An Analysis of the Relationship Between Food Deserts and Obesity Rates in the United States

By Katherine D. Morris

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Abstract

Defined as large geographic areas where residents have limited access to grocery stores, food deserts are thought to contribute to poor diets, especially among people with low incomes. In 2009, the Economic Research Service (ERS) at the United States Department of Agriculture (USDA) delivered a report to Congress that included the Food Desert Locator database, which provides a nationwide quantitative standard for categorizing a census tract as a food desert. In this study, I aggregate these data to the county level in order to conduct a cross-sectional analysis of the relationship between food desert intensity and obesity rates. I find that while there is a positive and statistically significant relationship between these two variables, the magnitude of this relationship is too small to have a compelling impact. These results suggest that the USDA's Food Desert Locator may have some promise as a nationwide measure, but they also suggest the need for additional testing and improvement in order to enhance the measure's utility as a guide for policymaking.

I. INTRODUCTION

Michelle Obama's "Let's Move" campaign to eliminate childhood obesity by 2030 has captured the attention of the public, the media, and lawmakers across the country. Pundits have given the first lady credit for securing the passage of the "Food Conservation and Energy Act of 2008" as well as the "Healthy Hunger-Free Kids Act of 2010" (Huber 2010; USDA ERS 2012b). The first lady's campaign has been so successful in part due to the widespread recognition of the problem of rising obesity rates. In 2008, 20 percent of children aged six through eleven were obese, compared to just 7 percent in 1980 (Centers for Disease Control 2012a). Obesity rates among older age groups are even higher, peaking at 31 percent among 45 through 64 year olds (Mendez 2010). Obesity also has a powerful effect on personal and public health-care costs. Compared to people of normal body mass index (BMI), obese people are estimated to have lifetime medical costs that are between 36 to 100 percent higher, and nearly 20 percent of current health-care costs in the United States are estimated to be obesity related (Hammond 2012).[1]

In addition, public health experts have noted that the segments of the population with the highest obesity rates have the lowest incomes and the least education (Drewnowski 2004). In investigating the relationship between poverty and obesity, scholars have begun analyzing the geographical distribution of healthy food (Clarke, Eyre, and Guy 2002; Whelan et. al. 2002; Wrigley 2002; Ver Plog 2010; Leete, Bania, and Sparks-Ibanga 2012). When residents of a local area have limited incomes and mobility, stores that sell healthy food are often scarce or difficult to access. Experts in the field have coined the term "food deserts" to describe areas with low access to healthy food that are often economically disadvantaged. The food desert phenomenon has gained so much visibility that "ensuring access to healthy food" has been incorporated as one of the five pillars of the Let's Move campaign (Let's Move 2011).

In light of these developments, this thesis seeks to determine whether food deserts can increase understanding about the causes of obesity. In this paper, I investigate whether food desert intensity is related to county obesity rates. My findings indicate that there is a positive and statistically significant relationship between these two variables. However, the magnitude of this relationship is quite small.

II. BACKGROUND

In 2009, in response to a federal directive to perform a year-long study of areas with limited access

[1] BMI is calculated by dividing weight in kilograms by height in meters and squaring the result. This measure serves as a simple and inexpensive approximation of body fatness that correlates with direct measures of body fat. The Centers for Disease Control (CDC) define weight categories based on BMI scores as follows: any score over 30 is considered obese, scores between 25 and 19.9 are overweight, scores between 18.5 and 24.9 are normal, and any score under 18.5 is underweight (2011).

to affordable and nutritious food, the United States Department of Agriculture's Economic Research Council (USDA ERS) delivered a report to Congress that included the *Food Desert Locator* database generated using a quantitative standard for categorizing census tracts as food deserts (USDA ERS 2012a).[2]

The USDA report, which was produced by the Healthy Food Financing Initiative (HFFI), defined a food desert as a census tract in which: a) at least 33 percent of residents live farther than one mile from a grocery store in urban areas or ten miles in rural areas and b) the poverty rate is 20 percent or higher and/or the median family income is 80 percent lower than the median family income for the surrounding area (USDA ERS 2012a).[3] Based on these standards, the HFFI identified 6,530 census tracts in the United States that fit its definition of a food desert. Almost 60 percent of US counties contain at least one food desert.[4]

[2] A census tract is a statistical area defined by the US Census Bureau. The areas are semi-permanent designations designed for use over time in order to be able to compare statistical data. Census tracts range between 1,200 and 8,000 people in population size.

[3] The HFFI is an inter-agency working group composed of members from the Treasury Department, the Agriculture Department, and the Department of Health and Human Services (Office of Community Services, 2011). In some smaller census tracts, if the percent of residents who live farther than the specified distance from a grocery store is above 33 percent, but the actual number of people is below 500, the tract is not classified as a food desert.

[4] This figure is calculated from the 3,138 US counties used in this study, which does not include counties in Puerto Rico or the five counties for which food desert and/or obesity data was unavailable.

The functional accuracy of the HFFI's categorization matters because it will affect how the debate over food access is framed and how the federal government allocates funds. For fiscal year 2013, the USDA requested $86.5 million in funding to combat food deserts through five different financial and technical assistance programs (USDA 2012). In concert with these USDA programs, in both 2011 and 2012 the Treasury Department's Community Development Financial Institutions Fund (CDFI) distributed 24 grants totaling $43.5 million to community enterprises and local lending institutions (The Reinvestment Fund 2012). The *Food Desert Locator* plays a large role in determining the geographical distribution of these grants and other assistance. Data from the *Food Desert Locator* database are made available to the public, in part to assist grant writers in making a case for their proposals (USDA ERS 2012).

Though finding that the *Food Desert Locator* is not predictive of obesity would not necessarily negate the underlying theory that access to grocery stores impacts health, it would highlight the constraints of the HFFI designation. Evaluating the validity of this metric is an especially important task since it directly impacts policy decisions. Along these lines, while the primary objective of this research is to evaluate the link between food deserts and obesity rates, a secondary goal of the study is to assess the utility of the *Food Desert Locator* as a guide for government funding decisions.

III. LITERATURE REVIEW

History of Food Desert Research

Despite the high level of public attention on food deserts, scholarly work on the subject is still developing. The first use of the term has been credited to British researchers analyzing food access in the United Kingdom during the early 2000s (Clarke et al. 2002; Whelan et al. 2002; Wrigley 2002). Later, as the concept began to gain traction in the United States, scholars used it as a framework to analyze food access at a local level. For example, the Mari Gallagher Research and Consulting Group (2006) found that Chicago census tracts with the least access to healthy food had the highest levels of health problems. Raja, Ma, and Yadav (2008) studied differences in food access between white and minority neighborhoods in Erie County, New York. Widener, Metcalf, and Bar-Yam (2011) studied how seasonal farmers markets relate to the distribution of food deserts in Buffalo, New York. Leete et al. (2012) compared several methods of defining food deserts in Portland, Oregon and found that more dispersed suburban areas also suffer from this problem despite the perception that food deserts are an inner city issue.

Food desert definition methodology has evolved over time, each study building on innovations from previous work. However, researchers have nonetheless used diverse criteria to define food deserts. As Leete et al. (2008) point out, each research team must decide on four basic criteria when creating a definition: the geographic unit of analysis, a definition of nutritious food, a geographical threshold for access to food, and a threshold for defining populations that are vulnerable to food-access limitations.

Comparison of Food Desert Definitions

The analysis by Raja et al. (2008) of Erie County and Widener et al.'s (2011) study of Buffalo both use census block data to identify food deserts. This approach allows for a relatively geographically precise definition of food deserts, as a census block is roughly analogous to a city block and is the smallest geographical area used by the Census Bureau (US Census Bureau 2011). Most other food desert studies use the census tract, which are larger statistical areas that have average populations of about 4,000 people, as their geographic unit of analysis (Ver Plog 2010; Leete et al. 2008).

The easiest method for defining access to nutritious food is to use large chain grocery stores as a proxy, since larger stores typically carry fresher and more diverse products. Both Ver Plog (2010) and Leete et al. (2008) use this approach. However, some researchers adopt a more fine-grained approach. For example, Widener et al.'s (2011) research team supplemented supermarket data with listings of seasonal farmers markets. A USDA research team (Mantovani et al. 1997) used a composite score based on the relative availability of the various foods in the government's "Thrifty Food Plan" sample basket. Raja et al. (2008) distinguished six categorizations of food retail store types. The Mari Gallagher Research and Consulting Group (2006) combined supermarket data with fast food restaurant data to create a food balance score, which attempts to capture access to healthy food relative to unhealthy food.

Researchers typically define thresholds for access to food either in terms of distance or travel time to healthy food retailers. Across all studies, the threshold for low access depends on urbanicity (USDA ERS 2012b). Standard distance for urban areas tends to be an approximately 15-minute walking time, though actual distances vary slightly based on the walking speed estimate that a given researcher assumes. Researchers' rural estimates vary more. Some studies use simple radial distance to a grocery store (Leete et al. 2008), whereas other studies calculate actual travel times based on available routes (Raja et al. 2008). Leete et al. (2008) also take into account that individual preferences may cause a family to forego the closest store for one that better meets their needs, and they use an average of the distance to the three nearest grocery stores as one of the three different measures of grocery store proximity in the study. Bader, Purciel, Yousefzadeh, and Neckerman (2010) point out that food access goes beyond distance to a grocery store; it can also be influenced by vehicle ownership, access to public transit, and neighborhood safety.

Food desert definitions differ greatly in their measurement of how vulnerable a community is to the problem of food access. Measures of economic resources such as income level (Ver Plog 2010; Leete et al. 2008) are the most commonly used measure of vulnerability, but race (Raja et al., 2008) and access to a car (The Reinvestment Fund 2012) have also been used as measures. However, some studies leave this dimension out of the analysis altogether (Widener et al. 2011; Mari Gallagher Research and Consulting Group 2006).

With such disparate ways of defining food deserts, results are difficult to compare across studies. However, the first numerically based, nationwide studies of food deserts in the United States may be starting to resolve this problem.[5] The HFFI created a standardized national database of food deserts at the census tract level based on income, population, and food retailer data (USDA ERS 2009). The HFFI defines households as having sufficient access to nutritious food if they are within a one-mile radius of a supermarket in urban areas and a

[5] The Food Conservation and Energy Act of 2008 mandated two studies of food deserts. This investigation relies on data from the first of these studies. A second major federal government report was produced by the Treasury Department's Reinvestment Fund (2012). This report defined "Limited Supermarket Access Areas" using census block groups. These areas were defined by combining census block data on income, car ownership data, and distance to a full service food retail store into a composite scale. The specificity of this measure allows for deeper analysis of patterns of food access within the report, but the opacity of the definition makes it less amenable to future application by other researchers.

10-mile radius in rural areas. They define economically vulnerable areas as census tracts with a poverty rate of 20 percent or higher and/or a median family income is 80 percent lower than the median family income for the surrounding area (USDA ERS 2009). Census tracts are classified as food deserts by the HFFI if they fall in the criteria for being economically vulnerable and a majority of the households within the census tract do not meet the criteria for having sufficient access to a supermarket.

Since the study of food deserts is still in its infancy, the majority of analysis of this topic focuses mainly on whether food deserts actually exist. Though some papers touch on why food deserts arise and their effects, this arena remains largely unexplored, especially at the national level. To help fill in this gap, the present investigation uses *Food Desert Locator* data to analyze the relationship between the concentration of food deserts and obesity using county-level data. In so doing, this study also evaluates the utility of the food desert categorization scheme created by the HFFI.

Additional Obesity Factors

Food deserts are one aspect of what public health researchers describe as the "built" food environment (Wright and Aronne 2012). The built food environment encompasses the structural aspects of the food retail market that encourage overeating such as increased portion size, increased calorie and fat content in foods, increased marketing of processed food products, and the food offerings at retail stores (Wright and Aronne 2012).

In addition to food deserts, there are several other factors that have been found to be associated with obesity. Notably, general health has several potential impacts on physical activity, which is closely related to obesity. Exercise is more difficult for people who are afflicted with incapacitating diseases. Heart disease, stroke, diabetes, and some forms of cancer are comorbid with obesity (Grundy 2000). Many of these conditions are likely mutually reinforcing (Ells et al. 2006). Furthermore, disability status and obesity are correlated. Thirty-six percent of adults with disabilities are obese, while 23 percent of adults without disabilities are obese (Centers for Disease Control 2012b). A number of common medications are also associated with increased weight gain (Wright and Aronne 2012). I control for general health factors in my model using three variables: mortality rate, years of potential life lost, and percentage of residents who report fair or poor health. Further description of these variables can be found in the data and methods section.

Demographic factors are also related to obesity rates. Economic circumstances can limit resources that could be devoted to purchasing and preparing healthy food, as healthy diets tend to be more expensive (Drewnowski and Specter 2004). Education levels have also been found to be correlated with obesity (Drewnowski and Darmon 2005). However, it is unclear whether this relationship is attributable to the income and social status benefits of additional education or if educational attainment directly improves dietary and exercise choices (Tai-Seale and Chandler 2010).

IV. CONCEPTUAL FRAMEWORK

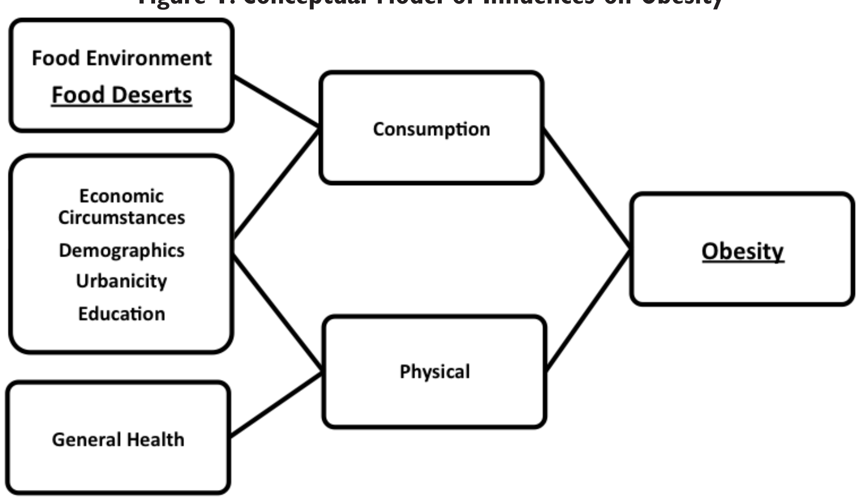
To understand the drivers of obesity rates at a macro level, factors related to individual weight gain must first be considered. The basic mechanism underlying weight gain is well understood: individuals gain weight when their calorie intake exceeds their calorie expenditure (Finkelstein, Ruhm, and Kosa 2005). However, reasons for calorie imbalance can be varied and diffuse. Any explanation of the causes of obesity must account for variation in calorie intake (called "consumption" in Figure 1 for simplicity) and calorie expenditure (called "physical activity" in Figure 1). The factors that influence obesity outlined in the literature review are diagramed in Figure 1. Controlling for these factors helps to reduce omitted variable bias in my regression analyses.

V. DATA AND METHODS

In this study, I estimate the association between county-level factors and obesity rates, focusing primarily on food deserts. In order to conduct this investigation, I used a cross-sectional county-level analysis. My data set contains information on 3,138 US counties and accounts for every county in the United States, with the exception of six counties for which data were not available.

A primary source of data for this study is the HFFI *Food Desert Locator*, maintained by the USDA's Economic Research Service. This dataset provides the numerator for my independent variable of interest, the number of people in a given county who live in a food desert. This variable was constructed by the HFFI using 2000 Census data on population

Figure 1. Conceptual Model of Influences on Obesity



characteristics and Supplemental Nutrition Assistance Program (SNAP) data on grocery store locations for the year 2006. Though these data are provided by the USDA at the census tract level, in order to match the observation level of my dependent variable, I sum the population of people living in food desert census tracts for each county and divide that sum by the population of the county.[6] Note that population and grocery store location measures within the *Food Desert Locator* are taken from different years. Since the availability of grocery stores is the most important dimension of the *Food Desert Locator*, whenever possible I use data from 2006 to measure the other variables in my model. The dependent variable for my regressions is the county-level obesity rate, taken from the Centers for Disease Control (CDC)'s *Diabetes Data and Trends* database for 2006.

Since rural residents tend to suffer from obesity more than urban residents (Tai-Seale and Chandler 2010), and the *Food Desert Locator* uses different standards of classification for rural and urban areas, I include a dummy variable for metropolitan counties in my regressions as a control.[7] This dummy variable is based on the USDA's most recent Rural-Urban Continuum codes from 2003. For simplicity, I took nine categories the USDA uses and collapsed them into a binary variable.[8]

To capture calorie expenditure, I include two control variables in the model: rate of physical inactivity and number of recreational facilities per person. The physical inactivity rate comes from the CDC's *Diabetes Data and Trends* for 2006. This variable reflects the proportion of negative responses to the question: "In the past month, outside of your regular job, have you participated in any physical activities or exercises such as running, calisthenics, golf, gardening, or walking for exercise?" The number of recreational facilities per person is taken from the USDA's *Food Environment Atlas* and reflects the number of establishments in the county that are primarily devoted to physical activity as defined by North American Industry Classification System (NAICS) code. While this variable does not capture how many people the facilities serve or how frequently, it gives an approximation of availability.

To capture other aspects of the food environment that are not included in the *Food Desert Locator*, I add the number of fast food restaurants per person and fast food expenditures per person as measured by the *Food Environment Atlas* (USDA 2012).[9] The *Food Environment Atlas* only provides the fast food expenditure data at the state level, so this aspect of the analysis is more vulnerable to measurement

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[6] The population figures used were census data averaged between the year 2000 and the year 2010.

[7] I also use this variable to divide the sample for a stratified analysis as shown in Table 2.

[8] Consistent with the Office of Management and Budget's delineation between metro and non-metro areas (USDA ERS, 2012), I collapsed codes one through three into the metro category and codes four through nine into the non-metro category.

[9] As these variables are highly correlated with the *Food Desert Locator*, I conducted a sensitivity test by estimating my model both with and without these variables.

error. Due to the high correlation of poverty and obesity (Chang and Lauderale 2005), I add the median income and the unemployment rate, averaged between the 2000 and 2010 Censuses, as control variables.

County-level controls for general health include the mortality rate, years of potential life lost (YPLL), and the percentage of residents who are in fair or poor health from the County Health Rankings and Roadmaps program.[10] The mortality rate is the number of deaths in the year 2011 for each county divided by its population. The YPLL variable is a measure of mortality where deaths occurring at younger ages are given greater weight to better capture premature deaths. The YPLL is generated by subtracting the age at which each death occurs from 75 (County Health Rankings and Roadmaps 2012). The fair or poor health measure reflects the percentage of residents who responded to a telephone survey, conducted by the CDC, by saying that, in general, their health is either "fair" or "poor" on a four-point scale.

I also use Census data to control for educational attainment. Education level is aggregated into four categories: "less than high school diploma," "high school diploma or equivalent," "some college," and "bachelor's degree or higher." These variables are expressed as percentages of the population age 25 and above, averaged between the 2000 and 2010 Censuses.

Since obesity rates vary systematically by age, I control for the median age of each county in the model (Mendez 2010). This variable is based on data averaged between the 2000 and 2010 Censuses.

I also include demographic controls for race in the model. Obesity rates in the US are consistently higher among blacks and Hispanics (Paeratakul et al. 2002; Cossrow and Falkner 2004), even when controlling for age, marital status, gender, employment, income, education, and region (Mendez, Newport, and McGeeney 2012). I construct race controls by averaging data from the 2000 and 2010 Censuses on the percentage of residents in each county who report being white, black or African American, another race, and Hispanic (regardless of race). Table 1 displays all the variables described above.

[10] The County Health Rankings and Roadmaps program is a non-profit collaboration between the Robert Wood Johnson Foundation and the University of Wisconsin Population Health Institute.

Table 1: Summary of Variables			
Variable	**Short Name**	**Source and Year**	**Unit of Measure**
Dependent Variable			
Obesity Rate	*Obesity*	CDC, 2006	The percentage of people with a BMI of 30 or greater living within a county during the year 2006.
Key **Independent Variable**			
Percent of People Living in a Food Desert	*Food Desert*	USDA Food Desert Locator, Mixed years	The number of people in each county living in census tracts that meet the USDA's definition of a food desert, divided by the county's population.
Urbanicity			
Metro Dummy (1= metro 0= nonmetro)	*Metro*	USDA, 2003	A dummy variable signifying whether the county is metropolitan (contains a census metropolitan statistical area) or non-metropolitan.
Physical Activity			
Rate of Physical Inactivity	*Physical Inactivity*	CDC, 2006	The percentage of people who report having no physical activity in the county.
Number of Recreational Facilities per 10,000 People	*Recreation*	Food Environment Atlas, averaged 2007 & 2009	Number of recreational facilities in the county per ten thousand county residents.
Food Environment			
Number of Fast Food Restaurants per Person[11]	*Fast Food Restaurants*	Food Environment Atlas, averaged 2007 & 2009	Number of fast food establishments in each county per ten thousand county residents.
Fast Food Expenditures per Capita	*Fast Food Expenditures*	Food Environment Atlas, averaged 2007 & 2009	State-level fast food expenditures per person.
Economic Factors			
Median Income	*Median Income*	Census data averaged for 2000 & 2010	County-level median income.
Unemployment Rate	*Unemployment*	Census data averaged for 2000 & 2010	Percent of people in the county labor force without a job.
General Health			
Mortality Rate[12]	*Mortality*	County Health Rankings, 2011	Number of deaths in the county for the year 2011 per thousand county residents.
Years of Potential Life Lost	*YPLL*	County Health Rankings, 2011	Number of deaths weighted to emphasize premature deaths. The measure is created by subtracting the age at which death occurs from 75.
Percent with "Fair" or "Poor" Health	*Fair/Poor Health*	County Health Rankings, 2011	Percent of county residents that self-report fair/poor health.

Table 1 Continued			
Variable	**Short Name**	**Source and Year**	**Unit of Measure**
Demographics			
Percent with less than high school diploma	*High School*	Census data averaged 2000 & 2010	The percentage of people in the county over 25 who have not completed high school or an equivalent (ex: General Education Development diploma).
Percent with High School Diploma or Equivalent	*Less than High School*	Census data averaged 2000 & 2010	The percentage of people in the county over 25 with a high school diploma or the equivalent and nothing more.
Percent with Some College	*Some College*	Census data averaged 2000 & 2010	The percentage of people in the county over 25 who have completed some college (including Associates degree holders) but do not have a four-year degree.
Percent with a BA or Higher	*BA Plus*	Census data averaged 2000 & 2010	The percentage of people in the county over 25 who hold a Bachelor's degree or higher.
Median Age	*Age*	Census data averaged 2000 & 2010	Median age in the county.
Percent White	*White*	Census data averaged 2000 & 2010	The percentage of people living in the county who self-report as White.
Percent Black	*Black*	Census data averaged 2000 & 2010	The percentage of people living in the county who self-report as Black.
Percent Other Race	*Other Race*	Census data averaged 2000 & 2010	The percentage of people living in the county who self-report to be a race other than Black or White (category includes Native Alaskan or American Indian, Asian, American Indian, Pacific Islander, another race, or two or more races).
Percent Hispanic (Any Race)	*Hispanic*	Census data averaged 2000 & 2010	The percentage of people living in the county who self-report as Hispanic regardless of race.

[11] This variable is at the state level.
[12] Mortality rate adjusted to give more weight to deaths occurring at younger ages.

Table 2. Summary Statistics Disaggregated by Food Desert Presence				
Variable		All Counties	Counties with Food Desert(s)	Counties without Food Desert(s)
Number of Observations		3,138	1,847	1,291
Variable of Interest				
People Living in a Food Desert per 10,000 County Residents	Mean	0.678	1.153	0
	s^2	1.805	2.234	0
	Min	0	0.0067	0
	Max	31.153	31.153	0
Dependent Variable				
Obesity Rate	Mean	27.46	27.42	27.51
	s^2	3.57	3.76	3.28
	Min	12.6	12.7	12.6
	Max	41.9	41.8	41.9
Urbanicity				
Non-Metro Dummy	Mean	0.653	0.617	0.704
(1= non-metro, 0=metro)	s^2	0.476	0.486	0.457
	Min	0	0	0
	Max	1	1	1
Physical Activity				
Physical Inactivity Rate	Mean	25.51	25.27	25.86
	s^2	5.28	5.21	5.37
	Min	9.4	9.4	11.4
	Max	43.8	43.4	43.8
Number of Recreational Facilities per 10,000 people	Mean	0.87	0.86	0.88
	s^2	0.87	0.78	1
	Min	0	0	0
	Max	13.78	9.98	13.78
Food Environment				
Number of Fast Food Restaurants per 10,000 People	Mean	5.92	5.96	5.86
	s^2	3.12	3	3.29
	Min	0	0	0
	Max	63.64	63.64	37.9
Fast Food Expenditures per Capita	Mean	641.78	644.05	638.55
	s^2	96.68	96.89	96.32
	Min	402.1	402.1	402.1
	Max	1043.86	1043.86	1036.48
General Health				
Deaths per 1,000 people	Mean	12.9	12.96	12.81
	s^2	3.42	3.38	3.47
	Min	0	4.36	0
	Max	30.09	30.09	26.43

Table 2 Continued				
Variable		**All Counties**	**Counties with Food Desert(s)**	**Counties without Food Desert(s)**
Years of Potential Life Lost Per Person	Mean	8382	8517.9	8187.6
	s^2	2491.5	2485	2488.8
	Min	0	2794.9	0
	Max	24829.4	24829.4	23605
Percent with "Fair/Poor" Health[14]	Mean	17.09	17.34	16.71
	s^2	5.7	5.43	6.04
	Min	2.1	3.5	2.1
	Max	44.8	40.7	44.8
Economic Factors				
Median Income	Mean	39,820	38,929	41,096
	s^2	10,076	9,814	10,309
	Min	17,578	18,223	17,578
	Max	98,111	93,233	98,111
Unemployment Rate	Mean	5.48	5.8	5.03
	s^2	2.18	2.19	2.09
	Min	0	0	0
	Max	20.6	20.6	20.25
Demographics				
Less than High School Diploma	Mean	18.12	18.32	17.83
	s^2	7.64	7.52	7.81
	Min	2.02	4.43	2.02
	Max	55.73	55.73	45.73
High School Diploma	Mean	34.83	34.02	35.98
	s^2	6.73	6.76	6.52
	Min	9.75	11.98	9.75
	Max	55.81	52.69	55.81
Some College	Mean	28.61	28.81	28.33
	s^2	5.54	5.45	5.65
	Min	12.23	12.76	12.23
	Max	48.43	48.43	45.04
Bachelor's Degree or Higher	Mean	18.44	18.85	17.86
	s^2	8.37	8.46	8.22
	Min	5.14	5.62	5.14
	Max	69.32	57.31	69.32
Median Age	Mean	38.84	38.42	39.43
	s^2	4.47	4.75	3.97
	Min	20.95	21.65	20.95
	Max	56.95	55.1	56.95

Table 2 Continued				
Variable		**All Counties**	**Counties with Food Desert(s)**	**Counties without Food Desert(s)**
Percent White	Mean	83.66	81.06	87.38
	s^2	16.65	17.34	14.82
	Min	3.7	3.7	3.7
	Max	99.3	99.3	99.2
Percent Black	Mean	8.83	10.49	6.46
	s^2	14.49	15.74	12.09
	Min	0	0	0
	Max	86.1	86.1	81.05
Percent Other Race	Mean	7.5	8.44	6.15
	s^2	10.2	10.52	9.58
	Min	0.45	0.45	0.7
	Max	96.2	96.2	96.15
Percent Hispanic (regardless of race)	Mean	7.24	8.45	5.52
	s^2	12.55	14.21	9.45
	Min	0.1	0.1	0.2
	Max	96.6	96.6	91.3

Using these variables, I estimate the following model:[13]

$$\textit{Obesity Rate} = \beta_0 + \beta_1 \textit{Food Desert} + \beta_2 \textit{Metro} + \beta_3 \textit{Physical Inactivity} + \beta_4 \textit{Recreation} + \beta_5 \textit{Mortality} + \beta_6 \textit{YPLL} + \beta_7 \textit{Fair/Poor Health} + \beta_8 \textit{Fast Food Restaurants} + \beta_9 \textit{Fast Food Expenditures} + \beta_{10} \textit{Unemployment} + \beta_{11} \textit{Median Income} + \beta_{12} \textit{Less than HS} + \beta_{13} \textit{HS} + \beta_{14} \textit{BA Plus} + \beta_{15} \textit{Age} + \beta_{16} \textit{White} + \beta_{17} \textit{Black} + \beta_{18} \textit{Hispanic} + u$$

Because the dependent variable is a continuous measure and my data are cross-sectional, I use ordinary least squares to estimate my regression model. Inclusion of the control variables specified above reduces the

[13] The variables "Some College" and "Other Race" are omitted from the model in order to avoid multicollinearity and serve as the reference groups for educational attainment and race, respectively.

[14] Data on the years of potential life lost and percentage of residents reporting fair or poor health were missing for 401 counties, and data on the number of deaths per 1000 people were missing for 95 counties. I imputed values for these missing variables in order to include these counties in my regression. I performed imputations by regressing each variable with missing values on the obesity rate, physical inactivity rate, poverty rate, median income, unemployment rate, education variables, percent age 60 or over, median age, percent white, percent black, and percent married, and I used the results of the regressions to produce predicted values for the missing data. A t-test showed that the mean of these imputed values was significantly different from the non-imputed values. Furthermore, a series of t-tests showed that there were significant differences in population size, median age, obesity rates, poverty rates, and racial composition between counties for which years of potential life lost were imputed and counties for which years of potential life lost were not imputed. See Appendix E for a representative selection of these analyses. I also conducted a sensitivity test by performing the regression analysis with and without the imputed values, and the results for the key independent variable were similar in both samples. See Appendix C for the results of the regression without imputed data.

amount of omitted variable bias in my estimate of the relationship between food deserts and obesity rates.

VI. DESCRIPTIVE ANALYSIS

Table 2 presents summary statistics for the variables included in the regression model, disaggregated according to whether counties contain food deserts. Counties with one or more food deserts account for 1,847 of the 3,138 counties, or 59 percent, used in this analysis. Contrary to expectation, obesity rates are similar between the two groups. Using a simple correlation analysis, the results of which are reported in Appendix A, I find that there is a small but statistically significant correlation between obesity rates and food desert intensity ($r = 0.0728$; $p=0.0000$).

Additionally, average values for the control variables for physical activity are very similar between the two groups. The rate of self-reported physical inactivity differs by only 0.59 percentage points between counties with food deserts and those without. The number of recreational facilities per 10,000 people is similar, but counties without food deserts have a higher variance.

The variables measuring general health differ a bit more between counties with food deserts and those without. The most striking difference is between the Years of Potential Life Lost: residents of counties containing food deserts tend to die at younger ages. Additionally, the number of residents who self-report being in fair or poor health is also higher in counties containing food deserts.

Counties without food deserts have higher median incomes and lower rates of poverty, unemployment, and food insecurity. Differences in education rates between the two groups of counties are almost non-existent. Racial composition differs notably between counties with food deserts and those without. Non-white racial groups disproportionately live in counties containing food deserts and whites disproportionately live in counties without any food deserts. Furthermore, the results reported in Appendix A show statistically significant correlations between food desert intensity and each of the racial composition variables. This finding is consistent with the results of other studies on the racial dynamics of food deserts (Raja et al. 2008).

VII. REGRESSION RESULTS

I estimated five ordinary least squares (OLS) regressions of the county-level obesity rate on the percentage of county residents living in a food desert and the aforementioned county-level controls. Table 3 displays the results of these regressions. The first model is the simplest, controlling for urbanicity, general health, education rate, and demographic factors. Model one is estimated without controls for median income and the unemployment rate because they are, to some extent, mechanically correlated with the food desert measure. However, since the correlation between poverty and

Table 3. OLS Regression Results

Variables	(1) All Counties	(2) All Counties	(3) All Counties	(4) Metro Counties	(5) Non-metro Counties
Variable of Interest					
Food Desert Rate	0.0214***	0.0224***	0.0222***	0.0358**	0
	(0.006)	(0.006)	(0.006)	(0.015)	(0.003)
Urbanicity					
Non-metro	-0.2728*	-0.2678*	-0.0671		
	(0.148)	(0.156)	(0.156)		
Physical Activity					
Physical Inactivity			0.2251***	0.2272***	0.2077***
			(0.032)	(0.039)	(0.021)
Recreational Facilities			-0.3561**	-0.6758**	-0.1635*
per 10,000 Residents			(0.175)	(0.322)	(0.085)
Food Environment					
Fast Food Restaurants			0.0176	0.0649	0.0117
per 10,000 Residents			(0.046)	(0.071)	(0.026)
Fast Food Expenditures			-0.0001	0.0001	-0.0057***
per Capita			(0.001)	(0.001)	(0.001)
Economic Factors					
Unemployment Rate		-0.0803	0.0654	0.0603	0.0753**
		(0.075)	(0.074)	(0.121)	(0.037)
Mean Income in Thousands		0.0053	0.003	0.0139	-0.0374**
		(0.012)	(0.013)	(0.015)	(0.015)
General Health					
Deaths per 1,000 Residents	0.0425	0.0592	-0.0499	-0.058	-0.0102
	(0.120)	(0.121)	(0.118)	(0.207)	(0.069)
Years of Potential Life Lost	0	0	0.0001	0	-0.0001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Fair/Poor Health Rate	0.0726**	0.0777***	-0.0145	-0.0326	0.0498***
	(0.029)	(0.028)	(0.029)	(0.046)	(0.018)
Demographics					
Less than High School	-0.0054	-0.007	-0.0448	-0.0055	-0.0557***
	(0.030)	(0.030)	(0.030)	(0.045)	(0.018)
High School	0.032	0.0297	-0.0491*	-0.0461	-0.0375**
	(0.023)	(0.023)	(0.025)	(0.039)	(0.017)
BA Plus	-0.1972***	-0.2066***	-0.2203***	-0.2175***	-0.2025***
	(0.023)	(0.026)	(0.025)	(0.032)	(0.024)
Median Age	-0.3351***	-0.3440***	-0.2705***	-0.3078***	-0.1194***
	(0.042)	(0.045)	(0.047)	(0.071)	(0.024)

Table 3 Continued					
	(1)	(2)	(3)	(4)	(5)
Variables	**All Counties**	**All Counties**	**All Counties**	**Metro Counties**	**Non-metro Counties**
Percent White	0.0740***	0.0728***	0.0687***	0.0878***	-0.0204**
	(0.012)	(0.012)	(0.014)	(0.017)	(0.009)
Percent Black	0.1247***	0.1267***	0.1003***	0.1092***	0.0632***
	(0.014)	(0.014)	(0.014)	(0.020)	(0.009)
Percent Hispanic	-0.0975***	-0.0970***	-0.0845***	-0.0921***	-0.0591***
	(0.016)	(0.016)	(0.016)	(0.021)	(0.008)
Constant	34.0692***	34.6485***	32.5298***	31.4318***	39.5540***
	(2.405)	(2.551)	(3.181)	(4.074)	(1.939)
Observations	3,138	3,138	3,138	1,090	2,048
R-squared	0.739	0.74	0.759	0.762	0.676

Robust standard errors are in parentheses. Significance: * p<0.10, ** p<0.05, *** p<0.01

obesity has been well established, leaving these variables out of the model may cause omitted variable bias. The first two models also omit the control variables for physical activity and food environment. These categories are omitted in part as a basic robustness check and in part due to the fact that the number of recreational facilities per 10,000 people and the number of fast food restaurants per 10,000 people vary strongly by metropolitan status, which is a key component of the food desert measure.[15] The third model adds physical activity and food environment control variables. The fourth and fifth models include the same variables as model three but divide the sample into metro and non-metro counties. I estimate each of these models with analytic weights for county population size, and I report robust standard errors for all coefficients.

In the first three models, the coefficient on the percentage of county residents living in a food desert per county is positive, of consistent magnitude, and statistically significant at the 99 percent level. This finding supports my hypothesis that the prevalence of food deserts has a positive relationship with obesity rates by county. It is important to note that the inclusion of control variables for economic factors, physical activity, and food environment have no meaningful impact on the coefficient of interest, which provides evidence for the robustness of the results. However, the magnitude of the coefficient is quite small. In models one through three, an increase of one percentage point in the proportion of county residents living in a food desert is associated with an increase of about 0.02 percentage points in the obesity rate. Since the average obesity rate across all counties

[15] Appendix D shows t-tests for the means of the variables measuring the number of recreational facilities per 10,000 people and the number of fast food restaurants per 10,000 people. Both variables differ significantly between metro and non-metro areas (p<0.0001), with metro areas having higher concentrations of both types of establishments per person.

is about 27 percent, this estimated relationship has little meaningful impact on the prevalence of obesity.

The results reported in columns four and five—in which the sample is divided into metro and non-metro counties—add greater insight. In the sample of metro counties, the coefficient on the percentage of county residents living in a food desert per county increases to 0.0358 and remains statistically significant. Meanwhile, the main coefficient of interest in the model of non-metro counties falls to less than 0.0001 and is not statistically significant.

VIII. SENSITIVITY TESTS

When the model is estimated without weights as reported in Appendix B, the estimated coefficients on the independent variable of interest are reduced in significance and magnitude. This is likely another reflection of the differences between metro and non-metro areas. In the weighted model, less populous counties, which are more likely to be non-metro, would be counted more.[16] As shown in models four and five in Table 3, the magnitude of the relationship between food deserts and obesity is weaker in non-metro counties. A sensitivity test of the influence of my missing data imputations on the results can be found in Appendix C. When observations with imputed data are removed from the sample, the main coefficient of interest remains significant and retains the same sign, but increases slightly in magnitude.

There are three key takeaways from these regression results. First, the main coefficient of interest is positive, robust, and significant. Second, the magnitude of this coefficient is small, which has implications for the central hypothesis of this thesis. Third, the food desert measure is more predictive of obesity rates in metro areas than in non-metro areas. These three findings each have relevant implications for policymaking, which are elaborated upon in the next section.

IX. DISCUSSION

The results of this study suggest that food desert intensity is unpredictive of obesity rates in non-metro counties and only very slightly predictive of obesity rates in metro counties. In metro counties, the regression models show that an increase of one percentage point in the proportion of county residents living in a food desert is associated with less than a tenth of a percentage point decrease in the obesity rate. Since the average obesity rate in the United States is about 30 percent, this finding suggests that food desert intensity does not impact obesity rates in a meaningful way.

These findings also have implications for the secondary purpose of this study, which is to evaluate the usefulness of the United States Department of Agriculture (USDA) *Food Desert Locator* as a metric. As one of the first nationwide food desert classification

[16] Appendix D displays a t-test of the statistical difference between populations in metro and non-metro counties.

schemes, the *Food Desert Locator* will influence the way policymakers, scholars, and the public think about food deserts. This measure will also play a role in the distribution of millions of dollars of grants. The insubstantial county-level correlation between the concentration of food deserts and obesity rates casts some doubt on the usefulness of the measure. While predicting obesity rates is not the only purpose of identifying food deserts, it is one of the central outcomes relevant for policy change.

The findings of this study should, however, be appreciated in context of its limitations. Although the *Food Desert Locator* is classified at the census tract level, I am compelled to aggregate the food desert data to the county level because that is the observation level of the obesity data. Therefore, I can evaluate the relationship between food desert intensity and obesity rates, but I cannot directly compare obesity rates between food deserts and non-food deserts. A study conducted at the census tract level rather than at the county level would produce more precise results.

Although the model of obesity presented in this paper outlines some of the main contributors to obesity rates, many of the concepts included are difficult to measure precisely. The proxies included in the model are the best data available to measure these factors, but they are not exact reflections of the dynamics that they are intended to measure. For example, the number of recreational facilities per 10,000 people is used as a proxy for physical fitness levels in each county. However, this variable is influenced by income levels, the real estate market, and urban planning strategies. The same could be said for the number of fast food restaurants per 10,000 people.

In addition, some food desert experts might argue that the research question at hand is overly ambitious. Obesity is influenced by a number of factors, including physical activity, general health, and genetics, all of which are difficult to measure and control for in a regression model. Obesity would be a more distal effect of the presence of food deserts than other concerns such as the healthfulness of food consumed and the amount of time spent procuring healthy food. These proximate effects of living in a food desert also have policy relevance, and their relationships with food desert presence might be easier to observe—especially in the short run—than second-order health outcomes such as obesity. This investigation seeks to understand the relationship between these two factors due to steadily climbing obesity rates and the health and policy problems this phenomenon creates, but a study of the more proximate predicted effects of food deserts might yield more robust correlations.

Despite these limitations, there are a number of ways in which the findings of this study can inform policymaking with regard to food access problems. Even if food deserts were definitively found to have no influence on obesity rates, systematic low access to healthy food would still pose a policy problem.

There are a number of other health outcomes that are affected by a poor diet, including diabetes, heart disease, and stroke. The fact that low-income individuals disproportionately suffer from the problem of limited food access, even when poverty measures are not included in food desert measures, is an indication that food deserts deserve further attention.

The most fundamental recommendation for further research involves the testing and improvement of food desert classification systems. The differing results for metro and non-metro areas in this study provide a good starting point for further investigation of food desert measure validity. Though the *Food Desert Locator* has different threshold distances from grocery stores for rural and urban areas, the USDA should consider amending these thresholds or adding another dynamic to the measure that varies between rural and urban areas. A more thorough food retail store classification system, like the one that Raja et al. (2008) use, could provide a model for more precisely capturing differences in food retail environments between rural and urban areas.

A valid, standardized, and nationwide food desert classification system would help to make regional academic studies of food deserts more comparable and would serve as a critical tool for policymakers and grant writers seeking to address the problem of limited food access. The creation of the *Food Desert Locator* was a valuable step forward in creating a useful and uniform metric of food deserts nationwide. Further investigation and improvement of this database would increase understanding of the phenomenon of food deserts and would better guide efforts to solve the problems that they create.

Appendix A. Bivariate Analysis

Variable	Correlation with Percent of People Living in a Food Desert
Obesity Rate	0.0728
	(0.0000)
Physical Inactivity Rate	0.0214
	(0.2312)
Mortality Rate	0.1536
	(0.0000)
Years of Potential Life Lost	0.1609
	(0.0000)
Median Income	-0.3385
	(0.0000)
Unemployment Rate	-0.0617
	(0.0005)
Percent White	-0.1123
	(0.0000)
Percent Black	0.0711
	(0.0001)
Percent Hispanic	0.075
	(0.0000)
Percent Other Race	0.0824
	(0.0000)

Appendix B. Unweighted Regression Results

Variables	(1) All Counties	(2) All Counties	(3) All Counties	(4) Metro Counties	(5) Non-metro Counties
Variable of Interest					
Food Desert Rate	0.0022	0	0.0016	-0.0022	0.0012
	(0.002)	(0.002)	(0.002)	(0.005)	(0.002)
Urbanicity					
Non-metro	-0.0757	-0.2445**	-0.1191		
	(0.100)	(0.108)	(0.097)		
Physical Activity					
Physical Inactivity			0.2625***	0.2225***	0.2642***
			(0.014)	(0.025)	(0.016)
Recreational Facilities			-0.1469***	-0.2854	-0.1386**
per 10,000 Residents			(0.055)	(0.175)	(0.056)

Appendix B Continued					
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Food Environment					
Fast Food Restaurants			-0.0152	0.1042**	-0.0347**
per 10,000 Residents			(0.018)	(0.050)	(0.015)
Fast Food Expenditures			-0.0057***	-0.0032***	-0.0074***
per Capita			(0.001)	(0.001)	(0.001)
Economic Factors					
Unemployment Rate		-0.0586**	0.0362	-0.0798	0.0451*
		(0.027)	(0.025)	(0.062)	(0.027)
Mean Income in Thousands		-0.0273***	-0.0081	0.0004	-0.0051
		(0.007)	(0.007)	(0.010)	(0.011)
General Health					
Deaths per 1,000 Residents	0.0044	-0.0012	0.0308	0.2565**	0.0159
	(0.035)	(0.036)	(0.035)	(0.100)	(0.036)
Years of Potential Life Lost	0.0001**	0.0001*	0	-0.0004***	0
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Fair/Poor Health Rate	0.0779***	0.0789***	0.0095	0.0003	0.0303**
	(0.012)	(0.013)	(0.012)	(0.023)	(0.014)
Demographics					
Less than High School	0.001	0.0032	-0.0498***	-0.0454**	-0.0482***
	(0.012)	(0.012)	(0.011)	(0.021)	(0.014)
High School	0.0439***	0.0476***	-0.0314***	-0.0186	-0.0325**
	(0.012)	(0.012)	(0.011)	(0.022)	(0.013)
BA Plus	-0.1632***	-0.1420***	-0.1726***	-0.1872***	-0.1657***
	(0.014)	(0.015)	(0.013)	(0.021)	(0.019)
Median Age	-0.1698***	-0.1667***	-0.1260***	-0.2257***	-0.0964***
	(0.015)	(0.016)	(0.015)	(0.039)	(0.016)
Percent White	-0.0022	-0.0109	-0.0135**	0.0579***	-0.0263***
	(0.007)	(0.008)	(0.007)	(0.015)	(0.007)
Percent Black	0.0719***	0.0666***	0.0568***	0.1312***	0.0514***
	(0.007)	(0.008)	(0.007)	(0.015)	(0.007)
Percent Hispanic	-0.0841***	-0.0851***	-0.0504***	-0.0343***	-0.0433***
	(0.006)	(0.006)	(0.005)	(0.011)	(0.006)
Constant	33.4480***	35.5540***	35.7437***	31.4209***	36.1932***
	(1.198)	(1.326)	(1.289)	(2.577)	(1.456)
Observations	3,138	3,138	3,138	1,090	2,048
R-squared	0.604	0.607	0.676	0.694	0.676

Robust standard errors are in parentheses. Significance: * p<0.10, ** p<0.05, *** p<0.01

Appendix C. Regression Results Without Imputed Data					
Variables	**(1)** **All Counties**	**(2)** **All Counties**	**(3)** **All Counties**	**(4)** **Metro Counties**	**(5)** **Non-metro Counties**
Variable of Interest					
Food Desert Rate	0.0249***	0.0262***	0.0252***	0.0363**	0
	(0.007)	(0.007)	(0.007)	(0.016)	(0.003)
Urbanicity					
Non-metro	-0.3120**	-0.2978*	-0.0977		
	(0.151)	(0.159)	(0.160)		
Physical Activity					
Physical Inactivity			0.2218***	0.2255***	0.2077***
			(0.032)	(0.040)	(0.021)
Recreational Facilities			-0.3816**	-0.6846**	-0.1635*
per 10,000 Residents			(0.187)	(0.329)	(0.085)
Food Environment					
Fast Food Restaurants			0.0064	0.0536	0.0117
per 10,000 Residents			(0.049)	(0.074)	(0.026)
Fast Food Expenditures			0	0.0001	-0.0057***
per Capita			(0.001)	(0.001)	(0.001)
Economic Factors					
Unemployment Rate		-0.0761	0.0708	0.0581	0.0753**
		(0.078)	(0.077)	(0.121)	(0.037)
Mean Income in Thousands		0.0068	0.0046	0.0142	-0.0374**
		(0.012)	(0.013)	(0.015)	(0.015)
General Health					
Deaths per 1,000 Residents	0.0518	0.0695	-0.0399	-0.0472	-0.0102
	(0.126)	(0.128)	(0.125)	(0.213)	(0.069)
Years of Potential Life Lost	0	0	0.0001	0	-0.0001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Fair/Poor Health Rate	0.0721**	0.0767***	-0.0127	-0.0313	0.0498***
	(0.029)	(0.029)	(0.029)	(0.046)	(0.018)
Demographics					
Less than High School	0.0003	-0.0012	-0.0407	-0.0029	-0.0557***
	(0.031)	(0.031)	(0.031)	(0.045)	(0.018)
High School	0.0325	0.0303	-0.0477*	-0.0446	-0.0375**
	(0.024)	(0.024)	(0.026)	(0.040)	(0.017)
BA Plus	-0.1970***	-0.2076***	-0.2189***	-0.2157***	-0.2025***
	(0.024)	(0.026)	(0.026)	(0.032)	(0.024)
Median Age	-0.3372***	-0.3475***	-0.2743***	-0.3116***	-0.1194***
	(0.044)	(0.047)	(0.049)	(0.072)	(0.024)
Percent White	0.0728***	0.0722***	0.0689***	0.0880***	-0.0204**
	(0.012)	(0.012)	(0.014)	(0.017)	(0.009)

Appendix C Continued					
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Percent Black	0.1227***	0.1249***	0.0990***	0.1089***	0.0632***
	(0.014)	(0.014)	(0.014)	(0.020)	(0.009)
Percent Hispanic	-0.1010***	-0.1004***	-0.0876***	-0.0931***	-0.0591***
	(0.016)	(0.016)	(0.017)	(0.021)	(0.008)
Constant	34.2293***	34.7067***	32.4938***	31.4620***	39.5540***
	(2.448)	(2.592)	(3.275)	(4.120)	(1.939)
Observations	2,737	2,737	2,737	1,035	2,048
R-squared	0.741	0.742	0.761	0.762	0.676

Robust standard errors are in parentheses. Significance: * p<0.10, ** p<0.05, *** p<0.01

Appendix D. Statistical Tests By Metro Status

Recreational Facilities per 10,000 Residents

Group	N	Mean	Standard Error	Standard Deviation
Metro	1090	0.985	0.0181	0.5975
Non-metro	2048	0.81	0.0217	0.9837
Summary				
t=5.3877 Degrees of Freedom=3136 p=0.0000				

Fast Food Restaurants per 10,000 Residents

Group	N	Mean	Standard Error	Standard Deviation
Metro	1090	6.495	0.0804	2.656
Non-metro	2048	5.608	0.073	3.303
Summary				
t=7.6475 Degrees of Freedom=3136 p=0.0000				

Population Size

Group	N	Mean	Standard Error	Standard Deviation
Metro	1090	224862	14721.97	486048
Non-metro	2048	24378	529.3505	23955.67
Summary				
t=18.6268 Degrees of Freedom=3136 p=0.0000				

Appendix E. Imputed Data T-tests

Metro versus Non-metro

Group	N	Mean	Standard Error	Standard Deviation
Non-Missing	2737	0.6218	0.0093	0.4850
Missing	401	0.8628	0.0172	0.3444
Summary				
t=9.6010 Degrees of Freedom=3136 p=0.0000				

Population Size

Group	N	Mean	Standard Error	Standard Deviation
Non-Missing	2737	106083	6157.013	322112.4
Missing	401	11664	504.1912	10096.42
Summary				
t=5.8686 Degrees of Freedom=3136 p=0.0000				

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