on the international scale is now the most significant contributor to ill health (Caballero, 2005). Current efforts by communities and health and economic policy-makers attempt to address the obesity epidemic in the absence of a complete understanding of the dynamic between food environment and obesity levels. Providing a more comprehensive picture of the relationship may be the first step in determining the most efficient strategies for improving the health of United States communities and populations world wide.

While current literature establishes the relationships between community characteristics and various food environment conditions, few studies analyze the relationship between the increasing prevalence of obesity and the comprehensive food environment. This paper fills this gap and better establishes the relationship between obesity rates and food environment conditions at the county-level across the United States, using a model based on previously-established relationships. Limited findings from previous research helped shape the central hypotheses for the study. Primarily, fast-food restaurants and convenience stores are positively correlated with obesity rates, while grocery stores and full-service restaurants are negatively correlated with obesity rates.

Controlling for variables previously demonstrated to be significant predictors of obesity rates, a United States county-level dataset was constructed that included 35 demographic, food environment, and community characteristic variables. Data were primarily retrieved from the Food Environment Atlas. Data from other sources were streamlined to match, and counties without enough data were removed from the dataset. Ten variables reflect county-level food environment components.

To analyze and understand the relationship, a model was constructed based primarily off of that used in a study by Maddock in 2004. Several limitations of Maddock's model and analysis were improved upon in this study. First, through county-level analysis, this study provides a much more specific level of analysis. In addition to a larger and therefore more representative dataset, county-level analysis captures more variation in obesity rates due to geographic disparities. In addition, this study accounts for all fast-food restaurants, thereby accurately representing the impact of the fast-food industry as a whole. Finally, this study is comprehensive in that it accounts for the wide variety of food environment components impacting obesity rates. In this way, the study fills a gap in the literature and captures the specific role of each component on obesity rates.

The implications from the analysis are numerous. The previously-established relationships between obesity rates and predictors including diabetes rate, median household income, and race were confirmed. Many of these variables were significant and reflected the anticipated coefficients, indicating their importance in predicting obesity rates. Several predictor coefficients contradict previous research findings. For example, this study finds the percent of the population over the age of 65 to be significant and negatively correlated with obesity despite conclusions from previous research that the two share a positive relationship. Other variables generating unanticipated results include expenditures per capita at both fast-food and full-service restaurants, and percent of high schoolers physically active. While these results are presented in more depth in Section 5, it is important to note the discrepancy. It is possible that by analyzing obesity trends at a more specific and representative level, the model more accurately explains the relationship between obesity rate and these predictors.

In analysis of the central hypothesis, food environment components play a significant but complex role in explaining county-level obesity rates across the United States. Confirming the hypotheses, convenience store and fast-food restaurant prevalence are significant and positively correlated with obesity rates, while grocery stores and full-service restaurants are significant and negatively correlated with obesity rates. These findings are noteworthy and significant, in that they capture the individual role of food establishments at the county level while accounting for the complete food environment.

In context, these results have various applications. First, they suggest that current OECD operatives to reduce obesity via improving diets are reasonable. As opposed to promoting physical activity, improving diet quality may be a cost-effective strategy for lowering obesity rates. Of 24 recommended strategies for the prevention of obesity by the Center for Disease Control and Prevention, less than half directly address the food environment (Center for Disease Control and Prevention, Recommended Community Strategies and Measurements for Preventing Obesity in the United States, 2009). Results of this study suggest that strategies improving the food environment such as zoning laws could have dramatic impacts on obesity rates. In the case of zoning laws, prohibiting the establishment of fast-food restaurants would prevent the increase of the county's obesity rate by approximately .01% per restaurant. Additionally, strategies to balance obesity-increasing and obesity-reducing food environment components might also be effective. For example, counties could theoretically maintain obesity rate by establishing new grocery stores to counteract increases in obesity rate caused by new fast-food restaurants or convenience stores.

In addition to validating these strategies, the results of the model also suggest that the promotion of physical activity as a method for combatting obesity may not be the most effective method. For example, the number of recreation and fitness facilities per 1000 population was only a significant predictor of obesity at the 90% confidence level in Model 3. This suggests that establishing new facilities may not effectively achieve the desired results. This result further reinforces the importance of diet quality on obesity rates.

While these findings are exciting, there is room for improvement in the model and in the study. First, at its best, the model only accounts for approximately 75% of the variation in county-level obesity rates across the United States. Though this is a large portion, a hefty amount of the variation is unaccounted for. This implies that the model may be excluding several predictors that are important in the determination of county-level obesity rates. There is a well-established relationship between obesity rate and average family size in current literature. Unavailable county-level data for this predictor led to its exclusion from the model. Weak evidence of correlation to obesity rates excluded other predictors from this study. These variables include type of grocery stores, prevalence of liquor stores, and smoking habits. It is possible that their roles in explaining obesity rates are underemphasized in previous research, and inclusion in this model would indicate their significance. Identifying other predictors of obesity rate such as those discussed above would help to further specify this model such that the results reliably and accurately reflect the relationship between obesity rates and the predictors.

Next, genetic testing is rapidly increasing our understanding of the role of various genes on obesity rates. While dozens of genes have been associated with causing obesity, new studies continue to provide evidence. A clinical trial at Boston Children's Hospital found that a mutated gene associated with inability to burn fat calories in mice is also present in a group of obese study participants (Sifferlin, 2013). Further, a clinical study at the University College of London found a specific gene to specifically increase cravings for unhealthy foods (Sifferlin, 2013). While genetic heritability is unaccounted for in this model, future research may attempt to incorporate genetics by sampling populations for correlated genes to determine the relative impact of genetics on obesity rate.

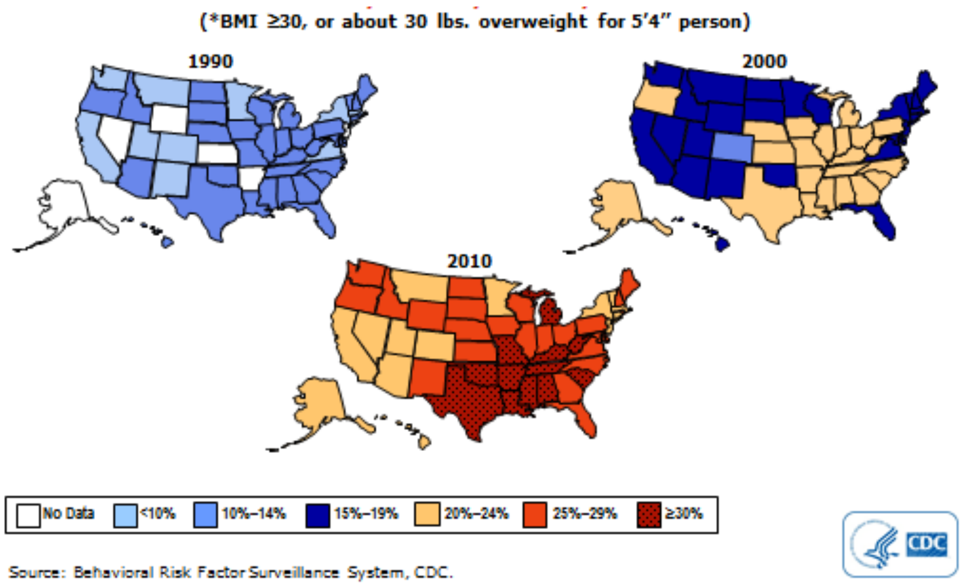
Finally, diagnostic testing of the models proved concerning to a small extent. Though the residuals of Model 3 graphically resemble normal distribution, the Chi^2 value was above the normality threshold. More careful examination of the data and diagnostic tests may improve the accuracy of the regression results while maintaining the assumptions of OLS analysis.

The model implemented in this study could be utilized in future research to understand the dynamics of various predictors on obesity rates. Additionally, the application of this model to other high-income countries may provide insight to the role of the food environment on community health. The results of this study provide significant and representative insight into the role of various food environment components in explaining county-level obesity rates. With new evidence and understanding, more effective policies and strategies can be implemented in the battle against the obesity epidemic.

Overall, this study fills an important gap in the literature. Though some previously established relationships are contradicted, this study concludes that the food environment components do play a significant but complex role on obesity rates across the United States. While the coefficients are small, the implications of the results are huge. With concrete evidence, effective health and economic policies may be implemented with the objective of lowering obesity rates.

APPENDIX A

Figure 6.1. Obesity rates across the United States between 1990 and 2010.

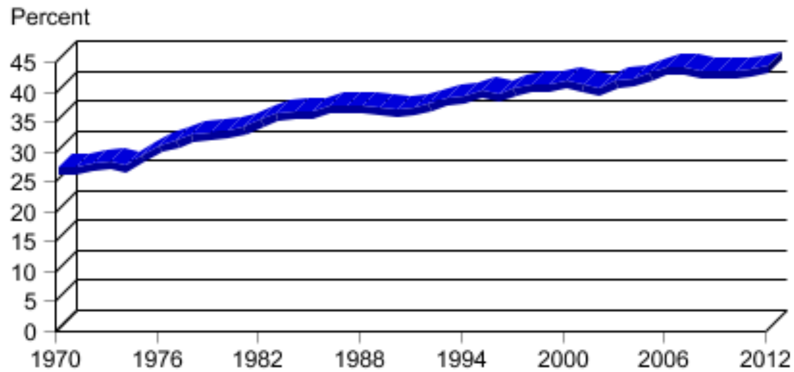


Source: Center for Disease Control and Prevention, Behavioral Risk Factor Surveillance System

APPENDIX B

Figure 6.2. Eating out expenditures as a share of household food expenditures between 1970 and 2012.

Food away from home as a share of household food expenditures has risen steadily since 1970, reaching its highest level of 43.1 percent in 2012



Food away-from-home expenditures divided by total food expenditures, for all families and individuals.

Total expenditures on food away from home include expense-account meals, food furnished to inmates and patients, and food and cash donated to schools and institutions. These items are not included in expenditures on food away from home for all families and individuals.

Source: Economic Research Service (ERS), U.S. Department of Agriculture (USDA), Food Expenditures
http://www.ers.usda.gov/data-products/food-expenditures.aspx

APPENDIX C

TABLE 6.1

COMPLETE SUMMARY STATISTICS

Variable	Count	Mean	Standard Deviation	Minimum	Maximum
OR	3138	30.55395	4.242072	13.1	47.9
DR	3138	10.71138	2.252997	3.3	19.4
CS	3138	39.1638	91.36109	0	2030
FFR	3138	68.90695	237.2122	0	7211
FSR	3138	72.38432	239.9401	0	7125
GS	3138	20.50701	84.81212	0	2117
S	3138	1.461759	3.4437	0	85
PctLA	3143	23.55933	20.25018	0	100
PctLIA	3143	8.374953	8.214988	0	72.27446
PctLIANC	3143	3.154496	3.207105	0	68.47041
GSper1000	3138	0.25926	0.2292617	0	3.095975
Sper1000	3138	0.015826	0.02121	0	0.24667
CSper1000	3138	0.598591	0.3141921	0	4.347826
FFRper1000	3138	0.561481	0.3021422	0	5.780347
FSRper1000	3138	0.773895	0.5933935	0	15.89595
ExpendpcFFR	3143	641.6179	96.64198	402.0978	1043.861
ExpendpcR	3143	624.5237	128.0708	371.8451	1930.156
MilktoSoda	3109	0.910495	0.1261585	0.637195	1.242792
FRMKETper1000	3137	0.035974	0.0701935	0	1.019888
PctHSPA	2506	24.22614	2.638785	17	27.8
RecFacper1000	3141	0.071338	0.0737543	0	0.62513
PctWhite	3143	78.2947	19.88815	2.667918	99.16318
PctBlack	3143	8.748643	14.42144	0	85.43878
PctHisp	3143	8.283674	13.19086	0	95.74477
PctAsian	3143	1.136731	2.469841	0	43.01469
Pct65	3143	15.88254	4.19021	3.470599	43.38472
Pct18	3143	23.41935	3.375268	0	41.57394
MedHI	3142	43144.87	10742.29	20577	119075
PovertyRate	3142	16.7612	6.24281	3.1	50.1
Urban	3143	0.371301	0.4832297	0	1
PctCollegeGrad	3143	19.76233	8.827307	3.2	74.4
PctMarried	3025	0.685698	0.0452653	0.29932	0.907303

Population	3143	98232.77	312901.2	82	9818605
FFperFS	3086	0.911464	0.6143429	0	9

Source: author's calculations.

Summary statistics for the dependent variable as well as independent variables.

APPENDIX D

TABLE 6.2

VARIABLE CORRELATION MATRIX

	OR	DR	CS	FFR	FSR	GS	S	PctLA	PctLIA	PctLIANC	Gper1000	Sper1000
OR	1											
DR	0.747	1										
CS	-0.1773	-0.1447	1									
FFR	-0.2344	-0.1889	0.905	1								
FSR	-0.2802	-0.2109	0.8487	0.9641	1							
GS	-0.1863	-0.1192	0.6326	0.8332	0.8251	1						
S	-0.1776	-0.18	0.8549	0.7813	0.7117	0.4447	1					
PctLA	-0.1421	-0.1952	-0.0195	-0.0255	-0.0252	-0.0547	0.0026	1				
PctLIA	0.0141	-0.0208	-0.0882	-0.0997	-0.1047	-0.0968	-0.0704	0.9027	1			
PctLIANC	0.4329	0.5352	-0.1855	-0.2103	-0.2115	-0.1598	-0.2053	0.0121	0.2009	1		
Gper1000	-0.0967	-0.043	-0.1097	-0.0469	-0.0299	0.0641	-0.1604	0.3324	0.2894	-0.0096	1	
Sper1000	0.0776	0.0256	0.0247	-0.0034	-0.0119	-0.0367	0.1676	-0.0857	-0.0658	-0.0388	-0.2521	1
CSper1000	0.1635	0.2483	-0.1675	-0.2133	-0.2131	-0.1668	-0.2108	0.1194	0.1743	0.1709	0.2099	-0.0828
FFRper1000	-0.231	-0.1832	0.1715	0.1937	0.1939	0.1278	0.1739	-0.01	-0.089	-0.1948	0.0025	0.1761
FSRper1000	-0.3791	-0.3201	-0.0363	-0.005	0.045	0.007	-0.0506	0.2559	0.1313	-0.169	0.3415	-0.0836
ExpendpcFFR	-0.0694	0.0823	0.0189	-0.0217	-0.0521	-0.0902	0.0464	-0.0145	0.0357	0.0316	-0.1469	0.0238
ExpendpcFSR	-0.4866	-0.3612	0.1631	0.1495	0.1757	0.1157	0.1254	0.0559	-0.0203	-0.166	0.0254	-0.078
PIMtoS	0.2237	0.401	0.1147	0.1041	0.1173	0.1451	-0.0003	-0.1307	-0.0921	0.2198	-0.0888	-0.0368
FRMKTper1000	-0.072	-0.098	-0.1025	-0.0864	-0.0738	-0.0548	-0.1083	0.0758	0.0239	-0.0075	0.1548	-0.0597
PctHSPA	-0.108	-0.1746	-0.0406	-0.0329	-0.0343	-0.0422	0.0073	0.1521	0.1514	-0.2078	0.0154	0.0007
RecFacper1000	-0.296	-0.2941	0.13	0.1446	0.1747	0.0955	0.1268	0.0027	-0.0975	-0.2483	-0.0543	0.0868
PctWhite	-0.1737	-0.1927	-0.2297	-0.2189	-0.1877	-0.1902	-0.1771	-0.0603	-0.2051	-0.2021	0.1171	0.0138
PctBlack	0.4357	0.4929	0.1352	0.1035	0.0715	0.0957	0.0754	-0.0989	0.0043	0.3936	-0.1081	0.0026
PctHisp	-0.2445	-0.2654	0.1387	0.1457	0.1378	0.1172	0.1332	0.12	0.181	-0.157	-0.0504	-0.0141
PctAsian	-0.3298	-0.3063	0.5029	0.5961	0.5876	0.5345	0.4374	0.014	-0.1022	-0.2469	-0.0986	0.0246
Pct65	-0.0438	0.2031	-0.2313	-0.2202	-0.1818	-0.1355	-0.2546	0.1556	0.1479	0.0389	0.3811	-0.12
Pct18	0.1684	-0.0194	0.057	0.0371	-0.0115	-0.0035	0.1134	0.0358	0.0898	-0.051	-0.151	0.0725
MedHI	-0.4823	-0.5676	0.2431	0.2836	0.2994	0.1852	0.2475	0.0802	-0.1965	-0.4824	-0.1062	-0.0282
PovertyRate	0.4663	0.5434	-0.0763	-0.1002	-0.121	-0.0456	-0.1009	-0.1191	0.1654	0.5628	-0.0511	0.0414
Urban	-0.1287	-0.1514	0.3632	0.3408	0.3301	0.2304	0.3654	-0.0393	-0.1552	-0.2047	-0.2604	0.0024
PctCollegeGrad	-0.6018	-0.589	0.3482	0.3943	0.4236	0.2689	0.3502	0.1419	-0.0656	-0.4198	-0.0017	-0.0011
PctMarried	-0.0803	-0.0881	-0.2209	-0.2337	-0.2461	-0.2119	-0.1456	0.0955	0.0237	-0.2039	0.0673	-0.0444
Population	-0.2277	-0.1867	0.9363	0.9829	0.9281	0.8077	0.8175	-0.0249	-0.1019	-0.21	-0.0673	-0.0022
FFtoFS	0.2309	0.2294	0.0621	0.0584	0.0068	0.0303	0.0731	-0.1764	-0.13	0.1294	-0.1928	0.1084

	CSper1000	FFRper1000	FSRper1000	ExpendPCFFR	ExpendPCFSR	PIMtoS	FRMKTper1000	PctHSPA	RecFacper1000	PctWhite	PctBlack
OR											
DR											
CS											
FFR											
FSR											
GS											
S											
PctLA											
PctLIA											
PctLIANC											
Gper1000											
Sper1000											
CSper1000	1										
FFRper1000	0.0456	1									
FSRper1000	0.2337	0.3857	1								
ExpendpcFFR	0.1273	0.0671	-0.1048	1							
ExpendpcFSR	-0.0513	0.0885	0.1723	0.3991	1						
PIMtoS	0.0704	-0.0057	-0.1883	0.2179	0.0232	1					
FRMKTper1000	-0.0395	-0.0528	0.15	-0.2055	-0.0146	-0.1519	1				
PctHSPA	0.0084	-0.0732	0.0834	0.1055	0.0525	-0.0907	-0.1246	1			
RecFacper1000	-0.1436	0.2031	0.1802	-0.1407	0.1024	-0.0826	0.1112	-0.0442	1		
PctWhite	-0.0712	-0.0385	0.1918	-0.4063	-0.1028	-0.3152	0.2201	-0.0442	0.1356	1	
PctBlack	0.1224	0.0017	-0.2351	0.1648	-0.0795	0.3671	-0.1487	-0.2682	-0.1196	-0.6348	1
PctHisp	-0.0044	0.0635	-0.007	0.4221	0.2247	0.0713	-0.1341	0.3186	-0.0626	-0.6024	-0.128
PctAsian	-0.26	0.2106	0.0024	-0.0346	0.177	0.1338	-0.0873	-0.0511	0.2123	-0.2009	0.07
Pct65	0.2378	-0.1376	0.2516	-0.1661	-0.0128	-0.0251	0.187	0.119	-0.0555	0.3694	-0.2478
Pct18	-0.0654	-0.0321	-0.2884	0.2092	-0.1471	-0.0793	-0.1816	0.046	-0.0759	-0.3706	0.074
MedHI	-0.3195	0.1652	0.1255	-0.0893	0.2344	-0.1276	0.0109	0.0031	0.3515	0.1949	-0.2531
PovertyRate	0.2143	-0.1107	-0.2583	0.2164	-0.1478	0.2793	-0.1255	-0.0982	-0.2978	-0.5307	0.4985
Urban	-0.3021	0.0994	-0.1519	0.0178	0.11	0.1005	-0.1575	-0.0978	0.1432	-0.0682	0.0956
PctCollegeGrad	-0.2651	0.3339	0.3003	-0.1149	0.2191	-0.0834	0.0406	-0.0145	0.4127	0.0591	-0.1205
PctMarried	0.0365	-0.1712	-0.0312	0.1613	-0.0406	-0.1211	0.0173	0.1933	-0.0794	0.3106	-0.4785
Population	-0.2247	0.1584	-0.0286	-0.0244	0.1608	0.1036	-0.092	-0.0248	0.1331	-0.221	0.0974
FFtoFS	-0.0303	0.3109	-0.4025	0.1702	-0.1128	0.1764	-0.1534	-0.1701	-0.0981	-0.2187	0.2959

	PctHisp	PctAsian	Pct65	Pct18	MedHI	PovertyRate	Urban	PctCollegeGrad	PctMarried	Population	FFtoFS
OR											
DR											
CS											
FFR											
FSR											
GS											
S											
PctLA											
PctLIA											
PctLIANC											
Gper1000											
Sper1000											
CSper1000											
FFRper1000											
FSRper1000											
ExpendpcFFR											
ExpendpcFSR											
PIMtoS											
FRMKTper1000											
PctHSPA											
RecFacper1000											
PctWhite											
PctBlack											
PctHisp	1										
PctAsian	0.1141	1									
Pct65	-0.1763	-0.3262	1								
Pct18	0.324	0.0349	-0.5595	1							
MedHI	-0.0142	0.4912	-0.3081	0.1429	1						
PovertyRate	0.1485	-0.2059	-0.0725	0.0458	-0.7827	1					
Urban	-0.0076	0.3829	-0.361	0.1199	0.4488	-0.2582	1				
PctCollegeGrad	-0.007	0.5873	-0.229	-0.0933	0.6904	-0.4876	0.3691	1			
PctMarried	0.1315	-0.2277	0.1806	0.3307	0.2171	-0.3763	-0.083	-0.216	1		
Population	0.1569	0.5807	-0.2215	0.0544	0.2864	-0.1043	0.3555	0.3768	-0.2114	1	
FFtoFS	0.0092	0.0435	-0.2782	0.1825	-0.0834	0.2279	0.1136	-0.1187	-0.0812	0.0544	1

Source: author's calculations.

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