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Two Studies on Childhood Obesity: Effect of Obesity on Academic Achievement and Effect of Food Store Access on Diet Quality

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TWO STUDIES ON CHILDHOOD OBESITY: EFFECT OF OBESITY ON ACADEMIC ACHIEVEMENT AND EFFECT OF FOOD STORE ACCESS ON DIET QUALITY

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ABSTRACT

This thesis includes two studies on childhood obesity. This first study investigates whether childhood obesity rates affect their academic achievement scores by using a school-level panel data set on Arkansas 4^{th} and 6^{th} grades. The main results indicate that childhood obesity rates do not significantly affect academic achievement scores. Controls for education inputs such as library volume, educational expenditures per student and teacher salary show consistently significant positive relationship to students' test scores in both whole sample and in subsample analyses by socio-economic and minority status. The second study examines the effect of a neighborhood food environment feature, specifically food retailer access on diet quality of young children. Binary and index diet quality measures are developed and proximity and density of food store access measures are computed at the census block level. In general, both proximity and density measures do not have any significant marginal effects on children's diet quality in the baseline model. When using instrumental variable (IV) approach, the food store proximity measure has a strong impact on consumption of fruit and density measure has significant marginal effects on likelihood of having risk of consuming both fruit and vegetables. Parents' mental health indicator of depression has a consistent negative impact on index diet quality measure in the baseline model but not in the IV model.

This thesis is approved for recommendation
to the Graduate Council.

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I. INTRODUCTION

During the past 20 years, there has been a dramatic increase in the obesity rate in the United States. According to the National Health and Nutrition Examination Survey[1], more than one-third of U.S. adults are obese and approximately 17% (or 12.5 million) children and adolescents aged 2-19 years are obese. In 2011, no state had a prevalence of obesity less than 20%. In addition, thirty-six states had a prevalence of 25% or more and 12 of these states had a prevalence of 30% or more. Arkansas, the focus of my study, is in one of these 12 states.

The increase in proportion of obese children has received considerable attention due to the associated health risks such as coronary heart disease, type2 diabetes, and respiratory problems. Also being obese can potentially affect academic accomplishment and quality of life as children become adults in the long run (Currie 2009). Freedman et al. (2005) showed that children who became obese as early as age 2 were more likely to be obese as adults. Health conditions play an important role on childhood learning and academic performance. Poor health can negatively impact students' educational performance (Ding et al. 2009). Obesity may affect students' education performance in different ways. For example, students who have obesity related illnesses and medical problems may result in more school day absences than average. Obese students may also experience prejudice and discrimination from teachers and peers in the school, resulting in stigmatization that lowers self-esteem and increases mental stress and depression. These negative mental health issues could make it more difficult for children to concentrate or be attentive in class or simply result in the child being less willing to attend school. In 2001, the United States government passed the No Child Left Behind Act (NCLB), which aims to improve individual outcomes in education. Under NCLB, schools have to meet

[1] See http://www.cdc.gov/obesity/data/trends.html#National

their established adequate yearly progress (AYP) goals or show adequate growth in all standard subject tests for all subgroups. AYP is a federally approved, state-specific standard that requires public schools to continuously and substantially improve student achievement in math and reading. The goal is to ensure that students meet or exceed their state's standard for proficiency in math and reading by 2014. The issue of whether childhood health, specifically obesity, really affects academic performance is an important and interesting topic for those who care about educational outcomes. Consequently, the first study in this thesis is to investigate whether there is an association between academic achievement and obesity rates among young children in Arkansas public schools. The reason we choose Arkansas is because Arkansas is an interesting case to study. First, Arkansas is one of the poorest and least healthy states and has one of the highest childhood obesity rates in the United States[2]. Furthermore, Arkansas is among the states that have the lowest student achievement test scores[3].

Uncovering and better understanding the causes of childhood obesity is also essentially important to the public and policy makers. Bad food choices and dietary intake have been documented to relate to many diseases and health problems, such as cardiovascular disease, and obesity (Gibson 1996; Johnson et.al. 2007). People's dietary habit and food choice could be closely related to the local food environment. People living in an area with limited access to supermarkets or large grocery stores are facing significant higher costs to purchase food items in terms of time, price of food, and travel cost. Instead, convenience stores that tend to sell high

[2] Based on National Conference of State Legislation, Arkansas had rates of overweight and obese children higher than 35.1% in 2007. See http://www.ncsl.org/issues-research/health/childhood-obesity-trends-state rates.aspx#2005_Map

[3] According to 2011 survey and assessment results from the National Assessment Education Progress (NAEP), reading and math scores earned by Arkansas fourth graders on the 2011 national exam were stagnant and below the national average.

calorie food items become the alternative food sources for those people (Alviola, Nayga and Thomsen 2013). Understanding the relation between local food environment, food choices and diet intake is important and beneficial to the efforts on the prevention of childhood obesity. Therefore, the second study in this thesis examines the effect of food store accessibility on children's diet quality.

The rest of this thesis is laid out as follows. Chapter 2 covers the study of the consequences of childhood obesity rates on educational outcomes targeting on grade 4 and 6 students from Arkansas public schools. In chapter 3 we switch the focus to the factors that contribute to childhood obesity, and mainly focus on investigating how accessibility of food retailers impact children's dietary intake quality. Chapter 2 and 3 each represent self-contained studies and include a review of existing literature, data description, statistical model specification and results. The last chapter gives conclusions and some discussion on the limitations of the two studies.

II. EFFECT OF CHILDHOOD OBESITY ON ACADEMIC ACHIEVEMENT

The aim in this study is to examine the issue of the effect of obesity rates on children's academic achievement scores. We utilize a grade level panel data set from 2005 to 2009 which contains school, school district and community level information. Different statistical regression models (pooled OLS, fixed effects and random effects) and subsamples are employed to access the relationship between childhood obesity prevalence and academic achievement.

A. Literature Review

Educational economists have carried out many studies analyzing the factors that affect students' educational performance and assessing different ways to improve students' academic achievement scores from the perspective of an education production function. On the one hand, a large body of research focused on the influence of inputs such as parental school involvement, family socioeconomic background, and household resources on children's cognitive, social and emotional development (Hill and Neill 1994; Muller 1995; Blau 1999; Okpala, Okpala and Smith 2001; Israel, Beaulieu and Hartless 2001; Hill and Taylor 2004; Yan and Lin 2005; Sirin 2005).They agree on the importance of parent child interaction and believe that parents' socioeconomic status plays a significant role in shaping children's educational performance. On the other hand, a multitude of studies have also been conducted on the impact of school inputs (e.g., school resources and facilities, financial budgets and expenditures, class and school size, and teacher characteristics) on students' educational outcomes. For instance, early work by Hanushek (1986, 1989), found out that there is no strong evidence to support the notion that teacher-student ratios, teacher education and teacher experience positively affect student achievement. However, more recent studies by Hedges, Laine and Greenwald (1994), Wayne and Youngs (2003), Rivkin, Hanushek and Kain (2005), Clotfelter, Ladd and Vigdor (2006) and Aaronson, Barrow and Sander (2007) not only agree that schools and teachers matter, but they also assert that these factors make significant contributions to students' educational outcomes. In addition, many other factors such as school learning environment and culture, students' peer impacts, and learning programs and approaches have been shown to be related to students' academic outcomes.

There are also studies that address the relationship between academic performance and student health and wellbeing along dimensions such as hunger, malnutrition, sleep, physical and emotional abuse, and chronic illness (Austin et al. 1998; Glewwe, Jacoby and King 2001; Taras 2005a, 2005b; Puskar and Bernardo 2007; Carlson et al 2008; Belot and James 2011). Recently, there are an increasing number of studies focusing on examining and verifying the link between childhood body weight and educational outcomes. The results are inconsistent. Many of them found a negative association between overweight and school performance (Crosnoe and Muller 2004; Datar, Sturm and Magnabosco 2004; Taras and Potts-Datema 2005; Datar and Sturm 2006; Sabia 2007; Gurley-Calvez and Higginbotham 2010; Averret and Stifel 2010). For instance, Datar, Sturm and Magnabosco (2004) used data from the Early Childhood Longitudinal Study-Kindergarten Class (ECLS-K) to investigate the association between childhood overweight and academic performance. They found out that overweight kindergartners scored significantly lower than their non-overweight peers on standardized tests but acknowledged that these effects could be attributed to potential confounding variables. Thus, they concluded that obesity is a marker as opposed to a causal factor when it comes to low academic performance. Gurly-Calvez and Higginbotham (2010) used West Virginia fifth grade school district level panel data to examine the relationship between childhood obesity and performance in schools based on different family income levels. Their results suggest that obesity has a negative effect on academic achievement in lower income school districts and that these effects for low-income children can be offset by additional educational spending. Sabia (2007) studied sample drawing from the National Longitude Survey of Adolescent Health and concluded that there is a negative relationship between body weight and academic performance among white females. Similarly, using individual children's data with mother's historic BMI as instrumental variable, study by Averret and Stifel (2010) found that overweight white boys have both math and reading scores about one standard deviation below that of their peers and obese black boys and girls have significantly lower reading scores but not math scores. However, some other papers found no relationship between body weight and achievement test scores. For example, in MacAcann and Roberts' study (2013), they found that obese students obtain equivalent test scores to nonobese students and they asserted that the differences in grades obtained between obese and nonobese students are due to the peer and teacher prejudice and discrimination. Again, Kaestner and Grossman (2009), and Schoolder et al. (2010) both claimed that there is no significant association between weight status and academic achievement in their paper.

B. Data and Summary Statistics

The data come from four different sources. The students' BMI measurements are provided by the Arkansas Center for Health Improvement (ACHI), which has been given a mandate by the state to conduct annual BMI assessment of Arkansas public school students. The BMI measurements were taken by trained personnel for children in even numbered grades from kindergarten through grade 10. An advantage of the ACHI data is that the BMI outcomes are based on physical measurements and are considered more accurate and reliable than either parent-reported or self-reported height and weight data that appear in many of the earlier studies. In this study, we use student BMI measurement equal to or above 85th percentile. The data are aggregated to the school level for each grade from 2005 to 2009. The students' standardized test scores and school-level measures are obtained from the Arkansas Department of Education (ADE). The standardized test used to measure students' math and literacy knowledge is the Arkansas Augmented Benchmark Exams [4]. National Office for Research, Measurement and Evaluation Systems (NORMES) provided additional school-level characteristics that matched with students' test scores dataset. The last source of our data is the 2000 Census, which includes information on a broad range of socio-demographic and economic characteristics of the school districts and the communities. We first merged our BMI data with the academic achievement scores data and NORMES dataset with matched school-level information[5]. Then we merged those with the 2000 census data by school district code and name[6].

Reverse causation

[4] The augmented benchmark exams include criterion-referenced tests (CRT) component, which focuses on measuring student performance on items specifically developed by Arkansas teachers, and norm-referenced tests (NRT) component, which focuses on rank-ordering student performance based on national norms and contains items in the subsections of reading comprehension, math problem solving, and language skills.

[5] The matched school-level information including enrollment, poverty statistics, language spoken at home, school average math or literacy test scores. The match of schools across all data sources was not perfect, but the number of non-matching schools was only 25-45 out of approximately 1,100 schools in all years.

[6] The 2000 Census data contain census block-level information and each block has a census school district unified code.

As emphasized by Gurley-Calvez and Higginbatham (2010), reverse causation can be problematic because poor academic performance might cause stress or depression and thereby contribute to weight gain. However, they argue that reverse causality is less problematic for young children compared to adolescents and adults because young children's diets and routines are mainly controlled by parents and schools. Hence, considering the possibility of reverse causality when analyzing older children, we limited our analysis only to children in the 4th and 6th grades in our sample. These are the youngest grades for which we have both standardized test scores and measures of obesity prevalence.

Descriptive Statistics

Table 1 gives the means and standard deviations of all the variables used in our analysis by grade. All variables are measured in percentages except for the students' test scores, the school library volume, district-average teacher salary, district expenditure per student, and district per capita income. The average percent of obesity children in grade 4 and 6 are 40.94% and 43.2% respectively with 2.08 percent difference. The students' test scores by year in both grade 4 and 6 are normalized[7]. Since free and reduced lunch participation depends on income eligibility, this variable can be viewed as an indicator of family income status. On average, about 63 percent of both 4th and 6th graders were eligible for participation in free and reduced price lunches. The two largest minority groups are comprised of African American and Hispanic students, which combined average to about 30 percent of school enrollment.

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[7] Same grade exam in different years could be different in format, contents, score weight in different sections and many other factors. Normalized test scores are more comparable cross years than non-normalized ones.

C. Model Specification

A panel data model of the form

is specified, where represents the average math or literacy test scores of grade i, in school j during year t; indicates the average obesity rates in grade i, in school j during year t; is the average enrollment percentage for grade i in school j; is a vector of school level characteristics; is a vector of school district and community level characteristics; and is the spherical error term. The coefficient is the parameter of main interest. It represents the expected marginal effect of students' obesity rates on their educational achievement scores. We first use pooled ordinary least squares and cluster the standard errors at the school district and community level to account for the possibility of having intra school correlation within the same school district. This clustering approach is robust to heteroskedasticity in the school level errors over time.

We also consider a fixed effects model to control for time invariant unobserved school specific effects that could potentially bias the estimates. The fixed effects equation is specified as:

where represents unobserved and unmeasured time variant school characteristics specific to the grade in question. The other regressors are the same as those in equation (1). The fixed effects model uses deviations from averages over time to remove the influence of unobserved heterogeneity. For example, although we cannot measure the effectiveness of each school's administration, school level fixed effects can absorb this effect and also implicitly control for unobservable characteristics that may vary across schools. They also implicitly control for other unobservable and unmeasured student, teacher and school characteristics that may vary across schools.

However, the fixed effects model has some limitations. The estimates generated by the fixed effects model are derived from within-school difference over time, which discards the information about differences across schools. So we would not be able to identify the effect of other interesting time-invariant variables after the equations are differenced. Consequently, we also estimate a random effects model. This allows estimation of coefficients for time-invariant variables but requires an additional strong assumption that the time invariant unobservables are not correlated with any of the observable covariates in the model. Given the advantages and disadvantages of these two estimation procedures, we present and compare both estimates in the discussion of our empirical results.

D. Results

The main objective of this study is to investigate whether childhood obesity has an influence on academic achievement scores. Tables 2(a) and 2(b) present the pooled OLS results for grades 4 and 6, respectively. In Table 2(a), the estimated effect of obesity on math test scores is -0.037, which means that an increase of one percent in average obesity rate will decrease the average math test score by 0.037 standard deviation. Although it is the expected sign if obesity rates lower students' school performance, the estimate is small in magnitude and is not statistically significant. Aside from the average obesity rate variable, all the other control variables have a statistically significant effect on students' average math test scores except for the percentage of females, the proportion of Asian students, and the proportion of students with Spanish as the language spoken at home. It is worth pointing out that the estimate for percentage of eligibility for free or reduced lunch, a proxy for home income level, has a negative sign at the 1% significance level, which is consistent with most common findings in education research that children's socioeconomic status and school performance are linked. From the second two columns of this table, we note that the effect of obesity rates on students' literacy test scores is also not statistically significant. The effects of other variables on literacy test scores appear to be similar to those on math test scores with few differences on their statistical significance. The estimates for grade 6 are presented in Table 2(b). The estimated effects of obesity rates on both math and literacy are positive, at 0.105 and 0.036 respectively, but are not statistically significant. Fewer control variables are statistically significant for grade 6. Although the magnitude are very small, parameter estimates for library volume, student expenditure and teacher salary are statistically significant for both grades 4 and 6.

As mentioned before, a limitation of these OLS results is that there may be omitted variables that are correlated with the obesity measure and test scores which can bias our estimates. Hence, we used fixed effects estimation to address this limitation by accounting for school specific fixed effects. We also consider the alternative random effects approach that assumes that the distribution for follows a normal distribution with mean 0 and variance, N (0,). We present estimates of both methods and obtain quantitatively similar results.

The fixed effects and random effects results for grade 4 students are displayed in Table 3(a). The effect of proportion of obese students on math scores is negative in both the fixed effects model and the random effects model, while the effect on literacy is positive. None of these effects, however, are statistically significant. It is worth mentioning that in the fixed effects model, although quite small in magnitude, only the three educational input variables library volume, students' expenditure, and teacher salaries have significantly positive effects at the 1% level. As expected this suggests that children perform better if they are in higher-input school districts. Previous studies have found abundant teacher sorting across schools and districts.[18, 40-43] School districts with higher teacher salaries are more likely to attract more experienced and qualified teachers. In the fixed effects model, all other control variables are not statistically significant. In comparison, there are more variables showing statistical significance in the random effects model and they appear to be of the same significance as those reported in the OLS model. Moving to Table 3 (b), we find no statistical evidence of a significant relationship between obesity rates and 6th grade students' achievement scores in both math and literacy. Again, library volume, student expenditure, and teacher salaries have significant and positive effects on students' achievement scores in both the fixed and random effects models.

Finally, to further investigate the effect of childhood obesity on educational outcomes, we also separate our sample into different subsamples. As mentioned before, eligibility for free or price reduced lunch is based on family income and so we use eligibility as a proxy for socioeconomic status (SES). We divide the full sample into low SES and high SES subsamples based on the percentage of students with free or price reduced lunch. We choose 60% as a cutoff as this is near the statewide mean reported earlier in Table 1. Schools that have free or reduced lunch eligibility greater than 60% on average across all years are classified as low SES schools with the rest being classified as high SES schools. Similarly, based on minority status, we also break the full sample into high minority and low minority subsamples by using the sum of the percentage of African American and Hispanic students. If this sum is greater than or equal to 30%, the school is classified as a high minority school. Otherwise, the school is classified as a low minority school. Figure 1 presents the average obesity rates of grade 4 and 6 students with different subsamples. In general, grade 6 students have relatively higher obesity rates compared to grade 4 students (i.e., 40.5% vs 38% in the high SES subsamples, 45.2% vs. 43.4% in the low SES subsamples, 41.3% vs. 39.5% in the low minority subsamples, and 44.5% vs. 41.8% in the high minority subsamples, respectively). Also, the average obesity rates of students from subsample with lower income and higher percent of minority families is higher than that of students from subsample with high SES and low percent of minority families.

Table 4 presents the estimates of obesity prevalence by subsample and by grade from both the fixed effects and random effects models. Interestingly, in the low SES grade 4 subsamples, both fixed effects and random effects estimates show a statistically significant positive effect deviation of obesity on literacy test scores but no significant effect on math test scores. In contrast, in the high SES grade 4 subsamples, the estimates from both the fixed effects and random effects models show a negative effect on math test scores at the 5% significance level but no effect on literacy. The estimates across the low and high minority sub-samples generally show no effect on the test scores for grade 4 or grade 6. Although not reported, all the educational input variables are positive and statistically significant at the 1% level in these subsample analyses for both grades.

Figure1. Grade 4 and 6 student average obesity prevalence with different subsamples

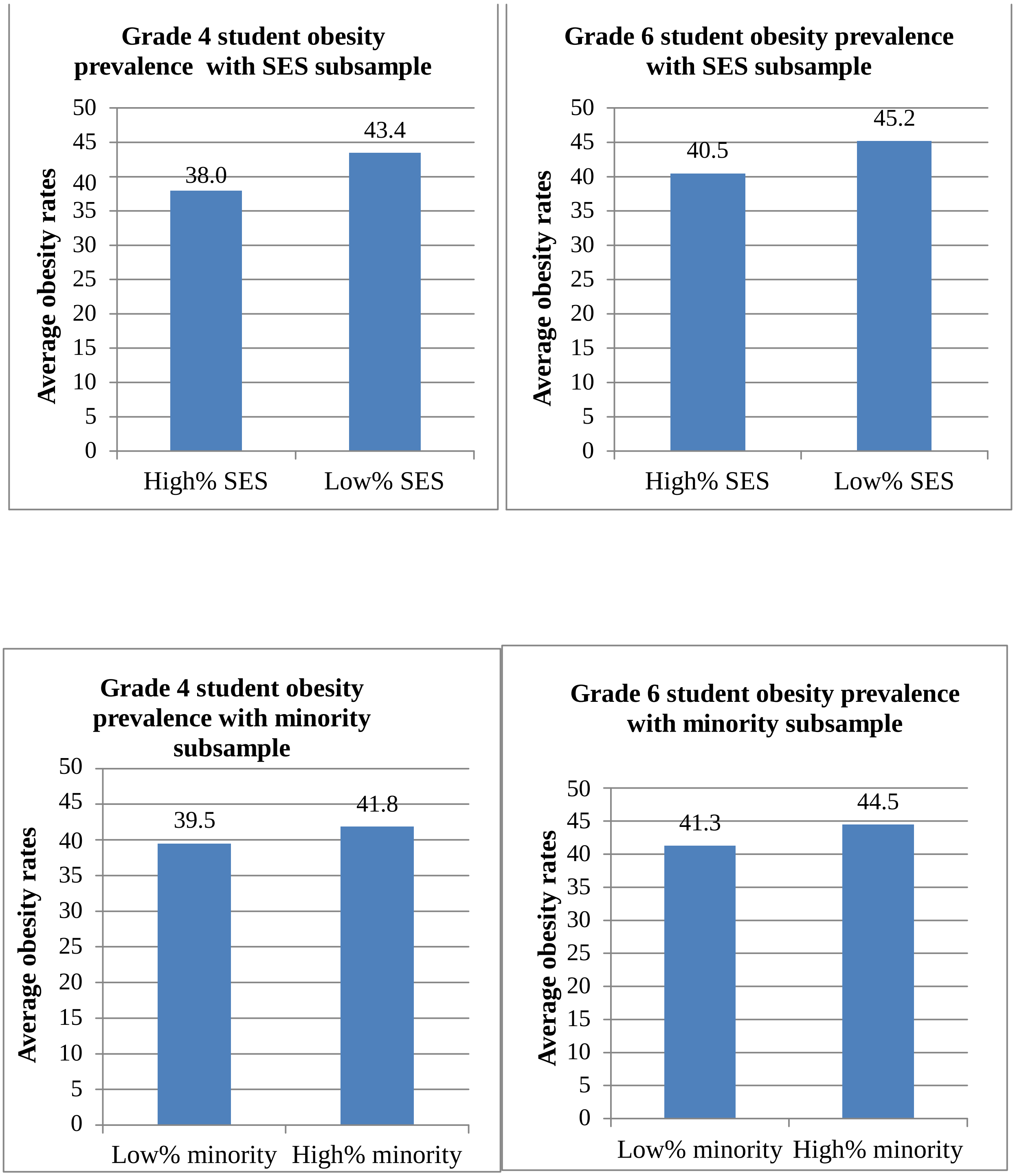

Table1. Descriptive Statistics, Arkansas, 2005-2009

	Grade 4		Grade6	
Variable	Mean	SD	Mean	SD
Percent of obese students	40.94	6.36	43.02	6.36
Standardized average math score	-0.04	0.92	-0.04	0.92
Standardized average literacy score	-0.04	0.94	-0.05	0.93
Enrollment proportion	18.43	7.92	23.95	13.01
Percent female students	48.61	2.57	48.56	4.14
Percent eligibility for free or reduced price lunch	62.62	20.10	62.94	17.96
Percent black students	24.09	30.51	20.99	28.89
Percent white students	66.20	30.91	71.58	29.38
Percent Hispanic students	7.71	12.23	5.73	9.48
Percent Asian students	1.36	2.45	1.04	2.04
Percent native American students	0.63	0.99	0.65	1.10
Percent English as home language	93.04	13.06	95.06	10.24
Percent Spanish as home language	6.00	11.72	4.27	9.12
Library volume	8724.20	3464.75	8218.99	3443.69
Average teacher salary ($)	43835.92	5313.08	41956.09	4681.41
Expenditure per student ($)	8123.63	1031.99	7956.38	906.22
Per capita income ($)	16720.86	2887.52	15764.00	2529.22
Percent urban	46.68	37.12	34.65	35.93
Percent of less than high school degree	25.29	7.59	27.69	7.15
Percent of high school degree or equivalent	34.58	5.68	36.30	5.08
Percent of some college or associates degree	24.19	4.53	22.84	4.53
Percent of Bachelor's degree	10.55	5.05	8.78	4.12
N	506		377	

1. School level variables. The proportion of students within the school.
2. School-district level variables. The proportion of population or households within the school district.

Table 2(a). Ordinary least square results for grade 4 (N=2,311).

Variable	Math		Literacy	
	Coefficient	SE	Coefficient	SE
Constant	-279.0	(262.4)	-579.4	(374.9)
Grade 4 obesity	-0.0371	(0.108)	0.0913	(0.166)
Female	0.0259	(0.293)	0.675	(0.481)
Asian	1.783	(1.738)	3.741	(2.500)
African American	-1.059***	(0.0904)	-1.684***	(0.132)
Hispanic	1.485**	(0.752)	1.801*	(1.087)
Native	-2.865***	(1.007)	-5.223***	(1.375)
English as home language	3.552*	(2.036)	5.520*	(2.924)
Spanish as home language	1.286	(2.244)	2.299	(3.282)
Free or price reduced lunch	-0.426***	(0.134)	-1.168***	(0.221)
Grade 4 enrollment	0.345**	(0.140)	0.277*	(0.163)
Library volume	0.000766**	(0.000359)	1.56e-06	(0.000514)
Expenditure per student	0.0108***	(0.00165)	0.0139***	(0.00236)
Teacher salary	0.00274***	(0.000578)	0.00284***	(0.000693)
Urban	0.166**	(0.0746)	0.299***	(0.0977)
Less than high school degree	4.092**	(1.658)	6.034***	(2.223)
High school degree or equivalent	4.081***	(1.494)	4.895**	(2.011)
Some college and associate degree	3.833**	(1.654)	5.266**	(2.266)
Bachelor's degree	6.263**	(2.469)	9.694***	(3.159)
Income per capita	-0.00368***	(0.00134)	-0.00595***	(0.00179)
R-squared	0.446		0.525	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2(b). Ordinary least square results for grade 6 (N=1,580).

Variable	Math		Literacy	
	Coefficient	SE	Coefficient	SE
Constant	-111.2	(264.4)	226.5	(311.2)
Grade 6 obesity	0.105	(0.131)	0.0361	(0.156)
Female	0.228	(0.218)	0.958***	(0.238)
Asian	1.977	(1.640)	0.427	(1.953)
African American	-1.041***	(0.0998)	-1.480***	(0.127)
Hispanic	1.868**	(0.753)	1.089	(1.046)
Native	-0.957	(1.131)	-0.266	(1.487)
English as home language	5.004**	(2.143)	2.898	(2.631)
Spanish as home language	2.491	(2.335)	0.342	(2.986)
Free or price reduced lunch	-0.274	(0.168)	-0.659**	(0.257)
Grade 6 enrollment	-0.207*	(0.124)	-0.410**	(0.183)
Library volume	0.00105**	(0.000464)	0.00104*	(0.000592)
Expenditure per student	0.00928***	(0.00199)	0.000887	(0.00262)
Teacher salary	0.00337***	(0.000569)	0.00262***	(0.000691)
Urban	0.0663	(0.0932)	0.152	(0.131)
Less than high school degree	1.432	(1.663)	1.444	(1.720)
High school degree or equivalent	1.212	(1.635)	0.890	(1.628)
Some college and associate degree	1.783	(1.708)	1.072	(1.841)
Bachelor's degree	2.114	(2.556)	4.214	(2.775)
Income per capita	-0.00345**	(0.00165)	-0.00442**	(0.00189)
R-squared	0.374		0.499	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3(a). Grade 4 results with full sample

Variable	FE				RE			
	Math		Literacy		Math		Literacy	
	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE
Constant	-425.7	(7,039)	4,035	(7,638)	-444.9***	(151.5)	-767.8***	(228.2)
Grade 4 obesity	-0.0931	(0.0889)	0.0571	(0.134)	-0.0694	(0.0864)	0.0496	(0.126)
Female	0.117	(0.397)	0.168	(0.463)	0.00498	(0.260)	0.401	(0.384)
Asian	1.801	(1.647)	1.973	(2.416)	1.275	(1.045)	2.719*	(1.552)
African American	0.0675	(0.397)	-0.876	(0.569)	-1.212***	(0.0653)	-1.936***	(0.0993)
Hispanic	1.295	(0.864)	0.855	(0.932)	1.320***	(0.444)	1.190*	(0.656)
Native	1.329	(1.481)	0.589	(1.895)	-1.968**	(0.957)	-3.651**	(1.433)
English	-0.607	(1.641)	1.155	(2.228)	2.794**	(1.178)	4.495**	(1.748)
Spanish	-0.923	(1.600)	1.087	(2.234)	0.550	(1.302)	1.754	(1.928)
Free/reduced lunch	0.157	(0.197)	-0.142	(0.300)	-0.213***	(0.0788)	-0.822***	(0.119)
Enrollment	0.204	(0.263)	0.196	(0.282)	0.464***	(0.122)	0.428**	(0.185)
Library volume	0.00345***	(0.000889)	0.00297***	(0.00107)	0.00140***	(0.000305)	0.000762*	(0.000462)
Expenditure/stud.	0.0202***	(0.00209)	0.0264***	(0.00260)	0.0167***	(0.000914)	0.0217***	(0.00135)
Teacher salary	0.00437***	-0.000815	0.00402***	(0.000840)	0.00401***	(0.000252)	0.00417***	(0.000374)
Urban	-0.995	(1.646)	-1.795	(2.741)	0.123**	(0.0544)	0.261***	(0.0836)
≤ HS degree	3.676	(69.18)	-51.23	(71.72)	5.132***	(1.057)	7.285***	(1.627)
HS or equivalent	9.220	(63.49)	-28.75	(69.91)	5.861***	(0.978)	7.162***	(1.504)
Some college	-21.09	(74.00)	-75.02	(75.66)	5.074***	(1.014)	6.902***	(1.560)
Bachelor's degree	-6.848	(73.56)	-28.97	(80.26)	7.970***	(1.735)	12.07***	(2.669)
Income per capita	0.0526	(0.0741)	0.0318	(0.0967)	-0.00430***	(0.000885)	-0.00670***	(0.00136)
Observations	2,311		2,311		2,311		2,311	
R-squared	0.448		0.291					
Number of id	506		506		506		506	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3(b). Grade 6 results with full sample

	FE				RE			
Variable	Math		Literacy		Math		Literacy	
	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE
Constant	-25,229***	(6,464)	-12,991*	(7,763)	-466.4**	(207.5)	-79.29	(254.8)
Grade 6 obesity	0.148	(0.102)	0.105	(0.146)	0.160	(0.105)	0.0886	(0.124)
Female	1.047***	(0.309)	1.285***	(0.345)	0.514**	(0.246)	1.119***	(0.297)
Asian	6.284***	(1.668)	2.596	(2.628)	2.584**	(1.281)	1.351	(1.554)
African American	-0.440	(0.463)	-1.748***	(0.594)	-1.283***	(0.0848)	-1.657***	(0.105)
Hispanic	1.011	(0.969)	-1.788	(1.389)	1.403*	(0.738)	-0.285	(0.890)
Native	3.258**	(1.476)	-0.0499	(1.559)	-0.667	(1.146)	-0.409	(1.392)
English	2.572	(1.945)	3.020	(2.357)	5.476***	(1.532)	3.986**	(1.849)
Spanish	3.995*	(2.203)	4.726	(3.063)	3.352*	(1.859)	2.888	(2.240)
Free/reduced lunch	0.819***	(0.190)	-0.0124	(0.229)	0.0133	(0.117)	-0.505***	(0.143)
Enrollment	-0.737***	(0.253)	-0.400	(0.344)	-0.189*	(0.106)	-0.336***	(0.130)
Library volume	0.00432***	(0.00103)	0.00314***	(0.000727)	0.00204***	(0.000408)	0.00165***	(0.000502)
Expenditure/stud.	0.0239***	(0.00251)	0.0117***	(0.00202)	0.0179***	(0.00120)	0.00732***	(0.00145)
Teacher salary	0.00394***	(0.000749)	0.00253***	(0.000830)	0.00438***	(0.000321)	0.00299***	(0.000387)
Urban	-3.126**	(1.383)	-0.210	(1.300)	0.0475	(0.0708)	0.151*	(0.0883)
≤HS degree	242.1***	(63.98)	119.0	(76.98)	2.656*	(1.485)	2.239	(1.861)
HS or equivalent	255.0***	(62.51)	134.6*	(75.14)	3.356**	(1.386)	2.291	(1.736)
Some college	292.0***	(76.15)	142.7	(91.11)	3.400**	(1.460)	2.232	(1.828)
Bachelor's degree	371.8***	(88.87)	183.2*	(102.1)	4.356*	(2.351)	5.611*	(2.943)
Income per capita	-0.0409	(0.0513)	0.00432	(0.0484)	-0.00402***	(0.00118)	-0.00464***	(0.00147)
Observations	1,580		1,580		1,580		1,580	
R-squared	0.503		0.136					
Number of id	377		377		377		377	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table4. Estimates for different subsamples for grade 4 and 6

			Grade 4				Grade 6			
Subsample	Model	Subject	Coefficient	SE	Obs.	# of Schools	Coefficient	SE	Obs.	# of schools
Low SES	FE	Math	0.0445	(0.120)	1229	275	0.205	(0.144)	812	204
		Literacy	0.336*	(0.171)			0.355*	(0.193)		
	RE	Math	0.0839	(0.117)			0.279*	(0.144)		
		Literacy	0.351**	(0.175)			0.376**	(0.176)		
High SES	FE	Math	-0.222*	(0.126)	1082	231	0.0869	(0.148)	768	173
		Literacy	-0.267	(0.198)			-0.192	(0.213)		
	RE	Math	-0.227*	(0.127)			0.0419	(0.152)		
		Literacy	-0.273	(0.180)			-0.178	(0.173)		
Low Minority	FE	Math	-0.0707	(0.135)	879	192	0.248	(0.154)	719	173
		Literacy	0.103	(0.208)			0.165	(0.218)		
	RE	Math	-0.0213	(0.130)			0.285**	(0.141)		
		Literacy	0.135	(0.197)			0.164	(0.174)		
High Minority	FE	Math	-0.0577	(0.120)	1432	314	0.0704	(0.142)	861	204
		Literacy	0.0869	(0.185)			0.0806	(0.208)		
	RE	Math	-0.0787	(0.114)			0.0423	(0.151)		
		Literacy	0.0370	(0.164)			0.0293	(0.177)		

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

III. EFFECT OF FOOD STORE ACCESS ON EARLY CHILDHOOD DIET QUALITY.

The objective of this study is to examine the extent to which accessibility of food stores around young children's home neighborhood impacts their dietary intake by using cross-section data on Head Starts (HS) children in Arkansas. We use proximity and density measures to represent food store access. Simple probit and OLS baseline models and instrumental variable approaches are utilized to examine the relationship between the children's neighborhood food environment features and their dietary consumption quality.

A. Literature Review

The increase of obesity prevalence in the past decades has led to increasing interest on analyzing the effect of food environment on obesity outcomes. The food environment includes not only food service establishments such as full-service restaurants and fast food outlets, but also retail food stores like supermarkets, grocery stores, drugstores and convenience stores. Typically, large grocery stores and full-service restaurants offer healthier foods than convenience stores and fast food outlets. Fast food has been blamed as one of the reasons for the prevalence of childhood obesity as some studies have documented evidence that access to fast food is associated with a higher BMI among children (Davis and Carpenter 2009; Currie et al. 2010; Alviola et al. 2011). For example, focusing on 9th grade children, Currie et al. (2010) find a significant effect of proximity to fast food restaurant on the risk of obesity. Especially they find that the presence of a fast food restaurant within a tenth of a mile of school is associated with at least a 5.2 percent higher obesity rate compared to a fast food restaurant present within 0.25 miles of the school. Similarly, using a sample of Arkansas public school children with a broad range of grades from kindergarten through 10th grade, Alviola et al. (2013) ascertain that the number of fast food restaurants within a mile of school is significantly positively related to childhood obesity rates.

In addition to fast food restaurants, food retailers make up another important component of the food environment. Large grocery retailers have been found to offer a wide variety of foods often at relatively lower prices. Compared to households in higher income neighborhoods, households in low income neighborhood often face fewer large grocery stores and more small food stores like dollar stores and convenience stores (Morland et al. 2002; Powell et al. 2006; Blanchard and Lyson 2007; Wang et al. 2007). Due to limited access to healthier and cheaper food choices, these families may potentially consume more energy dense foods, which can lead to weight gain. Many studies that examined the effect of food deserts[8] on childhood obesity suggest that increasing the availability of supermarkets in the local area is associated with a lower incidence of childhood obesity while the presence of convenience stores is linked to higher incidences of childhood obesity (Liu et al. 2007; Powell et al. 2007; Galvez et al. 2009; Leung et al. 2011).

While more attention has been focused on the effect of food environment on health outcomes like BMI in the literature, less attention has been given directly to the linkage between food environment features and diet. BMI is a result of many factors, but people's dietary intake might be more closely influenced by the neighborhood environment. Kyureghian and Nayga (2013) examine whether access to food retailer outlets is a significant predictor of the probability

[8] Food deserts are defined as areas where people do not have easy access to an affordable and healthy diet (Cummins and Macintyre 2002).

of shopping at those outlets to purchase healthy food like fruits and vegetables. Their results, suggest that availability of different types of food stores does not have a significant effect on the likelihood of patronizing any specific type of food stores when purchasing fruits and vegetables. Furthermore, Pearson et al. (2005) and Laska et al. (2010) do not find any statistically significant association between the accessibility of food stores and vegetable and fruit purchases and consumption. In contrast, some other studies found different results. Drawing a sample from different states in the nation, result findings by Morland, Wing, and Roux (2002) suggest that there are some associations between the local food environment and residents' diets. They find that people living in areas with supermarkets have healthier diets in terms of fruits and vegetables, total fat and saturated fat. Hanson et al. (2004) draws a similar conclusion that increasing household availability of healthy food choices can enhance the consumption of fruit, vegetables and dairy foods.

One limitation of these prior studies is that they largely focused on each individual dietary components intake (e.g. fruit and vegetables intake). Foods are usually not consumed in isolation, however. Due to the potential of synergy among foods, using alternative measurement like diet indices to measure the quality of diet could potentially provide additional insight (Moore et al. 2008). For instance, employing the Alternative Healthy Eating Index (AHEI) measure, Moore et al. (2008) found that people living in areas with poor food environments were much less likely to have a healthy diet than those around rich food environments. Another limitation of many of previous work that try to find a causal relationship between food environment features and diet intake or health outcomes is that they do not take into consideration the potential endogeneity issues of accessibility of food stores on the grounds that people tend to select where they live partially based on neighborhood characteristics (e.g. the proximity between their homes and certain stores and services) and their food purchase and consumption is a function of price of food, which is partially determined by the availability and travel costs to acquire the food.

In order to closely examine the relationship between the accessibility of food stores and children's diet quality, we analyze both individual dietary components intake and a diet quality index called Family Map Healthy Eating Index (FMHEI) in this study. In addition, we utilize both proximity and density measures to assess the accessibility to the food stores. In contrast to Moore et al (2008) who use adults aged 45 to 84 from 3 big metropolitan areas, our study particularly focuses on low income family children from small cities in relatively rural areas in Arkansas. Arkansas is an interesting case to study since it has one of the highest childhood obesity rates in the United States. In addition, we are more cautious about the potential endogeneity issues and apply an instrumental variable approach in the model to analyze the relationship between the food store access and diet quality.

B. Data and descriptive statistics

The main dataset we use in this study is based on Arkansas Family Map (FM) data in school year 2006-2007. FM is a structured interview assessment that targets head start (HS) children aged from 3 to 5. There are 161 HS children in our study sample, majority of HS children are from five major towns and they are Russellville, Clarksville, Dardanelle, Morrilton, and Plumerville, Arkansas[9]. We select these places as our study areas because these are the only areas where FM data can provide the geo-code of centroid of census block where each HS student's home locates. Since the objective of FM is to assess multiple aspects of the family to identify concerns in the home that could potentially lead to poor child development, a series of critical home and family information of children is elicited and collected by HS teachers during the home visit interviews. The interview questionnaire has 12 sections in total covering different aspects of the family information including demographics, routines, school readiness, monitoring, environment safety, discipline, health, basic need, home and car safety, social integration, and an end of visit observation. In this study, the main focus is on the parents' reported dietary intake information of the children.

Food retailer geo-locations data are from Dun and Bradstreet (D&B), a commercial data source that provides related business and commercial information. This data provide a broad variety of types of food establishments. In this study, we only cover three major types of food establishments and they are convenience stores, drug stores, and large grocery stores. The large grocery stores in our study are defined as containing full line of grocery items, including a full fresh produce department with annual sales more than $500,000.

We also use zoning map of the five major towns to construct instrumental variables. Zoning maps are obtained from the each town's government office. A Geographic Information

[9]The number of children from the major five towns comprises over 90 percent. 25 of them are from Dardanelle, 29 of them are from Morrilton, 41 of them are from Clarksville, 51 of them are from Russellville, and 5 of them are from Plumerville. The rest of students are from other surrounding small towns.

System (ArcGIS) is used to geo-process those zoning maps and create the desired data for regression analysis.

Diet quality measure

Dichotomous measure

The dietary intake information contains questions about how frequently the child consumes healthful foods as well as less healthy food. There are 10 questions and each question pertains to certain group of food. The food groups are dairy products (like milk, cheese, yogurt, etc.); meat (like beef, chicken, fish, eggs, etc.); beans (like dried beans/peas, peanut butter, veggie burger, bean soup, baked/canned beans, etc); bread (or grain substitutes like rice, pasta, cereals, tortilla breads etc.); vegetable (Dark green or orange/yellow vegetables like greens, carrots, broccoli, squash, sweet potatoes); fruit (like apples, oranges, bananas, grapes, peaches, applesauce); 100% fruit juice; sweets (like cakes, cookies, candy, etc.); sugar drinks (like cola, Kool-aid, Yohoo, and fruit flavored drinks etc.); and sports drinks (like Gatorade, Power Aid, etc.).

Parents give answers on how frequent the child eats the foods from each different group (excluding food eaten at HS) by choosing answers from multiple choices. There are five choices and they are none, once per week, 2-6 times a week, once per day, and more than once per day. Grey shaded areas and non-shaded areas on the survey instrument separate the answers so that the interviewer can easily identify and assess whether a child is at risk in terms of eating a balanced diet. The parents being interviewed do not see the shaded area on the survey instrument. With healthy groups of food, grey shaded areas indicate inadequate consumption.

For dairy, vegetables, and fruits groups, less than once a day answers (e.g. none, once per week, 2-6 times a week) fall within the grey shaded area. If a child's parents choose those answers, the child is considered at risking having sufficient consumption. Therefore improvement on consuming more these groups of food should be considered as a family goal in the future. For beans, meat and bread, the grey area cutoff answer is 2-6 times a week. If a child's parents choose answers none or once a week, the answers fall into the grey area. With less healthy groups of food, grey areas indicate excessive consumption. For juice, sweets, sports drinks and sugar drinks, taking more than once a day is considered at risk excessively consuming these groups of food for children.

Table 1 gives the proportion of children who are at risk of consuming each group of food (insufficient consumption of healthy food and excessive consumption of less healthy food) with different sample size. The first column represents the whole sample. It is notable that for the healthy groups of food such as vegetables and fruit, there are about 57.1% of HS children who are having trouble consuming adequate dark green or orange/yellow vegetables (less than once a day) and 28.6% of them at risk of consuming adequate fruits. Also, there are about 15.8% of answers falling into the grey shaded area for the question on frequency of consumption of sweets, which indicates that those children are at risk of overeating sweets (more than once per day). Moving to the next column, we limit our sample to the HS children who have risk on consuming enough either fruit or vegetables. Interestingly, compared to the full sample, the risk rate on sweet and sugar drink consumption falls to 15% and 13% respectively, although not much. No children have a problem with sport drinks either. We also separate the full sample by gender. Columns 3 and 4 report the percentage of risk on different group of food consumption for boys and girls respectively. Boys have less risk rate on taking enough vegetables and fruits than girls. For example, for fruit group, the difference of the risk rate between girls and boys is 11.4% with 34.2% for girls and 22.8% for boys. On the other hand, however, boys have a higher risk rate on consuming less healthy foods than girls.

Index measure

The Health Eating Index (HEI) is a scoring measure system that is developed and used by the U.S. government to assess diet quality and compliance with dietary guidelines for Americans (Kennedy et al. 1995; Guenther et al. 2007). The Youth Healthy Eating Index (YHEI) is a modified scoring system developed to address dietary issues of children and adolescents explicitly (Feskanich et al. 2004). Following the YHEI, a simplified and modified eating index called Family Map Healthy Eating Index (FMHEI) specific for the family map HS children is constructed in this study. Besides using intake frequency information of each group of food, two additional questions pertaining eating habit and environment under routines section are also used. The two questions are asking how many days the family ate dinner at a regular time and how many days the family stick to regular morning routines. Consequently, the FMHEI is an absolute score that is the sum all the scores contributed by the answer of all the included questions. FMHEI consist of 14 components and the total scale ranges from 0 to 100. The higher scores the index, the better the diet quality is implied. Table 2 lists the scoring criteria for each component.

Dairy, bread, vegetable, fruit, and sweets can score up to 10 points for each group. The less frequent the child eats the healthy group of food the lower score contributes to the index, while it is the opposite for less healthy group of food. For example, for vegetables, 0 points is scored when the frequency answer is none while 10 points is given when frequency answer is more than once a day. For sweets, it is the opposite way, 0 point is awarded for an answer of more than once a day and 10 points are scored for an answer of none. The three choices in between these values are equally spread out into 2.5, 5 and 7.5 points.

Since meat and beans are substitutes for sources of protein, each is assigned a maximum of 5 points with a total of 10 points for these two groups together (total protein servings). Similarly, up to 5 points is assigned to answers on sports drinks and sugar drinks with a total of 10 points for these two groups together because they are both sugary beverages. For the juice group, none and more than once a day choices are both assigned 0 points[10]. and the scores are spread among the rest three choices with maximum 5 points for choice once per day. However, the FM data do not collect any information about salty snacks like potato chips, corn chips, popcorn, pretzels, and crackers, which is a major source for sodium intake. We arbitrarily assign 3.75 points to every child in the sample with a maximum 5 points for this category, which is an assumption that children consume salty snacks at least once a week.

To take into consideration of the effect of eating habit and environment on children's diet, up to 5 points are assigned to components that ask how many times do a family eats dinner at regular time and follows morning routines in a week. Few days are given lower scores[11].

[10] A child will get too much sugars or carbohydrates from it if he or she overdrinks juice. Study shows that excess fruit juice consumption can contribute to obesity (Dennison, Rockwell and Baker 1999).

[11] There are 8 answer choices for these two questions: none, 1 day, 2 days, 3 days, 4 days, 5 days, 6 days, and 7 days. 0 point is assigned to those who choose answer 1 and 2, 1.67 points are

Compared to YHEI, the FM data do not contain information about how often the children take multivitamins, have margarine and butter, and consume fried foods outside the home and consume animal visible fat[12]. Therefore, we put all this missing information into one category called "other" and assign a total of 5 points for everybody.

Based on above scoring criteria, the mean of the FMHEI score in our sample is 67.19 with a minimum of 42.9 and maximum of 85.0. Figure 2 presents the histogram of FMHEI. Using midpoint method plotting, the most frequent scores are between 60 and 72, with 53 out of 161 scoring around 72 points.

Food store access measure

Distance is one of the important factors that people consider where to shop foods because travel cost to food stores can be regarded as an implicit cost of the food. The shorter the distance from home to food retailers, the less time and cost people use. In our study, we use proximity which is the radius distance in miles from each HS child's residence to the nearest different types of food store to measure food store access. However, the distance to the closest food retail stores can vary substantially among households living in rural and urban areas. Alternatively, we also consider density measure that is the constructed by accounting for the number of the certain

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assigned if the choice is either answer 3 or 4, 3.67 points are assigned if the choice is either 5 or 6, and finally, maximum of 5 points are assigned to those who choose either answer 7 or 8.

[12] Multivitamins with minerals provide calcium and iron, which are essential during growth and sexual maturity. Margarine is a major contributor toward trans-fatty acids in diet and butter is a source of saturate fat. Fried foods contribute to a high energy intake and fried foods outside of home is likely be high in trans-fatty acids. Visible fat on meat contributes toward saturated fat in the diet and total fat (Feskanich et al. 2004).

types of food stores within 0.5 mile radius buffer[13]. Table 3 contains summary statistics of food store access measures for the three types of food retailers in this study. The average distance of a HS child's family to large grocery store is 1.56 miles with minimum 0.1 miles and maximum 8.23 miles which points an uneven access to large grocery stores across sample size due to different household locations between urban and rural areas. The average distance to nearest drug store and convenience store are 1.55 miles and 0.88 miles respectively. For density measure, the minimum counts within 0.5 mile buffer is 0 for all three types of store and the maximum accounts are 2 for large grocery stores and drug stores, and 3 for convenience stores. Since there are only a few different counts, figure 1 shows a histogram of the frequency of each density count for three different types of food stores. It is easy to see that the majority of the HS families do not have any type of store within the 0.5 mile buffer of their census block of residence. For HS families that have 2 large grocery stores, 3 convenience stores, and 2 drug stores within 0.5 radius buffer, the numbers of frequency are only 6, 2 and 11 respectively.

<u>Control variables</u>

We also include some related variables in predicting the children's diet quality as control variables in the model. Table 4 presents the summary statistics of control variables[14]. There are 40.4% of white children and 12.7% of African American children. The rest are considered as one group called other races that includes Asian, Hispanic, biracial/multiracial and etc. Boys and

[13] 0.5 mile is the most reasonable distance to create a radius buffer for each HS household due to the relatively small size of the towns in my sample.

[14] In order to keep enough degree of freedom in our analysis, we decide only include a few control variables and do not include other possible control variables such as caregivers' education level, marital status, and work status.

girls are almost equally represented. In additional to gender and race, another important control variable included in the model is the caregiver's mental health condition. This variable is derived from the 2 questions: (1) during past 2 weeks, how often do you have been bothered by feeling down, depressed, or hopeless; (2) how often do you have been bothered by having little interest or pleasure in doing things. We create a variable called depression and define it as a binary variable. It equals to 1 if parents choose any of the following choices (several days, more than ½ the days and nearly every day) in either question (1) or (2) and equals to 0 otherwise. The reason we include this variable in our model is that we believe that mental health play an important role on parenting. Caregivers who are suffering mental health problem are also less likely to create a pleasant home environment for their children, which may indirectly affect the child's diet.

C. Statistical Method

Baseline probit and OLS models are used to measure the association between diet quality and food store access for each individual child. The general structure is represented as:

(1)

where represents the diet quality measure for each individual child i; is the food store access measure (proximity or density) for individual i; is a vector of control variables that includes children's gender, race, and caregivers' mental health condition; is the error term; and and are the coefficient estimates. When is defined as a dichotomous measure, the probit model is used to estimate the effect of accessibility of food stores on the likelihood of a child having an unbalanced diet based on the frequency of consumption of each individual group of food. takes a value of 1 if a child is at risk for consuming a certain group of food and 0 otherwise. To gain additional insight, we also replace the dichotomous measure with a continuous measure named FMHEI in the baseline model to analyze the effect of food store access on children's diet quality. When FMHEI is utilized, the baseline model is regarded as a simple OLS model.

In the baseline model, the coefficient estimates are unbiased based on the assumption that the error term is not correlated with the regressors in the equation. This assumption, however, is likely to be violated due to omitted unobserved variables. For example, people may select where they live based on some subset of neighborhood characteristics and individual preferences. These factors may be correlated with people's neighborhood environment features such as accessibility to food retailers, which, in turn, may be correlated with people's food purchase and consumption behavior that is partially determined by the cost of travel (Chen, Florax and Snyder 2009). Also young children's food choices and preference are mostly controlled and determined by parental grocery purchase decision. Thus, there is possible endogeneity that when parents are making decision on their children's diet based on what they purchase from available stores in their neighborhood. Consequently, the above directly produced regression estimates are likely to be biased. Given these concerns, we introduce an instrumental variable strategy in our analysis. Chen, Florax and Snyder (2009) use city zoning maps to determine the amount of land available for fast food restaurants to locate within a half mile radius of a person's residence as an instrument to evaluate the effect of the number of fast food restaurants on adults' obesity rates.

Following their approach, the first stage relation involving the instrumentation of the availability of food stores can be specified as:

(2)

where is the instrumental variable representing the percentage of land within 0.5 mile radius of a child's family zoned for commercial use, is defined as before, and is an error term. Consequently, a two-stage estimation technique can be employed in the case of a reduced-form structural model. The first stage predicts the food store access measure as a function of the instrument and covariates and the second stage predicts the outcome based on the first stages' predicted variable and the covariates.

When is a binary variable that indicates whether the child has risk on consuming each group of food, an ivprobit model is utilized. It is based on the assumption that the error terms in the reduced-form probit equation for the endogenous regressor is bivariate normally distributed. When is represented by the continuous variable FMHEI, a two-stage limited information maximum likelihood (LIML) estimation is used[15].

As mentioned above, this analysis considers measures of food store accessibility (proximity and density). When using proximity as an indicator for food store accessibility, we directly use the distance to the nearest to food stores for each type. However, when using a density measure, we change the variable to a binary variable and use it in the model. The measure equals 1 if there are any stores within a 0.5 mile radius buffer and 0 if there are none.

[15] LIML has superior small sample performance than 2-stage least square (2sls) with weak instruments.

We do not use the actual counts for each type of food store in our model because a large portion of the count is 0. Figure 1 gives the frequency of counts for each type of store. Because the binary measure is still considered endogenous, a similar regression strategy is applied here as with distance measure.

D. Results

In the interpretation of the estimates of food store access, we are particularly interested in the marginal effects of the accessibility of food stores on children's different diet intake. Table 5 shows the baseline marginal effect estimates of distance to the nearest stores along with other control variable on HS children's diet quality. The table is divided into three panels including large grocery stores, drug stores, and convenience stores so that the relationship between the children's dietary quality and accessibility of each type of food stores is examined individually. Within each panel, regressions are run with different dependent variables. For binary dependent variables, a probit model is employed[16], while for the continuous dependent variable (FMHEI), OLS with robust standard errors is used.

Theoretically, we would expect that the closer a child's home to large grocery stores, the less likely the child's risk of consuming adequate healthier groups of food like fruit and vegetables. In this case, more points will be contributed to the healthy eating index, thus raising

[16] In family map interview data, there are 10 different groups of food in total. However, only 8 groups of the food are included in our proximity regression analysis and the two groups that are not included in the regression analysis are bread and sport drink. These two groups have a perfect separation problem with some of the regressors, thus we are unable to estimates the marginal effects due to the nonexistence of the maximum likelihood estimation.

higher FMHEI score. On the other hand, we would expect that the closer children live to drug stores or convenience stores, the more likely the risk for over-consuming unhealthy food like sweets and sugar drinks because drug stores and convenience stores usually tend to sell a large amount of high energy dense foods and sell few fruit or vegetables. In this case, FMHEI scores will be lower. When examining the marginal effect of proximity on both binary and index dietary measures, however, we notice that none of the estimates are statistically significant. Increasing the distance from a child's house to any type of food stores by one mile influences neither the probability of having risk on consuming any group of food regardless of healthy food (consuming too less) and unhealthy food (consuming too much) nor the healthy eating index.

An interesting finding from this table is that the mental health condition of a child's parents has a significant negative impact on the integrated dietary measure FMHEI but not on each individual binary dietary measure across all groups of food. It appears that if a caregiver is suffering mental depression or stress, it is expected to affect the child's healthy eating index by about -3.5 points at a 5 percent significance level. This result is consistent with our expectation that parents who are bothered by depression, feelings of hopeless, lack of interest or pleasure doing things are less likely to provide high quality childcare or parenting, which may indirectly affect a child's diet quality. Depression does not have a significant effect on the risk of the binary dietary measure but only on the eating index. A likely explanation is that the eating index is comprised of more components such as eating environment and habit than just food intake information. When parents are mentally stressed or depressed, it is very less likely that they would create a pleasant family eating environment for their children or follow a regular eating habit or routine, which can contribute to a lower score on the FMHEI. It is also worth pointing out that our individual group of food intake information is only a binary diet measure that only indicates whether or not the child is at risk of consuming certain group of food, while the FMHEI is a continuous diet measure capturing more information on the child's diet information. Therefore, the results imply that parents' mental health conditions result in no change in the probability of having risk of consuming each group of food but change in child's eating index as an integrated measure.

Demographic variables such as gender and race show some significant effects in a few regressions. For example, under the large grocery stores panel, girls have 7% less probability of having risk in consuming insufficient meat than boys. Although very small in magnitude, the result is statistically significantly at 5 percent level. Compared to other races, African American children have 25 percent greater probability of having risk on consuming inadequate beans and 28 percent higher probability of having risk on over-consuming juice. Also, under the juice column, being white shows a negative significant influence on the probability of having risk of consuming excessive juice. Like the proximity and depression variables, however, demographic variables do not show any significant effect on consumption of any other interesting groups of food like fruit, vegetables, sweets and sugar drinks. These results are consistent across three different types of food store.

In an attempt to limit the bias from endogeneity, we employ an instrumental variable approach targeting at each child's family location decision and food store location decision. A valid instrumental variable should only impact a child's dietary quality through its effect on food store locations and will only correlate with the food store access but not child's dietary quality measure. The instrumental variable we use to identify our model is the percentage of land that was zoned as commercial within a 0.5 mile radius buffer of each child's residence. The logic is that food store establishments not only first locate to the commercial zoning area, but they also tend to choose to locate to places where neighborhood residences can easily access to their establishments and where business can capture sales. Figure 3 provides the maps of the food stores, indicating the available land for food stores to locate within a 0.5 mile buffer of a child's residence for all five major towns. A visual inspection of the map for each town in figure 3 confirms the correlation between of the food store location and the instrument[17]. Unfortunately, the two weak identification diagnostic F test statistics[18] are quite small, which indicate that we fail to reject the null hypothesis that our equation is weakly identified. To compare to the marginal effects in baseline model, we present the second stage results of the IV model, however.

Table 6 provides the marginal effects of food store access on children's dietary quality with IV approach for large grocery stores, drug stores and convenience stores. It is surprising that many of the marginal effects of proximity become strongly statistically significant. For example, increasing one mile of distance to the nearest large grocery store will increase the chance of having trouble on consuming beans and meat by 19 percent and 18 percent respectively. The probability of a child having trouble consuming fruits and vegetables will both increase approximately 20 percent if the family must travel one more mile of distance to shop at the large grocery stores from their home. Moving to drug stores, the effect of the proximity has

[17] Plumerville is a very small city in Conway county in state Arkansas. The population is only 854. The fact is that people who live at Plumerville shop at Morrilton where the stores concentrate.

[18] Cragg-Donald Wald F statistic is 0.13 and Kleibergen-Paap Wald rk F Statistic is 0.17.

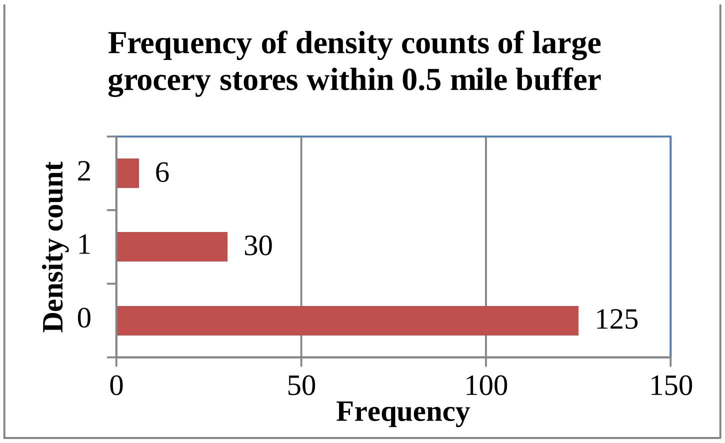
the opposite effect on the risk of bean and fruit consumption. The further the child's home to the drug stores, the less likely the child will have risk on fruit consumption, and this magnitude is 16.5 percent, at 1 percent level of statistical significance. This implies that the further the drug stores to the child's home, the more likely they will consume healthier foods. We would also expect that the further the drug stores, the more likely the children will have risk on over-consuming sweets and sugar drink. However, those estimates are not statistically significant, although the signs are as expected. Turning to the convenience store panel, the negative effect of distance to nearest convenience stores on risk of fruit consumption is twice as large as the effect of drug stores proximity on risk of fruit consumption, and this is the only effect of convenience stores proximity on any risk of food intake.

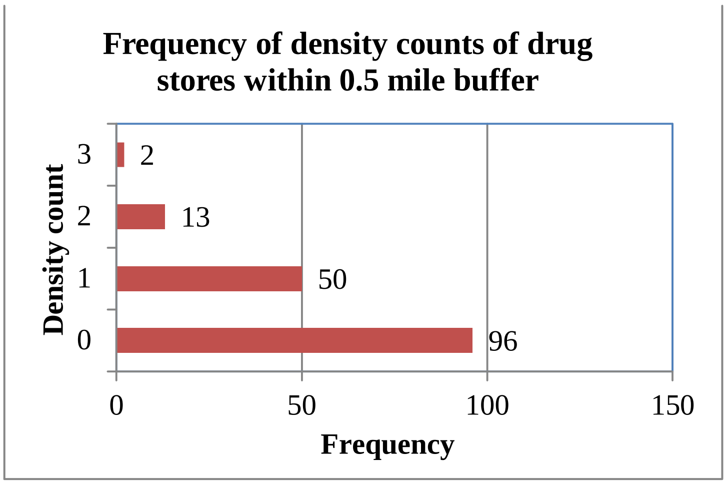
However, distance to the closest drug store and convenience store does not show any impact on vegetable consumption like large grocery stores. Moreover, no impacts of distance to the closest drug store and convenience store appear on the consumption of unhealthy foods like sweets and sugar drinks. Demographic variables show some interesting impacts on risk for consumption of some groups of food. For instance, in panel two, compared to other races, white children are less likely to have problem with consuming beans, vegetables and fruit while African American children are more likely to have trouble taking adequate those foods. In panel three, girls show about 15 percent greater risk on consuming fruit than boys. Again, like the marginal effects in Table 5, depression doesn't show any significant influence on any of the binary measures. When using FMHEI as a diet quality measure, the significant effect by depression observed in Table 5 disappears when IV strategy is adopted here.

In Table 7 and Table 8, we switched the food store access measure to density and present marginal effects of variables [19] in the baseline model and instrumental variable model as presented in Table 5 and Table 6. As we mentioned before, we alter the density to binary variable with the case that the majority of the count is zero. Results in these two tables are similar to the proximity model results. The food store access density measure does not have any association with the integrated diet quality measure FMHEI in either baseline or IV model. However, the density measure presents a different influence on the binary diet measures between the baseline and IV models. For instance, compared to HS children who live at the location that does not have any large grocery stores within a 0.5 mile buffer, children who live in the neighborhood that can reach large grocery stores within 0.5 mile are 53 percent less likely to have trouble consuming vegetable and 71 percent less likely to have risk of consuming fruits. On the other hand, the difference between the impact of having a convenience store within 0.5 mile neighborhood and not having one on children’s probability of having problem consuming fruit and vegetables is about 51 percent. Again, having one or more drug stores within 0.5 mile tends to increase the risk of children consuming sweets and sugar drink by 50 percent chance. Finally, similarly as before, the significance of the effect of depression on FMHEI disappears when included in the IV model.

[19] For the binary dependent variable, we only include 7 groups of food in the density model. The excluded group is the meat group. The existence of the perfect separation problem with some of the regressors does not allow us to estimate the marginal effects due the nonexistence of the maximum likelihood estimation.

Figure1. The frequency of density measure for each types of food store





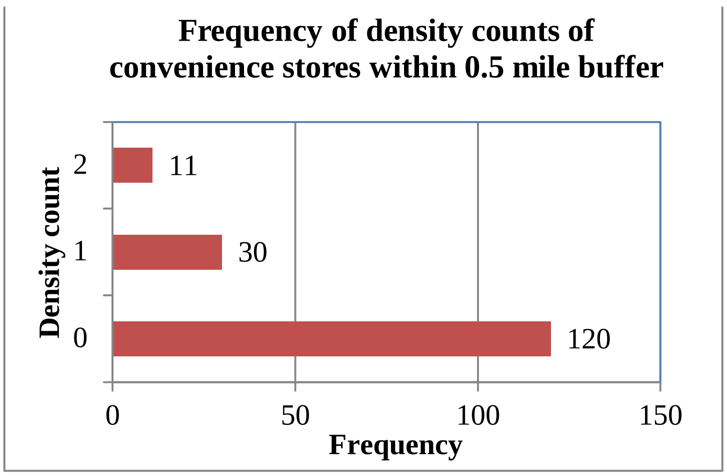


Figure2. Frequency for FMHEI

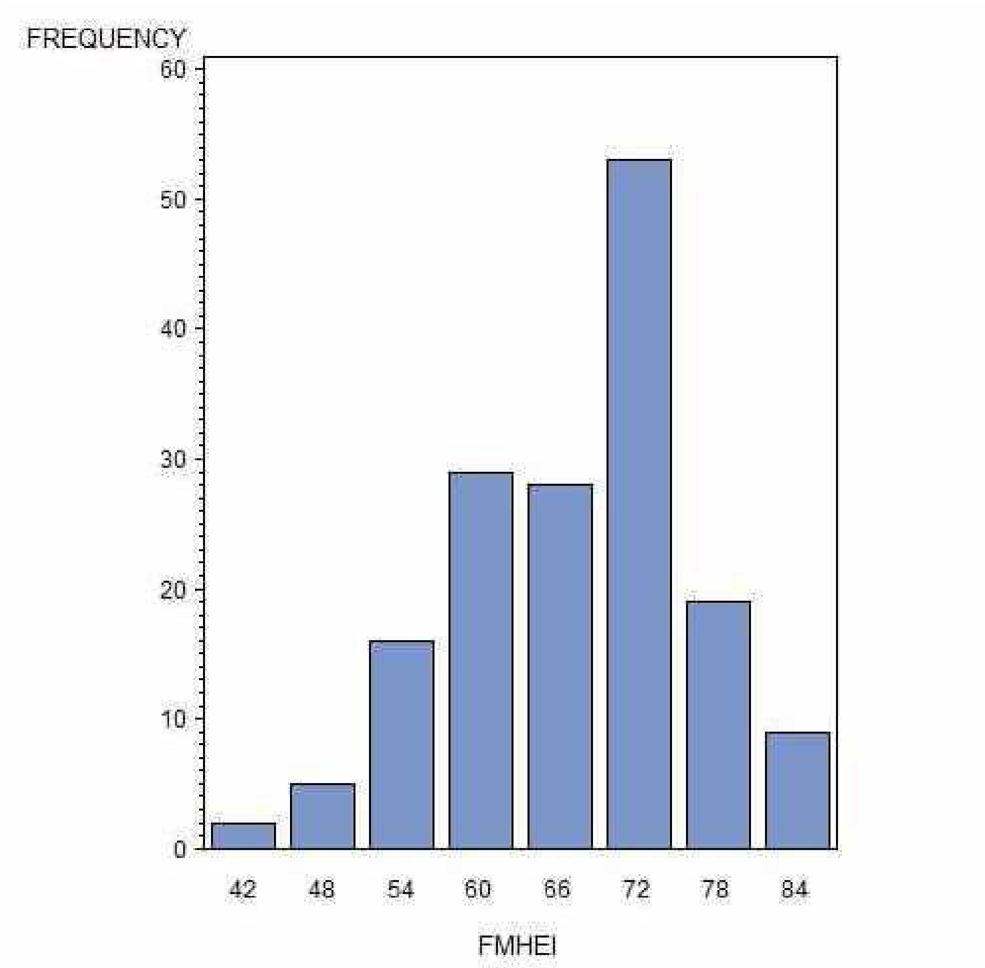


Figure 3(a)

Food stores in Clarksville, Arkansas

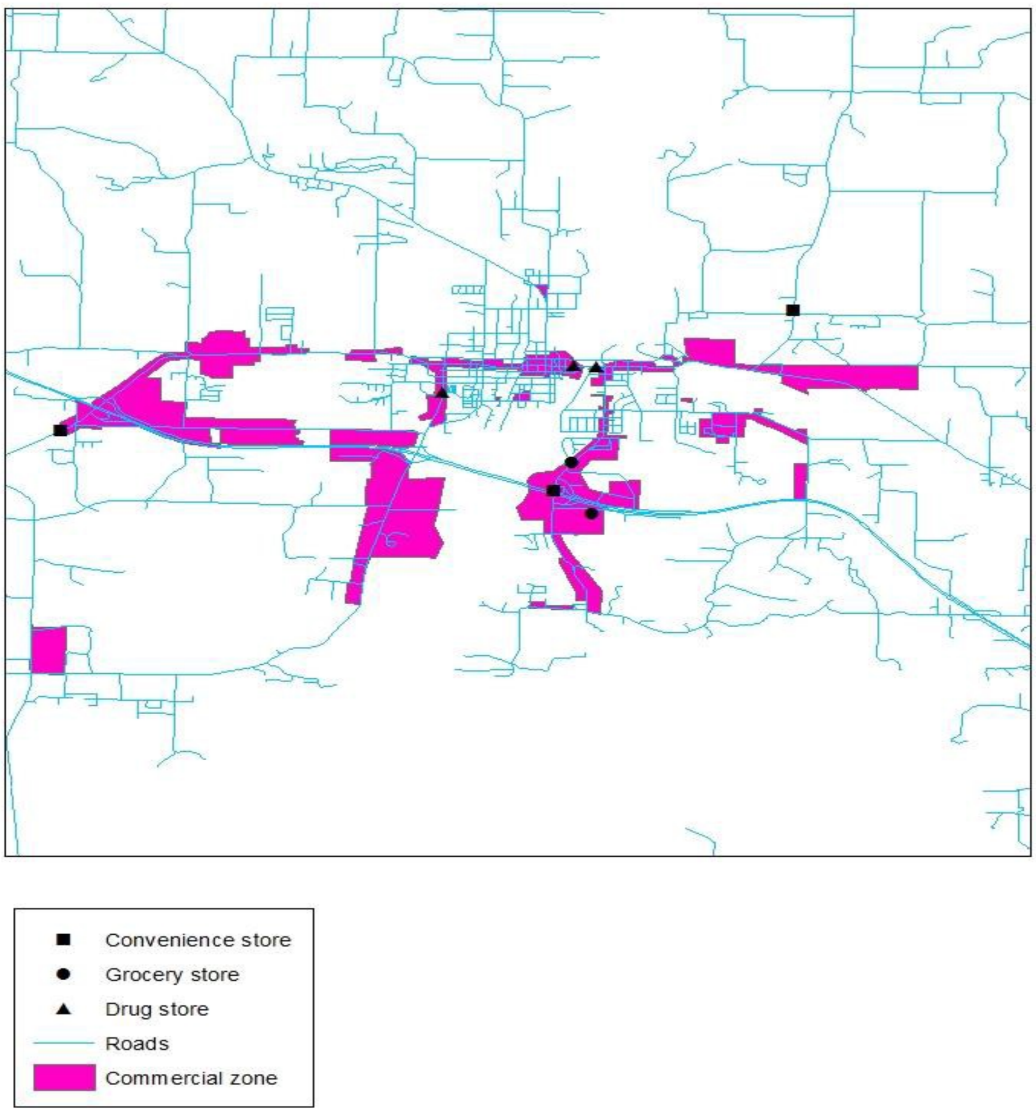


Figure 3(b)

Food stores in Morrilton, Arkansas

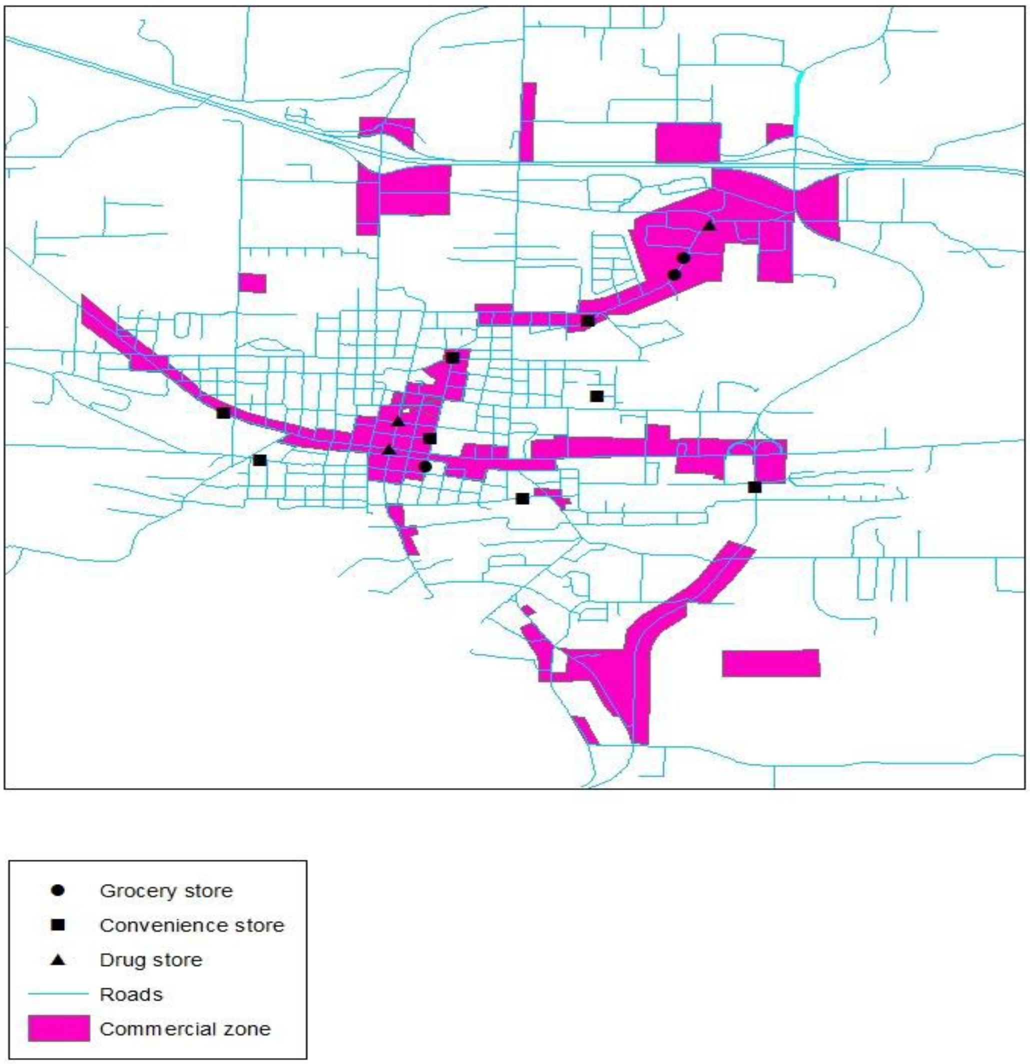


Figure 3(c)

Food stores in Russellville and Dardanelle, Arkansas

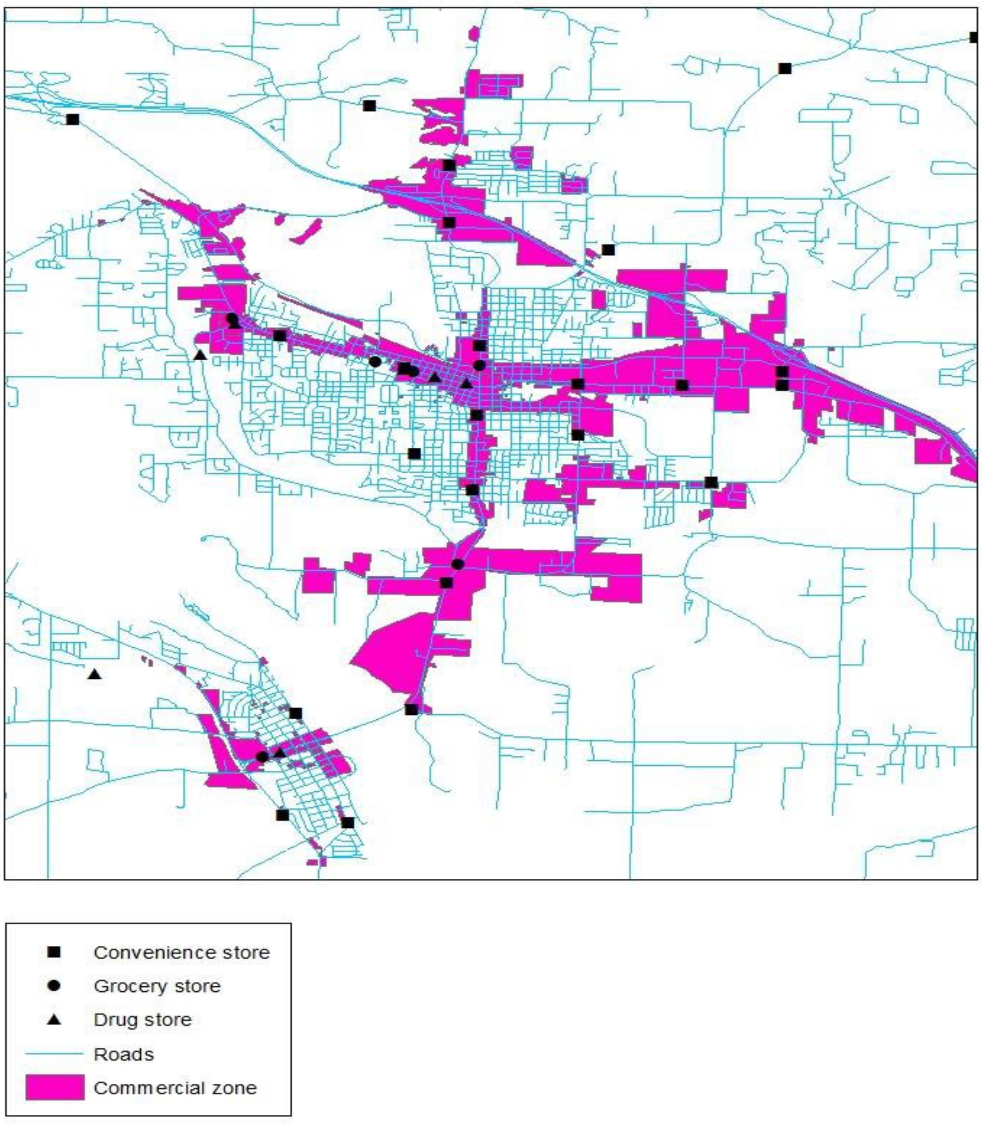


Figure 3(d)

Food stores in Plumerville, Arkansas

Table1. Proportion of risk on HS children consuming each group of food with different sample size

Group	Full sample	Risk on F or V	Male	Female
Dairy	11.18%	15.84%	13.92%	8.54%
Meat	4.38%	3.96%	7.69%	1.22%
Beans	23.90%	29.00%	26.92%	20.99%
Bread	1.88%	1.98%	1.28%	2.44%
Vegetables	57.14%	91.09%	53.16%	60.98%
Fruits	28.57%	45.54%	22.78%	34.15%
Juice	22.15%	23.23%	21.05%	23.17%
Sweets	15.82%	15.00%	19.23%	12.50%
Sugar drink	13.38%	13.00%	14.67%	12.20%
Sport drink	1.89%	0.00%	2.53%	1.25%
Sample size	161	101	79	82

Table2. Family Map Healthy Eating Index (FMHEI) scoring criteria

FMHEI total (0-100)		FMHEI Scoring Criteria	
FMHEI components		Requirements for max score of 10	Requirements for min score of 0
		Frequency	
1	Dairy	≥1 time/day	0
2	Bread	≥1 time/day	0
3	Vegetables	≥1 time/day	0
4	Fruits	≥1 time /day	0
5	Sweet snacks	0	≥1/day
		Requirements for max score of 5	Requirements for min score of 0
		Frequency	
6	Beans	≥1 time/day	0
7	Meat	≥1 time/day	0
8	Sugar drink	0	≥1 time/day
9	Sports drink	0	≥1 time/day
10	Juice	2-6 times/week	0 or ≥1 time/day
11	Family eating dinner at regular time	≥6 times/week	≤1 time/week
12	Follow morning routines	≥6 times/week	≤1 time/week
13	Salt snack[1]	3.75	
14	Others[2]	5	

1. Salt snacks include potato chips corn chips, nachos, popcorn, pretzels, and crackers
2. Others include multivitamin use, margarine and butter, fried foods outside home and visible animal fat

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Table3. Descriptive statistics for food store access measure

Food store access measure	Mean	SD	Min	Max
Distance to the nearest large grocery store	1.56	1.55	0.10	8.23
Distance to the nearest convenience store	0.88	0.80	0.04	4.66
Distance to the nearest drug store	1.55	1.86	0.07	11.10
Density of large grocery stores within 0.5 mile radial distance	0.26	0.52	0.00	2.00
Density of convenience stores within 0.5 mile radial distance	0.51	0.70	0.00	3.00
Density of drug stores within 0.5 mile radial distance	0.32	0.60	0.00	2.00

Table4. Characteristics of control variables

Variables	Proportion
Race	
White	40.35%
African American	12.66%
Other	46.99%
Target Child Gender	
Female	49.36%
Male	50.64%
Depression	32.92%

Table5. Marginal effects of baseline proximity model

				Large Grocery Stores					
Variables	Dairy	Beans	Meat	Vegetable	Fruit	Juice	Sweets	Sugar Drink	FMHEI
Proximity	-0.0267	0.00499	0.00672	0.00757	0.00544	0.0118	0.00991	-0.0142	0.0306
	(0.0215)	(0.0217)	(0.00946)	(0.0255)	(0.0230)	(0.0192)	(0.0180)	(0.0191)	(0.488)
Female	-0.0400	-0.0245	-0.0703**	0.0216	0.103	0.0623	-0.0698	-0.00173	-1.195
	(0.0471)	(0.0671)	(0.0330)	(0.0778)	(0.0710)	(0.0636)	(0.0566)	(0.0531)	(1.377)
Black	0.0944	0.246*	-0.0404	0.0633	0.113	0.277*	0.0545	0.0774	-3.611
	(0.0888)	(0.134)	(0.0366)	(0.125)	(0.126)	(0.150)	(0.104)	(0.118)	(2.353)
White	0.0824	-0.0947	0.0234	-0.0589	0.00387	-0.267***	0.0200	-0.0877	-0.263
	(0.0692)	(0.0913)	(0.0487)	(0.108)	(0.0994)	(0.0804)	(0.0815)	(0.0722)	(1.845)
Depression	0.0834	-0.0636	-0.0199	-0.133	-0.00628	0.0906	-0.00377	-0.0168	-3.508**
	(0.0790)	(0.0867)	(0.0381)	(0.107)	(0.0972)	(0.0938)	(0.0777)	(0.0695)	(1.633)
				Drug Stores					
Proximity	-0.0151	-0.00719	0.00435	0.00414	0.00153	0.00194	0.00905	-0.00777	0.0479
	(0.0174)	(0.0188)	(0.00803)	(0.0215)	(0.0194)	(0.0165)	(0.0151)	(0.0159)	(0.381)
Female	-0.0405	-0.0262	-0.0707**	0.0214	0.103	0.0612	-0.0698	-0.00139	-1.192
	(0.0473)	(0.0671)	(0.0330)	(0.0778)	(0.0711)	(0.0637)	(0.0565)	(0.0532)	(1.374)
Black	0.0915	0.255*	-0.0401	0.0640	0.115	0.284*	0.0519	0.0758	-3.634
	(0.0890)	(0.134)	(0.0369)	(0.126)	(0.127)	(0.149)	(0.104)	(0.118)	(2.377)
White	0.0841	-0.106	0.0235	-0.0597	0.00143	-0.272***	0.0240	-0.0867	-0.229
	(0.0709)	(0.0907)	(0.0496)	(0.109)	(0.100)	(0.0796)	(0.0830)	(0.0730)	(1.894)
Depression	0.0821	-0.0599	-0.0201	-0.132	-0.00522	0.0945	-0.00477	-0.0173	-3.518**
	(0.0793)	(0.0873)	(0.0381)	(0.108)	(0.0975)	(0.0941)	(0.0775)	(0.0696)	(1.634)

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Table5. Marginal effects of baseline proximity model (cont.)

	Convenience Stores								
Variables	**Dairy**	**Beans**	**Meat**	**Vegetable**	**Fruit**	**Juice**	**Sweets**	**Sugar Drink**	**FMHEI**
Proximity	0.00551	-0.00822	0.0191	0.00550	-0.0722	-0.0297	0.0152	-0.0215	-0.0972
	(0.0311)	(0.0449)	(0.0186)	(0.0500)	(0.0513)	(0.0417)	(0.0354)	(0.0377)	(0.664)
Female	-0.0386	-0.0232	-0.0748**	0.0196	0.122*	0.0678	-0.0735	0.00368	-1.176
	(0.0475)	(0.0680)	(0.0336)	(0.0786)	(0.0716)	(0.0642)	(0.0569)	(0.0537)	(1.403)
Black	0.0757	0.248*	-0.0397	0.0669	0.125	0.290**	0.0611	0.0714	-3.585
	(0.0846)	(0.133)	(0.0362)	(0.125)	(0.125)	(0.147)	(0.104)	(0.117)	(2.350)
White	0.105	-0.0993	0.0219	-0.0631	-0.0194	-0.279***	0.0169	-0.0858	-0.314
	(0.0725)	(0.0896)	(0.0474)	(0.107)	(0.0962)	(0.0773)	(0.0807)	(0.0728)	(1.855)
Depression	0.0723	-0.0603	-0.0200	-0.131	0.00671	0.102	-0.00408	-0.0164	-3.488**
	(0.0782)	(0.0876)	(0.0379)	(0.107)	(0.0972)	(0.0945)	(0.0780)	(0.0697)	(1.609)

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Table6. Marginal effects of IV proximity model

				Large Grocery Stores					
Variables	Dairy	Beans	Meat	Vegetable	Fruit	Juice	Sweets	Sugar Drink	FMHEI
Proximity	-0.213***	0.1903***	0.182***	0.198***	0.195***	0.164	-0.201	-0.208***	-3.735
	(0.0395)	(0.045)	(0.072)	(0.037)	(0.024)	(0.373)	(0.042)	(0.015)	(17.08)
Female	-0.041	0.0115	-0.023	0.024	0.032	0.042	-0.045	-0.018	-1.459
	(0.085)	(0.051)	(0.112)	(0.053)	(0.0601)	(0.3005)	(0.092)	(0.052)	(2.270)
Black	0.159	-0.057	-0.114	-0.091	-0.091	0.085	0.132	0.137	-4.402
	(0.149)	(0.164)	(0.066)	(0.105)	(0.0902)	(1.436)	(0.097)	(0.105)	(4.141)
White	-0.106	0.125	0.146**	0.134	0.1502**	-0.071	-0.148	-0.189	-3.064
	(0.213)	(0.114)	(0.075)	(0.106)	(0.068)	(1.795)	(0.086)	(0.1)	(13.00)
Depression	0.093	-0.0603	0.055	-0.083	-0.049	-0.01	0.051	0.045	-0.207
	(0.137)	(0.066)	(0.059)	(0.1104)	(0.063)	(0.545)	(0.073)	(0.074)	(3.841)
				Drug Stores					
Proximity	0.089	-0.151**	-0.136	-0.512	-0.165***	-0.087	0.108	0.013	1.267
	(0.125)	(0.064)	(0.098)	(0.805)	(0.029)	(0.155)	(0.096)	(0.085)	(5.008)
Female	-0.023	-0.036	-0.129	-0.00998	0.023	0.042	-0.0.39	0.105	-1.084
	(0.066)	(0.0596)	(0.083)	(0.270)	(0.071)	(0.078)	(0.072)	(0.051)	(1.360)
Black	-0.015	0.262**	0.066	0.613	0.184**	0.305***	-0.048	-0.048	-3.104
	(1.161)	(0.119)	(1.623)	(0.802)	(0.088)	(0.122)	(0.128)	(0.126)	(2.685)
White	0.1996	-0.234***	-0.148	-0.789	-0.197***	-0.340***	0.143	0.077	1.326
	(0.104)	(0.081)	(1.50)	(1.038)	(0.080)	(0.119)	(0.130)	(0.166)	(6.769)
Depression	0.026	0.016	0.019	-0.138	0.062	0.117	-0.039	-0.053	-1.504
	(0.117)	(0.101)	(0.105)	(0.457)	(0.077)	(0.089)	(0.072)	(0.065)	(2.635)

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Table6. Marginal effects of IV proximity model (cont.)

	Convenience Stores								
Variables	Dairy	Beans	Meat	Vegetable	Fruit	Juice	Sweets	Sugar Drink	FMHEI
Proximity	0.012	-0.247	-0.186	-0.202	-0.336***	-0.112	0.166	0.178	1.324
	(0.218)	(0.166)	(0.200)	(0.194)	(0.010)	(0.238)	(0.195)	(0.179)	(5.230)
Female	-0.065	0.035	-0.078	0.063	0.149**	0.084	-0.102*	-0.040	-1.482
	(0.067)	(0.077)	(0.071)	(0.078)	(0.062)	(0.077)	(0.060)	(0.066)	(2.016)
Black	0.063	0.221*	-0.036	0.075	0.115	0.284**	0.040	0.047	-3.324
	(0.089)	(0.124)	(0.094)	(0.110)	(0.104)	(0.144)	(0.1002)	(0.109)	(2.159)
White	0.138	-0.149	-0.044	-0.112	-0.095	-0.295***	0.059	-0.031	0.180
	(0.086)	(0.086)	(0.097)	(0.100)	(0.086)	(0.089)	(0.094)	(0.106)	(2.636)
Depression	0.055	-0.023	-0.012	-0.083	0.043	0.110	-0.020	-0.036	-0.942
	(0.085)	(0.096)	(0.083)	(0.118)	(0.086)	(0.095)	(0.075)	(0.069)	-1.455

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Table7. Marginal effects of baseline density model

	Large Grocery Stores							
Variables	Dairy	Beans	Vegetable	Fruit	Juice	Sweets	Sugar Drink	FMHEI
Density	-0.0332	-0.00142	-0.0252	-0.107	0.0239	-0.0211	-0.0612	1.508
	(0.0530)	(0.0809)	(0.0941)	(0.0785)	(0.0784)	(0.0652)	(0.0560)	(1.600)
Female	-0.0399	-0.0251	0.0193	0.0953	0.0619	-0.0712	-0.00441	-1.110
	(0.0474)	(0.0672)	(0.0779)	(0.0710)	(0.0637)	(0.0566)	(0.0532)	(1.387)
Black	0.0739	0.248*	0.0665	0.107	0.286*	0.0623	0.0717	-3.522
	(0.0840)	(0.133)	(0.125)	(0.125)	(0.147)	(0.104)	(0.116)	(2.332)
White	0.105	-0.0980	-0.0636	0.00494	-0.274***	0.0121	-0.0781	-0.347
	(0.0714)	(0.0897)	(0.106)	(0.0972)	(0.0781)	(0.0798)	(0.0728)	(1.844)
Depression	0.0687	-0.0624	-0.133	-0.0158	0.0982	-0.00239	-0.0276	-3.369**
	(0.0771)	(0.0871)	(0.108)	(0.0960)	(0.0945)	(0.0779)	(0.0668)	(1.591)
	Drug Stores							
Density	0.0330	0.143*	-0.0428	-0.0627	-0.0326	0.0263	-0.0378	0.776
	(0.0571)	(0.0836)	(0.0911)	(0.0784)	(0.0724)	(0.0674)	(0.0581)	(1.484)
Female	-0.0388	-0.0323	0.0223	0.104	0.0611	-0.0724	0.00192	-1.226
	(0.0474)	(0.0664)	(0.0777)	(0.0709)	(0.0636)	(0.0566)	(0.0533)	(1.385)
Black	0.0803	0.275**	0.0623	0.108	0.284*	0.0660	0.0674	-3.496
	(0.0854)	(0.133)	(0.125)	(0.126)	(0.148)	(0.105)	(0.115)	(2.347)
White	0.0974	-0.126	-0.0558	0.0118	-0.270***	0.00861	-0.0744	-0.443
	(0.0708)	(0.0866)	(0.108)	(0.0993)	(0.0794)	(0.0797)	(0.0737)	(1.890)
Depression	0.0763	-0.0578	-0.131	-0.00764	0.0947	3.70e-05	-0.0229	-3.488**
	(0.0778)	(0.0860)	(0.107)	(0.0970)	(0.0939)	(0.0783)	(0.0680)	(1.598)

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Table7. Marginal effects of baseline density model (cont.)

	Convenience Stores							
Variables	Dairy	Beans	Vegetable	Fruit	Juice	Sweets	Sugar Drink	FMHEI
Density	-0.0754	-0.0407	-0.0522	-0.0285	0.0260	-0.0178	-0.0605	1.490
	(0.0508)	(0.0698)	(0.0803)	(0.0738)	(0.0656)	(0.0585)	(0.0569)	(1.461)
Female	-0.0440	-0.0315	0.0115	0.0972	0.0651	-0.0733	-0.00688	-0.938
	(0.0472)	(0.0679)	(0.0790)	(0.0722)	(0.0645)	(0.0571)	(0.0533)	(1.426)
Black	0.0687	0.248*	0.0669	0.115	0.285*	0.0620	0.0612	-3.562
	(0.0820)	(0.134)	(0.124)	(0.126)	(0.147)	(0.104)	(0.112)	(2.369)
White	0.117	-0.0955	-0.0590	0.00312	-0.275***	0.0148	-0.0669	-0.460
	(0.0726)	(0.0902)	(0.106)	(0.0980)	(0.0779)	(0.0802)	(0.0735)	(1.865)
Depression	0.0651	-0.0660	-0.132	-0.00523	0.0976	-0.000862	-0.0262	-3.466**
	(0.0765)	(0.0867)	(0.107)	(0.0971)	(0.0940)	(0.0781)	(0.0674)	(1.581)

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Table8. Marginal effects of IV density model

Variables	Dairy	Beans	Vegetable	Fruit	Juice	Sweets	Sugar Drink	FMHEI
Large Grocery Stores								
Density	0.378	-0.629**	-0.527*	-0.714***	-0.375	0.441	0.458*	5.885
	(0.418)	(0.248)	(0.295)	(0.0715)	(0.705)	(0.288)	(0.259)	(23.71)
Female	-0.0100	-0.0519	-0.0178	0.000891	0.0309	-0.0216	0.0275	-0.886
	(0.0740)	(0.0578)	(0.0652)	(0.0686)	(0.0919)	(0.0806)	(0.0496)	(1.575)
Black	0.0816	0.105	0.0170	0.0139	0.220	0.0645	0.0720	-3.592*
	(0.0916)	(0.162)	(0.109)	(0.0992)	(0.223)	(0.0890)	(0.0962)	(1.842)
White	0.0668	-0.0371	-0.0194	0.0267	-0.250**	-0.0102	-0.0735	-0.459
	(0.123)	(0.102)	(0.0940)	(0.0732)	(0.128)	(0.0687)	(0.0784)	(1.885)
Depression	0.0941	-0.0927	-0.128	-0.0636	0.0473	0.0405	0.0263	-1.109
	(0.0759)	(0.0791)	(0.0956)	(0.0740)	(0.136)	(0.0747)	(0.0781)	(1.526)
Drug Stores								
Density	0.438	-0.615***	-0.564***	-0.667***	-0.501	0.490**	0.499**	6.058
	(0.320)	(0.155)	(0.202)	(0.0321)	(0.730)	(0.241)	(0.229)	(24.69)
Female	-0.0406	0.0112	0.0302	0.0526	0.0661	-0.0552	-0.0172	-1.365
	(0.0486)	(0.0568)	(0.0517)	(0.0622)	(0.0643)	(0.0613)	(0.0454)	(1.729)
Black	0.109	0.0157	-0.0392	-0.0510	0.153	0.0985	0.105	-4.040
	(0.0805)	(0.173)	(0.113)	(0.0942)	(0.340)	(0.0814)	(0.0892)	(2.585)
White	-0.0248	0.0792	0.0811	0.129**	-0.160	-0.0872	-0.136**	-1.404
	(0.163)	(0.115)	(0.102)	(0.0627)	(0.364)	(0.0763)	(0.0594)	(4.833)
Depression	0.0532	-0.0341	-0.0693	-0.0108	0.0651	0.00835	-0.00389	-0.596
	(0.0867)	(0.0798)	(0.111)	(0.0665)	(0.120)	(0.0607)	(0.0643)	(2.105)

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Table8. Marginal effects of IV density model (cont.)

	Convenience Stores							
Variables	Dairy	Beans	Vegetable	Fruit	Juice	Sweets	Sugar Drink	FMHEI
Density	-0.546***	0.514***	0.523***	0.519***	0.507***	-0.536***	-0.534***	-7.543
	(0.0806)	(0.0502)	(0.0160)	(0.0241)	(0.114)	(0.0444)	(0.0515)	(31.90)
Female	-0.102	0.0848*	0.0917**	0.0943**	0.100	-0.103	-0.0903**	-2.301
	(0.0763)	(0.0438)	(0.0425)	(0.0473)	(0.0702)	(0.0837)	(0.0403)	(5.191)
Black	0.00614	0.0345	0.0202	0.0189	0.0785	-0.00119	-0.00244	-2.799
	(0.116)	(0.135)	(0.0828)	(0.0764)	(0.360)	(0.0871)	(0.0815)	(3.978)
White	0.0894	-0.0692	-0.0682	-0.0597	-0.136	0.0637	0.0496	0.757
	(0.165)	(0.0706)	(0.0691)	(0.0531)	(0.385)	(0.0585)	(0.0767)	(4.804)
Depression	0.00451	0.00481	-0.00431	0.0119	0.0346	-0.0121	-0.0159	0.523
	(0.105)	(0.0656)	(0.102)	(0.0545)	(0.130)	(0.0570)	(0.0591)	(6.537)

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IV. DISCUSSION AND CONCLUSION

A. Childhood obesity and academic achievement

The objective of this study is to investigate whether there is an association between academic achievement and obesity rates among young children in Arkansas public schools. Using grade level panel data, our results suggest that there is no evidence showing that obesity rates in grades 4 and 6 are associated with math and literacy achievement scores. This finding is robust across our pooled OLS, fixed effects, and random effects models. These results are also consistent with the findings of some of the previous studies (MacCann and Roberts, 2013; Kaestern and Grossman, 2009; Scholder et al., 2010). Admittedly, our finding of no significant relationship between childhood obesity and academic achievement scores does not imply that obesity has no causal impact at all on educational outcomes. While we controlled for time invariant unobservables, our analysis does not mitigate time varying unobservables that may affect both academic performance and obesity prevalence. We were not able to take this issue into account due to lack of potential instruments in our data. While it is indeed a challenge to find valid instrumental variables, future studies should attempt to replicate our analysis using not only fixed effects models but also instrumental variable models.

We found additional interesting results when we separated our sample between low and high SES schools and between low and high minority schools. For example, our results indicate that obesity prevalence has a positive effect on grade 4 students' literacy test scores in the low SES subsample but a negative effect on math test scores in the high SES subsample. The behind mechanism for the positive effect on grade 4 literacy scores of students in the low SES category is not clear. More research is needed to more definitively examine the linkage between obesity prevalence and academic performance. What is consistently clear in our results is that although the magnitude are small, educational input measures have a positive relationship to students' achievement scores and this finding is robust across the different models and subsamples.

B. Food store access and childhood diet quality

This study explores the effect of food store access on 3-5 year old HS children's dietary quality by using cross sectional sample of 2006-2007 Arkansas family map interview data. One of the key strengths of this paper is that in addition to investigating the effect of food store access on risk of each individual group of food consumption, we create the FMHEI, an integrated measure that contains not only information about consumption of each group of food but also information about children's eating environment and habit, to gain a more comprehensive view on the linkage between food store access and children's dietary quality. Another advantage of this paper is that while exploring the relationship between the food store access and children's diet quality, we are more cautious about the existence of potential endogenous issue that most of the prior papers did not take into account. We use an instrumental variable strategy in the model to tackle the problem by using zoning regulations to calculate the percentage of land for commercial use within the 0.5 mile buffer of each child residence with ArcGIS software. In addition, we evaluate the effect of food store access on dietary quality with both proximity and density measures

In general, food store accessibility measures (proximity and density) do not show any significant effect on either the binary diet measures or diet quality index measure in the baseline models. However, both proximity and density measures have very significantly strong impacts on the risk of some of individual group of food consumption when instrumental variable strategy is applied to a probit model. A one mile increase of distance to the closest large grocery store is expected to raise the probability of risk of consuming both fruit and vegetable for HS children by 20 percent and reduce the chance of risk on consuming sugar drinks by 20 percent. The longer the distance from the children's homes to drug stores and convenience stores, the less likely the children will have risk on fruit consumption. The difference between the effect of having any type of food stores within a 0.5 mile neighborhood and not having them on the risk of consuming any group of food is strong as well. Available large grocery stores within a 0.5 mile buffer from the home tend to reduce the likelihood of having trouble consuming vegetables by 53 percent and reduce the likelihood of having trouble having fruits by 71 percent. On the opposite, the existence of convenience stores within a 0.5 mile buffer will increase the risk of having vegetables and fruits by both 52 percent. An interesting finding is that the variable depression, the indicator for parents' mental health, has a closely association with the diet quality of the HS children in baseline model and its significance disappears when the instrumental variable approach is applied.

One limitation in this study is that the distance is the direct measure between two locations from the map, not the actual travel routes based on the networking analysis in ArcGIS. The real distance based on actual networking could be much longer than the way we calculate for the HS family to travel to the nearest food stores. The density measure could potentially change correspondingly based on the networking buffer instead of the direct radius buffer. A second limitation of this study is that the sample size is fairly small. When the instrument variable we use is weak, the estimates generated by the IV approach with small sample size are biased and theoretically the results are no better than simple OLS. In our study, we tried to improve the performance of the estimates by using LIML while executing the IV estimation with the continuous variable FMHEI. For the instrumental variable approach with binary dependent measure, to our knowledge, there is not an available technology for us to improve the small sample estimation properties. Another problem with small simple size for our study is that we are unable to break our sample to further explore the effect of food store access on different group of children's diet quality. Finally, the data we use is only cross sectional data, and we lack of panel data that would allow us to control for more factors over time. Future studies should replicate this study by improving upon the aforementioned limitations.

References

Aaronson, D, L Barrow, W Sander. 2007. "Teachers and Student Achievement in the Chicago Public High Schools." *Journal of Labor Economics,* 25 (1): 95-135.

Alviola, P, RM Nayga, Jr., M Thomsen, D Danforth, J Smartt. 2013. "The Effect of Fast-Food Restaurants on School-Level Obesity." *Economics and Human Biology,* forthcoming.

Alviola, P, RM Nayga, Jr., M Thomsen. 2013. "Food Deserts and Childhood Obesity." *Applied Economic Perspectives and Policy*, 35 (1): 106-124.

Averett, SL, DC Stifel. 2010. Race and Gender Differences In the Cognitive Effects of Childhood Overweight. *Applied Economics Letters*, 17: 1673-1679.

Austin, JK, TJ Huberty, GA Huster, DW Dunn. 1998. "Academic Achievement in Children with Epilepsy or Asthma." *Developmental Medicine and Child Neurology,* 40(4): 248-255.

Bacolod, M. 2007. "Who Teaches and Where They Choose to Teach: College Graduates of the 1990s" *Educational Evaluation and Policy Analysis,* 29 (3): 155-168.

Belot, M, J James. 2011. "Healthy School Meals and Educational Outcomes." *Journal of health Economics*, 30 (3): 489-504.

Blau, DM. 1999. "The Effect of Income on Child Development." *The Review of Economics and Statistics,* 81 (2): 261-276.

Blandchard T, T Matthews. 2007. "Retail Concentration, Food Deserts and Food Disadvantaged Dommunities in Rural America." *Remaking the North American Food system*, 201-215. Lincoln: University of Nebraska Press.

Bonesronning, H, T Falch, B Strom. 2005 "Teacher Sorting, Teacher Quality, and Student Composition." *European Economic Review*, 49 (2): 457-483.

Carlson, SA, JE Fulton, SM Lee, MM, DR Brown, HW Kohl III, WH Dietz. 2008. "Physical Education and Academic Achievement in Elementary School: data from the Early Childhood Longitudinal Study." *American Journal of Public Health*, 98 (4): 721-727.

Chen S.E., RJGM Florax, SD Snyder. 2009 "Obesity in Urban Food Markets: Evidence from Georeferenced Micro Data" Research report, Dept. Agricultural Economics, Purdue University, Lafayette.

Chen S., Florax R.J.G.M., and Miller C.C. 2010. "Obesity and Access to Chain Grocers". *Economic Geography*, 86(4): 431-452.

Clotfelter, Charles T., Helen F. Ladd and Jacob L. Vigdor. 2006. "Teacher-Student Matching and the Assessment of Teacher Effectiveness." *The Journal of Human Resources*, 41 (4): 778-820.

Crosnoe, R, C Muller. 2004. “Body Mass Index, Academic Achievement, and School Context: Examining the Educational Experiences of Adolescents at Risk of Obesity,” *Journal of Health and Social Behavior*, 45: 393-407.

Cummins, SS. Macintyre. 2002. “Food Deserts-Evidence and Assumption in Health Policy Making.” *British Medical Journal*, 235: 436-438

Currie, J. 2009. “Health, Wealthy, and Wise: Socioeconomic Status, Poor Health in Childhood, and Human Capital Development.” *Journal of Economic Literature*, 47(1): 87-122 (36).

Currie, J, S DellaVigna, E Moretti, S Pathania. 2010. “The Effect of Fast-Food Restaurants on Obesity and Weight Gain.” *American Economic Journal: Economic Policy*, 2(3), 32-63.

Datar, A, R Sturm, JL Magnabosco. 2004. “Childhood Overweight and Academic Performance: National Study of Kindergartners and First-Graders.” *Obesity Research*, 12 (1): 58-68

Datar, A, R Sturm. 2006. “Childhood Overweight and Elementary School Outcomes.” *International Journal of Obesity*, 30: 1449-1460.

Davis, B., Carpenter, C. 2009. “Proximity of Fast-Food Restaurants on Schools and Adolescent Obesity.” *American Journal of Public Health*, 99 (3): 505-510

DeCuri-Gunby, JT, JD Taliaferro, D Greenfield. 2010. “Educators’ Perspectives on Culturally Relevant Programs for Academic Success: The American Excellence Association.” *Education and Urban Society*, 42 (2): 182-204.

Dennison, BA, RL. Helen, SL Baker. 1997. “Excess Fruit Juice Consumption by Preschool-aged Children is Associated with Short Stature and Obesity.” *American Academy of Pediatrics*, 99 (1): 15-22.

Ding, WL, SF Lehrer, JN Rosenquist, J Audrain-McGovern. 2009. “The Impact of Poor Health on Academic Performance Using Genetic Markers”. *J of Health Economics*, 28; 578 – 597.

Feskanich, D, RH Helaine, RD Graham, A Colditz. 2004. “Modifying the Healthy Eating Index to Assess Diet Quality In Children and Adolescents.” *Journal of the American Dietetic Association*, 104(9): 1375-1383.

Freedman, DS., LK Khan, MK Serdula, WH Dietz, SR Srinivasan, GS Berenson. 2005. “The Relation of Childhood BMI to Adult Adiposity: The Bogalusa Heart Study.” *Pediatrics*, 115: 22-27.

Gibson, SA. 1996. “Are High-fat, High-sugar Foods and Diets Conducive to Obesity?” *International Journal of Food Sciences and Nutrition*, 47: 405-415.

Glewwe, PH, G Jacoby EM King. 2001. “Early Childhood Nutrition and Academic Achievement: A Longitudinal Analysis.” *Journal of Public Economics*, 81: 345-368.

Guenther, PM, J Reedy, SM Krebs-Smith, BB Reeve, PP Basiotis. 2007 “Development and Evaluation of Healthy Eating Index-2005: Technical Report. *Center for Nutrition Policy and Promotions, U.S. Department of Agriculture.*

Gurley-Calvez, T, A Higginbotham. 2010. “Childhood Obesity, Academic Achievement, and School Expenditures.” *Public Finance Review*, 38 (5): 619-646.

Galvezm, MP, L Hong, E Choi, L Liao, J Godbold, B Brenner. 2009. “Childhood obesity and neighborhood food-store availability in an inner-city community.” *Academic Pediatrics*, 9:339-343.

Hanson, NI, D Neumark-Sztainer, ME Eisenberg, M Story, M Wall. 2004. “Association between Parental Report of the Home Food Environment and Adolescent Intakes of Fruits, Vegetables and Dairy Foods”. *Public Health Nutrition*, 8(1): 77-85.

Hanushek, EA. 1986. “The Economics of Schooling: Production and Efficiency in the Public Schools.” *Journal of Economic Literature*, 49 (3): 1141-1177.

Hanushek, EA. 1989. “The Impact of Differential Expenditures on School Performance.” *Educational Researcher*, 18 (4): 45-62.

Hanushek, EA, JF Kain, JM Markman, SG Rivkin. 2003. “Does Peer Ability Affect Student Achievement?” *Journal of Applied Econometrics* 18:527-547.

Hedges, LV, RD Laine, R Greenwald. 1994. “Does Money Matter? A Meta-Analysis of Studies of the Effects of Differential School Inputs on Student Outcomes.” *American Educational Research Researcher*, 23 (3): 5-14.

Hill, AM, J O’Neill. 1994. “Family Endowments and the Achievement of Young Children with Special Reference to the Underclass.” *Journal of Human Resources*, 29 (4): 1065-1100.

Hill, NE, LC Taylor. 2004. “Parental School Involvement and Children’s Academic Achievement: Pragmatics and Issues.” *Current Direction in Psychological Science*, 13 (4): 161-164.

Israel, GD, LJ Beaulieu, G Hartless. 2001. “The Influence of Family and Community Social Capital on Educational Achievement.” *Rural Sociology*, 66(1): 43-68

Jackson, KC. 2009. “Student Demographics, Teacher Sorting, and Teacher Quality: Evidence from the End of School Desegregation.” *Journal of Labor Economics*, 27 (2): 213-256.

Johnson, RJ, MS Segal, Y Sautin, T Nakagawa, DI Feig, DH Kang et al. 2007. "Potential Role of Sugar (Fructose) in the Epidemic of Hypertension, Obesity and the Metabolic Syndrome, Diabetes, Kidney Disease, and Cardiovascular Disease." *The American Journal of Clinical Nutrition*, 86: 899-906.

Kaestner, R, M Grossman. 2009. "Effects of Weight on Children's Educational Achievement." *Economics of Education Review*, 28(6): 651-661.

Kennedy ET, J Ohls, S Carlson, K Fleming. 1995. "The Healthy Eating Index: design and applications." *Journal of American Diet Association*, 95: 1103-1108.

Kyureghain, G, RM Nayga Jr., 2013. "Food Store Access, Availability, and Choice When Purchasing Fruit and Vegetables." *American Journal of Agricultural Economics*, in press.

Lankford, H, S Loeb, J Wyckoff. 2002. "Teacher Sorting and the Plight of Urban Schools: A Descriptive Analysis." *Education Evaluation and Policy Analysis*, 24 (1): 37-62.

Laska, MN, MO Hearst, A Forsyth, AF Pasch, KE Pasch, L Lytle. 2010. "Neighborhood Food Environments: Are They Associated with Adolescent Dietary Intake, Food Purchases and Weight Status?" *Public Health Nutrition*, 13(11): 1757-1763.

Lavy, VM, D Paserman, A Schlosser. 2008. "Inside the Black of Box of Ability Peer Effects: Evidence from Variation in the Proportion of Low Achievers in the Classroom." *National Bureau of Economic Research, Inc*, Working papers: 14415.

Leung, CW, BA Laraia, M Kelly, D Nickleach, NE Adler, LH Kushi et al. 2011. "The Influence of Neighborhood Food Stores on Change in Young Grils' Body Mass Index." *American Journal of Preventive Medicine*, 41 (1): 43-51.

Liu, GC, JS Wilson, R Qi, J Ying. 2007. "Green Neighborhoods, Food Retail and Childhood Overweight: Differences by Population Density." *American Journal of Health Promotion*, 21 (4): 317-325.

MacCann C, RD Roberts. 2013. "Just as Smart But Not as Successful: Obese Students Obtain Lower School Grades But Equivalent Test Scores to Nonobese Students." *International Journal of Obesity*, 37: 40-46.

Moore LV, AD Roux, V JA, Nettleton, DR Jocobs, Jr. 2008 "Association of the Local Food Environment with Diet Quality- A Comparison of Assessments based on Surveys and Geographic Information Systems." *American Journal of Epidemiology*, 167(8): 917-924

Morland K., S Wing, AD Roux, C Poole. 2002. "Neighborhood Characteristics Associated with the Location of Food Stores and Food Service Places." *American Journal Prevention Medicine*, 22(1): 23-29

Morland K., S Wing, AD Roux 2002. "The Contextual Effect of the Local Food Environment on Residents' Diets: The Atherosclerosis Risk in Communities Study." *American Journal of Public Health*, 92(11): 1761-1767.

Muller, C. 1995. "Maternal Employment, Parent Involvement, and Mathematics Achievement among Adolescents." *Journal of Marriage and Family,* 57 (1): 85-100.

Okpala CO, AO Okpala, FE Smith. 2001. "Parental Involvement, Instructional Expenditures, Family Socioeconomic Attributes, and Student Achievement." *The Journal of Educational Research,* 95 (2): 110-115.

Pearson, T, J Russell, M Campbell, M Barker. 2005. Do Food Deserts Influence Fruit and Vegetable Consumption? A Cross-Sectional Study." *Appetite,* 45: 195-197.

Powell, L.M., MC Auld, FJ Chaloupka, PM O'Malley, LD Johnston 2008 "Association Between Access to Food Stores and Adolescent Body Mass Index." *American Journal of Preventive Medicine*, 33(4S): S301-307.

Powell, LM, S Slater, D Mirtcheva, Y Bao, FJ Chaloupka. 2007. "Food Stores Availability and Neighborhood Characteristics in the United States." *Preventive Medicine,* 44: 189-195.

Puskar, KR, LM Bernardo. 2007. "Mental Health and Academic Achievement: Role of School Nurses." *Journal of Specialists in Pediatric Nursing,* 12(4): 215-223.

Rivkin, SG, EA Hanushek, JF Kain. 2005. "Teachers, Schools and Academic Achievement." *Econometrica,* 73 (2): 417-458

Sabia, JJ. 2007. "The effect of Body Weight on Adolescent Academic Performance." *Southern Economic Journal*, 73 (4): 871-900.

Scholder, S, von HK, GD. Smith, DA Lawlor. 2010. "Genetic Markers as Instrumental Variables: An Application to Child Fat Mass and Academic Achievement." *Health Econometrics and Data Group,* Working paper.

Sirin, SR. 2005. "A Meta-Analytic Review of Research." *Review of Educational Research* 75 (3): 417-453.

Slavin, RE, C Lake. 2008. "Effective Programs in Elementary Mathematics: A Best-Evidence Synthesis." *Review of Educational Research* 78 (3): 427-515.

Taras, H. 2005a. "Nutrition and Student Performance at School." *Journal of School Health,* 75 (6): 199-213.

Taras, H. 2005b. "Physical Activity and Student Performance at School." *Journal of School Health,* 75 (6): 214-218.

Taras, H, W Potts-Datema. 2005. “Obesity and Student Performance at School.” *Journal of School Health*, 75 (8): 291-5.

Wayne, AJ, P Youngs. 2003. “Teacher Characteristics and Student Achievement Gains: A Review.” *Review of Education Research*, 73 (1):89-122.

Wang, MC, S Kim, AA Gonzalez, KE MacLeod, MA Winkleby 2007. “Socio-economic and Food-Related Physical Characteristics of the Neighborhood Environment Are Associated with Body Mass Index.” *Journal Epidemiol Community Health*, 61(6): 491-498.

Yan, W and Q Lin. 2005. “Parental Involvement and Mathematics Achievement: Contrast across Racial and Ethnic Groups.” *The Journal of Educational Research*, 99 (2):116-127.