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Submitted Article

Food Deserts and Childhood Obesity

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Abstract *We utilize a panel data set from 2007 to 2009 on the state of Arkansas to identify and determine the effect of food deserts on school district obesity rates. We define food deserts as low-income areas with limited food access. Using both classical panel data models and spatial error models, we find no statistically significant relationship between school district obesity rates and the existence of food deserts in Arkansas. This finding is consistent across different model specifications, in spatial, panel or cross-sectional analysis, and with or without urban school districts in the data.*

Key words: Childhood obesity, Food deserts, Panel regression methods, Panel spatial error models.

JEL codes: I12, I14, I15.

Introduction

Areas where access to healthy foods is limited or constrained are known as food deserts. The residents of these areas face significant time and transport costs when purchasing food items in supermarkets, and generally have low incomes. Convenience stores and gasoline stations, which tend to sell energy-dense foods, often become the alternative food sources in these areas. Blanchard and Matthews (2007) find that food deserts have a relatively higher density of convenience stores. Several studies have also pointed out that individuals residing in food deserts are likely to pay higher prices for food and have limited options in terms of purchasing healthy foods such as fresh fruits and vegetables (Blanchard and Matthews 2007; Blanchard and Lyson 2002).

Living in a food desert can impact an individual's nutritional and health status. Blanchard and Matthews (2007) show that in rural areas, residents in food desert areas are less likely to consume fresh fruits and vegetables than individuals that reside in non-food desert areas. Even

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after controlling for education, they find that residents of non-food desert areas consume more fresh fruits and vegetables than residents of food desert areas, which suggests that food deserts may diminish the otherwise positive correlation between education and healthy behaviors. Hendrickson, Smith, and Eikenberry (2006) argue that individuals residing in food deserts face a higher likelihood of developing chronic diseases such as diabetes, cancer and heart disease because they face high cost, low quality and limited food choices.

Living in a food desert can also make the management of chronic health conditions more difficult. Smith and Morton (2009) conducted focus group discussions involving low-income residents in rural Midwestern communities with limited grocery store access. These residents reported difficulty adhering to dietary restrictions required for the management of diabetes, heart disease and other obesity related health problems.

The evidence is mixed, however, on the effect of key factors associated with food desert areas on changes in either Body Mass Index (BMI) or fruit and vegetable consumption. For example, Pearson et al. (2005) found that the various factors associated with food desert areas such as the price of fruits and vegetables, distance to supermarkets and low socio-economic status were not statistically associated with vegetable and fruit consumption. Their study suggests that cultural differences including age and gender influence differences in vegetable and fruit consumption. Stafford et al. (2007) also found little evidence on the link between the number of supermarkets and individual BMI, while Macdonald et al. (2011) found that distance of residence to a supermarket was not statistically associated with BMI and fruit and vegetable consumption.

Many studies related to the effects of food deserts are focused on adult outcomes. However, the problems associated with living in a food desert may be magnified in vulnerable groups such as school children. Schafft, Jensen, and Hinrichs (2009) (hereafter referred to as the SJH study) examined the effect of food desert areas on school children's overweight rates in rural Pennsylvania. In their paper, they used school district boundaries as the principal unit of analysis in terms of classifying food desert areas. Their findings indicate that a 1% increase in the population residing in a food desert district results in a 0.06% increase in the proportion of students who are overweight or at risk of being overweight. Other studies exploring the linkage between the built environment and childhood obesity also suggest that food deserts may be important. Specifically, these studies show that the presence of supermarkets in the neighborhood is associated with a lower incidence of childhood obesity, while the presence of convenience stores is associated with higher incidence of childhood obesity (Liu et al. 2007; Powell et al. 2007; Galvez et al. 2009; Grafova 2008). Liu et al. (2007) found that increasing the distance of the child's residence to the nearest large supermarket was associated with an increased risk of being overweight. Likewise, Powell et al. (2007) examined whether the availability of local food stores affects obesity rates in 8th and 10th grade students. According to their findings, an addition of a supermarket per 1,000 people was associated with a 0.11 percentage point decline in BMI units, while an addition of a convenience store per 1,000 people was associated with 0.03 percentage point increase in BMI units. Galvez et al. (2009) also observed an associative link between the presence of neighborhood food stores such as convenience stores and fast-food restaurants and

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childhood BMI, and found that the presence of convenience stores is associated with higher obesity levels in children. Similarly, Grafova (2008) examined the effect of the built environment on the weight outcomes of children and found that the child's likelihood of being overweight increases as more convenience stores cluster around the neighborhood.

There is evidence that the availability of different types of food stores differs by the level of socio-economic status (SES) of the neighborhood. Booth, Pinkston, and Poston (2005) found that high levels of neighborhood deprivation were generally associated with higher BMI rates, especially in children. These authors also found that high SES neighborhoods have more supermarkets, whereas low SES neighborhoods have more convenience stores and fast-food restaurants.

Given the above discussion, we revisit the issue of the effects of food deserts by using a criteria of a food desert that involves both low income and limited food access status. We focus on childhood obesity as our outcome measure of interest, given its immense public policy importance. Specifically, we utilize a panel data set from 2007 to 2009 to identify and determine the effect of food deserts on school district obesity rates in Arkansas. Arkansas is an interesting case to examine since it is one of the states with the highest poverty and obesity rates. Our study is similar to the SJH study in that we conducted the analysis at the school district level. However, we differ from the SJH study in several respects. First, their study focused on rural areas (i.e., rural Pennsylvania), while ours covers both rural and urban areas in Arkansas (although we also analyze rural school districts separately). Second, there are some differences in how we classify healthy food stores, with our main criteria being that the stores contain a fresh produce department. Third, our methodology for classifying school districts as food deserts follows the approach used by the United States Department of Agriculture, Economic Research Service (U.S. Department of Agriculture, Economic Research Service 2009), where classification of a school district as a food desert is determined by the district being both a limited food access area and also a low income area. Moreover, our research has several advantages over the SJH study. Unlike the SJH study, our research utilized a panel data structure that controls for unobserved time invariant factors, and we addressed spatial correlation issues by estimating a spatial panel error model. We measured the food environment at the census block level, which is a finer level of spatial detail, and we telephoned food stores in our database to carefully classify stores that offer fresh fruits and vegetables. In contrast to the SJH study, our findings suggest that there is no statistically significant relationship between food desert areas and school district obesity rates. This finding is robust to various model specifications.

The next section of the paper discusses the data we use in our analysis, and explains how we classify food stores and how we identify low food access and low income areas. This is followed by a presentation of the various models we use to estimate and test the robustness of food desert effects. We then discuss the results of these empirical models and present the conclusions.

Data

School district obesity rates from 2007 to 2009 were obtained from the Arkansas Center for Health Improvement (ACHI). A notable feature of the

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Table 1 Characteristics of School Districts Used in the Study ($N = 230$)

	Square Miles	Population	Enrollment
Mean	217	10,090	1,758
Median	182	5,075	917
Std. deviation	149	16,151	2,724
Minimum	22	1,134	305
Maximum	922	178,112	25,299

Notes: Population is an aggregate of 2000 census blocks within the school district boundaries. Enrollment represents three-year average student enrollment from 2007–2009.

ACHI BMI dataset is that it is based on actual height and weight measurements of students. Measurements are taken annually for students in even-numbered grades through 10th grade (i.e., kindergarten, 2nd, 4th, 6th, 8th, and 10th grades). Our outcome measure is the proportion of measured children that are classified as obese.

Our dataset includes 230 school districts, as the school district is the finest geographic unit for which statewide shape files can be matched to the BMI data. In Arkansas, school districts are organized primarily around municipalities. Key features of Arkansas school districts are presented in table 1. As shown, most are small. The median population living within a school district is only 5,075 residents, and the median 2007–2009 average number of students by district is only 917. However, population and enrollment statistics are in proportion to size of the municipality. Little Rock, the largest school district, contained 178,112 residents, with a 2007–2009 average enrollment of 25,299 students. A map showing school district boundaries as they existed in 2009 is presented in figure 1.

Food Store Classification

Food store location data were purchased from Dun and Bradstreet (D&B). Archival data were purchased for 2007–2009 to measure the commercial food landscape in each year included in the study. We started with all establishments classified by D&B as either supermarkets or grocery stores. It was clear that many convenience stores were included in this classification. Consequently, these establishments were screened to identify those that provided fresh fruits and vegetables. Kaufman (1999) used a $500,000 annual sales cut-off in order to filter out small grocery stores. Following Kaufman, stores with sales in excess of $500,000 were included in our study. However, we did engage in ground-truthing efforts (using street-view images within the Google search engine, or placing telephone calls to the store) whenever a store was not part of a major national or regional grocery chain, or whenever there were reasons to doubt the accuracy of the classification provided in the D&B records. Walmart stores were checked to ensure that only supercenter or neighborhood market formats were included in our study. Finally, to avoid inadvertently missing stores offering fresh fruits and vegetables, telephone calls were placed to establishments with sales between $400,000 and $500,000. We found very few that offered fresh fruits and vegetables, but those that did were classified as food stores for the purposes of our study. Additional

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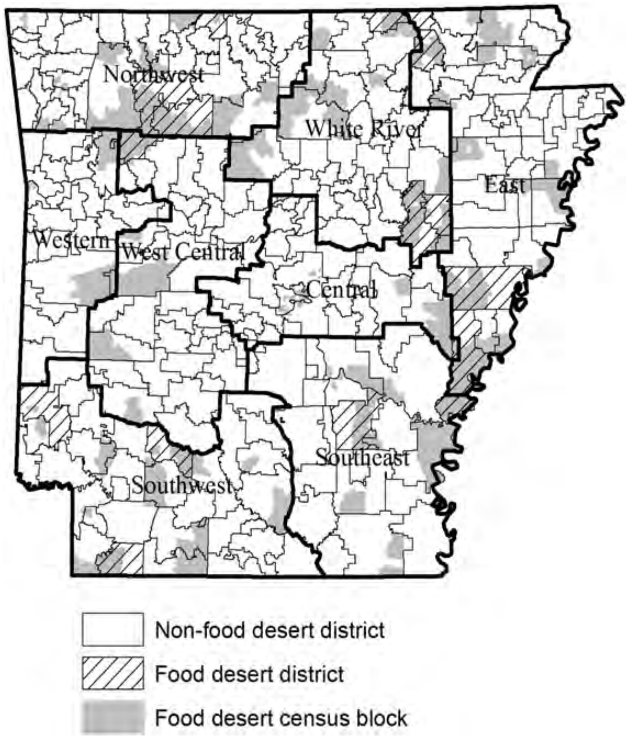
Figure 1 Locations of Food Desert Districts in Arkansas, 2009



grocery stores with sales less than $400,000 were then called randomly, and none of these stores offered fresh fruits and vegetables.

Defining Food Deserts

In characterizing food desert areas, studies have utilized several methods to define the spatial nature of limited or constrained access in a food desert. The main approaches include determining the food store count within a specific radial distance (Apparicio, Cloutier, and Shearmur 2007; Berg and Murdoch 2008; Block, Scribner, and DeSalvo 2004), and measuring the nearest distance of either residential units or population weighted centers to food stores (Algert, Agrawal, and Lewis 2006; McEntee and Agyeman 2010; Sharkey and Horel 2008). Both approaches make use of a geographic information system (GIS) to calculate the radial food store count and/or nearest distance to food store.

In this paper we use the USDA/ERS criteria of food deserts as being areas with both low income and low access to retail supply of healthy foods such as fresh fruits and vegetables. We adopted the low access and low income area criteria found in the USDA/ERS Food Desert Locator[1]. The Food Desert locator defines low access areas as areas where 33% of the census tract population or at least 500 people in the census tract travel more than one mile to access a supermarket in urban areas, or ten miles to access large grocery stores in rural areas. The one mile and ten mile distance thresholds have been used in the literature as a means of measuring

[1] *http://www.ers.usda.gov/data/fooddesert/about.html.*

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food access in both urban and rural areas (Blanchard and Matthews 2007; Schafft, Jensen, and Hinrichs 2009; U.S. Department of Agriculture, Economic Research Service 2009). For example, the one mile threshold used in urban areas is usually based on a feasible walking time, where walking more than 30 minutes at a rate of two miles per hour to a supermarket or large grocery store may constitute a low access scenario (U.S. Department of Agriculture, Economic Research Service 2009). On the other hand, the ten mile distance threshold applied in rural areas is based on a point-to-point drive time of 20 minutes, at an average rate of 30 miles per hour (Blanchard and Matthews 2007; Schafft, Jensen, and Hinrichs 2009). This threshold is slightly higher than the average distance of eight miles that a U.S. resident travels when doing grocery trips (Blanchard and Matthews 2007).

To measure access to food stores, we used ArcGIS to compute the distance from each census block centroid to the nearest food store. The Census Geographic Identifier (CGI) file was used to determine whether each census block was urban or rural, and also to obtain the population within the block. Blocks were assigned to one of two categories: (1) limited access to food stores, that is, urban and non-urban blocks whose distance from the nearest food store were greater than 1 and 10 miles, respectively, and (2) access not limited.

District level measures of food store access were then obtained by aggregating block level populations up to the school-district level. If the percentage of population that was classified as having limited access to food stores within the school district was equal to or greater than 33% (U.S. Department of Agriculture, Economic Research Service 2009), the district was classified as a limited access district. It is worth emphasizing that our access measure reflects proximity of food stores in neighboring districts that are accessible to district residents. The food environment is initially measured at the census block level, which is a very fine spatial level; and computed distances are to the nearest food store, regardless of whether the food store is or is not contained within the boundaries of the census block. Only afterwards do we aggregate up to the school district in order to obtain a measure that reflects the same aggregation as the BMI prevalence measures.

This approach to identifying low access areas differs in some important respects from the earlier study of SJH, who classified food stores offering fresh fruit and vegetables in terms of employee count ($\geq$50) and used a 10-mile buffer zone around the population-weighted zip code centroids of one or more food stores, and an additional 5-mile buffer zone for those zip code centroids that were near interstate highways. If the geographic center of the zip codes fell beyond the two thresholds, then the zip code was classified as a food desert zip code. The authors then aggregated the zip codes up to the school district level. If at least 50% of the population resided in a food desert zip code, then they classified the school district as a food desert district.

We used the poverty and median income measures from the 2000 Census of Population to classify a school district as a low income area or not. Criteria included: (1) whether 20% or more of the population was in poverty; (2) whether median family income for metropolitan statistical areas (MSA) did not exceed 80% of the statewide family median income; and (3) whether median family income for non-metropolitan statistical

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areas (MSA) did not exceed 80% of the statewide median income. If any of these criteria applied to a school district, the school district was classified as a low income district.

As noted above, a food desert district is defined as a district that is both low access and low income. Figure 1 shows a map of school districts in Arkansas that are classified as food deserts. Note that because we aggregated the food environment measures up to the district level, there can be areas within non-food desert districts with low access to food stores.

Other School District Data

Other control variables at the school district level were collected from the Arkansas Department of Education (ADE) and the U.S. Census of Population (see table 2). The ADE data included student enrollment counts by grade, gender, race, and ethnicity, and the percentage of students eligible for free and reduced lunch. Other measures of socio-demographic and economic characteristics of the school district, such as information on commuting, female labor force participation, education and children living with single parents, were based on the 2000 Census block level data found in the 2000 Census. These census blocks have a Census School District Unified Code for the year 2000. These were then matched with the ADE school district codes using the list of codes and the corresponding school district from the Census State Data Center in Arkansas. Finally, regional indicator variables were included to address broad regional trends in Arkansas. These were defined according to Arkansas Planning and Development Districts and appear in figure 1 as bold outlines.

As exhibited in table 2, the sample mean of the school-district level obesity rate[2] is approximately 21.36%, while the mean value of the food desert indicator variable is 0.053, suggesting that about 5% of the school districts are considered food desert areas. The mean percentage of population with limited access is 15.14, while the average value of the proportion of students receiving free and reduced lunch is 0.602.

Model Specification

In this research we first use a random effects panel model to examine the relationship between school district obesity rates and the existence of urban and non-urban food deserts in Arkansas. Consider the generalized panel regression model as:

$$Y_{it} = \beta \boldsymbol{X}_{it} + \; c_i + \mu_{it} \tag{1}$$

where subscript i is the i$^{\text{th}}$ individual/entity, and subscript t denotes the time period. The variable Y_{it} represents the response variable and $\boldsymbol{X}_{it}$ is a vector of variable drivers predicting Y_{it}. The variable c_i is the effect of unobserved time-invariant variables, and μ_{it} is the randomly distributed error term that is uncorrelated with the values of $\boldsymbol{X}_{it}$. We modify and

[2]*School district obesity rates are defined as the proportion of children with Body Mass Index (BMI) scores greater than or equal to the 95th percentile as defined by gender-specific CDC growth charts.*

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Table 2 Descriptive Statistics for Variables Used in the Study ($N = 683$)

Variable	Unit	Mean	Std. Dev.	Min.	Max.
Percentage of obese schoolchildren[a,b]	Percentage	21.356	4.377	7.840	37.980
Percentage of population with limited access	Percentage	15.413	23.440	0.000	1.000
Food desert	Binary	0.053	0.224	0	1.000
Free and reduced lunch[b]	Proportion	0.602	0.165	0.185	1.000
Kindergarten enrollment[b]	Proportion	0.078	0.011	0.050	0.120
Grade 2 enrollment[b]	Proportion	0.076	0.010	0.041	0.113
Grade 4 enrollment[b]	Proportion	0.076	0.009	0.048	0.106
Grade 6 enrollment[b]	Proportion	0.076	0.009	0.043	0.108
Grade 8 enrollment[b]	Proportion	0.078	0.010	0.041	0.115
Grade 10 enrollment[b]	Proportion	0.081	0.011	0.052	0.125
Male students[b]	Proportion	0.515	0.018	0.448	0.578
Asian[b]	Proportion	0.009	0.015	0.000	0.111
Black[b]	Proportion	0.158	0.246	0.000	0.973
Native[b]	Proportion	0.007	0.012	0.000	0.146
Hispanic[b]	Proportion	0.048	0.077	0.000	0.532
Percent urban[c]	Proportion	0.232	0.295	0.000	0.996
Work commute 15–35 minutes[c]	Proportion	0.139	0.061	0.030	0.296
Work commute >35 minutes[c]	Proportion	0.049	0.023	0.010	0.151
Females in labor force[c]	Proportion	0.218	0.035	0.105	0.325
High school degree or equivalent[c,d]	Proportion	0.377	0.043	0.223	0.483
Some college or associates degree[c,d]	Proportion	0.222	0.044	0.137	0.334
Bachelor's and advanced degrees[c,d]	Proportion	0.078	0.033	0.023	0.219
Children living with single parent[c,d]	Proportion	0.267	0.099	0.122	0.651
Regional indicator variables[e]					
Southeast	Binary	0.075	0.263	0	1
Northwest	Binary	0.138	0.345	0	1
West-Central	Binary	0.151	0.358	0	1
East	Binary	0.173	0.378	0	1
White River	Binary	0.145	0.352	0	1
Southwest	Binary	0.132	0.338	0	1
West	Binary	0.100	0.300	0	1
Central	Binary	0.088	0.283	0	1

[a]*Obesity measures are based on students in even-numbered grades, Kindergarten through 10th grade.*
[b]*School district-level variables. Proportions represent share of students within the school district.*
[c]*School district-level variables. Proportions represent share of population or households within school district boundaries.*
[d]*Measures are based on population 25 years of age and older.*
[e]*Regional control variables correspond to Arkansas Planning and Development Districts.*

expand equation (1) by specifying our baseline empirical model as:

$$O_{it} = \beta \boldsymbol{X}_{it} + \gamma PLOW_{it} + \delta FD_{it} + \varphi FRL_{it} + c_i + \mu_{it} \tag{2}$$

where variable O_{it} represents the proportion of children that are obese in the i^{th} school district in period t ($t = 2007$ to 2009), and $\boldsymbol{X}_{it}$ is a vector of control variables affecting school district obesity rates. The variable $PLOW_{it}$ is the percentage of the population residing in a limited access area. The variable FD_{it} is an indicator variable representing whether the school district is a food desert or not. Thus, holding other factors constant,

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the coefficient δ measures the difference in school-district obesity rates between school districts that are classified as food deserts and school districts that are not food deserts. The FRL_{it} is the proportion of students who are eligible for free and reduced lunch. The advantages of using the free and reduced lunch measure as an income control is that it reflects the same individuals for whom we observe obesity prevalence, and it varies over time within a given district. The free and reduced lunch measure is also highly correlated with district-level income and poverty measures derived from the Census of population.

One estimation issue is that school district observations are likely to be correlated across space. This will affect the efficiency of the estimates and can occur if unmeasured neighborhood characteristics that impact child weight outcomes are clustered in space (Chen, Florax, and Snyder 2009; Chen et al. 2010). To address this, we also estimate equations (3) and (4) below to allow for a spatial error model that accounts for the spatial correlation between the unobserved determinants of school district obesity rates (Elhorst 2010; Anselin, Le Gallo, and Jayet 2008). The panel spatial error model is specified as:

$$O_{it} = \beta \boldsymbol{X}_{it} + \gamma PLOW_{it} \ + \ \delta FD_{it} + \varphi FRL_{it} + c_i + \ \mu_{it}, \tag{3}$$

where

$$\mu_{it} = \ \rho W \mu_{it} + \epsilon_{it}. \tag{4}$$

The spatially autocorrelated error term (μ_{it}) follows an autoregressive process denoted by equation (4). The term ρ denotes the spatial autocorrelation coefficient, and W is an nxn spatial weight matrix. Finally, ε_{it} represents the error term that is randomly distributed. In this paper the construction of the weight matrix W utilized the queen contiguity approach. The queen contiguity weight construction characterizes the adjacency between school districts to include all common boundaries and vertices. Thus, in this study if school district x is adjacent to school district y but not school district z, then the matrix element corresponding to school district x and school district y will be 1 and 0 for school district x and school district z. The matrix is row-normalized prior to estimation. The diagonal values of the weight matrix will be zero since a school district is not considered to be its own neighbor. The SPLM package in R is used to estimate equation (3).

The use of panel data is important to our analysis because earlier studies have shown the need to address endogeneity in studies linking features of the food environment to weight outcomes. Of specific concern is that food store locations and residence locations are the result of equilibrium outcomes that depend on individual characteristics that may also be correlated with childhood weight. Some recent food environment studies focusing on the role of fast food restaurants address the endogeneity problem through the use of instrumental variables (Dunn 2010; Chen, Florax and Snyder 2009). However, finding valid instruments is very difficult. When panel data are available, the use of panel data estimators is another way to address endogeneity since it could at least take into account unobserved time-invariant factors (Verbeek 2012). In this respect our study is similar to Currie et al. (2010), who use an indicator variable

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to measure the food landscape within a panel data framework. In our study, the Hausman (1978) test was used to determine whether the random effects model estimates were significantly different from estimates generated by the fixed effects model. Based on a chi-square test, we failed to reject the null hypothesis that the random effects estimates were similar to their fixed effects analog. Therefore, we focus our analysis in the following section on estimates from the random effects model.

It is worth emphasizing that our baseline model as presented in equation (2) includes the percentage of population with limited access to food stores, and the free and reduced lunch participation rate, in addition to the food desert indicator variable. This is an over-specification in the sense that the food desert indicator variable depends on both food store access and income. The concern is that as a binary variable, the food desert indicator is less informative than either of the two continuous measures, and so this baseline provides a benchmark against which to compare other specifications where we include only the food desert indicator measure or only the limited access and free reduced lunch measures. In essence, the goal is to determine whether being classified as a "food desert" is meaningful to obesity outcomes beyond continuous measures of food store access and income (as reflected in free and reduced lunch participation). Finally, as discussed below, we include several other empirical strategies to assess the robustness of our findings.

Results

Table 3 provides estimates of random effects models with pooled OLS estimates reported for purposes of comparison. Our baseline specification is represented as Specification A in the first two columns of table 3. Specification B only includes the food desert binary variable, while Specification C contains only the percentage of population with limited access and the free and reduced lunch measure. Regardless of specification, we find no statistical evidence that a district's status as a food desert area, the degree of food store access, or the proportion of students eligible for free and reduced lunch (a district-level measure of income status) are linked to obesity rates. The pooled and random effects estimates on food desert and limited access measures are positive, which is the expected sign if distance to food stores with healthy options raises childhood obesity rates. However, these estimates are not statistically significant, and the magnitudes of the coefficients are small in comparison to those reported in the earlier SJH study. In both the pooled and random effects models across the three specifications, other variables such as the proportion of kindergarten enrollment, proportion of Native American student enrollment, commuting time and educational attainment are statistically associated with lower obesity rates, whereas the proportion of Hispanic student enrollment is positively associated with school district obesity rates. The coefficients from the regional indicator variables imply that school districts located in northwest, west and central regions of the state tend to have lower obesity rates compared to school districts located in the east. The east region is predominantly defined by the Mississippi Delta and is primarily an agricultural district; this district by far has the highest percentage of its population living in poverty in the State of

Table 3 Pooled and Random Effects Regressions ($N = 683$)

	Specification A		Specification B		Specification C	
Variables	**Pooled**	**RE**	**Pooled**	**RE**	**Pooled**	**RE**
% of pop. with limited access	0.002	0.004	_	_	0.005	0.007
	(0.009)	(0.009)			(0.009)	(0.008)
Free and reduced lunch	2.170	2.525	_	_	2.242	2.566
	(1.911)	(1.753)			(1.895)	(1.748)
Food desert	0.554	0.687	0.743	0.965	_	_
	(1.046)	(1.024)	(1.022)	(0.96)		
Kindergarten enrollment	−35.674***	−21.365*	−35.859***	−22.087**	−35.705***	−21.467*
	(13.729)	(11.002)	(13.815)	(11.054)	(13.735)	(11.012)
Grade 2 enrollment	−6.147	8.547	−7.377	7.706	−5.587	9.094
	(15.596)	(12.107)	(15.542)	(11.908)	(15.479)	(11.921)
Grade 4 enrollment	−16.314	−2.060	−16.509	−2.123	−16.599	−2.161
	(15.271)	(12.72)	(15.234)	(12.759)	(15.241)	(12.711)
Grade 6 enrollment	4.908	10.751	2.898	10.170	5.351	10.913
	(13.492)	(11.031)	(13.341)	(11.121)	(13.567)	(11.095)
Grade 8 enrollment	19.293	16.653	19.450	16.888	19.066	16.533
	(13.812)	(11.974)	(13.653)	(11.988)	(13.71)	(11.951)
Grade 10 enrollment	11.285	8.219	12.007	8.632	11.589	8.368
	(12.57)	(10.99)	(12.589)	(11.057)	(12.625)	(10.991)
Male students	10.727	19.958	11.360	20.217**	10.415	19.773**
	(10.558)	(9.227)	(10.468)	(9.156)	(10.718)	(9.287)
Asian	−11.022	−14.556	−9.383	−12.891	−11.810	−15.259
	(11.623)	(9.476)	(11.116)	(9.111)	(11.423)	(9.305)
Black	3.024	2.842	4.025**	4.041**	2.972	2.795

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Table 3 *Continued*

	Specification A		Specification B		Specification C	
Variables	**Pooled**	**RE**	**Pooled**	**RE**	**Pooled**	**RE**
	(2.129)	(2.1)	(2.008)	(2.003)	(2.125)	(2.095)
Native	−30.689***	−24.006*	−29.395***	−22.652*	−29.152***	−22.363*
	(10.822)	(13.748)	(11.059)	(13.494)	(10.29)	(13.137)
Hispanic	9.898***	9.379***	10.862***	10.588***	9.765***	9.232***
	(2.521)	(2.552)	(2.446)	(2.449)	(2.548)	(2.574)
Percentage urban	0.337	−0.063	0.276	−0.138	0.303	−0.106
	(1.043)	(1.036)	(1.043)	(1.034)	(1.028)	(1.02)
Work commute 15-35 mins.	−2.340	−2.577	−2.196	−2.394	−2.431	−2.681
	(1.983)	(1.96)	(1.969)	(1.951)	(1.964)	(1.939)
Work commute > 35 mins.	−8.285***	−8.818***	−8.292***	−8.750***	−8.314***	−8.847***
	(2.856)	(2.815)	(2.884)	(2.827)	(2.869)	(2.83)
Females in labor force	3.293	3.551	0.422	0.133	3.471	3.702
	(6.009)	(5.989)	(5.504)	(5.54)	(5.889)	(5.876)
High school degree	−7.725	−6.900	−7.942	−6.964	−8.314	−7.661
	(7.447)	(7.587)	(7.251)	(7.456)	(7.471)	(7.627)
Some college or associate’s degree	−23.388***	−21.942***	−24.247***	−22.918***	−23.677***	−22.313***
	(6.226)	(6.245)	(6.107)	(6.136)	(6.169)	(6.18)
Bachelor’s and advanced degrees	−27.225***	−26.410***	−29.923***	−29.467***	−27.311***	−26.584***
	(5.561)	(5.451)	(4.98)	(5.095)	(5.578)	(5.481)
Children living with single parent	−1.288	−0.622	−1.283	−0.676	−1.143	−0.434
	(5.004)	(4.949)	(4.993)	(4.988)	(4.972)	(4.908)
Southeast	−0.453	−0.303	−0.587	−0.464	−0.459	−0.311
	(0.989)	(0.969)	(0.976)	(0.957)	(0.989)	(0.968)

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Table 3 *Continued*

	Specification A		Specification B		Specification C	
Variables	**Pooled**	**RE**	**Pooled**	**RE**	**Pooled**	**RE**
Northwest	−2.180***	−2.364***	−2.194***	−2.384***	−2.135***	−2.310***
	(0.805)	(0.812)	(0.814)	(0.822)	(0.81)	(0.818)
West-Central	−0.975	−0.956	−0.966	−0.945	−0.991	−0.976
	(0.819)	(0.825)	(0.823)	(0.831)	(0.82)	(0.826)
White River	−0.192	−0.242	−0.204	−0.258	−0.152	−0.193
	(0.683)	(0.692)	(0.684)	(0.693)	(0.698)	(0.711)
Southwest	−0.403	−0.422	−0.613	−0.654	−0.398	−0.422
	(0.766)	(0.791)	(0.796)	(0.817)	(0.762)	(0.784)
West	−2.059**	−1.979***	−2.090***	−2.016***	−2.052**	−1.972**
	(0.8)	(0.772)	(0.777)	(0.751)	(0.806)	(0.777)
Central	1.274*	1.248*	1.196	1.151	1.273*	1.243*
	(0.744)	(0.738)	(0.737)	(0.736)	(0.745)	(0.737)
Intercept	29.628***	20.718***	31.815***	23.326***	29.951***	21.103***
	(7.801)	(7.396)	(7.452)	(7.045)	(7.892)	(7.473)
F-value	15.950***		17.710***		16.260***	
Wald Chi-square value		450.280***		451.650***		449.870***

*Notes: Robust standard errors are in parentheses. ***, **, *denote the coefficient being significant at the 1%, 5% & 10% levels, respectively.*

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Arkansas. The northwest region is composed of growing cities like Bentonville, Springdale, Rogers and Fayetteville, which have relatively lower poverty levels.

Estimates from the spatial error models are reported in the first two columns of table 4. The package used to estimate these models (SPLM package in R) requires a balanced panel, and so this resulted in a slight reduction in the number of observations. Again, there is no statistical evidence that classification as a food desert district, or the degree of food store access is linked to obesity rates.[3] The percentage of students eligible for free and reduced lunch programs shows up as being marginally significant in the pooled version of Specification A and in Specification C. Interestingly, the spatial error estimates (rho) are statistically insignificant, indicating the absence of any systematic spatial effects. The signs, magnitudes, and significance levels of the other covariates reported in table 3 are very similar in the spatial models and so are not reported again in table 4. In general, standard errors are slightly lower in the spatial error models. There appears to have been a small improvement in efficiency that results from accounting for spatial autocorrelation, even though the estimate for rho was not statistically different from zero.

To provide further evidence of statistical robustness, we conducted separate cross section regression analyses for the years 2007, 2008, and 2009 using the same three model specifications A, B, and C. These are reported in the middle three columns of table 4. Again, none of the estimates are statistically significant across the different model specifications. In fact, the magnitude of coefficients for the food desert indicator, percentage eligible for free and reduced lunch, and food store access measures in the cross section regressions are close in magnitude to the estimates reported earlier in table 3. Cross sectional spatial error models (not reported) point to the same conclusions.

To facilitate comparison with the SJH study, we again estimated the models using only the rural districts in our sample, with rural districts classified as possessing a percentage of urban residents accounting for less than 60% of the population. The three specifications presented earlier in table 3 were estimated for this subsample of rural districts. Results are presented in the rightmost two columns of table 4. The estimates from this analysis of the rural subsample are similar in magnitude to those for the full sample. We do not find any statistical evidence linking school district obesity rates with the percentage of the population residing in a limited access area, the food desert indicator, or the proportion of students eligible for free and reduced lunch programs. Again, analogous spatial error models estimated on the rural schools (not reported) indicated the same conclusions.[4]

We also re-estimated our models by defining the food desert indicator with a threshold of 50% of the school district's population having limited food store access as opposed to the 33% threshold used in the models reported above. The 50% cutoff is the same as that used to measure food deserts in the earlier SJH study. Our results (not reported) are similar to

[3] *Spatial lag models (Elhorst 2010) were also estimated but yielded statistically insignificant results.*

[4] *Models, including spatial error models, using the prevalence of overweight or obese children (those above the 85th percentile) as a dependent variable were also used as a robustness check. Again, no statistical evidence was found linking the food desert indicator, degree of food store access, and proportion of students eligible for free and reduced lunch with this alternative specification of the dependent variable.*

Table 4 Regressions for Spatial Error Model (SEM), Cross-section and Random Effects for Rural School Districts[a]

	SEM (N = 654)		Cross Section Regressions			Rural School Districts (N = 573)	
Variables	**Pooled**	**RE**	**2007 (N = 228)**	**2008 (N = 230)**	**2009 (N = 225)**	**Pooled**	**RE**
Specification A							
% of pop. with limited access	0.0002	0.001	0.004	0.001	−0.004	0.002	0.003
	(0.007)	(0.009)	(0.011)	(0.013)	(0.013)	(0.01)	(0.009)
Free and reduced lunch	2.642*	2.923	1.787	0.906	2.679	2.073	3.336
	(1.453)	(1.780)	(2.415)	(2.415)	(2.847)	(2.304)	(2.038)
Food desert	0.350	0.537	−0.430	0.055	2.197	0.472	0.592
	(0.709)	(0.920)	(1.12)	(1.335)	(1.444)	(1.125)	(1.094)
Rho	−0.036	−0.052					
	(0.065)	(0.071)					
F-value			17.940	9.040	10.940	15.610	
Wald Chi-square value							415.590
Specification B							
Food desert	0.460	0.665	−0.176	0.138	2.051	0.658	0.902
	(0.618)	(0.791)	(0.978)	(1.282)	(1.409)	(1.063)	(0.999)
Rho	−0.049	−0.048					
	(0.065)	(0.072)					
F-value			18.610	9.740	11.760	17.250	
Wald Chi-square value							438.890

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Table 4 *Continued*

	SEM (N = 654)		Cross Section Regressions			Rural School Districts (N = 573)	
Variables	**Pooled**	**RE**	**2007 (N = 228)**	**2008 (N = 230)**	**2009 (N = 225)**	**Pooled**	**RE**
Specification C							
% of pop. with limited access	0.002	0.004	0.002	0.001	0.007	0.004	0.006
	(0.006)	(0.008)	(0.009)	(0.013)	(0.013)	(0.01)	(0.009)
Free and reduced lunch	2.675*	2.944*	1.697	0.917	2.786	2.198	3.423
	(1.451)	(1.780)	(2.395)	(2.381)	(2.886)	(2.241)	(2.005)
Rho	−0.037	−0.054					
	(0.067)	(0.072)					
F-value			19.040	9.040	10.400	15.740	
Wald Chi-square value							409.610

*Notes: Standard errors are in parentheses. ***, **, *denote the coefficient being significant at the 1%, 5% & 10% levels, respectively.*
[a]Estimated coefficients of other covariates are not reported.

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those already shown. Again, we found no statistical association between school district obesity rates and the food desert indicator.

Summary and Conclusions

In this paper we examined whether food deserts contribute to childhood obesity in Arkansas. Our analysis is similar to the SJH study in that we examine district-level obesity rates. However, whereas the SJH study focused on rural areas (i.e., rural Pennsylvania), our study covered both rural and urban areas, as well as multiple years. There are also some differences in how we classified food stores, with our main criteria being that the stores contain a fresh produce department. Our methodology for classifying school districts as food deserts followed the approach adopted by USDA/ERS (U.S. Department of Agriculture, Economic Research Service 2009) using food access and income factors.

We find no statistical evidence linking food deserts with school district obesity rates, and this is consistent across different model specifications, in spatial, panel or cross-sectional analysis, and with and without urban school districts in the data. However, one can argue that school children often are not the ones making food purchase decisions and that food shopping could be done outside the school district's boundaries. Such issues might be behind our insignificant results. That being said, approvals of out-of-district student transfers are rare and usually require special circumstances. Moreover, we were careful to design the measurement of food-store access in a manner that reflects food shopping opportunities outside of district boundaries, but accessible to district residents.

So should private and public initiatives targeting the food desert and childhood obesity issue be discarded, given our results? Our paper represents only one study with a given set of contexts (i.e., school district-level analysis, only 3 years of data, only focused on the state of Arkansas, and a specific set of food desert measures). It would be possible for future studies to obtain different results from ours given a different set of contexts. Given the importance and enormous attention this issue has received, not only from researchers from various fields but also from policy-makers and the current First Lady of the United States, there is no question that more work is needed to definitively identify the effect of food desert areas on childhood obesity.

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