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Abstract

We utilize clinical records of successive visits by children to pediatric clinics in Indianapolis to estimate the effects on their body mass of environmental changes near their homes. We compare results for fixed-residence children with those for cross-sectional data. Our environmental factors are fast food restaurants, supermarkets, parks, trails, and violent crimes, and 13 types of recreational amenities derived from the interpretation of annual aerial photographs. We looked for responses to these factors changing within buffers of 0.1, 0.25, 0.5, and 1 mile. We found that cross-sectional estimates are quite different from the Fixed Effects estimates of the impacts of amenities locating near a child. In cross section nearby fast food restaurants were associated with higher BMI and supermarkets with lower BMI. These results were reversed in the FE estimates. The recreational amenities that appear to lower children's BMI were fitness areas, kickball diamonds, and volleyball courts. We estimated that locating these amenities near their homes could reduce the weight of an overweight eight-year old boy by 3 to 6 pounds.

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Introduction:

Child obesity in the United States has been markedly increasing since the early 1980s. This trend is troubling because there are well-established connections between child obesity, other childhood diseases, and subsequent adult diseases. While reducing child obesity is a high priority in public policy, its precise causes and, consequently, effective public policies for its reduction, are far from clear. Although the physiology of weight gain or loss is attributable to calorie consumption and expenditure, the determinants of a child's calories or energy expenditure have yet to be explained. Simple addition of the impacts of all of the variables that have statistically-significant effects on child weightleaves more than two thirds of the change in child body mass index (BMI) unexplained.

Increasingly, environmental factors are being examined as candidates for obesity interventions. The built environment is potentially a good target for public policy interventions to increase physical activity or reduce calories consumption because environmental interventions have the potential to impact energy balance behaviors of entire communities. Moreover, the built environment may more susceptible to public policy interventions than either the home or the school. At home time constraints from work and commuting hours among two-earner and single-parent families can cause them to rely heavily on pre-packaged calorie-dense meals. Public policies are unlikely to change time saving behavior. Social marketing campaigns about the importance of incorporating fruits and vegetables have had no discernable effect. Shifting to schools, several experimental interventions in sets of primary schools that combined nutrition education, healthier school meals, removal of soft drink and snack food vending machines, and more physical education had no effect on children's weights (Kolata, 2006).[1]So far no one has proposed spending enough money on physical education from kindergarten through high school to use schools as the primary venue for reversing the child obesity epidemic. Low test scores and low graduation rates have kept the idea of a national "No Obese Child Left Behind" program for schools off the table for public policy.

This paper describes a study using eleven years of clinical data to identify natural experiments wherein changes in nearby physical or social environmental factors may be examined as causes of change in child weight. Electronic medical records for patients who received care at a large academic health care system in Indianapolis between 1996 through 2006 were processed to extract anthropometric, demographic, and geographic data for over 60,000 children between the ages of 3 and 18 years of age. A basic assumption in the study is that any changes in the physical environment were exogenous to children that stayed at the same address before and after the change. This approach addresses a major limitation of many other studies examining associations between environment and child obesity. The weakness common to many studies of built

[1] There is a some preliminary evidence of an effective in-school intervention. An experiment with school menus, nutrition education, and physical education programs, sponsored by the Agatston Foundation, appear to reduce BMI (HOPS, 2008).

environment and obesity is that they utilize cross-sectional designs, which cannot identify causal effects attributable to nearby environmental amenities. Cross-sectional studies of the built environment are confounded by families self-selecting their locations. For example, families that highly value exercise may be more likely to live near a park. Consequently, cross-sectional results on the relationship between children's weight and distance from their residence to the nearest park would provide inconclusive information for describing causal effects of a park on weight. An example of this endogeneity issue in the body-weight context is a recent finding that the cross-sectional relationship of urban sprawl on weight was not maintained in a sample of adults who changed cities, i.e. migrants from high- to low-sprawl cities maintained their weights and vice versa. (Plantinga and Bernell, 2007).

The changes we studied are fast food restaurants, convenience stores, supermarkets, violent crimes, recreation trails, and thirteen specific publicly-accessible recreational amenities, such as basketball courts and pools. We test the exogeneity assumption by comparing the trend in BMI for children who will gain an amenity in the future to the trend for children who never gain an amenity. We found that, except for supermarkets, all of the amenities had largely the same trends for children who would in the future gain an amenity and those who would not.

The remaining sections of the paper are a literature review, a description of the data, the estimation strategy, results, and conclusions.

Literature Review:

Burden of disease

National surveys with measured heights and weights have documented the increases in child weights since the early 1980s. (Ogden et al. 2002, Hedley et al. 2004). Childhood obesity leads to numerous physical and mental health problems including, but not limited to: metabolic disorders such as type-2 diabetes (American Diabetes Society, 2000); hypercholesterolemia, hypertension, and heart disease (Freedman et al., 1999); sleep apnea (Wittels, 1990); social marginalization (Strauss, 2003); and orthopedic disorders (Kortt and Baldry, 2002, DiPietro, 1994).

Environmental influences on the prevalence of obesity

How does genetic endowment interact with environmental factors in causing obesity? "One analogy is that genes load the gun and a permissive or toxic environment pulls the trigger." (Bray, 2005, p. S21) Genetic factors are thought to account for 25-40% of the point-in-time variance in BMI by determining differences in resting metabolic rate and weight gain in response to overfeeding. (Bouchard, 1994, Price, 2002) However, it is highly improbable that changes in genetic factors explain the rapid increases in obesity prevalence over the past two decades. The obesity epidemic appears to be rooted in environmental factors that promote excessive caloric intake and sedentary lifestyle (Gortmaker et al., 1993, Hill and Peters, 1998, Epstein et al., 2000). These environmental factors are worsening, so that the already-high rate of obesity is expected to climb (Foreyt and Goodrick, 1995). The recent U.S. environment is characterized by convenient, inexpensive, palatable, energy-dense foods, coupled with a lifestyle requiring negligible amounts of physical activity for subsistence (Hill and Peters, 1998).

Availability of food

Although American diets have been shifting toward processed foods for more than a century, it is not clear why obesity rate accelearted in the 1980s. Gerrior and Bente (2002) have estimated that since the early 1900s, Americans have increased consumption of fats and sugars by 67% and 64%, respectively. Moreover, consumption of vegetables has decreased by 26% since 1909 and dietary fiber intake has decreased by 18%. Heiland and Frank (2007) have examined recent food-pricing trends and found that prices stopped declining in the midst of the epidemic rise in child obesity, suggesting that decreased food costs were not a significant cause of the epidemic. Kaushal (2007) used a natural experiment in the availability of food stamps to show that they had no effect on mothers' weights

Movement toward a more sedentary lifestyle

Numerous environmental factors promote decreased energy expenditure. Despite the clearly-documented health benefits of routine physical activity, approximately one-quarter of Americans remain largely inactive, and leisure-time inactivity is up to three times more common in lower-income populations (Mokdad et al., 2000). Suburban communities may lack sidewalks, and neighborhood layout can impede walking even short distances to stores and recreation; instead, urban design has been more focused on facilitating automobile traffic (Ewing and Cervero, 2001). Individuals in urban settings report reluctance to exercise outdoors because their neighborhoods are perceived as unsafe.

Studies have documented that children watch an average of 28 hours of television per week and that the amount of television viewing is directly related to the likelihood of obesity (Gortmaker et al., 1996). Changes in television time since the early 1980s cannot account for any of the trend in weight gain (Anderson and Butcher, 2006b), even though longitudinal studies of television hours show that young children who watch more television become heavier teens and young adults (Boone et al., 2007). The difficulty in accounting for the effect of changes in sedentary time on trends in BMI is that there are no consistent long-term series that measure children's time in sedentary activities. The time now used for video games or text messaging may or may not have been at the expense of other sedentary activities among pre-epidemic children or it may have

School environments

While schools decreased the availability of daily physical education (Hill and Peters, 1998) during the epidemic,Cawley et al. (2007) found that changes in hours of required physical education had no effect on children's weights. Anderson and Butcher (2006b) found that changes in access to candy and soft drinks by students via school vending machines could account for about one-fifth of the weight gains among 12- to 19-year-olds between 1988 and 2000. Access to vending machines in schools is much less common for children under 12. Tchernis et al. (2007) found that changes in calories per school lunch or breakfast served or changes in the proportion of children receiving free or subsidized school meals have had little effect in reducing child obesity.

Family characteristics, poverty, and other social environment factors

In addition to physical environmental factors, changes in social environment also has a bearing on obesity. Studies have also examined variables that pertain mostly to parents rather than their children. Courtemanche (2007) estimates that changes in mothers' labor force participation and hours of work account for 7.7% of the increases in children's weight from 1968 to 2001. Obesity is currently more prevalent among persons of lower socioeconomic status. However, this association has only recently been observed with consistency in the pediatric age groups. Garn et al. (1975) found that obesity was associated with higher socioeconomic status in early childhood, and lower socioeconomic status in adolescent females. A review of the literature through the late 1980s by Sobal and Stunkard (1989) regarding socioeconomic status and childhood obesity found that published studies were widely disparate in the reporting of the direction of a relationship between socioeconomic status and obesity, or even the existence of any relationship. Sorenson et al. (1997) reported a 2.2-fold increased incidence of childhood obesity in children living in dilapidated living conditions. Strauss and Knight (1999) reported the results of a prospective study in which children from low-income families had an almost threefold increased risk of developing obesity. Typically, those with socioeconomic disadvantage have worse health status; however in the case of childhood obesity, the role that socioeconomic factors play in determining levels of health and influencing behavioral and psychosocial risk factors remains unclear.

Disparities in obesity rates by race/ethnicity

There are significant disparities in rates of overweight and obesity between people of different race and ethnicity. Haas et al. (2003) found that in childhood, Latinos and Blacks are more likely to be overweight than Whites, whereas in adolescence Latinos and Asians/Pacific Islanders demonstrated higher rates of overweight. Numerous reasons for ethnic variation in rates of overweight have been proposed; again, complex interactions between genetic lineage and environmental factors certainly underlie racial/ethnic disparities. Differences in acculturation, cultural beliefs and practices, geographic segregation, community resources, and social capital are just a few of the correlates that have been identified as important considerations for obesity risk. (Day, 2006, Popkin and Udry, 1998, Parnell, 1966, Neff et al., 1997)

Environmental factors and child weight status:

Numerous reports have repeatedly echoed a call for obesity interventions that focus on environmental changes (King, 1995, Sallis et al., 1998, Margetts, 2004). Most of the attempts to prevent obesity have adopted educational approaches aimed at improving knowledge and motivation that in turn would presumably alter individual lifestyle choices (Kumanyika, 2001). Such approaches have been largely ineffective (Jeffery, 2001). Redirecting approaches to target environmental factors that modify behavior may enable prevention to succeed because an environmental approach does not exclusively rely on individual will (Kumanyika, 2001, Glanz et al., 1995). Efforts to modify environmental factors may have the additional benefit of diminishing health disparities among disadvantaged or minority populations.

Fewer studies have examined the effect of either physical or social environment specifically on childhood overweight and obesity. Burdette and Whitaker (2004) did not find significant relationships between distances to playgrounds or fast food establishments and prevalence of overweight among low-income preschool children in cross-sectional data. In that study and in a subsequent study (Burdette and Whitaker 2005), they found no relationship between overweight and levels of crime in the children's neighborhoods. Cross-sectional studies focusing on the built environment's role as a determinant of childhood overweight remain inconclusive. For example, a study of childhood obesity and neighborhoods that used straight-line distances between children's residences and opportunities for exercise concluded that there was no difference between obese and non-obese children (Hanratty, McLaughlan, and Pettit, 2003). The study by Burdette and Whitaker (2004) used a more sophisticated approach of modeling street network distances, but was cross-sectional, included only children ages 3 to 5 years, and was limited to Black and White racial groups.

Approaches incorporating broader samples of children and techniques to control for endogenous location choices are needed to understand how the urban form impacts child health. Despite the lack of an evidence base, policy makers are implementing regulations on urban development to try to reduce child obesity. For example, the City of Los Angeles has banned new fast food restaurant construction in South Los Angeles for the next year (L.A. Times). The area affected by the ban has half a million residents. South

Los Angeles is well known as a high-crime area. An important question regarding the bans on new fast food restaurants or other restrictive policies applied to urban areas is whether high crime rates attenuate the effect of fast food restaurants by forcing children to stay away from these restaurants.

The endogeneity question for fast-food effects on adults living in rural areas was addressed in a recent working paper (Anderson and Matsa, 2008), which used location near an interstate highway exit as an instrument for fast food location. Highway exits have fast food restaurants to serve travelers; they provide more fast food outlets than would otherwise be supported by small communities. The paper relies on self-reported weights and is limited to adults. The conclusion is that fast food has no causal effect on adult BMI.

In contrast to Anderson and Matsa, Currie et al (2008) have very large sample, 3.06 million student-year observations for ninth graders in California for 1999 and for 2001 through 2007, with precise locations of their schools and the fast food restaurants. They do not have data on individual children. Obesity rates are reported for all 9th graders in a school. The measurements on the children are taken during the Spring semester and represent approximately 30 weeks of exposure to a near-to-school fast food restaurant for a child entering high school. They find a 5.2 percent increase in the incidence of obesity, relative to the mean of 32.9 percent, for schools that have a fast food restaurant within 0.1 miles. They found no effect to fast food within buffers of 0.25, 0.5, and 1.0 mile from the school. They attribute this statistically significant and economically important effect within 0.1 miles as being due to the 9th graders having to walk to the fast food restaurants and having little time either before the school day, during the school day, or after school to visit a restaurant. Consistent with this limited-time explanation, other types of restaurants had no effect on 9th grade school obesity rates.

Since Currie et al have no individual data on children, they cannot know if the children who gained a nearby fast food restaurant by enrolling in high had also recently gained a fast food restaurant near their homes or if a higher proportion of the children whose schools have fast food restaurants within 0.1 mile entered the 9th grade were already obese. Going across years, they find no trend in obesity rates at schools that will gain a fast food restaurant in the future. However, they have very little temporal variation at the level of the school in the number of fast food restaurants within 0.1 miles. Specifically, they have 13 schools that ever gain a fast food restaurant, 8 that lose, and one that gains and loses.

Data:

The main sources of our data are: (1) clinical records from pediatric ambulatory visits to the Indiana University Medical Group between 1996 and 2006; (2) annual inspections by the Marion County Health Department of all food establishments; (3) aerial photographs, used to identify and verify recreational amenities; (4) reports of violent crimes from the Indianapolis Police Department and the Marion County Sheriff's Department; (5) birth certificates; and (6) the U.S. Census. These six data sources are described in more detail below.

(1)*Clinical records from well-child visits*
The Regenstrief Medical Records System (RMRS), in existence since 1974, is an electronic version of the paper medical chart. It has now captured and stored 200 million temporal observations for over 1.5 million patients. Because RMRS data are both archived and retrievable, investigators may use these data to perform retrospective and prospective research. The RMRS is distributed across 3 medical centers, 30 ambulatory clinics, and all of the emergency departments throughout the greater Indianapolis region. RMRS supports physician order entry, decision support, and clinical noting, and is one of the most sophisticated and most evaluated electronic medical record systems in the world.

Using the RMRS, we identified medical records in which there are simultaneous assessments of height and weight in outpatient clinics for children ages 3-18 years inclusive. For these clinic visits, we extracted the visit date, date of birth, gender, race, insurance status, and visit type (e.g. periodic health maintenance versus acute care). We found that too few patients had private insurance for this variable to have any predictive power. Because height and weight measurements are routinely performed as part of pediatric health maintenance, these measures should be present for virtually all children receiving preventive care at each of the study sites. The data generated by pediatric visits in the RMRS include higher representation oflow-income and minority households compared to the demographics of the study area because the associated clinics serve a population that is mostly publicly insured or has no insurance. The over-representation of minorities and low-income households in the RMRS, we contend, is a decided advantage. Poorer households are more sensitive to their immediate neighborhood because they face financial constraints against motorized transit (e.g. reduced car ownership, less money for gasoline, and less money for bus fares). Indianapolis has a vestigial public transportation system. It has been described as the worst city system in the Midwest (Quigley, 2003). If the built environment has any effect on child weights it should be most readily observed in poorer households in a city with minimal public transportation. Moreover, obesity is more prevalent in poorer households and among poorer children. Knowing what interventions reduce and exacerbate child overweight in this population would be valuable.

The initial age range of subjects in this study is three to eighteen years. National guidelines for well-child visits advocate annual visits between ages 3-6 years and at least biannual visits thereafter. We observed much more frequent well-child visits for girls age 16 or above than forboys, presumably because the former often use these visits to obtain gynecologic care such as a prescription for contraception. We extracted ICD-9 codes or other diagnoses list data for identifying children who may have systematic bias in growth or weight status (i.e. pregnancy, endocrine disorders, cancer, congenital heart disease, chromosomal disorders, and metabolic disorders), and excluded observations for such children. We also excluded patient encounters prior to 1996 because the RMRSdid not archive address data before this date.

(2) *Food establishment data*
We received annual inspection data on 8,641food service establishments in Indianapolis that received permits from the Marion County Board of Health between 1993 and 2007, inclusive. Of these, 5,550 are restaurants and 1,507 are in the grocery category. Fast-food establishments have been a particular focus of research on adult obesity and child overweight. Defining and identifying fast-food restaurants is problematic. Fast-food establishments in our study have been defined in two ways. Chou, Rashad, and Grossman (2005) identified a set of 41 national fast-food chains when they studied the effect of local advertising on child overweight. We will refer to that as the "national chains" list. The national chains are of special interest because they advertise more than local restaurants and local chains, and their restaurants are generally larger, in higher-traffic locations, and more likely to have a drive-up window. The second method of identifying fast food relied on the Census Bureau's counts of restaurants by Standard Industrial Classification (SIC) codes. Chou, Grossman, and Saffer (2002) used the Census Bureau data for state-level counts of establishments in the SIC 5812/40. These are establishments with a limited menu of items such as pizza, barbecue, hotdogs, and hamburgers. We refer to these restaurants as limited-service restaurants. Full-service restaurants (SIC 5812/10), in contrast, have at least 15 seats, table service, and serve prepared food from a full menu.

We have 735 establishments in Indianapolis in the national chains list and 1138 establishments in the broader limited-service list. Data-cleaning challenges included repeated counting due to slight changes in names of restaurants at the same address. Of the 735 fast food restaurants on the national chains list, 393 were opened between 1994 and 2004,whichallows a natural experiment investigating change in food environment as a possible cause of change in child body mass index.

There were 1,507 retail food establishments in the data. Again, we had to do some data cleaning. From the perspective of a Marion County food inspector a sushi retailer that rents space in a supermarket is a separate inspection entity, but from the consumer's perspective it is part of the supermarket. After a first cut at data cleaning, there were 114 supermarkets. The Indianapolis market, not atypically, has been roiled by the entry of supermarket chains, as well as discount stores with embedded supermarkets such as Meijer, Walmart, and Target. The city's largest chain, Kroger, has had a substantial expansion. Some of the entrants failed, such as Cub Foods, and have left behind stores that are still empty. Among supermarkets there is even more variation, proportionally, than among the national chains fast-food establishments. Fifty of the 114 supermarkets would satisfy the temporal requirement for a natural experiment because they opened after the first year, closed before 2004, or both.

(3)*Recreational amenities*
The study began with a geographic database of recreational amenities and associated features (such as parking lots), in vector form, developed from 2001 data provided by the Indianapolis Parks and Recreation Department. Each individual amenity, such as a basketball court or soccer field, was included as a feature in the database. We

incorporated three other similar databases for later periods, also provided by the Indianapolis Parks and Recreation Department.

Additional recreational amenities were identified for the years 1995 through 2006 through the interpretation of aerial photographs. We chose thirteen specific recreational amenities for identification. These were thought to be the most likely to be used by children in the study population and to be amenable to identification from aerial photographs, as well as sufficiently numerous to measure an effect. The chosen categories and their quantifications within 0.1, 0.25, 0.5, and 1 mile buffers centered on the child's home are:

1. baseball and softball field, count of fields in buffer
2. outdoorbasketball court, count of hoops in buffer
3. family center (indoor recreation center), area of facilities in buffer
4. fitness course, area in buffer
5. football field, count of fields in buffer
6. kickballfield, count of fields in buffer
7. playground without permanent equipment, area in buffer
8. playground with permanent equipment, area in buffer
9. swimming pool, area of water in buffer
10. soccer field, total area available for playing in buffer
11. tennis court, count of courts in buffer
12. track and field facility, area of facilities in buffer
13. volleyball court, count of courts in buffer

Nine photo interpreters participated in the process; they were assigned specific areas of the county, generally strips half a mile wide running north-to-south. To control for quality of interpretation, amenities lying on the borders of assigned interpretation areas were to be analyzed by both relevant interpreters. The resulting border features were then compared, to each other and to the photographs. Where the features differed, the more accurate interpretation was selected for the final dataset, and corrected if necessary. Additionally, errors that appeared in this process were treated as potential systematic errors; the other features interpreted by the responsible interpreter were examined for evidence of the same error repeated. If present, such errors were corrected, and if errors were found while the process was ongoing, the interpreter was retrained to avoid the error. An appendix contains the full details of the photo interpretation process.

(4) *Crime data*

During the study period, the primary law enforcement responsibility for Marion County was divided between the Indianapolis Police Department (IPD), which had responsibility for the area within the original Indianapolis boundary, the Marion County Sheriff's Department (MCSD), which had responsibility for most of the outlying areas of the county, and the police departments of the four small excluded municipalities of Speedway, Lawrence, Southport, and Beech Grove. When the city limits of Indianapolis were expanded tothe border of Marion County in 1970, the original police jurisdictions were not affected. In 2007 the Indianapolis Police Department and the Marion County Sheriff's Department were merged into the Indianapolis Metropolitan Police Department.

From the Indianapolis Police Department, for the IPD service area in which they had primary responsibility, we have a dataset of the geo-coded locations of all crimes reported for the Federal Bureau of Investigation's Uniform Crime Reports (UCR), from 1992 through 2005. From the Marion County Sheriff's Department, for the area in which they had primary responsibility, we have a dataset on the point locations of a wide range of crimes and other incidents, including the UCR crimes, from 2000 through 2005. We are using information on the crimes from both datasets that are included in the UCR violent crime categories: criminal homicides, rapes, robberies, and aggravated assaults. The dataset includes the date and time of the crime, and more detailed information on the specific type of crime within each of those four categories. Because of the manner in which these data have been assembled, we have reason to believe that these are accurate locations and that the classification of the type of crime is accurate.

To summarize, we have the following coverage for violent crimes:

1) Up through 1999, for the IPD service area only.
2) From 2000 through 2005, for both the IPD service area and the MCSD jurisdiction.

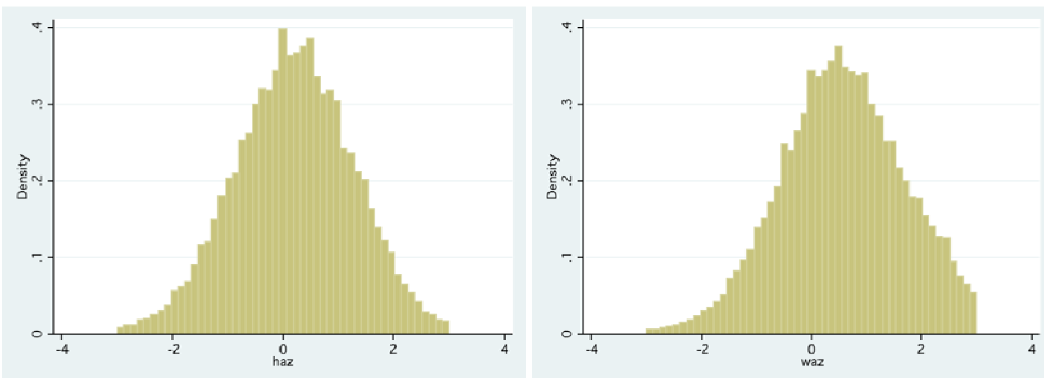
No crime data are available for any time period for the jurisdictions of the four small excluded municipalities that are within Marion County.

(5) Birth certificate data from the Marion County Health and Hospital Corporation.
We matched children's clinical data with Marion County Health and Hospital Corporation data on birth certificates by date of birth, gender, mother's surname, and child's given name. We were able to match 34.3% of the children in the clinical data. For a match to be possible the child must have been born in Marion County. The birth certificate data include birth weight, sex, race, mother's age and intention to breastfeed, parents' marital status, and one or bothparents' education, race, and eligibility for Women, Infants, and Children (WIC) aid (all, of course, at time of birth). In the few cases where reported race changed between the birth certificate and the clinical record, we used the race identified in the clinical record.

(6) Neighborhood characteristics
Neighborhood characteristics were estimated for 0.5-mile and 1.0 mile buffers surrounding each residence. These include five variables derived from Census 2000 data: population density, proportion African-American, proportions graduated from high school and from college, and median family income. The first two are estimated from the block data, the remainder from the block group data. Two variables are measures of the density and interconnectedness of the road network. The types of land use diversity in the area are measured using the proportion of land in commercial and residential use. Detailed information on the data sources and procedures used to create these variables are provided in an appendix.

Data cleaning
In examining the height and weight data from the clinical records we found highly improbable patterns, such as a child shrinking five inches in height from one well-child visit to the next. We calculated *z* scores for height and weight measures based on year 2000 US Centers for Disease Control and Prevention (CDC) growth charts. We used CDC statistical programs to identify biologically implausible values for heights and weights (CDC, 2000). Figure 1 shows the histograms of heights and weights, excluding biologically implausible values with *z*-scores greater than +3.0.

Figure 1
Histograms of Standardized Height (haz) and Weight (waz) Scores after Dropping Observations with *z*-scores at or Above 3

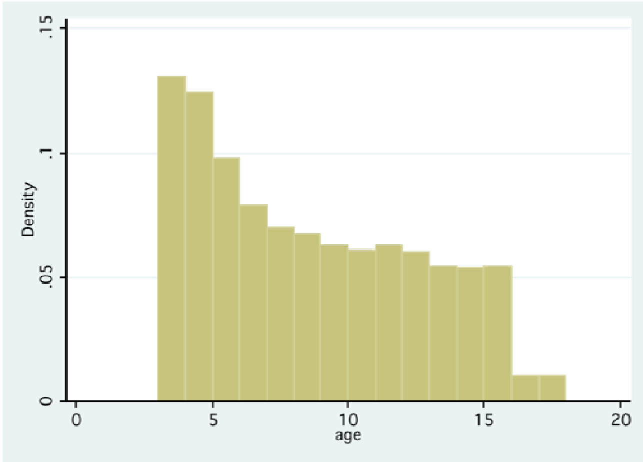


Visually, there is a small amount of truncation for the heights in the right tail of its distribution. As can be seen in the second graph, the truncation in the right tail of the body weight distribution is substantial. The CDC Growth Chart reference population spans the period 1963 to 1994, and thus does not fully cover the epidemic in child obesity of the past two decades. Another visual indicator of the extent of the epidemic is how much the distribution has shifted to the right relative to the mean of the reference population. We treated observations with weight-for-height and weight-for-age *z*-scores equal to or exceeding +5.0 as outliers likely resulting from data entry error or measurement errors.

Descriptive Statistics:

The histogram of the ages of all children at the time of their well-child visits is shown in Figure 2. Since well-child visits for preschool-age children are more frequent, the higher bars around ages 3, 4, and 5 were expected, as well as the steady decline thereafter. Prior to age 16 the genders at the well-child visits are split nearly 50-50. For age 17 the ratio is more than 80-20 females-to-males.

Figure 2
Histogram of Age at Time of Clinic Visit



To simplify our analysis we restricted our sample to children under the age of sixteen. The 16- and 17-year-olds are clearly a different population. There is not an obvious age at which children in the range of 3 through 15 gain significantly more control over their food and exercise choices. Although obtaining a driver's license does give a child much more independence, our exclusion of children age 16 or greater eliminates this factor. Lacking any a priori basis for splitting the sample by age, our split was dictated by the data. Almost exactly 50% of our observations are below age 8. For each amenity we tested whether the coefficients for children younger than 8 were the same as for children 8 or older. Some of our amenities are clearly suited for younger children, such as playground equipment, and others for older children, such as volleyball courts, tennis courts, and football fields.

Most studies of child weight determinants use the body mass index percentile compared to the pre-epidemic population sampled in the National Health and Nutrition Examination Survey (NHANES) I from 1971 to 1974. Absolute thresholds for overweight or obesity are not applied to children because the amount of body fat changes with age and differs between girls and boys. The mean body mass index percentile in our data is 65.5. A disadvantage to using the percentiles of the reference population is truncation. For the 205 well-child visits in our sample that were at the 100th percentile, we cannot observe any responses to amenities that increase their weight. We use the term "amenities" to mean any environment factor, desirable or undesirable. For the 5,049 well-child visits at or above the 99th percentile, there is limited ability to observe weight increase responses. To avoid the truncation problem inherent in the percentiles we used the BMI *z* score as the dependent variable.

Table 1 has the descriptive statistics for the data used in the cross-sectional analysis. The definitions and procedures used to create the neighborhood characteristics variables are in an appendix. All of the data were restricted to children whose age was under 16, and who had an absolute value of the *z* score of height relative to the reference population less than

3, a *z* score of weight relative to the reference population between –3 and 5, and a *z* score of BMI relative to the reference population also between –3 and 5

Table 1
Descriptive Statistics for the Cross-Sectional Analysis

Clinical Observations by year

Year	N
1996	1,811
1997	10,744
1998	13,437
1999	13,289
2000	12,242
2001	12,034
2002	11,945
2003	11,502
2004	8,135
2005	7,795

Clinical Data	N	Mean	St. D.	min.	max.
BMIZ	102,955	0.68	1.17	-2.99	4.99
Well-Child Visit	102,955	0.82	0.38	0.00	1.00
Female	100,937	0.48	0.50	0.00	1.00
White	102,955	0.29	0.45	0.00	1.00
Black	102,955	0.53	0.50	0.00	1.00
Hispanic	102,955	0.13	0.33	0.00	1.00
Neighborhood characteristics					
Population Density	102,955	9.32	4.23	0.00	27.35
Percent Black	102,954	0.43	0.35	0.00	0.98
Percent High School	102,954	0.70	0.13	0.38	1.00
Percent College	102,954	0.12	0.11	0.00	0.85
Median Family Income	102,954	37,540	12,302	11,202	157,951
Road Network Density	102,955	3.60	1.24	0.00	9.27
Number of Road Intersections	102,955	25.10	15.78	0.00	109.00
Commercial Land Use	102,955	0.07	0.09	0.00	0.89
Residential Land Use	102,955	0.64	0.21	0.00	1.00
Marion County Birth certificate Data:					
Child's Birth weight (g)	54,066	3141.55	630.21	170.00	5443.00
Father's age	26,827	27.23	7.37	14.00	91.00
Father's years of education	25,562	11.66	2.10	1.00	26.00
Mother's age	54,171	23.10	5.64	11.00	50.00
Mother's education	53,095	11.21	1.90	1.00	24.00
Intention to Breastfeed	50,487	0.22	0.41	0.00	1.00
Marital Status (1=married)	54,986	0.28	0.45	0.00	1.00
WIC eligibility (1 = yes)	50,890	0.74	0.44	0.00	1.00

Table 2 has the environmental variables that are based on the annual Marion County food establishment inspections, Indianapolis Department of Parks and Recreation records, the Indianapolis and Marion County crime reports, and on our photo interpretation of recreational amenities. These are reported within buffers of 0.1 mile, 0.1 to 0.25 miles, 0.25 to 0.5 miles, and 0.5 to 1 mile. The table reports the average values by buffer over the study period.

Table 2
Amenity Variables

	Mile Radius	Mean	St. D.	min.	max.	N
Fast Food Restaurants	.1	0.03	0.20	0.00	4.00	98,541
	.1 - .25	0.22	0.66	0.00	7.00	98,541
	.25 - .5	0.87	1.40	0.00	11.00	98,541
	.5 - 1	3.44	2.99	0.00	20.00	98,541
Supermarkets	.1	0.01	0.08	0.00	1.00	98,541
	.1 - .25	0.06	0.25	0.00	3.00	98,541
	.25 - .5	0.22	0.48	0.00	4.00	98,541
	.5 - 1	0.78	0.82	0.00	4.00	98,541
Convenience Stores	.1	0.03	0.18	0.00	2.00	98,541
	.1 - .25	0.17	0.43	0.00	3.00	98,541
	.25 - .5	0.54	0.83	0.00	7.00	98,541
	.5 - 1	1.98	1.85	0.00	11.00	98,541
Trails (m)	.1	12.72	106.14	0.00	2100.67	102,955
	.1 - .25	108.83	478.02	0.00	7110.42	102,955
	.25 - .5	503.92	1323.73	0.00	12646.57	102,955
	.5 - 1	2419.53	4091.35	0.00	40526.93	102,955
Violent Crimes (annual)	.1	4.18	5.37	0.00	49.00	98,541
	.1 - .25	16.09	17.56	0.00	135.00	98,541
	.25 - .5	47.16	49.13	0.00	354.00	98,541
	.5 - 1	155.80	144.66	0.00	739.00	98,541
Baseball Diamonds	.1	0.07	0.35	0.00	7.00	102,955
	.1 - .25	0.47	1.05	0.00	12.00	102,955
	.25 - .5	1.67	2.09	0.00	16.00	102,955
	.5 - 1	6.31	4.09	0.00	27.00	102,955
Basketball Hoops	.1	0.25	0.78	0.00	9.00	102,955
	.1 - .25	0.98	1.63	0.00	18.00	102,955
	.25 - .5	3.05	2.97	0.00	21.00	102,955
	.5 - 1	10.40	5.94	0.00	56.00	102,955
Family Centers (m^2)	.1	1.43	34.52	0.00	1430.10	102,955
	.1 - .25	13.72	130.18	0.00	3483.40	102,955
	.25 - .5	88.92	389.36	0.00	3483.40	102,955
	.5 - 1	357.66	755.85	0.00	5517.90	102,955
Fitness areas (m^2)	.1	2.37	63.89	0.00	4099.10	102,955
	.1 - .25	23.09	266.94	0.00	5423.90	102,955
	.25 - .5	69.10	462.40	0.00	11786.00	102,955
	.5 - 1	390.63	1343.81	0.00	11786.00	102,955
Football Fields	.1	0.02	0.16	0.00	2.00	102,955
	.1 - .25	0.10	0.34	0.00	5.00	102,955
	.25 - .5	0.27	0.61	0.00	8.00	102,955
	.5 - 1	1.03	1.19	0.00	11.00	102,955

	Mile Radius	Mean	St. D.	min.	max.	N
Kickball Diamonds	.1	0.01	0.11	0.00	3.00	102,955
	.1 - .25	0.06	0.26	0.00	4.00	102,955
	.25 - .5	0.21	0.50	0.00	5.00	102,955
	.5 - 1	0.65	1.01	0.00	7.00	102,955
Playgrounds, no equipment (m^2)	.1	72.99	316.35	0.00	4559.50	102,955
	.1 - .25	309.05	684.31	0.00	10268.30	102,955
	.25 - .5	982.75	1300.46	-0.10	12972.40	102,955
	.5 - 1	2981.93	2373.51	0.00	14253.70	102,955
Playgrounds with equipment (m^2)	.1	133.70	372.93	0.00	6818.80	102,955
	.1 - .25	486.26	797.68	0.00	10165.20	102,955
	.25 - .5	1408.51	1617.50	-0.10	15141.80	102,955
	.5 - 1	5170.40	3557.66	0.00	21986.30	102,955
	.1	22.24	85.19	0.00	1717.80	102,955
Pools (m^2)	.1 - .25	69.27	193.09	0.00	2825.10	102,955
	.25 - .5	201.78	344.25	0.00	5526.10	102,955
	.5 - 1	710.51	811.61	0.00	7247.30	102,955
	.1	39.42	464.84	0.00	23207.30	102,955
Soccer (m^2)	.1 - .25	481.89	2275.35	0.00	77155.50	102,955
	.25 - .5	1937.60	6346.88	0.00	137783.10	102,955
	.5 - 1	8364.20	15137.73	0.00	193082.40	102,955
	.1	0.10	0.51	0.00	12.00	102,955
Tennis	.1 - .25	0.45	1.18	0.00	32.00	102,955
	.25 - .5	1.48	2.67	0.00	35.00	102,955
	.5 - 1	5.41	5.63	0.00	47.00	102,955
	.1	47.92	467.45	0.00	15158.00	102,955
Trackand field (m^2)	.1 - .25	394.62	1725.75	0.00	19316.10	102,955
	.25 - .5	1052.36	2940.19	0.00	25371.70	102,955
	.5 - 1	4024.17	6037.80	0.00	39704.60	102,955
	.1	0.03	0.17	0.00	2.00	102,955
Volleyball	.1 - .25	0.10	0.35	0.00	4.00	102,955
	.25 - .5	0.30	0.61	0.00	5.00	102,955
	.5 - 1	0.92	1.12	0.00	9.00	102,955

The definitions of the recreational amenities are in an appendix.

One striking number from the descriptive statistics is the amount of crime. The violent crimes included are criminal homicides, rapes, robberies, and aggravated assaults. The maximum value for the tenth-mile buffer was 49.

Estimation Strategy:

Our initial dataset consists of fixed information on the child (race, sex, family composition at birth), changing information on the child (height, weight, and age at each clinic visit), fixed information on the parents (race, mother's and possibly father's education at the child's birth), changing information on the family (residence), the built environment near the residence in each year, crime counts by year within buffers around the child's home, and some information on neighborhood characteristics for buffers around each residence, including information on the road network, and land use, and the population density from the census,.

As was mentioned above, to control for the normal variations in BMI as the child ages we use age-sex adjusted base-periodBMI *z* scores as the dependent variable.We estimate two main types of models, Ordinary Least Squares (OLS) and Fixed Effects (FE) for a child at a stable address across serial clinic visits.

The key identifying assumption in the FE estimation is that households that stay at the same location after an amenity is placed near their residence retain the same preferences they had before the amenity was added. Under this assumption the household fixed effect would remove constant-over-time preferences for location amenities and any other unobserved variables that did not change for each household. For example, the parents' discount rate over future consumption by either themselves or their children and their altruism toward their children would wash out in the fixed effects specification.

What are the potential criticisms of this estimation strategy? People might move, or more generally they might change preferences, in response to changes in their child's overweight status, in which case the FE design wouldnot remove the bias. However, we doubt that preferences change rapidly.

Another potential criticism is that there are unobserved variables common to households that are located near the new amenity. If the households in a neighborhood lobbied the parksdepartment to obtain the playground or pool built near them, then there would be some common-to-the-neighborhood but unobserved-to-the-econometrician interest in exercise that would bias the estimates. A pool placed near a neighborhood where the parents had lobbied (presumably because they were anxious to have their children use the new pool) would have a smaller effect on child overweight. This is the endogeneity problem in another guise.

More problematic is the location of privately-owned amenities such as fast food restaurants or supermarkets. These types of firms often employ market researchers to identify areas where households will be the most receptive to a fast food outlet or the most likely to buy fresh produce. We can use robust estimators that yield consistent estimates of the standard errors when there are common-but-unobserved differences at a neighborhood level, but without the original information that was in the hands of the market researchers, we cannot fully control for differences among households in receptiveness to fast food or fresh produce. At least the direction of any potential bias is clear. We will have upperbound estimates on child overweight effect of these privately-owned amenities. Thus, if any of them turn out to have a negligible estimated effect, we can be confident that public policy aimed at increasing or reducing these amenities would have no impact. Further, by looking at the trends in BMI *z* score (bmiz) before amenities such as fast food arrived, we can test whether the children who will gain an amenity in the future differ from those who will not.

Another issue that we plan to address in future studies is continuing effects of a given change. Our FE model shows the impact for children of a given age of an increase or decrease in an amenity on bmiz from one visit to the next, provided the visits are in different calendar years. The exact duration of the exposure to the changed amenity is not known, even though the dates of the well-child visits are exact, because the food inspections and aerial photographs are only updated annually. Our FE estimates reflect the average duration of exposure to a change in an amenity from one calendar year to the next. We estimate the impacts on bmiz of amenity change in year t in $t + 1$. We have not estimated the bmiz effects for years $t + 2$ or higher.

Suppose that unobservable household variation could be reduced to a single relevant characteristic, such as a fondness for calorie-dense food *and* being sedentary. Call this unobserved variation in preferences τ. A further issue we intend to address in future studies is exploiting the differences between households that stay at the same location after an amenity is introduced or removed near them, versus households who move to a new location that is either near an amenity they did not have or far from an amenity they used to have close by, versus households that have a mix of periods with fixed locations and changing amenities and movements toward or away from amenities. Children in high-τ households would have a greater bmiz response to the advent of nearby sources of calorie-dense food, such as fast food restaurants or convenience stores. They would also show a smaller bmiz response to the advent of recreational amenities. Households that move near to an amenity must, on average, have a higher preference for that amenity, i.e. movers to nearby fast food locations would tend to have higher values of τ while movers to nearby recreational amenities would tend to have a lower value of τ. The differences in bmiz response to a given amenity among the movers, stayers, and households that mix periods of moving and staying can bound the value of the bmiz response for children in households that have average levels of τ.

Results:

To see how much of the variation in bmiz can be accounted for by the fixed mother and child characteristics, bmiz was regressed on all of the variables in Table 1, using robust standard errors clustered on the child's ID. Three of the year-indicator variables were significant at the 10% level but these are omitted. The results are also reported separately for children under age 8 and over age 8. Age is measured at the time of the clinic visit and is a continuous variable.

Table 3
OLS Regression of Fixed Mother and Child Characteristics and Neighborhood Characteristics

Variable	All Ages	Age < 8	Age > 8
Age	0.098**	0.218**	0.220**
Age Squared	-0.003**	-0.014**	-0.008**
Well Child Visit	-0.052+	-0.035	-0.074+
Female	0.027	-0.050+	0.140**
White	-0.155*	-0.125+	-0.156
Black	-0.066	-0.083	-0.034
Hispanic	0.356**	0.336**	0.251
Mother's weight gain	0.001	0.001	0.001
Mother's age	0.009**	0.008**	0.012**
Birth weight	0.379**	0.434**	0.293**
WIC	0.033	0.016	0.063
Mother's Marital Status	0.012	0.006	0.02
Intention to Breastfeed	0.008	0.02	-0.023
Mother's Education	-0.015+	-0.025**	0.003
Population Density	0.004	0.005	0.003
Proportion Black	-0.146**	-0.226**	-0.021
Proportion HS. Grad.	-0.208	-0.165	-0.249
Proportion College Grad.	0.268	0.340+	0.148
Median Family Income	-0.004*	-0.004+	-0.004+
Road Network Density	-0.014	-0.015	-0.018
Number of Road Nodes	0.457	1.395	-0.248
Prop. Commercial Land	0.007	0.081	-0.094
Prop. Residential Land	0.055	0.018	0.099
Constant	-0.890**	-1.271**	-1.581**
Observations	42890	25436	17420
R-squared	0.07	0.08	0.05

Robust standard errors in parentheses
+ significant at 10%; * significant at 5%; ** significant at 1%

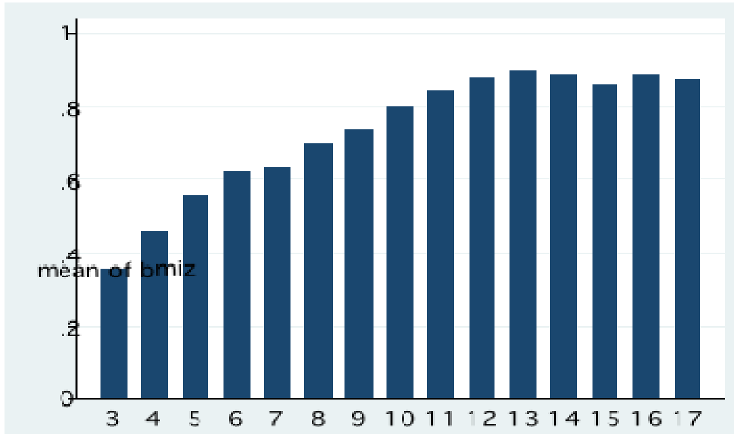
About 7.4% of the overall variation in bmiz can be accounted for by fixed child characteristics, mother's characteristics, and neighborhood characteristics. The explanatory power is 8% for the younger children and 5% for the older children. The increased explanatory power of the model for younger children may be attributable to the birth certificate data more accurately representing the current socioeconomic environment of the study subject. The well-child visit indicator is significant overall and for the older children; the sign is negative. The negative association between child weight and well-child care is counter-intuitive. The well-child variable, in theory, represents the health status of the child, with poorer-health-status children having systematicallylower body mass index. Recall that visits with diagnostic codes known to affect body weight were dropped from the dataset (pregnancy, endocrine disorders, cancer, congenital heart disease, chromosomal disorders, and metabolic disorders).

The well-child variable may reflect behavior practices of the child's caregivers. Caregivers who less frequently access routine health maintenance for their children, or primarily bring their children in for sick-child visits, may be less supportive of child health behaviors associated with optimal child weight (e.g. promoting routine physical activity or a nutritious diet). This behavioral interpretation is supported by an HMO study that found that overweight children were less likely to have well-child visits (Estabrooks and Shetterly, 2007).

> "Interestingly, over a 3-year period, overweight children show significantly fewer well-child visits. This couldindicate that overweight children receive well-child visitcare during sick visits that occur at a time that is proximal to a future well-child visit. It could also indicate thatparents of overweight children feel that well-care visitsare not necessary as a result of a higher frequency of sickvisits. Finally, it could also indicate that overweight children avoid well-care visits as a method to avoid receiving advice about their weight." (p. 226)

Relative to the reference population, bmiz is increasing rapidly with age. As children age from the sample minimum of 3 to the maximum of 16 years their predicted bmiz increases by 0.6. The mean bmiz scores for children in the age range 3 to 4 is 0.43, while for children in the age range 15 to 16 it is 0.85. The age and age squared specification is parsimonious, but a histogram suggests a rapid increase up to age 13, and level bmiz thereafter.

Figure 3
Mean BMIZ by Age



The bmiz gain appears to be largely a permanent cumulative process. Children (Wilfley et al., 2007) and adults (Jeffery et al., 2000) are often able to lose weight in the short-term but find it much more difficult to sustain any loss from their peak weight over a long period. Large recorded *z*-score gains are rarely reversed at later visits.

To assess how often large gains in weight were reversed we looked at the subset of children with large bmiz gains, defined as +0.5 in bmiz from the first visit to the second visit. At the mean of the reference population a *z*-score gain of 0.5 would be 27 percentile points. The count of big gainers that have at least three visitswas 338. Among these big gainers, the count of those who were above their initial *z* score by the third visit was 2743. The big gainers who were at or below their first-visit *z* score by the third visit was 638. Only 19% of the big gainers recovered.

There is some noise in the weight and the height data that are likely due to data entry or measurement errors at the clinics. If observations of big gainers between the first and second visits were primarily due to such errors, we would expect them to largely disappear by the next visit. Because only a small proportion of the big gains were reversed, we can be confident that they are not primarily due to recording errors. Further, the irreversibility of most of the big gains supports our conclusion that the weight gains are largely cumulative.

The age effect,due to tendency of children to accumulate weight relative to the reference population and rarely lose any of it, is quite strong.Consequently, we will include age and age squared in subsequent regressions, which always have a maximum age of 16. What these regressions can tell us is the extent to which the addition or removal of an amenity can alter the pronounced bmiz-age pattern.

The birth certificate variables are available for only one third of the dataset. This is too small a sample size to detect many amenity effects. In Table 4 we drop the birth certificate variables and add the amenity variables.

Table 4: OLS with Birth Certificate Variables Excluded

	tenth of mile			quarter mile			half mile			one mile		
Variables	All Ages	Age < 8	Age > 8	All Ages	Age < 8	Age > 8	All Ages	Age < 8	Age > 8	All Ages	Age < 8	Age > 8
Age	0.093**	0.185**	0.217**	0.093**	0.185**	0.216**	0.093**	0.184**	0.217**	0.093**	0.188**	0.212**
Age Squared	-0.003**	-0.012**	-0.008**	-0.003**	-0.012**	-0.008**	-0.003**	-0.012**	-0.008**	-0.003**	-0.012**	-0.008**
Well-Child Visit	-0.026	-0.001	-0.053*	-0.027	-0.001	-0.054**	-0.028+	-0.003	-0.054**	-0.028+	-0.004	-0.054**
Female	0.002	-0.072**	0.081**	0.002	-0.071**	0.080**	0.003	-0.070**	0.081**	0.002	-0.071**	0.079**
White	0.02	-0.013	0.078+	0.018	-0.017	0.078+	0.02	-0.012	0.076+	0.022	-0.009	0.077+
Black	0.007	-0.089*	0.114**	0.005	-0.094*	0.117**	0.005	-0.091*	0.115**	0.01	-0.087*	0.119**
Hispanic	0.366**	0.371**	0.298**	0.367**	0.369**	0.300**	0.368**	0.372**	0.300**	0.365**	0.371**	0.295**
Population Density	0.004	0.004	0.003	0.004+	0.003	0.006+	0.004	0.004	0.005	0.007**	0.008**	0.007*
Proportion Black	-0.110**	-0.221**	0.01	-0.122**	-0.228**	-0.003	-0.108**	-0.216**	0.017	-0.141**	-0.217**	-0.053
Proportion with College	-0.057	-0.038	-0.08	-0.065	-0.048	-0.063	-0.026	0.029	-0.063	-0.215+	-0.148	-0.275
Family Income	-0.002+	-0.001	-0.002+	-0.001	-0.001	-0.002+	-0.001	-0.001	-0.002	-0.001	-0.001	-0.001
Proportion Residential	-0.061	-0.087	-0.052	-0.062	-0.069	-0.076	-0.073+	-0.091+	-0.08	-0.057	-0.073	-0.058
Fast Food	0.082*	0.041	0.134**	0.019+	0.01	0.030*	0.003	0.002	0.003	-0.003	-0.004	-0.002
Supermarkets	-0.185*	-0.195*	-0.168	-0.013	-0.036	0.021	0.023	0.027	0.019	0.011	0.015	0.006
Convenience Stores	0.07	0.022	0.121*	-0.02	-0.01	-0.03	0.012	0.012	0.015	-0.007	-0.003	-0.011
Trails	-0.746	-1.321+	-0.066	-0.266*	-0.331*	-0.128	-0.053	-0.032	-0.043	0.030+	0.035	0.028
Crime	-0.009	0.21	-0.171	0.033	0.084	-0.015	0.009	0.015	0.003	0.003	0.001	0.006
Baseball/Softball	0.006	-0.02	0.037	-0.002	-0.001	-0.003	0.002	-0.001	0.006	-0.003	-0.008**	0.003
Basketball	-0.004	0.01	-0.018	-0.002	0.005	-0.010+	0.003	0.009**	-0.003	0.001	0.001	0.002
Family Centers	-1.544	0.038	-3.811	0.614	0.402	0.736	0.645**	0.871**	0.342	0.204*	0.370**	0.002
Fitness Areas	-0.716	-1.539+	-0.318	0.25	0.071	0.442	0.124	-0.068	0.355+	0.029	-0.002	0.067
Football	-0.078	-0.046	-0.119	0.016	0.031	-0.002	0.009	0.022	-0.006	0.001	0.007	-0.006
Kickball	0.112	0.172+	0.038	0.042	0.073*	0.005	0.007	0.016	-0.007	0.006	0.001	0.01
Playgrounds (no equipment)	-0.329	-0.355	-0.238	-0.056	-0.063	-0.056	-0.043	-0.026	-0.082	-0.036	0.008	-0.085+
Playgrounds (with equipment)	-0.042	-0.301	0.311	0.018	0.024	0.04	0.001	-0.026	0.028	-0.022	-0.001	-0.038
Pool	-0.808	-1.292	-0.08	-0.517	-0.119	-0.929+	-0.215	-0.267	-0.126	0.154	0.144	0.151
Soccer	0.055	0.237	-0.134	0.002	-0.014	0.015	-0.009	-0.004	-0.01	0.002	0.004	0.002
Tennis	-0.014	-0.029+	0.004	-0.002	-0.005	-0.001	-0.003	-0.003	-0.004	-0.003*	-0.002	-0.004*
Track and Field	0.294	0.09	0.729**	0.004	-0.007	0.022	-0.013	-0.011	-0.016	0.011	0.022	-0.002
Volleyball	0.068+	0.094*	0.031	0.009	0.002	0.01	0.016	0.008	0.018	0.009	-0.001	0.019*
Constant	0.242**	0.053	-0.557*	0.235*	0.043	-0.550*	0.196*	0.008	-0.605**	0.164	0.041	-0.620**
N (observations)	96522	50503	45951	96522	50503	45951	96522	50503	45951	96522	50503	45951
R-squared	0.03	0.04	0.01	0.03	0.04	0.01	0.03	0.04	0.01	0.03	0.04	0.01

Robust standard errors in parentheses. + significant at 10%; * significant at 5%; ** significant at 1%

The amenities that are significant show up at various distances. There is no reason to expect the real effects of different amenities to operate over the same distance. Also, in the smaller circles there may be real effects but too few observations to yield statistically significant results. In discussing the results in Table 4, we concentrate on the signs and significance levels rather than the values of the coefficients. We do this because we are primarily interested in how the OLS results contrast with the FE results. We think the OLS results are telling us more about who chooses to live near an amenity, such as a school with open recreational facilities or a fast food restaurant that is near a major road.

Age and age squared are highly significant in every OLS regression. In cross section the well-child visit indicator is always negative. It is significant in six of the nine regressions. Thus, across different children a sick-child visit is associated with higher bmiz. The Female indicator variable should not be significant because the bmiz variable adjusts for gender in the reference population. The consistent negative and significant coefficients for the younger children and the positive and significant coefficients for the older children indicate that relative to boys in the same age range the younger girls are not gaining bmiz as fast while the older girls are gaining bmiz faster than older boys. The differential may be due to a trend toward an earlier age of puberty for girls.

In terms of racial differences, the striking result is the high bmiz values for Hispanics relative to the omitted category—Asian and other. There are two variables related to African Americans. One refers to the race of the child. Older black children are significantly heavier than the omitted category and than whites. The second variable refers to the neighborhood. Other things equal, living in a neighborhood with a higher proportion of blacks is associated with a lower bmiz. Since proportions run from 0 to 1 the interpretation of the coefficient is straightforward. For children under the age of 8 hypothetical neighborhoods with no African Americans have higher bmiz, by about 0.22, than neighborhoods that are entirely African American. The proportion of residents in the neighborhood with a college education is almost never significant (one of nine at the 0.10 level). The median family income in the neighborhood and proportion of dwellings that are residential are similar (both have two of nine at the 0.10 level). In the neighborhoods our children live in, college education is rare and incomes are generally low.

The fast food variable is significant in four of the nine OLS regressions. The significant coefficients are always positive. This positive effect on BMI is the conventional result for fast food in cross-sectional regressions. The significant coefficients are for the closer buffers, within 0.1 and 0.25 miles. The supermarket variable (OLS) also has the conventional result that supermarkets are associated with lower bmiz when they are close. The signs on the first five coefficients are negative. Of those, just two are significant. Supermarkets also tend to be located on major roads that are on commuting routes. Households that live near a supermarket are likely to differ from households that live far from the nearest supermarket. The convenience store variable has little explanatory power in the OLS regression. Only one of the nine coefficients is significant. Crime is never significant in the OLS regressions.

Very few of the recreational amenities have a significant negative sign. These include trails (<8 at 0.1 miles, all ages at 0.25 miles, and <8 at 0.25 miles), baseball/softball (<8 for 1.0 mile), pools (>8 at 0.25 miles), and tennis (<8 at 0.1 miles, all ages at 1.0 miles). Even some of the results that do have a negative and significant sign are counter-intuitive, e.g. how many children under 8 play tennis?

The problems with the OLS results are that they have little explanatory power, most of the demographic variables have limited policy implications, and most importantly, it is impossible to know if the associations are causal. For example, track and field facilities and football fields are almost all located at middle schools and high schools. Even if they had been statistically significant, would the bmiz differences associated with these variables be due to children using these amenities or simply to unobserved differences in the families that chose to live near these schools? The fast food restaurants, supermarkets and even convenience stores tend to be located on major roads that are commuting routes from the city center to the suburbs. Below we have provided some clear maps showing these amenities lined up on the commuting routes. Are the bmiz associations of these amenities due to proximity to these food sources or to unobservable differences in households living near major roads?

FE regressions:

Before reporting the FE regressions we report in Table 5 below how many children had changes in each of the amenities.

Table 5
Counts of Children Having Any Change by Amenity and by Buffer

	0.1 mile	0.25 mile	0.5 mile	1 mile
Fast food	29	342	1446	4980
Supermarkets	8	79	337	1290
Convenience Stores	33	270	1066	3686
Trails	73	258	715	2085
Crime	14643	17782	18923	19946
Baseball/Softball	50	371	1168	4252
Basketball	179	1041	3519	9655
Family Centers	0	16	429	614
Fitness Trails	18	39	271	477
Football Fields	4	64	232	1070
Kickball Diamonds	35	187	622	2112
Playgrounds no equipment	143	572	3596	5764
Playgorund with Equipment	483	1942	7561	13601
Pools	93	329	2702	3447
Soccer Fields	19	192	1733	3847
Tennis Courts	84	250	734	2133
Track and Field	7	28	835	939
Volleyball Courts	14	78	299	1019

The large number of children having changes in the amounts of crime is due to the underlying variable counting individual crimes. At the smallest buffer, within 0.1 miles, many of the amenities have so few children facing changes that it is unlikely we would observe any effect. These include supermarkets, family centers, fitness trails, football fields, soccer fields, track and field, and volleyball courts. Except for the family centers, by the 0.25-mile buffer there are enough children with observed changes that if changes in the amenity indeed had an effect on BMI at that distance we have a good chance of observing the effect. We added the 0.1-mile buffer for all amenities because the Currie et al paper found a fast food effect within 0.1 miles of child's school. The vast majority of the changes in amenities that are in counts were a gain or loss of one unit, e.g. one fast food restaurant. Of these the modal change was from 0 to 1 unit with the next most frequent being from 1 unit to 0.

Data on individual children have more variation than data on high schools. Our sample of children is 3.2% of the Currie et al sample. Their sample is based on observations of 3.06 million student years and our data on 98,541 clinic visits among children with two or more visits while residing at the same address. We have 29 changes in the number of fast food restaurants within the 0.1-mile buffer compared to 22 in the Currie et al sample.

In the FE regressions below, we dropped all variables that are constant at the level of the child. Again, this sample is restricted to observations in which a child remains at the same address between clinic visits. The same restrictions on age and biologically implausible values of bmiz, height, and weight are also applied. The covariates to the environmental/amenity variables are age and age squared, year of clinic visit indicator variables, an indicator for a well-child visit, and crime.

Again, the coefficients on the year dummy variables are not reported. In the FE regressions, the children under 8 years of age are gaining bmiz faster relative to the reference population than the children over age 8, roughly by 0.13 bmiz units a year. This younger versus older child differential did not appear in the OLS regressions. The well-child variable is now positive and significant at the 10% level for all children. This FE result sharply contrasts with the OLS result for the well-child visit variable, which was always negative, and significant in six of the nine OLS regressions.

There are very few overlaps from the OLS to the FE results of the same amenity being significant at the same distance. Adding a fast food restaurant within a quarter mile of the same child appears to significantly *reduce* the child's bmiz. Recall that in the cross-sectional results at the tenth-mile buffer, the association between bmiz and fast food was positive.

From a public policy perspective, the FE results for the recreational amenities are somewhat discouraging. The variables with negative and significant coefficients are fitness areas for all children and younger children at 0.25 miles; kickball for all children and younger children at 0.1 mile, all children at 0.25 miles, and older children at the 0.5 and 1.0 mile buffers; playgrounds without equipment for younger children at 0.5 miles; tennis for older children at 0.25 miles; and volleyball for older children at the 0.1 mile buffer and older children at the mile buffer. The division across amenities that might be associated with reducing bmiz in younger versus older children appears plausible, e.g. younger children use playgrounds and kickball fields while the older ones use volleyball courts.

As a check on whether their estimated fast food effects on percentages of boys in a high school who were overweight (defined as the 85^{th} percentile) could plausibly be due to the calories from an extra fast food meal per day, Currie et al. calculated the weight *gain* required for a median height 14 year old boy to move from the 80^{th} to the 85^{th} percentile of the bmi distribution. This weight gain was 3.6 pounds. To get a sense of what our estimated coefficients imply for weight gains we will use boys, to match Currie et al. but change the age to 8, which is the median for our data. We will start at the 85^{th} percentile, their end point, and calculate the implied weight *loss* for some amenities that were estimated to statistically significant effect in reducing weight. Adding a kickball diamond within a tenth mile is associated (based on the equation for all ages) with a reduction of 2.8 pounds. The weight reduction for adding a playground within a half mile (based on the under age 8 regression) is 4.1 pounds. The weight reduction for adding a volleyball court within a tenth mile (based on the age 8 or over regression) is 6.9 pounds. Recreational amenities that could reduce the weights of overweight 8 year-old boys within a year of being located near their homes by anything in the range of 2.8 to 6.9 pounds would be economically significant.

Switching to the statistically significant effects for food venders, at a mile distance the addition of a fast food restaurant was associated (in the all ages regression) with a weight tiny gain, 0.14 pounds. The addition of a supermarket within a mile (all ages regression) is associated with a gain of 0.42 pounds. The addition of a convenience store within a mile (under age 8 regression) was associated with a gain of 0.36 pounds. The weight changes associated adding a food vendor, even when statistically significant, are smaller than the weight losses associated with the few recreational amenities that have negative and significant coefficients.

Some of our results are counter-intuitive. Fast food is associated with weight reduction in at a quarter mile. Trails are only significant for the older children. This trails result is partly intuitive because younger children walking on the trails could wander into the paths of runners, bicyclists and in-line skaters. We see more young children riding in strollers or in bicycle carriers or tandem bicycles than those traveling entirely on their own power. However, what the counter-intuitive part is that all of the coefficients that are significant have a positive sign.

If the reported results were causal effects, then bmiz-reducing policy would be to build fast food restaurants within a quarter mile of the child’s home and surround the child’s home with a fitness area, a kickball diamond, and a playground, all at their respective optimal distances. Before much credence can be given to these estimates, the issue of the endogeneity of the placement of these amenities must be addressed.

The FE framework allows for separate consideration of gains and losses in amenities. We tested whether the coefficient on a gain was the same as for a loss for every amenity and could not reject the null hypothesis of equality in a single case. Also, we looked at assumption of linearity of effects, e.g. that a gain from 0 to 1 is the same as a gain from 1 to 2. A very high fraction of all of the changes we observed in counts of amenities were in the range of 0 to 1 or from 1 to 0. We could not reject the null hypothesis of linearity largely because we observed too few higher-order changes.

Table 6
Fixed Effects Regressions

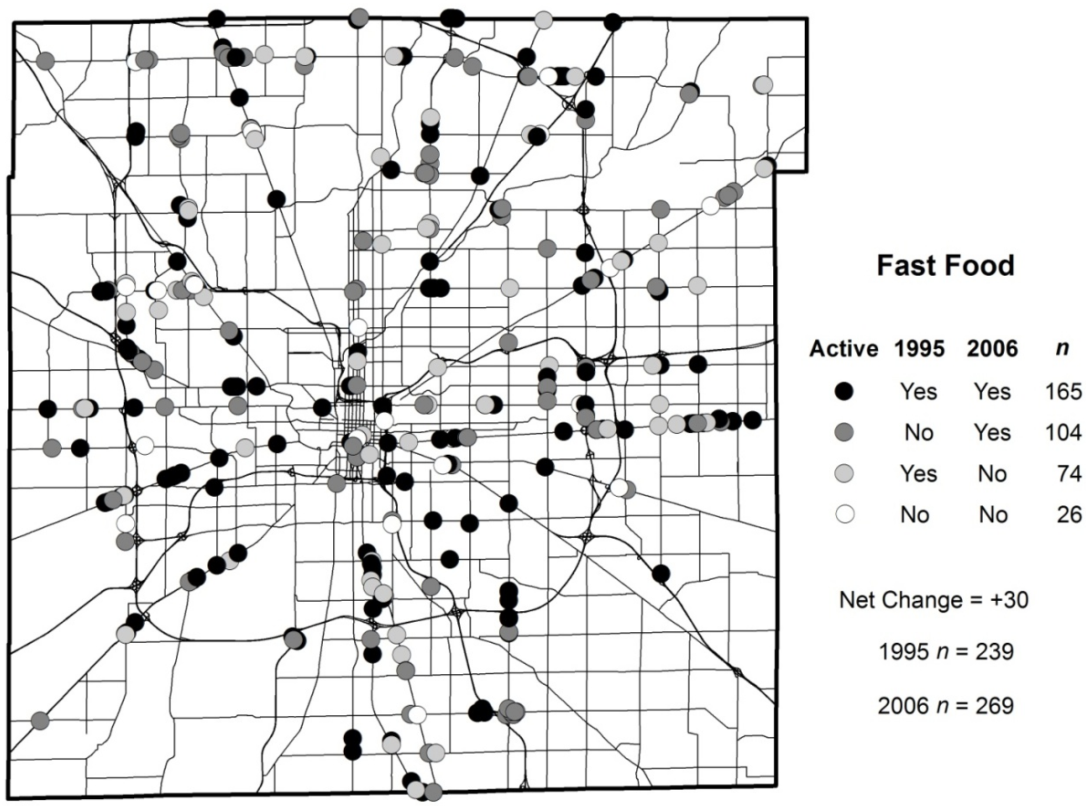
	tenth of mile			quarter mile			half mile			one mile		
Variables	All Ages	Age < 8	Age > 8	All Ages	Age < 8	Age > 8	All Ages	Age < 8	Age > 8	All Ages	Age < 8	Age > 8
Age	0.117**	0.279**	0.151**	0.117**	0.280**	0.153**	0.117**	0.280**	0.153**	0.118**	0.279**	0.155**
Age Squared	-0.003**	-0.017**	-0.005**	-0.003**	-0.017**	-0.005**	-0.003**	-0.017**	-0.005**	-0.003**	-0.017**	-0.005**
Well-Child Visit	0.014+	0.019	0.007	0.014+	0.02	0.008	0.013+	0.018	0.008	0.013+	0.017	0.007
Fast Food	-0.134	-0.074	-0.109	-0.077**	-0.084	-0.038	-0.021+	-0.037	-0.012	0.015*	0.024*	0.003
Supermarkets	0.052	-0.169	-0.255	-0.046	-0.054	-0.096	0.028	0.044	0.042	0.01	0.028	0.043**
Conveniece Stores	0.009	-0.096	-0.004	0.029	0.024	0.011	0.004	0.036	-0.025+	0.013+	0.036*	-0.007
Trails	-0.557	-1.214	1.802*	0.014	-0.333	0.368*	0.04	-0.056	0.088	0.017	0.023	0.033+
Crime	-0.098	0.069	-0.186	-0.096*	-0.162*	-0.057	-0.050**	-0.088*	-0.023	-0.013	-0.031*	0.002
Baseball/Softball	0.081+	0.187*	-0.008	0.013	-0.006	0.026	-0.001	0.015	-0.011	-0.005	-0.013	0.008
Basketball	0.001	0.01	-0.035	-0.01	-0.007	-0.015	-0.003	-0.007	0.004	0.001	-0.002	0.004+
Family Centers	-	-	-	-0.812	-6.09	0.659	1.099	1.124	1.122	-0.818+	-0.184	-0.18
Fitness Areas	-12.278	-62.440*	25.365	-2.262**	-4.813**	0.651	0.095	-0.247	0.385	0.07	0.182	0.077
Football	0.433	0.507	-0.082	0.09	0.074	-0.007	0.104**	0.116+	0.015	-0.006	-0.001	-0.01
Kickball	-0.322**	-0.416*	-0.049	-0.084*	-0.103	-0.046	0.008	0.04	-0.047*	-0.004	0.013	-0.048**
Playgrounds (no equip.)	-0.28	-1.434	2.643**	0.08	-0.571	0.464*	-0.007	-0.478*	0.296*	-0.056	-0.112	-0.013
Playgrounds (with equip.)	0.516	1.365	-0.257	0.851**	1.291**	0.393	0.416**	0.706**	0.072	0.029	0.113	-0.037
Pool	-1.49	-3.33	-2.08	-1.149	-2.097	-0.169	-0.147	-0.12	-0.949	0.458	1.228+	-0.205
Soccer	-0.067	0.042	-0.133	0.016	-0.059	0.024	0.015	0.027	0.003	0.015*	0.026*	0.006
Tennis	-0.014	0.004	-0.008	-0.003	0.014	-0.027*	0.005	0.014	-0.003	0.005	0.001	0.006
Track and Field	8.515	12.495	-	-0.076	0.193	-0.029	0.156	0.364+	0.143	0.091+	0.201*	0.073
Volleyball	0.09	0.113	-0.904**	-0.018	-0.073	-0.074	0.038	0.051	-0.021	-0.013	-0.026	-0.030+
Constant	-0.218	-0.622+	-0.343**	-0.174	-0.497**	-0.369**	-0.310**	-0.739**	-0.373**	-0.304*	-0.844**	-0.440**
N (observations)	98541	50521	47952	98541	50521	47952	98541	50521	47952	98541	50521	47952
N (child/address)	54823	30304	26615	54823	30304	26615	54823	30304	26615	54823	30304	26615
R-squared	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02

Standard errors in parentheses
+ significant at 10%; * significant at 5%; ** significant at 1%

Endogeneity of amenity location:

The sharp differences in significance levels and signs between the OLS and FE regressions raise questions about the endogeneity of the location of fast food restaurants.

Figure 4
Fast Food Locations and Changes in Indianapolis



Recall that we defined the fast food establishments as belonging to chains with national advertising. These high-volume restaurants are clearly concentrated on the major surface roads leading in and out of the city center. For example, the two roads at the bottom center of the map with many fast food locations are the main commuting routes to and from downtown for residents living in south side suburbs. Traffic flow data would be useful as an instrument to predict fast food location. Unfortunately, public traffic flow data are outdated and have limited and highly-uneven coverage.

The supermarkets, shown in the map in Figure 5, are also located primarily along major streets. The difference between the supermarkets and the fast food restaurants is a relative dearth in the inner city (the poorest area). The fast food restaurants are well represented in the inner city.

Figure 5
Supermarket Locations and Changes in Indianapolis

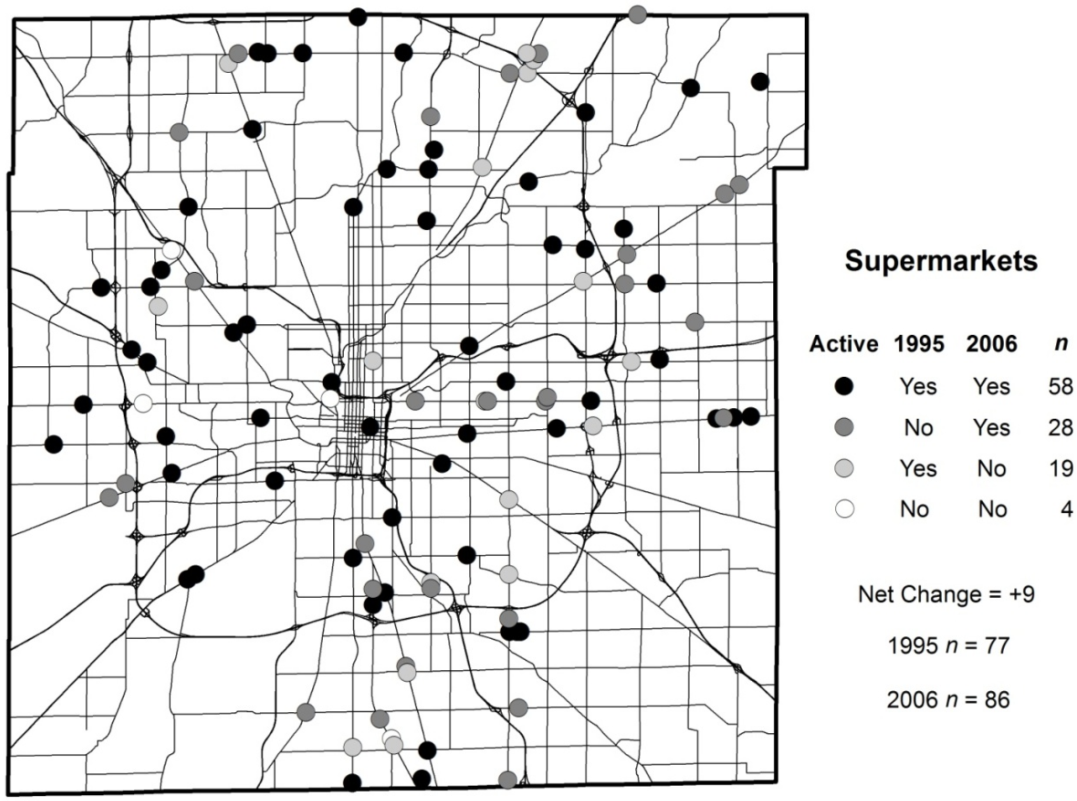


Figure 6
Limited-Service Restaurant Locations and Changes in Indianapolis

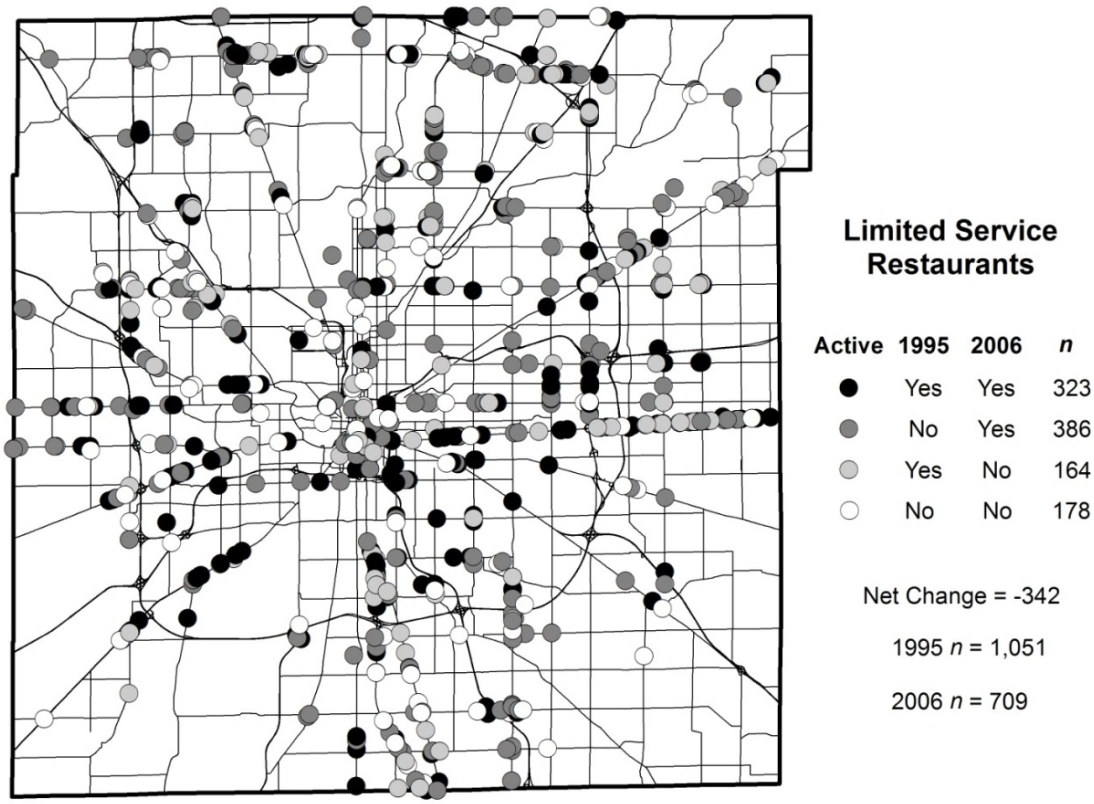


Figure 7
Convenience Store Locations and Changes in Indianapolis

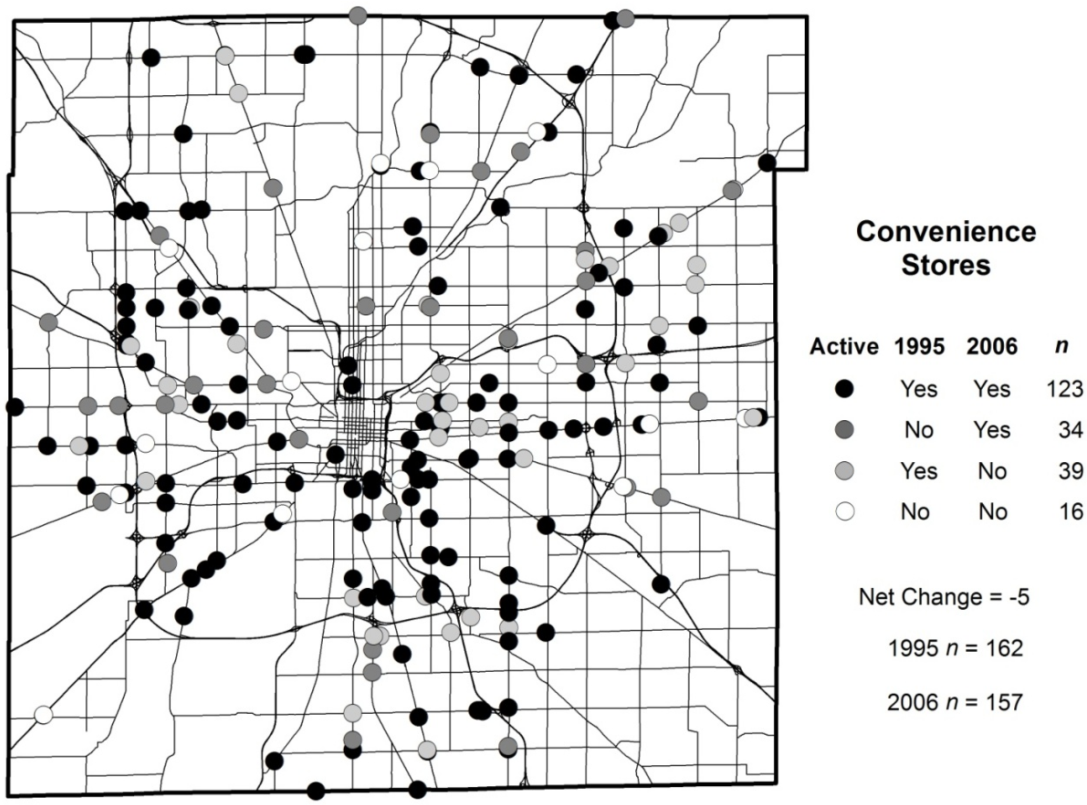


Figure 6 and 7 depict locations and changes of limited-service restaurants and convenience stores. The southwest and southeast corners of the county are still largely rural. Other than in those undeveloped areas, there are limited-service restaurants and conveniences stores widely distributed across the county.

One means of addressing the endogeneity of amenity locations is to check whether the children living near future locations differed in terms of bmiz trends from the children who will not have the same type of amenity move near them. To test whether the location of new amenities is related to trends in children's weight, we regressed children's weight prior to the arrival of new amenities on the indicator of whether the new amenity locates next to the child in the future. We looked at differences between average *z*score of children's BMI as well as differences in time trends of *z*scores of children's BMI. Table 7 shows these results. The positive or negative symbol represents the sign of the coefficient on the future amenity indicator and of the interaction term of that indicator with the time trend variable, provided they are significant at the 5% level. The results show that only the location of supermarkets is preceded by differences in children's weight, as well as differences in trajectories of children's weight gain.

The positive trends observed at all four buffers for supermarkets undercut the claim that their new locations were selected independently of the prior changes in children's bmiz.

Thus, the FE results that supermarkets increase children's weights at the half-mile buffer are suspect. Fast food restaurants appear to be entering areas with higher child bmiz values and higher rates of child obesity, at least for the quarter- and half-mile buffers. However, these initial differences in levels may not predict the change that will occur after the arrival of a new fast food restaurant. Our assumption is that gains in bmiz will be the same for a given stimulus over a broad range of initial bmiz. We believe having the same trend in bmiz for children with and without future fast food gives us an unbiased estimate of the response to the arrival of an amenity. Our negative coefficient quarter-mile fast food result along with no difference in bmiz trends prior to arrival of the fast food align with the Anderson and Matsa result cited above. While fast food meals are notoriously calorie-dense, they can have no bmiz effect if children or adults offset the additional calories by eating less food at other meals or by eating fewer meals. Alternatively, there may be so much fast food in Indianapolis that any child so inclined could readily access a fast food restaurant whether one was within a tenth mile or a quarter mile or not. Either way, as a means of attacking the child obesity epidemic, the Los Angeles freeze on new fast food restaurants mentioned in the introduction may be misplaced.

Fast food and supermarkets are the highest-profile amenities. Of the remaining 60 trend terms (15 amenities times 4 buffers), 11 are significant. These are scattered such that none of the other amenities has a significant trend term for more than one buffer. Either the locations of these remaining amenities are not being selected on the basis of differences in bmiz trends, or we do not have enough data to detect differences in bmiz trends.

Table 7
Signs of Significant Coefficients for Future Amenities

		Radius			
		.1	.1 - .25	.25 - .5	.5 - 1
Fast Food Restaurants	BMIZ		+	+	
	Trend				
Trails	BMIZ		+		
	Trend			+	
Supermarkets	BMIZ		+	+	+
	Trend	+	+	+	+
Convenience Stores	BMIZ		+	+	
	Trend			+	
Parks	BMIZ	-	-	-	-
	Trend	+		-	-
Baseball/Softball Diamonds	BMIZ	-			+
	Trend				+
Basketball Courts	BMIZ				-
	Trend		+	+	
Family Centers	BMIZ				-
	Trend				
Fitness Centers	BMIZ				-
	Trend				+
Football Fields	BMIZ				
	Trend			+	
Kickball Diamonds	BMIZ		+		-
	Trend	+		+	
Playgrounds without equipment	BMIZ				
	Trend				
Playgrounds with equipment	BMIZ				
	Trend				
Pools	BMIZ		+		
	Trend	-			
Soccer Fields	BMIZ				
	Trend	+			
Tennis Courts	BMIZ			+	+
	Trend				
Track and Field	BMIZ		-		-
	Trend				
Volley Ball Courts	BMIZ				
	Trend		+		-

Conclusion:

Our first conclusion is that cross-sectionalresults differ dramatically from the FE results. We believe that the cross sectional results tell us more about who chooses to live near an amenity than what adding that amenity might do. In cross section, nearby (tenth-mile) fast food increases children's bmiz. Our cross section regression has controls for child's age, race, gender, mother's age at child's birth, mother's education, WIC eligibility, intention to breastfeed, and many neighborhood characteristics. These are as comprehensive a set of covariates as we have seen for child BMI regressions. Other study strengths include directly measured height and weight data for a large sample size that includes high proportions of African American and Hispanic children. Still, in the fixed effects framework, nearby (quarter-mile) fast food appears to reduce children's weights, with no difference in the trend of bmiz gain prior to the arrival of the fast food. While we doubt that fast food really reduces children's bmiz, the results of the fixed effects models cast doubt on the highly publicized policies to reduce fast food exposure as interventions for preventing obesity.

A second conclusion is that if the arrival of amenities (other than supermarkets) is unrelated to prior trends in bmiz, then there appears to be little in the way of surefire interventions for reducing children's bmiz, through either recreational amenities or food vendors. The best candidates appear to be fitness areas, kickball fields, and volleyball courts. Weight reductions for overweight children (defined as at the 85th percentile of the pre-epidemic distribution) in the range of 3 to 6 pounds, as estimated for 8 year-old boys for these amenities, would be valuable interventions.

Our results look at the short term. They look for bmiz responses within the year the amenity arrives. It may be that a recreational amenity does have a bmiz-reducing effect on nearby children if it is measured years after its arrival. However, we have few observations with long runs of time after the arrival of an amenity.

Our study examined associations between bmiz and proximity to amenities within four buffer distances. We used relatively-simple methods to measure spatial proximity – straight line (Euclidean) buffers. In future work we will explore more complex measures of proximity, including network buffers and travel time models that consider movement along street networks. This will allow us to test other specifications for built environment variables, including specific distances or travel times to individual amenities, average distance or time to the closest three amenities of a given type, and more general measures of accessibility to amenities.

A general assumption of our methods used in this paper is that proximity is a proxy for exposure to amenities. We don't have direct observational data on whether or not children and their families use (or are even aware of) the amenities we measured. In future prospective work, we hope to collect detailed observational data on spatial and temporal interaction with amenities through survey and GPS tracking. This may allow us to better infer causal effects of the built environment on children's weight.

NIH-funded R21 studies are meant to test the feasibility of a new research design. Our study demonstrates that it is feasible to collect detailed longitudinal data on selected components of the built environment surrounding the homes of a large sample of children in a metropolitan area. In total, it took our team about 20 months to assemble and clean the built-environment data used in the analytical portion of this study. As spatial information technologies continue to become more widespread and agencies (such as police, parks, and food safety departments) increasingly collect and organize data on amenities in forms that are easily extended to spatial analysis, it should be easier to extend the methods used in this study both spatially (to include larger populations in multiple cities) and temporally (to include longer-term longitudinal experiments). We plan to seek funding for a six-city extension of the present study. A six-fold increase in the sample size over different regions of the country would provide much more reliable results.

Further, our study demonstrates the benefits of an interdisciplinary team of economists, a physician, an urban planner, and geographers. It would have been impossible to assemble these data without the interdisciplinary collaboration.

Lastly, the present paper is our first effort in using these data. We mentioned earlier that our estimated effects were short term, specifically within a year, and that we intend to look for persistent effects from changing amenities. We also mentioned earlier that by looking solely at children at a fixed address who had changes in nearby amenities, we missed potentially useful information from children who moved toward or away from specific amenities. We concentrated on the stayers who gained or lost amenities because we thought that group was least subject to bias due to the endogeneity of amenity locations. We believe these data are rich enough to yield many more insights.

Bibliography:

(a) Anderson, Patricia M., Butcher, Kristin F: Reading, Writing, and Refreshments: Are School Finances Contributing to Children's Obesity?.Journal of Human Resources 2006; 41(3):467-494.

(b) Anderson, Patricia M., Butcher, Kristin F: Childhood Obesity: Trends and Potential Causes, The Future of Children. Childhood Obesity 2006; 16(1): 19-45.

Anderson, Michael, Matsa, David A.: Are Restaurants Really Supersizing America?, December 30, 2007, University of California Berkeley Working Paper.

Boone Janne E, Gordon-Larsen Penny, Adair Linda S, and Popkin Barry M: Screen time and physical activity during adolescence: longitudinal effects on obesity in young adulthood. International Journal of Behavioral Nutrition and Physical Activity 2007; 4: 26.

Bouchard C: Genetics of obesity: Overview and research direction. In The genetics of obesity, edited by Bouchard C, pp. 223-233. Boca Raton, 1994.

Birch LL, Fisher JO: Development of eating behaviors among children and adolescents. Pediatrics 1998; 101:539-49.

Bray, George A, Champagne, Catherine M: Beyond Energy Balance: There Is More to Obesity than Kilocalories. J Am Diet Assoc. 2005;105:S17-S23.

Brownson RC, Baker EA, Housemann RA, et al.: Environmental and policy determinants of physical activity in the United States. Am J Public Health 2001; 91:1995-2003.

Burke, Mary A,Heiland, Frank: Social Dynamics of Obesity. Economic Inquiry 2007; 45(3): 571-91.

Burdette HL, Whitaker RC: Neighborhood playgrounds, fast food restaurants, and crime: relationships to overweight in low-income preschool children. Preventive Medicine 2004; 38:57-63.

Burdette, HL, and Whitaker, RC: A National Study of Neighborhood Safety, Outdoor Play, Television Viewing, and Obesity in Preschool Children. Pediatrics 2005; 116(3): 657-662.

Cawley, John,Meyerhoefer, Chad,Newhouse, David: The Impact of State Physical Education Requirements on Youth Physical Activity and Overweight. Health Economics 2007; 16(12): 1287-1301.

CDC, A SAS Program for the CDC Growth Charts, www.cdc.gov/nccdphp/dnpa/growthcharts/resources/sas.htm

Chou S, Grossman M, Saffer H:An Economic Analysis of Adult Obesity: Results from the Behavioral Risk Factor Surveillance System NBER Working Paper #9247, National Bureau of Economic Research. Cambridge, MA, 2002.

Chou, Shin-Yi, Rashad, Inas, Grossman, Michael: Fast-Food Advertising on Television and Its Influence on Childhood Obesity.NBER Working Paper No. 11879, December 2005.

Clement K, Ferre P: Genetics and the pathophysiology of obesity. Pediatr Res 2003; 53:721-5.

Consensus Panel: "Type 2 diabetes in children and adolescents." American Diabetes Association, http://care.diabetesjournals.org/cgi/reprint/23/3/381.pdf.

Cordain L, Miller JB, Eaton SB, et al.: Macronutrient estimations in hunter-gatherer diets. Am J ClinNutr 2000; 72:1589-92.

Corless J, Ohland G: Caught in the crosswalk: Pedestrian safety in California, 2001 [http://www.transact.org/ca/caught99/caught.htm].

Courtemanche, Charles: Working Yourself to Death? The Relationship Between Work Hours and Obesity. Working Paper, Washington University, St. Louis. (October 5, 2007)

Cressie, N, Chan NH: Spatial Modeling of Regional Variables. Journal of the American Statistical Association 1989; 84(406): 393-401.

Currie, Janet, DellaVigna, Stefano, Moretti, Enrico, Pathania, Vikram: The Effect of Fast Food Restaurants on Obesity, NBER Working Paper 14721, February 2009.

Day, Kristen: Active living and social justice: Planning for physical activity in low-income, black, and Latino communities. Journal of the American Planning Association 2006; 72(1): 88-99.

Dietary Reference Intakes for Energy, Carbohydrate, Fiber, Fat, Fatty Acids, Cholesterol, Protein, and Amino Acids (Macronutrients): A Report of the Panel on Macronutrients, Subcommittees on Upper Reference Levels of Nutrients and Interpretation and Uses of Dietary Reference Intakes, and the Standing Committee on the Scientific Evaluation of Dietary Reference Intakes, 2002.

DiPietro L, Mossberg HO, Stunkard AJ: A 40-year history of overweight children in Stockholm: life-time overweight, morbidity, and mortality. Int J ObesRelatMetabDisord 1994; 18:585-90.

Epstein LH, Paluch RA, Gordy CC, et al.: Decreasing sedentary behaviors in treating pediatric obesity. Arch PediatrAdolesc Med 2000; 154:220-6.

Estabrooks, Paul A; Susan Shetterly: The Prevalence and Health Care Use of Overweight Children in an Integrated Health Care System. Arch PediatrAdolesc Med. 2007;161:222-227.

Ewing R, Cervero R: Travel and the Built Environment: A Synthesis. Transportation Research Record 1780, 2001.

Foreyt J, Goodrick K: The ultimate triumph of obesity. Lancet 1995; 346:134-5.

Freedman DS, Dietz WH, Srinivasan SR, et al: The relation of overweight to cardiovascular risk factors among children and adolescents: the Bogalusa Heart Study. Pediatrics 1999; 103:1175-82.

Garn SM, Clark DC: Nutrition, growth, development, and maturation: findings from the ten-state nutrition survey of 1968-1970. Pediatrics 1975; 56:306-19.

Gerrior S, Bente L: Nutrient Content of the U.S. Food Supply, 1909-99: A Summary Report. U.S. Department of Agriculture, Center for Nutrition Policy and Promotion. Home Economics Research Report No. 55. 2002.

Glanz K, Lankenau B, Foerster S, et al.: Environmental and policy approaches to cardiovascular disease prevention through nutrition: opportunities for state and local action. Health Educ Q 1995; 22:512-27.

GortmakerSL, Must A, Sobol AM, et al.: Television viewing as a cause of increasing obesity among children in the United States, 1986-1990. Arch PediatrAdolesc Med 1996; 150:356-62.

Gortmaker SL, Must A, Perrin JM, et al.: Social and economic consequences of overweight in adolescence and young adulthood. N Engl J Med 1993; 329:1008-12.

Haas JS, Lee LB, Kaplan CP, et al.: The association of race, socioeconomic status, and health insurance status with the prevalence of overweight among children and adolescents. Am J Public Health 2003; 93:2105-10.

Hedley, AA, Ogden, CL, Johnson, CL, Carroll, MD, Curtin, LR, Flegal, KM: Overweight and obesity among US children, adolescents, and adults, 1999-2002. JAMA 2004; 291:2847-50.

Hill JO, Peters JC: Environmental contributions to the obesity epidemic. Science 1998; 280:1371-4.

Hogan JW, Tchernis, R: Bayesian Factor Analysis for Spatially Correlated Data, with Application to Summarizing Area-Level Material Deprivation from Census Data. Journal of the American Statistical Association 2004; 99(466): 314-324.

HOPS, Healhier Options for Public School Children, http://agatstonresearchfoundation.org/HOPS_Study_Preliminary_Results_HOPS_1_and_HOPS_2.pdf

Horgen K, Choate M, Brownwell K: Television and children's nutrition. In: Singer D, Singer J, eds. Handbook of children and the media. San Francisco: Sage, 2001:447-461.

Jeffery RW: Public health strategies for obesity treatment and prevention. Am J Health Behav 2001; 25:252-9.

Jeffery RW, Drewnowski A, Epstein LH; et al.: Long-term maintenance of weight loss: current status. Health Psychol. 2000;19(1)(suppl):5-16.

Kaushal, N: Do Food Stamps Cause Obesity? Evidence from Immigrant Experience.Journal of Health Economics 2007; 26(5): 968-91.

King AC, Jeffery RW, Fridinger F, et al.: Environmental and policy approaches to cardiovascular disease prevention through physical activity: issues and opportunities. Health Educ Q 1995; 22:499-511.

King AC, Castro C, Wilcox S, et al.: Personal and environmental factors associated with physical inactivity among different racial-ethnic groups of U.S. middle-aged and older-aged women. Health Psychol 2000; 19:354-64.

Kolata G, Thinning the Milk Does Not Mean Thinning the Child. New York Times February 12, 2006.

Kortt M, Baldry J: The association between musculoskeletal disorders and obesity. Aust Health Rev 2002; 25:207-14.

Kumanyika SK: Minisymposium on obesity: overview and some strategic considerations. Annu Rev Public Health 2001; 22:293-308.

L.A. Times: www.latimes.com/news/local/politics/cal/la-me-fastfood30-2008jul30,0,7844906.

Margetts B: WHO global strategy on diet, physical activity and health. Editorial. Public Health Nutr 2004; 7:361-3.

Mokdad AH, Serdula MK, Dietz WH, et al.: The continuing epidemic of obesity in the United States. Jama 2000; 284:1650-1.

Neff LJ, Sargent RG, McKeown RE, et al.: Black-white differences in body size perceptions and weight management practices among adolescent females. J Adolesc Health 1997; 20:459-65.

Ogden CL, Flegal KM, Carroll MD, Johnson CL: Prevalence and trends in overweight among US children and adolescents, 1999-2000. JAMA 2002; 288:1728-32.

Parnell K, Sargent R, Thompson SH, et al.: Black and white adolescent females' perceptions of ideal body size. J Sch Health 1996; 66:112-8.

Plantinga, Andrew J, Bernell Stephanie: The Association between Urban Sprawl and Obesity: Is It a Two-Way Street?,Journal of Regional Science 2007; 47(5): 857-79.

Popkin BM, Udry JR: Adolescent obesity increases significantly in second and third generation U.S. immigrants: the National Longitudinal Study of Adolescent Health. J Nutr 1998; 128:701-6.

Price R: Genetics and common obesities: background, current status, strategies, and future prospects. In Handbook for obesity treatment, edited by Wadden T, Stunkard AJ, pp. 73-94. New York, NY, Guilford Press 2002.

Quigley, Fran: Indianapolis is missing the bus: IndyGo is worst-funded system in Midwest, Nuvo 2003; www.nuvo.net/archive/2003/12/24/indianapolis_is_missing_the_bus.html

Sallis JF, Bauman A, Pratt M: Environmental and policy interventions to promote physical activity. Am J Prev Med 1998; 15:379-97.

Schadt EE, Monks SA, Drake TA, et al.: Genetics of gene expression surveyed in maize, mouse and man. Nature 2003; 422:297-302.

Snyder EE, Walts B, Perusse L, et al.: The human obesity gene map: the 2003 update. Obes Res 2004; 12:369-439.

Sobal J, Stunkard AJ: Socioeconomic status and obesity: a review of the literature. Psychol Bull 1989; 105:260-75.

Sorensen HT, Sabroe S, Rothman KJ, et al.: Relation between weight and length at birth and body mass index in young adulthood: cohort study. BMJ 1997; 315:1137.

Strauss RS, Knight J: Influence of the home environment on the development of obesity in children. Pediatrics 1999; 103:e85.

Strauss RS, Pollack HA: Social marginalization of overweight children. Arch PediatrAdolesc Med 2003; 157:746-52.

Tchernis, Rusty; Millimet, Daniel; Hussain, Muna: School Nutrition Programs and the Incidence of Childhood Obesity, Center for Applied Economics and Policy Research, Economics Department, Indiana University Bloomington, CAEPR Working Papers: 2007-014, 2007, 37 pp.

Wilfley DE, Stein RI, Saelens BE, Mockus DS, Matt GE, Hayden-Wade HA, Welch RR, Schechtman KB, Thompson PA, Epstein LH. Efficacy of maintenance treatment approaches for childhood overweight: a randomized controlled trial. JAMA 2007; 298(14):1661-73.

Wittels EH, Thompson S: Obstructive sleep apnea and obesity. OtolaryngolClin North Am 1990; 23:751-60.

Appendix on Photo Interpretation

Orthorectified aerial photograph mosaics were available for most study years. The primary exception was 1996, for which no photographs of Marion County were available. Small, scattered areas were missing from the 1995 photographs. Photographs were available for 1998 for most of the county. Owing to a problem with the initial flight for 1998, no photography was available for a narrow band of the county running north to south through the center. This area was reflown in early 1999 using the same techniques; the resulting photographs were treated differently in this study from the 1998 photographs, as well as from a complete set of photographs taken later in 1999 using different techniques.

The photographs varied greatly in quality; only the last four years were in color, and later years were generally of higher spatial resolution than earlier years, though the 1998 (and matching early 1999) photographs were significantly coarser than other years. Contrast was also starker and thus of lower quality in earlier years, particularly in 1995.

All photographs were provided to a team of photo interpreters in digital format. In one case, 2005, images were available from Indiana University's spatial data portal, representing the same original photography as the 2005 file photographs, but reproduced at higher resolution. Photographs were examined on computer display in ArcMap 9.2, generally at scales of 1:1000 to 1:2500. Accompanying this was a copy of the amenities database (described above in the section on data), in which interpreters were to save any changes.

The county was divided into interpretation areas, usually consisting of a linear strip half a mile wide, running north to south; each area was assigned to a particular interpreter, though much of the county was eventually analyzed by more than one interpreter. The tasks of the interpreter were two: first, to locate recreational amenities of the selected types and add them to the database (through heads-up digitizing), and second, to determine during which years each amenity was present. This information was recorded as attributes of the feature in the database, along with information on the type of amenity, and the source of the feature, whether a particular interpreter or one of the original files. If a previously-digitized feature was modified in shape, size, or location by an interpreter, that information was noted as well. If interpreters were unable to determine the presence of an amenity (owing to the absence of photographs), a no-data value of -9 was recorded as that year's attribute. Finally, features which lay on the border between one interpretation area and another were flagged with a special attribute, so that duplication could be avoided. As a quality check on individual interpreters, border features were to be digitized by *both* interpreters, and the results compared.

The study team decided to quantify each amenity type in a way judged most likely to capture the relative recreational opportunities that each provided, with a few practical constraints. In the case of standardized playing areas, such as tennis courts and football fields, a count of amenities was deemed appropriate. In the case of scalable amenities, such as swimming pools and playgrounds, the area of the amenity was deemed the best measure. The opportunity available to each child would be taken as the sum of these measurements, as they fell within a given distance of the child's home address. For example, if 23 m^2 of a swimming pool fell within a half-mile radius around the child's address, this 23 m^2 was added to the value of the child's swimming pool opportunity.

Guidelines for digitizing were as follows:

•For baseball/softball, basketball, football, kickball, tennis, track and field, and volleyball, the playing area was to be digitized, as marked where possible.

• Specific guidelines were: For baseball and softball, the boundaries of infield and outfield were to be digitized; where the outfield was unclear, an arc of radius about twice the size of the infield was to be digitized. For football, the field was to be digitized goal line to goal line. For kickball, the infield only was to be digitized. For volleyball, where markings are seldom present, an approximation of the playing area was sufficient.

• In the case of basketball, if no court were marked, a simple polygon around the hoop was to be digitized.

• Backyard amenities, specifically swimming pools and playground equipment, were to be ignored; the inclusion of all such amenities was deemed impractical. Beyond that, no distinction was made between public and private amenities, since the photography would not have informed us whether children could access the amenities or not. Private ownership, as might be determined from a plat overlay, would also not settle the question, as amenities owned by apartment complexes, homeowner groups, and private schools might well be accessible to the public.

• Tennis courts were to be digitized wherever found, to maintain consistency with the practice in creating the original file, and because these were relatively few and unambiguous.

• Equipment playgrounds with a mulched or sandy area surrounding the equipment were to be digitized to that area. In the absence of such an area, a convenient shape, a circle or rectangle, was to be placed around the equipment.

• Swimming pools were to be digitized to the water's area only; any previously-added pools in which the deck area was also included were to be modified.

• Family centers were to be digitized to the building's footprint; though these facilities were few and none additional identified during the process.

• As soccer fields are not always permanently marked and goals moved frequently as needed, interpreters were instructed to digitize the entire area which, in their judgement, was set aside for playing soccer.

• In the case of fitness, the entire area in which fitness activities takes place was to be digitized.

•Any areas where track or field events take place, including tracks, infields, or obviously-designated external areas, were to be digitized.

•In cases where a particular area is clearly used for more than one of the chosen activities, overlapping polygons were to be created, according to the previous guidelines.

Limitations on the final product:

• For amenity types that were to be quantified by count, interpreters were instructed not to correct minor inconsistencies in the original file, so long as general location and number were accurate. For instance, if a tennis court were digitized to its surrounding fence, rather than its playing surface, this was deemed sufficient. Thus, the inclusion or non-inclusion of marginal features within a buffer will be inconsistent by a few meters in the final data.

•While the quantification of playground equipment might be refined conceptually, none of these methods was practical for aerial-photograph interpretation. The footprint area of a jungle gym, for instance, might best capture the opportunity represented by it, but trials showed this to be impractical, given the presence of shadows and inadequate resolution.

• Playgrounds were to be quantified by area; but the area of playgrounds is difficult to interpret consistently. Hard-surface playgrounds are often not demarcated clearly, as they co-exist not only with basketball courts and kickball fields, but with parking lots. The presence of cars on a surface may be a temporary condition at the time the photograph was taken, which does not significantly alter the recreational opportunity in a longer timeframe. Playground equipment is often located in a mulched area, but this mulched area is not always consistent from one year to the next. Such changes in area, therefore, were to be disregarded, so long as the playground equipment remained.

• Even in the presence of quality controls, the quality of interpretation must vary substantially with the individual, and nine individuals contributed to the final interpretation.

Each interpreter’s completed work was selected from within his or her file; the areas covered by this work were assembled into a mosaic of recreational amenities. Border features were examined and redundancies removed, and any systematic errors discovered through the comparison were corrected; errors in naming were corrected, and any features marked as unknown were examined by a second interpreter, and either classified within one of the chosen types, or discarded. Finally, in those cases in 1996 and 1998 where no photographs were available, but where the preceding and following years matched in value, either both showing present or both showing absent, that value was substituted for the missing data. The four sets of Euclidean buffers used elsewhere in the larger study were intersected with the features in the recreational-amenities file.

We next performed a merger of all intersected vector features by original amenity, so that each resulting feature represented a single polygon resulting from the intersection of one buffer with one amenity. At this point areas in square meters were calculated for all features. For those features that were to be quantified by area, this area was substituted as the value for each year in which the original amenity was present. Two copies of the file were created; in one file, every missing value was substituted with 0, and in the other file, every missing value was substituted with -9999999. A dissolve was then performed on the intersected features in each file, preserving buffer identification but grouping by amenity type, and summing the values for each year.

The resulting values in each feature were taken, in theory, as a measurement of recreational opportunity, as available to the child living at the center of each buffer, sorted by amenity type, with a value for each year. In the file in which 0 was substituted for missing data, the final measurement would represent a minimum. In the file in which -9999999 was substituted, every measurement in which any component value had been missing would be negative (as a single value of -9999999 would be greater than any possible value within the largest buffer used in the study), thereby allowing identification of the uncertain quantities. The file with the minimum values was used for the regressions in this study.

Appendix on Land Use Variables:

This appendix describes the data created for a set of social and physical environmental variables for use in the child obesity research. Data are provided for quarter-mile and half-mile buffers surrounding the children's residences. The variables for the quarter-mile buffers end in *25* and the variables for the half-mile buffers end in *5*.

<u>Census Variables</u>

Population density and the proportion of the population African-American were created from the 2000 census block data from Summary File 1. The education and income variables were created from the census block group data from Summary File 3. Data from the surrounding counties were included, so there are no boundary issues near the border of Marion County.

Population density – popden25 and popden5

This is the gross population density in persons per acre. Block population density was converted to a grid theme using 50-foot grid cells (used in all of the data creation). The values are the means of the grid cell densities in the quarter-mile and half-mile buffers.

Proportion of the population African-American – prblk25 and prblk5

Block total population density and the population density African-American were converted to the grid cells, the means for the buffers were calculated, and these were divided to obtain the proportion African-American. Areas with zero population could not have a proportion calculated. This affected the variable *prblk25*, which has one missing value.

Proportion graduated from high school – prhs25 and prhs5

This is the proportion of the population aged 25 and over who have graduated from high school. The densities of the population aged 25 and over and the numbers graduated from high school were converted to the grid cells, the means for the buffers were calculated, and these were divided to obtain the proportion graduated from high school. Areas with zero population aged 25 and over could not have a proportion calculated. This affected the variable *prhs25*, which has one missing value.

Proportion graduate from college – prcoll25 and prcoll5

This is the proportion of the population aged 25 and over who have graduated from college. The densities of the population aged 25 and over and the numbers graduated from college were converted to the grid cells, the means for the buffers were calculated, and these were divided to obtain the proportion graduated from college. Areas with zero population aged 25 and over could not have a proportion calculated. This affected the variable *prcoll25*, which has one missing value.

Median family income – faminc25 and faminc5

This is an estimate of the median family income for the buffers. The block group median family income was converted to the grid cells, and the means for the buffers were calculated. Areas with no families and no median family income reported did not have values. This affected the variable *faminc25*, which has one missing value.

Road Network Variables

The planning literature suggests that greater density and interconnectedness of the road network (indicated by the density of intersections or nodes) should be associated with greater pedestrian use and physical activity. Data creation begins used the Etak road network for 2000. This was selected because it represented the network during the middle of the period for the obesity data, which seemed more reasonable than using the current road network. Limited-access highways and road segments associated with the interchanges were deleted from the network as these would not contribute to pedestrian activity. Data from the surrounding counties were included, so there are no boundary issues near the border of Marion County.

Road network density – rdlen25 and rdlen5

This is the sum of the length in miles of the road segments with their centroids within the buffers. The road segments were converted to a point layer with the line centroids, this was converted to the grid cells, and the results were summed for the buffers.

Number of nodes – nodes25 and nodes5

The layer of road features was converted to a point layer of nodes. Dangling nodes and pseudonodes were deleted from this layer, leaving those nodes that represent intersections between roads. This layer was converted to the grid cells, and the count of the number of nodes in the buffers was obtained by summing those results.

Land Use Variables

The planning literature suggests that mixed land use, especially the presence of commercial land uses, should be associated with greater pedestrian use and physical activity. A parcel-based layer of land use in Marion County in 2002 from the Indianapolis Department of Metropolitan Development was used. Areas of streets and roads were not included in the delineation of land use. This dataset covered only Marion County, so the proportions of land use near the boundaries reflect only land use within Marion County.

Proportion land use commercial

This is the proportion of the classified areas of land use (not including areas of roads) that were classified in one of the commercial (retail and office) land use categories. The land use data were converted to the grid cells with values of 1 if commercial, 0 if other land use, and no data if road area. The means of these values were determined for the buffers to provide the proportion commercial.

Proportion land use residential

This is the proportion of the classified areas of land use (not including areas of roads) that were classified in one of the residential categories. The land use data were converted to the grid cells with values of 1 if residential, 0 if other land use, and no data if road area. The means of these values were determined for the buffers to provide the proportion residential.